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Céline Rozenblat
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Methods for Multilevel Analysis and Visualisation of Geographical Networks

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Methods for Multilevel Analysis and Visualisation of Geographical Networks

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Preface

During the last decade, research on networks has developed rapidly in most scientific disciplines. Several factors explain this sudden interest, which has led to an exponential growth in the dedicated literature from the natural to the social sciences. Technical advancements have certainly facilitated this exceptional development. Although graph theory and analytic concepts about graph structure and dynamics did exist before the 1960s (Berge, 1958), the processing of large connectivity matrices remained limited for a long time by the insufficient power of computers. On the empirical side, relational data were scarce or were very expensive to construct. Indeed, the significant increase in the speed of computing that has occurred recently as well as the proliferation of new types of empirical relational data that have been made viable because of the Internet have boosted the creation of powerful tools for network analysis. In parallel, many important modern societal trends have emphasized the need for developing adapted concepts and theories to help understanding these trends, which include the globalization processes that mainly operate through networking relationships; the trend toward decentralized management, the trend toward more participative or cooperative organization than the classical hierarchies; and the unfolding of individual connections through increasing mobility and educational level of population accompanied by various communication tools, to the extent that social networks are now considered to be a major source of "big data".

Among all of the social sciences, geography is well advanced in analyzing and modeling networks. Physical networks, such as the hydrographic, transportation or infrastructure networks, are part of the structuring of the geographical space. The descriptions of these networks were formalized decades ago, for instance, by models such as Horton's laws or accessibility and connectivity indices (Garrison, Berry, Marble, Nystuen, & Morrill, 1959). Thereafter, exchanges of goods, people and information between places were considered to be a possible fundamental explanation of geographical diversity leading to a conception of geography as a science of "spatial interaction" (Ullmann, 1954). Theoretical and operational models of spatial interaction were already well established in the 1970s (Wilson, 1970). The gravity model representing trip distribution was even considered to be "the first law of geography" (Tobler, 1970).

However, until recently, there were few methods for fully exploiting the vision of geographical space as a relational space, defined according to the many possible configurations by the interactions between georeferenced entities. Introducing that vision is the most salient aspect of this book. This book develops an integrated set of theoretical interpretations and adapted methods for exploring a variety of networks. These original and reproducible methods were elaborate, due to a long and involved interdisciplinary collaboration, between a laboratory of data processing and a network of geography researchers. A geographer, Céline Rozenblat, and a computer scientist, Guy Melançon, together developed a theoretical conception of geographical networks produced by dynamic processes in complex systems. They also conceived and adapted methods and software for visualizing the specific configurations of relational spaces that are operating at different scales of analysis within these networks. These scholars both succeeded at stimulating interest and animating a group of scientists from Canada, France and Switzerland, who worked together since 2005 when the SPANGEO program was initiated.

A major achievement of this project is the continuous development of the TULIP software, which is dedicated to the visualization of large networks according to the measurements of centralities and proximities in a variety of ways. As the networks analyzed by the geographers connect located objects, they are often rather strongly structured by the constraints that the distance exerts on the practices of communication or displacement. Explaining their structure implies combining the identification of topological organization (for example, small world configuration) and measurement of metrics on weighted interaction flows (representing, for instance, group cohesion). Moreover, as urban centers are the places where social interaction organizes in networks on many scales, from daily commuting patterns to worldwide air transportation system, there was a specific need for integrating within the measurement procedure—the hierarchical structure of urban systems that guides the many patterns of socio-spatial interaction. In addition to the usual methods for detecting communities within the network through various clustering methods, the TULIP software allows for a multi-level analysis of connections that are considered both at the intra-urban and the inter-urban level. This component is especially useful, for instance, in applications to urban economy when exploring the diversity of linkages among firms or among scientific researchers inside—as well as between—cities. This type of tool opens the door to a more specific appraisal of the so-called agglomeration economies, which may in fact represent "network effects".

Thanks to the efforts of the SPANGEO interdisciplinary group, we warmly welcome the novel feasibility of approaching the geographical space as a relational space. In the contemporary expansion of methods for network analysis, too many workers are satisfied with implementing standard algorithms or measurements on data files that are collected quickly, which yields results that are trivial or are difficult to interpret. This type of data appraisal was not followed in this work. Instead, this work proposes a method that fully integrates geographical theory with topological analysis, providing relevant measurements of centralities and proximities inside a method of visualization. Historically, geographers have used the integrative power of eyesight to envision the peculiarities of landscapes and places, constructing maps for encoding the accumulated knowledge from this process. It is now time to integrate sophisticated visualization tools in the cognitive elaboration of models and theories of spatial interaction that are occurring within the complex geographical systems and, in the process, continuously reshaping them.

Paris, France Denise Pumain
December 2012

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Contents

Chapter 1
Introduction

Céline Rozenblat and Guy Melançon

Geography is primarily concerned with society in space. Places are locations that interact through many types of flows: people moving to a different town or commuting between home and the workplace to benefit from services and to socialise; airplanes and ships travelling varying distances through webs of corridors; goods being traded; and information and financial flows that govern the spatial division of labour and organise companies into a complex hierarchies of subsidiaries. The interaction of these flows with a territory's inherent constraints and dynamics reveals the individual and collective goals that motivate these flows. The heterogeneity of social space, which is produced by unequal resources and the spread of wealth, as well as asymmetrical spatial relations, creates a "structural duality", due to continual trade-offs between structure and dynamics (Giddens, 1984). Dicken, Kelly, Olds, and Yeung (2001) claim that social networks are simultaneously structural and relational: they are structural because they are composed of established networks, such as infrastructure networks or networks of forces, and they are relational because they link agents – institutions, objects and knowledge, as well as individuals – across a wide variety of domains (Latour, 2005; Monge & Contractor, 2003). Many network interactions involve exchanges of information and human energy-producing power (Castells, 2009; Raffestin, 1980) that intertwine, nest and overlap with each other (see Fig. 1.1); these exchanges may exhibit cooperation, competition or both in "coopetition" (Badaracco, 1991; Doz, Santos, & Williamson, 2001).

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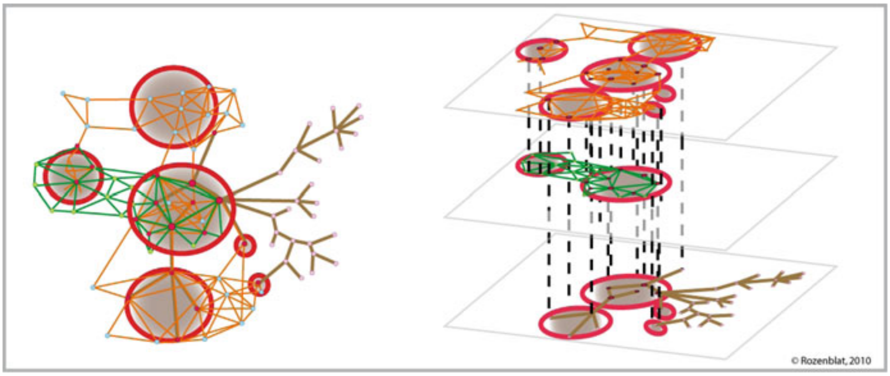

Fig. 1.1 The city as the connector of multiple networks

Thus, cities can be considered to be “connectors” that favour the emergence of new links and maximise interaction, and a city’s wealth depends on the heterogeneity that this valuable combination creates (Allen, 1999; Castells, 1996; Jacobs, 1969). Each type of network develops its own particular rules, regulations, conventions and values (Castells, 2009; Storper & Salais, 1997; Uzzi, 1997).

From a geographical perspective, the assumption that transformations of places strongly depend on their components’ internal and external relations with other places makes the positions of places in networks at different geographical scales crucial. Geographical interactions can be studied through networks that are represented as graphs. To date, most geographical network studies have been based either on “gravitation models” (Wilson, 1967) or general measures of graph connectivity or accessibility (Kansky, 1963). Graph theory – in particular, Watts’ small-world networks model (Watts, 1999) – can contribute to this research area and enrich spatial analysis by complementing systems theory.

Through graph theory, network analysis has also been associated for a long time with sociology (Freeman, 2004). Graph visualization was employed much earlier than is typically reported. Freeman identified kinship trees (Morgan, 1851) and simple graphs of two-step marriage prohibitions (Macfarlane, 1883) as seminal graphical representations. Hobson’s (1909) study of the interlocking directorates of the De Beers and Rand Mines industry in South Africa was the first example of two-mode data collection (Hobson, 1909).

Freeman (2004) noted that these pioneers were followed by a succession of twentieth-century schools that incorporated new issues and methods into the study of social networks – among them, Lund University’s leading geographer, Hägerstrand.His approach to spatial diffusion (Hägerstrand, 1952), which assumed that the social network acted through space and time, highly influenced structural approaches to geography in the 1960s(Berry, 1964; Dacey, 1964; Garrison, 1960; Garrison, Berry, Marble, Nystuen, & Morrill, 1959; P. Gould & White, 1974; Tobler, 1965). However, Freeman criticised the lack of communication between social geographers and other social scientists that prevented the exchange and diffusion of ideas between these scientific communities. Similarly, many researchers in sociology, mathematics and physics, such as Rashevsky, Landau, Landahl, Lazerfeld, Merton, Moreno, and White in sociology and Erdős, Rényi, and Rapoport in mathematics, continued to develop the field of network analysis to evaluate network structure and the relative position of different network nodes. However, their structural network theories exerted little influence on research in social geography and spatial analysis, which focused investigations at the territorial scale (Chorley & Haggett, 1969).

Networks, which are organised through both direct links and indirect paths, induce topological proximities that simultaneously integrate spatial, social, cultural and organisational dimensions. Although the spatial systems approaches that emerged in the 1970s and the new paradigms of the 1990s have increasingly examined networks in which the "space of flows" interacted with the "space of places" (Castells, 1996), the framework guiding empirical studies of "networks in spatial systems" continues to lack relevant tools and concepts.

Network synergies based either on the similarities or complementarities between and within cities create specialised and relatively stable proximities between these entities (Powell, 1990). Interrelations between geographical levels of organisation also provide information regarding the equilibrium or disequilibrium of the territories that emerge at different geographical scales. From a geographical perspective that focuses on spatial interactions, the concepts and methods of the small-world model are particularly relevant because these interactions can be described and studied using large volume exchange and similarity matrices.

To the best of our knowledge, the field of geography has not employed this type of empirical model, which integrates a "network theory" approach with specialised methods. This perspective is based on Small-World Theory (Sect. 1.1 below), Scaling laws (Sect. 1.2), and multilevel approaches (Sect. 1.3), which lead to the multiscale (Sect. 1.4) and multidimensional (Sect. 1.5) analyses that are presented in this volume.

1.1 "Small-World" Networks

Networks develop privileged links between subset of nodes that subsequently are distinct from other nodes, while the network globally establishes a "small-world" web. This "small world" approach first appeared in the Hungarian writer Karinthy's "Chain-links" story, which described a fictional world in which all individuals were connected with each other through five acquaintances (Karinthy, 1929, as cited in Newman, Watts, & Barabasi, 2006). The Milgram experiment, which involved sending a document from a random panel of "starting persons" to a "target person", empirically evaluated the "six degrees of separation" concept (Milgram, 1967; Travers and Milgram, 1969) and was inspired by Pool and Kochen, who addressed this problem in a 1958 working paper that was not published until 1978 (Pool & Kochen, 1978, cited in Newman et al., 2006). The "small world" model was explicitly reintroduced by Watts in the 1990s (Watts, 1999; Watts & Strogatz, 1998). Pred (1974, 1977) identified the potential consequences of the structural properties of these networks for geographical places, particularly for cities, which accentuate "small world" structures in virtue of internal connectivity and interurban channels. The organisation of the overall society into a "space of networks and space of places" (Castells, 1996) create complex systems of "multiterritories" (Hassaert da Costa, 2004) with properties that exhibit multilevel, multiscale and multidimensional characteristics.

1.2 Scale-Free Networks

A multi-territory is a system of interconnected territories. However, every territory does not exhibit the same level of connection and integration within the system because the hierarchy is based on past uneven diffusions and new diffusions of innovations. Cities with established connections to multiple networks are more likely to attract new connections, as demonstrated by Batty's simulation (2006) of the formation of urban systems. Batty found that preferential attachment provided a better explanation for the formation of urban system hierarchies, which conform to Zipf's law (1949) rather than to Gibrat's "law of proportional effect" (Gibrat, 1931; Guerin Pace, 1995; Pumain, 1982). Airline networks illustrate this process: cities of secondary importance attempt to become airline hubs to more rapidly develop links to the principal worldwide network (Amiel, Melançon, & Rozenblat, 2005; Guimerà, Mossa, Turtschi, & Amaral, 2005).

The scale-free model describes the distribution of networks as a type of power law "because a power law is the only distribution that is the same whatever scale we look at it on" (Newman, 2005, p. 334). In the same paper, Newman noted that "'Zipf's law' and 'Pareto distribution' are effectively synonymous with 'power-law distribution'" (p. 327). Newman found that although the Yule "richer-get-richer" effect continued to explain power-law distributions (Simon, 1955; Willis & Yule, 1922; Yule, 1925), it also could reflect processes of self-organising systems and critical phenomena. The power law effect is estimated by two kinds of adjustments: the log-log distribution of the cumulative frequencies of a variable, which is commonly termed a "power law distribution", or the interaction of the log-distribution of a variable with the log-distribution of another variable describing the general size of the system, which is termed a "scaling law distribution", which characterises certain functions or specific phenomena based on cities' populations (Pumain, 2006).

Although physicists have proposed a single "universal" model, empirical studies reveal many different cases and interpretations (Newman, 2005). For example, three classes of "small-world" networks have been identified based on their adjustments of "power law distributions" (Amaral, Buldyrev, Havlin, Salinger, & Stanley, 1998), and "Apollonian networks" specifically describe networks as simultaneously scale-free, ultra-small-world, Euclidean, matching and space-filling (Andrade, Herrmann, Andrade, & Da Silva, 2005).

For urban systems more generally, the process implemented at the level of actors and organisations is primarily responsible for establishing the urban hierarchy. The hierarchy is not unitary but is composed of multiple subsystems that are simultaneously interwoven at different thematic and specialised levels of geographical space (Batty, 2006; Dicken, 2011; Rozenblat, 2007).

1.3 Multilevel Networks

Social networks are multilevel because different levels of aggregation allow the emergence of collective processes. Regardless of their spatial scope, networks are created, maintained and destroyed by individual actors or organisations that deploy assets and relationships to consolidate or improve their position in a space that is structurally identified and perceived at different spatiotemporal scales (Pumain, Paulus, Vacchiani-Marcuzzo, & Lobo, 2006). Due to the immediacy of access (within timespans of an hour), these networks rely on local territories – cities – from which they extract, exchange and expand human, material and informational resources to varying degrees (see Fig. 1.2).

As Pumain et al. (2006, p. 172) note:

> [N]ew properties emerge and characterize the city as a collective entity. Some of these new properties can be directly related to the intention of some institution, but most of the time they are the unexpected (and sometimes unwanted) result of collective interaction.

The city operates at an intermediate level in the organisation of societies, which Pumain (2006) termed the "meso level" (see Fig. 1.2). The intermediate level catalyses the social system daily on a local scale in a self-organising fashion (Batty 2005, 2006; Pumain, 1997; Pumain, Sanders, & Saint-Julien, 1989; Wilson, 2000). These places, which exhibit "immediacies of access" in interactions at the regional, national, continental or global level, due to actors' competitive or collaborative global strategies, comprise the total urban system that constitutes the macro level (Berry, 1964; Pred, 1977; Pumain et al., 1989; Sanders, 1992). This macro level provides feedback to the meso level that integrates the inner city's networks into larger interurban networks. However, the initial power belongs to individual micro level actors who create, maintain or destroy social and economic networks, although this process operates under macro and the meso-level constraints despite bottom-up feedback effects.

The "small-world" network approach identifies network components, termed "clusters", that are denser and more cohesive than the entire network (Barabasi, 2002; Barabasi & Albers, 1999; Newman et al. (2006); Watts, 1999; Watts & Strogatz, 1998). Clusters not only exhibit a high level of dependency between individual components but also a low level of "vulnerability" in networks that contain many redundancies (Burt, 2000, 2005). Thus, networks organise new topological "proximities" through direct links and more indirect pathways that are simultaneously spatial, social, cultural and organisational. Geography incorporates economic and

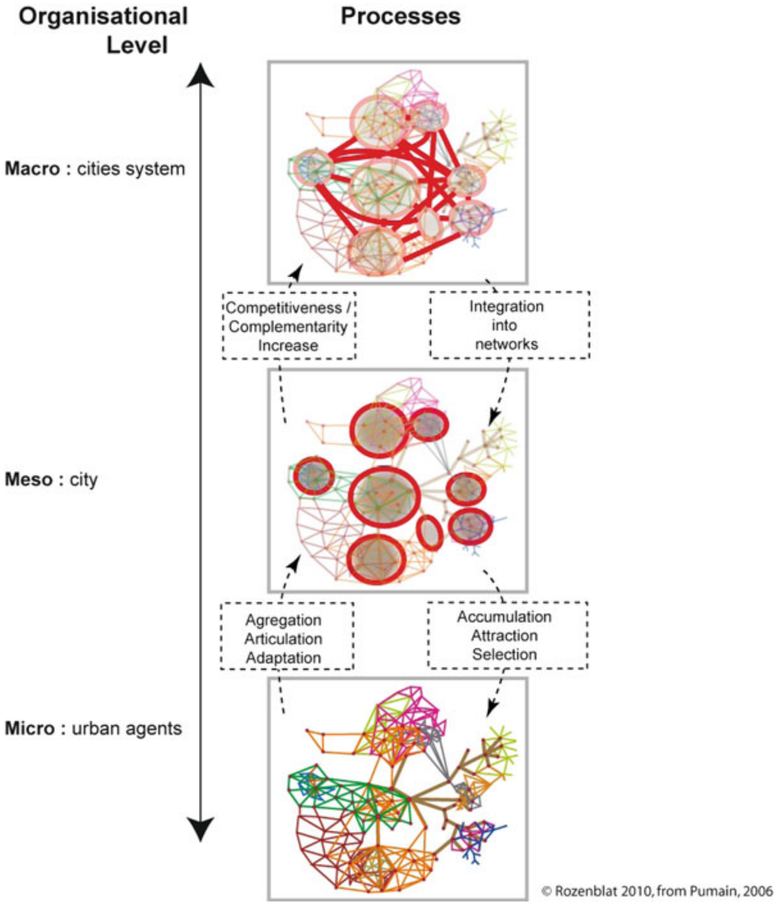

Fig. 1.2 The multilevel organisation of cities

social phenomena through the powerful and extremely relevant notion of level. Social relations naturally contribute to multilevel network dynamics. Although the view that the population dynamic simultaneously acts at the individual and group levels is plausible, formulating and validating a multilevel model is a painstaking endeavour. From the computer science perspective, the "level" concept provides strategies for downsizing data and potential methods for handling extremely large datasets. Modelling networks and flows as weighted graphs involves the use of graph theory, which transforms a multilevel network into nested subgraphs. Actors or entities interacting at a lower level establish higher-level entities that interact with each other, and flow exchanges at lower levels establish higher-level flows.

Incorporating cities into multilevel networks appears to have occurred not only in the field of transportation but also in the area of social and organisational networks (Dicken, 2011; Grabher, 2006). Although agent networks transcend the limitations of geographical scales (Castells, 2000), organisational levels of the "global commodity chain" are currently transforming from local to worldwide scales (Whitley, 1998).

1.4 Multiscale Networks

The multiscale analysis and visualisation of graphs enhances the study of networks. A careful visual analysis of the ways in which networks link similar actors provides insight into the reinforcement of social proximities, specialisations and segregations, as well as the extent to which transportation, communication, social and economic networks increase the anisotropy of space.

These networks thus produce a multiscale system. Although Ohmae (1990) claimed that multinational corporations develop within homogeneous and open territories, multiscale analysis reveals that these firms transversally weave together a system of potentially overlapping territories with their own rules and regulations. The structure of the "transnational field", which continues to be strongly influenced by the "international field", still depends on "the exchange rates, labor and fiscal regulation, those 'externalities' of which the company can take advantage, and the size and quality of the market" (Dollfus, 2001, pp. 104–105). From this perspective, the continental level increases its cohesion through the creation of free-trade zones that reinforce continental systems (Ohmae, 1995; Pomfret, 2007; Rozenblat, 2004; Rugman, 2001; Yeung, 2002), although it is not the only level from a multidimensional perspective.

Similarly, intense economic specialisation creates groups of cities that are increasingly interrelated – a tendency that is reinforced by "poles of excellence" or "poles of competitiveness" policies. The most striking example is financial specialisation, which has created a "global city" linking New York, London and Tokyo (Sassen, 1991). The financial capitals of the world link themselves to each other either directly or indirectly by forming specialised and/or geographical subgroups.

"Relay" cities provide "mandatory pathways" between these ensembles of highly interlinked cities. For example, national capitals host the national head-offices of the foreign subsidiaries of multinational corporations that, in turn, invest in businesses or organisations elsewhere in the host country. This situation is also observed for continental centres at a continental level (Alderson & Beckfield, 2004; R. Gould & Fernandez, 1989; Rozenblat, 2004; Rozenblat & Pumain, 1993, 2007; Rugman, 2001). Personnel meetings are often held at these "intermediate" head-offices. At the city level, capitals serve as "bridges" to other national cities; for example, capital cities provide preferred locations for representational offices (e.g., Brussels in Europe). Through this role of "display relay" to the country's other cities, proportionally more relevant relationships – upstream and downstream as well as national and international – are concentrated within the capital city. Serving as a "relay" or "bridge" provides the capital city with better access to the entire network, as well as increased control over information transfers (Burt, 2005). Additionally,

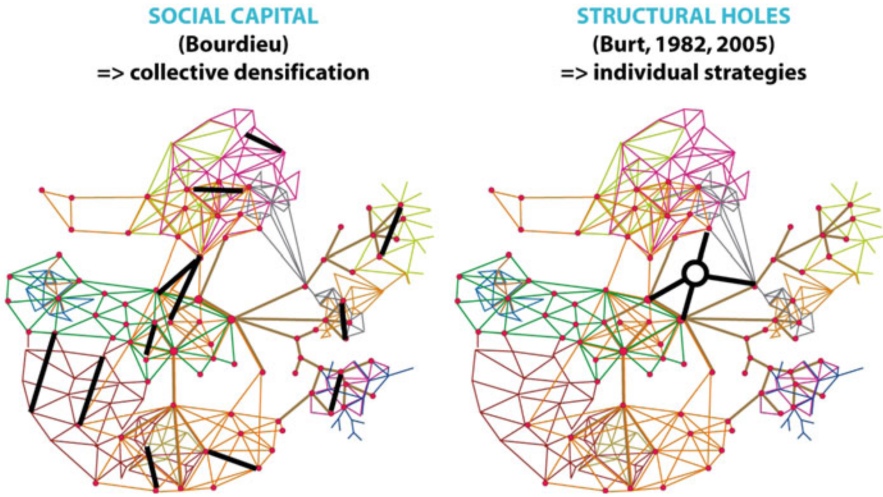

Fig. 1.3 Structural holes opposing social capital reproduction

the network positions of cities that share similar attributes of "dependency" with regard to "relay" cities display "equivalent" characteristics. Each "subgroup" maintains the hierarchy of cities' levels of centrality in the network, while other cities remain peripheral and are attached only indirectly to the network through their connection to participating cities. The recent reinforcement of the centrality of European national capitals reflects this process (Rozenblat, Bohan, & Benet, 2008; Rozenblat & Cicille, 2003).

Adopting sociologists' argument, we can claim that this cumulative process of concentration reinforces the social capital of large cities at the micro level (Walker, Kogut, & Shan, 1997; see Fig. 1.3).

Following Walker et al. (1997), we claim that Burt's "bridges" (1992, 2005) could be distinguished from places that "reproduce social capital" (Bourdieu, 1980) because they are places where nobody is located; this distinction focuses on the "structural holes" that individual actors might exploit to obtain a competitive advantage over other cities located in the same places. These places might generate network innovation by developing new kinds of spatial or social organisations that are disconnected, at least initially, from the dominant networks (Burt, 2005).

1.5 Multidimensional Networks

Innovative networks also appear at the crossing of different networks, which creates shared synergies. Differences between networks can be found in the endogenous network structure, as well as in the exogenous variables characterising the network. For example, the economic dimension of the network is composed of three levels, which Capello & Rietvelt (1998) have defined as the network itself (micro level), its economic relationships (the meso level) and the urban or regional organisation as a whole (the macro level). Thus multiple dimensions – each consisting of several levels – contribute to the development of networks. Any account of the spatial dimension of networks must consider these other dimensions. For example, in the "Global Commodity Chain", Gereffi (1996) identified four major dimensions that determine the distribution of functions and forces between different production units that are often distant from each other: the input-output economic structure of production, services and resources; the governance structure; the differentiated spatial field; and territorialised institutions. In a territorialised approach, the spatial and institutional dimensions are incorporated in the single dimension of the territory. This system posits three interdependent dimensions: corporate governance; the economic system in which it functions; and the territory that produces it (Dicken & Malmberg, 2001; Rozenblat, 2007). This three-dimensional system particularly applies at the urban system scale because the relational properties of amplitude, connectivity and diversity provide the variety, flexibility and stability that networked businesses require (Camagni, 1999).

1.6 Inherent Spatial Properties of Networks: The SPANGEO Project

Although increasing our knowledge of the properties of networks of cities is essential, these properties can be measured at the city level and must be assessed by analysing actor networks. The shift from the actor level to the city level must consider the processes that develop within each individual city because there are many processes that permit the emergence of urban properties in which "the whole becomes not only more than but very different from the sum of its parts" (Anderson (1972) cited in Lane (2006)).

The present volume, which seems similar to an earlier volume, "Methodology and epistemology of multi-level analysis" edited by Courgeau (2003), shifts the focus from the individual to the group and from individualism to holism (known here as the territory) because it focuses less on individual characteristics and more on the interactions of actors and institutions that create functional territories in which the structure of existing links constrains emerging links. Rather than basing explanations on external factors, the goal is to determine the extent to which network properties reflect spatial distributions and create local synergies at the meso level that are incorporated into global networks at the macro level where different geographical scales occur. Although the multilevel analysis developed by Courgeau proposes that *a priori* groups and levels explain differences between individuals, the goal of the present volume is to use the graphs' structure to identify empirically relevant groups and levels that explain dynamics. This initial exploration applies network analysis and visualisation to determine spatial path dependencies and the emergence of functional territories as clusters forming a whole multiterritoriality.

The convergence of the network multiterritoriality paradigm collaboratively formulated and manipulated by geographers and computer scientists produced the SPANGEO project (Spatial Networks in Geography) in 2005. Although the methods inspired by graph analysis and visualisation could improve the ability to comprehend large, complex networks and flows, geographers still must confirm the relevance of these methods through solid and informative conclusions based on the data. The robustness of the computing methodologies can only be assessed based on the knowledge that the proposed technology enables geographers to acquire. The entire project was developed by the Visual Analytics Loop (Thomas & Cook, 2006; van Wijk, 2005) in which geographers contributed to the visualisation design. Insights based on the data and its visualisation inspired geographers to adopt methods for exploring the phenomena underlying different data through an iterative loop that began on the first day and continued until the project's end. SPANGEO, which was supported by the ANR in France from 2005 to 2008, initially involved a core team that continuously expanded to include new teams and new people through support from European Research Group S4 (Spatial Simulations for Social Sciences) under the direction of Denise Pumain.

The increasing amount of available networks data presents a challenge to quantitative geography. Compared to other disciplines, most of the data are available through population surveys, although the networks data in international comparative studies is not always homogeneous. The computer sciences offer geographers the opportunity to fully exploit their data and confront complex issues that require new methodologies and strategies of analysis. Until recently, the primary tool for visualising and analysing geographical and social data was use visual cues to superimpose quantities over a world map (e.g. Bertin, 1973). Currently, it is possible to employ cybergeography and new visual and analytical paradigms that complement and improve the traditional visualisations using world maps. Because new visualisations generate new issues, the multilevel analysis and visualisation of geographical networks transforms the geographical approach to the definition of places and hierarchies (Pumain, 2006).

1.7 Outline of This Volume

The multilevel, multiscale and multidimensional aspects of spatial analysis provided a privileged terrain that geographers and computer scientists shared within the SPANGEO project. This volume assembles some of the contributions based on this collaborative project. Most of the papers represent collaborations between geographers and computer scientists. Many conferences and workshops created a common language and conceptual background to develop approaches and methods to address questions in geography. New issues also emerged from the SPANGEO project research.

In the first section, Céline Rozenblat and Guy Melançon – a computer scientist with 5 years of practice and training in geographical issues – describe the "multilevel and multitheoretical framework for geographical studies" that they developed. This paper provides the initial formalisation of the process of creating a coherent corpus for the Spangeo project. Incorporating the concepts of centrality and proximity developed in physics, information visualisation, sociology, and regional science, the two authors describe how the concepts might be adapted to fit the geographical context. Next, Alain L'Hostis describes how the concept of anisotropic space developed in geography – in particular, by Tobler (1963) – contributes to this approach. The vision of networks from the computer scientists' point of view, is developed by Antoine Lambert, Romain Bourqui and David.

The methods developed by the SPANGEO team – in particular, the TULIP software[1] designed by the LaBRI team in Bordeaux – are presented in a second part with three papers. Guy Melançon describes the basic measures for identifying graph centralities and clustering, and Jean-François Gleyze presents specific approaches to the topological aggregation of graphs. Finally, Pierre-Yves Koenig explains the various methods for analysing and visualising networks and their inherent or exogenous properties.

The papers in a third part describe five applications of these methods, which are presented at the global scale, the European scale and the city scale. Cesar Ducruet describes sea networks, and Céline Rozenblat, Romain Bourqui and Guy Melançon describe air traffic networks. At the global scale, sea and air transportation networks exhibit different types of clustering based on internal network structures. These transport networks have the methodological advantage of being quasisymmetrical, unrestricted by physical limits, and global. The clustering methodologies of these applications operate at the global scale and at the macro level of urban systems. The third paper by Charles Bohan and Berengere Gautier presents a micro-level analysis of multinational firms' behaviour at the global scale and introduces space as exogenous variable that makes it possible to compare worldwide networks of corporations through graphs and DAGMaps. Marie-Noelle Comin describes research networks at the European scale that define classes of cities according to their specialisations, associations or type of research, alternating between the macro level of the urban system in which groups are based on topological proximities and the meso level of processes occurring within cities due to the diffusion of innovations and specialisations. Finally, Patrice Tissandier, Trung Tien Phan-Quang and Daniel Archambault couple topological and geographical proximities, describing the polycentrism that emerged in cities from 1975 to 1999 and describe commuting networks, which are explicitly positioned at the meso-level of the cities because they involve people's daily movement but also involve the macro-level because people increasingly fragment their work and home lives between distant locations by commuting weekly or tele-commuting.

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[1]The TULIP Software is free and open access: http://tulip.labri.fr/

All these presentations describe the emergence of networks at different levels through diachronic analysis. To develop dynamic models of networks, it was necessary to explore the temporal and attribute structure of the different networks in depth. Thus, we wanted to share this collaborative work with readers to identify the issues in adapting these methods to different themes, scales and levels.

The successful cross-disciplinary work presented in this volume should promote further collaborative efforts. For the participants, this collaboration was a valuable opportunity that forced each author to explicitly define the "basic" concepts of his or her field for colleagues in other disciplines. The process required an open mind, as well as the ability to view the knowledge and principles of our fields critically. This volume is unique and original, not only because it provides information on the state of the art, but also because it represents a product of collaboration. We hope that the enthusiasm we share will persuade readers in the fields of geography, sociology, computer science and related areas to contribute to this fruitful cross-disciplinary endeavour.

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Part I
Concepts and Visualizations of Multilevel Spatial Networks

Chapter 2
A Small World Perspective on Urban Systems

Céline Rozenblat and Guy Melançon

2.1 Introduction

The increasing complexity of spatial organizations, in particular the organization of cities, challenges the study of spatial distributions. Places tend to be seen more and more as nodes in specialized networks, and their future is undoubtedly strongly dependent on their position in these networks (Castells, 1996). Geographical distances and accessibility always matter in spatial dynamics, but in parallel, other distances appear as relevant: social, economical, cultural and organizational distances can also interfere in spatial dynamics. As a consequence, geography, as a science of society in space, must work at defining and measuring how spatial accessibility dynamics influence other kinds of distances and how processes emerge from spatial or territorial dimensions. From this perspective, in a social-science division of work, geography could be defined as the science dedicated to the identification of spatial patterns and their implications at specific geographical levels of scale.

These geographical levels are themselves evolving according to systems of social processes. For example, globalization processes are developing as transport and communication speeds are increasing (and as costs are decreasing) but are also changing according to organizational transformations of society, deriving from actors themselves, like companies and subsidiaries, social groups and institutional arrangements. These types of interactions and their dynamics explain why

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globalization has been developed at a worldwide scale for stock exchange, while "global value chains" of production are developing, most of the time, at a continental scale, leveraging from "regional" international trade arrangements (Dicken, Kelly, Olds, & Yeung, 2001; Doz, Santos, & Williamson, 2001).

The hypothesis we just stated suggests that all transformations strongly depend on the internal and external relations of network components, calling for a study of the relative positions of places in networks and at different geographical scales. Geographical interactions can be studied through multi-dimensional networks, which can be considered as graphs. To date, most geographical network studies were based either on gravity models (Wilson, 1967) or on general indexes of graph connectivity or accessibility (Kansky, 1963). Graph theory and more particularly Watts' theory of small-world networks (Watts, 1999) can feed this trend of research and enrich spatial analysis as a complement to systems theory. Networks indeed organize through direct links or by indirect paths, inducing topological proximities that simultaneously involve spatial, social, cultural or organizational dimensions. Network synergies, either based on the similarities or the complementarities between or inside cities, create specialized and more or less stable proximities between these entities (Powell, 1990). Interrelations between geographical scales of organization also allow an understanding of the equilibrium or disequilibrium of territories emerging at different geographical scales. The concepts and methods of the small-world theory are particularly relevant to geography, in which spatial interaction is mainstream and where interactions can be described and studied using large numbers of exchanges or similarity matrices. As far as we know, this type of empirical approach combining a conceptual approach of the "small-world theory" and dedicated tools has not been developed in geography.

Multi-level analyses and the visualization of graphs bring new questions. How do networks link similar actors, reinforcing their social proximities as well as spatial specializations and segregations? In this sense, how do networks (not only transport and communication networks but also social and economic networks) increase the anisotropy of space? How far are networks from random processes, instead creating densely connected groups of nodes separated from others, like "small-world" networks (Watts, 1999; Watts & Strogatz, 1998)? What are the properties of these networks, and what consequences can we infer for geographical places, especially for cities?

In this presentation, we will stress the advantages of analyzing and visualizing networks using their network properties (Sect. 2.2). Then, we will underline topological positions in a static state as well as from a dynamic perspective (Sect. 2.3) and transfer them onto properties of city systems (Sect. 2.4). The final section discusses levels of organizations, taking into account empirical findings on hierarchical clustering (Sect. 2.4).

2.2 Small World Theory and Scale-Free Networks

This chapter is devoted to the introduction of small-world theory and scale-free networks. Introducing these formal notions in a separate section will allow us to freely build the discussion around the examples studied by members of the SPANGEO project without having to pause for mathematical digressions. The next chapter goes into technical details and formally defines and compares the various network indices that we refer to throughout the book. Here, we aim to introduce the main concepts that we transpose from graph theory to geography.

Graph theory, developed especially by Erdös and his school since the 1950s, was based on the concept of a "random graph", making the strong assumption that all relationships are likely to occur with equal probability (Erdös & Rényi, 1959, 1960). Put simply, a random graph is one in which edges are drawn at random, playing heads or tails; that is, there are no regions in the graph where edges have a higher probability to appear, leading to uniformly distributed connections among nodes.

Since the late 1990s, many researchers have proposed alternatives to this model, showing the importance of "small worlds" in the organization of societies and their dynamics, where networks are not seen as homogeneous (Newman, 2000; Newman, Watts, & Barabàsi, 2006). Small worlds are built from groups of tightly connected communities, themselves connected through privileged nodes. The small-world phenomena, experimentally identified by Milgram (1967) in social networks, was observed in many other fields, giving this notion a hint of universality. In biology, for instance, networks of interacting proteins show a small-world character, where communities of proteins embody cell functions (Vespignani, 2003). The internet is another well known and extensively studied example, beginning with Adamic (1999). Two main properties typify these networks:

- The average path length from one individual to another is small and compares to the average path length of random graphs (with the same number of nodes and edges);
- The networks have a strong propensity to create sub-groups (also called communities or clusters). This propensity is the strongest characteristic of small-world networks and is the result of several micro processes, like transitivity, homophily, and the range of ties.

In parallel to Watts and Strogatz's theory of small worlds, some authors observed and investigated another property of networks, referring to the networks as being scale-free. These networks organize into an order hierarchy with respect to the degree of nodes and evolve along a basic process. According to Barabási and Albert (1999) (see also Barabási, 2002), who popularized these "scale-free networks", this order hierarchy is due to the "preferential attachment" that characterizes the development of networks: new links preferentially link to nodes that already have a greater number of links, favoring the hierarchy. In reality, we can find early explanations of the Zipf law proposed by Simon (Simon, 1955), referring to the "Yule process" (Yule, 1925). This process thus induces the degree distribution of the nodes to follow a power law; that is, the frequency of nodes of degree k is approximately given by $p(k) \sim c \cdot exp(-k)$. In other words, a sharp inequality exists between strongly central entities and others who cling to these centralities (the interested reader is referred to Bornholdt & Schuster (2003) or Newman (2010), for instance).

The scale-freeness of spatial networks makes sense, as the forthcoming sections shall explain. However, this property makes their visual exploration and (automatic) analysis much harder. Most often, networks show both characteristics simultaneously. That is, networks do contain small communities of interacting entities, while the overall organization of the network is dominated by a scale-free process. The high-degree nodes thus make it hard to identify communities or bridges and hide the small-world structure. Hybrid approaches must be designed to reveal the structure and properties of these complex networks.

2.3 Visualizing Topological Proximities in Geographical Networks

Visualizations are common tools for geographers, who use cartography to stress geographical organizations and patterns. Nevertheless, because geographical distance is not the only factor constraining a system and its dynamics, a topological representation can be much more useful to highlight organizational structures.

A basic geographical example is the worldwide container-traffic networks, for which visualization allows a good overview of the overall structure (Fig. 2.1) (Ducruet, Rozenblat, & Zaidi, 2010). On one hand, the representation ignores the geographical coordinates of ports. On the other hand, the ports' location in the graph is determined by applying a layout based on topological proximities for maritime exchanges. Therefore, the geographical situation is preserved due to the continuum of movements from one port to another.

Fundamentally, two main sub-systems exist: Asia-Pacific and Europe-Atlantic. These sub-systems are connected through a limited number of nodes: the Panama and Suez canals. Removing those two global pivots would thus split the world system in two parts, although one may notice some other links (e.g., Magellan Strait and Cape of Good Hope), but those links remain very limited compared to the main trunk lines concentrated at the two canals. Also, port ranges appear, such as the Scandinavian range in the top left of the Fig. 2.1, close to American ranges.

Another example maintaining some geographical position in a topological network representation is the movement of commuters (Fig. 2.2). The example of Switzerland shows especially the linguistic proximities among municipalities with three visible isolated zones: French Swiss speaking at the left, Italian speaking at the right, and Swiss German in the center, cut into two parts between a system around Bern (the political federal capital) and another around Zürich (the economic capital).

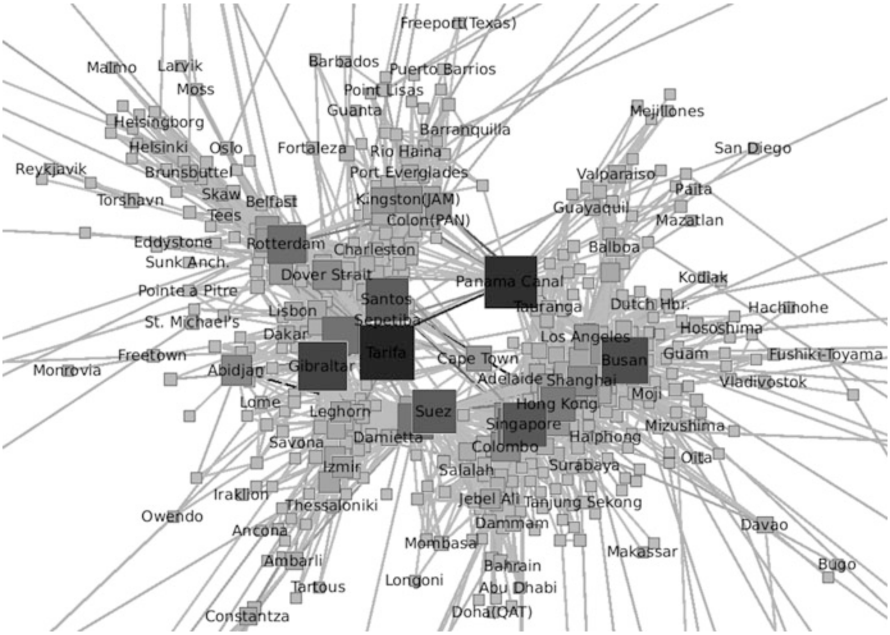

Fig. 2.1 Worldwide container traffic network 2006

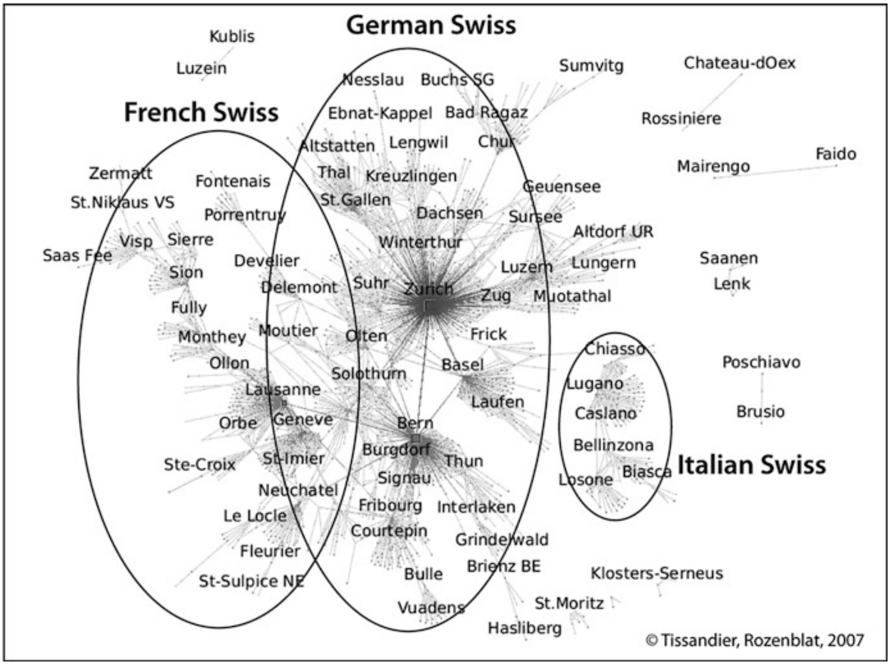

Fig. 2.2 Commuters between Swiss Municipalities in 2000

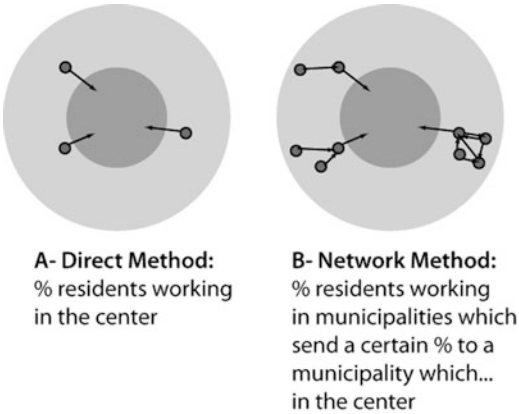

Fig. 2.3 Urban-area delineation using transitivity properties

2.4 Network Properties As Cities Systems Properties

The small-world property has a clear interpretation for territories in general and for urban systems in particular. The short average distance between entities can be seen as a consequence of redundant paths through different routes between city networks, strengthening direct and/or indirect interaction. This mutual interaction is mainly through "clusters", which can form inside cities or towns and that are heavily connected by groups at another level between cities.

2.4.1 Urban Systems As Small Worlds

Empirical evidence of these networks is founded on some basic properties reinforcing these strengths (Monge & Contractor, 2003), which, in transposition, could make sense for geographical network organizations:

- Transitivity: This elementary property was shown early by sociologists (Weimann, 1980): If an individual A is linked to B, and B is linked to C, then A is most likely linked to C.

  In geographical perspectives, we can transpose this property to interaction and interdependency effects. If a place A is closely related and interdependent on B, and B is linked to C then A is interdependent on C. For example, commuter exchanges between municipalities create these kinds of chain dependencies (Fig. 2.3). If a factory employing several thousands of people in A suddenly closes, it will affect the residential population of B that sends commuters to A, but in consequence, it also will affect C sending commuters to B. Sometimes, this transitive relation is materialized by real exchanges (like commuters), but even if there are not such direct materialized exchanges, interdependencies also occur through indirect effects. Therefore, some local chains create tangled networks, allowing very integrated local systems of territories (see Chap. 12).

At the inter-urban scale, interdependencies also make sense in mutual exchanges (symmetric or not), increasing proximities in terms of space (e.g., local or regional economical networks) or specialization (e.g., worldwide clusters linked through multinational firms' global value chains or through research centers). These new proximities stimulate the growth of exchanges, strengthening the closeness of some specific groups of cities or territories in spatial, economic, social or cultural proximities.

- Homophily: Networks between actors, territories or cities with similar attributes have a greater probability of occurring. These exogenous criteria actually interact with networks because exchanges could also transform places as they transform individuals with imitative behaviors and diffusions of many types of ideas, concepts and technologies.
- Range: In parallel to homophily, diversity of the elements of places and cities linked by networks seems essential to the reproduction and renewal of territorial systems. This diversity could be seen in terms of exogenous (for example, the diversity of activity sectors) and endogenous characteristics (the diversity of links to other places).

2.4.2 Urban Systems As Scale-Free Networks – Hierarchies of Individuals

There is evidence in urban systems that innovations spread preferentially from the largest cities, already a concentration of multiple networks, to the smallest ones (Batty, 2005; Pumain, 2006). At a micro level of individual behavior, these processes are largely due to the search for security rather than maximization, in a context of partial information in game theory (Luce & Raiffa, 1957, Chapter 3, Section 2). The "bounded rationality" concept mainly developed by Simon (1955, 1972, 1999) explains why, in a context of a random probability of meeting opportunities, individuals choose the first satisfactory opportunity rather than the best one. These trends lead to a strengthening of major cities, where opportunities are more diversified and where interactions are maximized, decreasing transaction costs (Coase, 1937). This process allows some specific properties of centralities, equivalence or structural equivalence for places or groups of places according to the positions of located individuals.

- Centralities: inequalities between places in terms of their relative position in networks are obviously dependent on accessibility or reachability into some set of places in a certain context and at a certain period (Bretagnolle, Pumain, & Rozenblat, 1999). Many kinds of indexes allow close analysis of these central

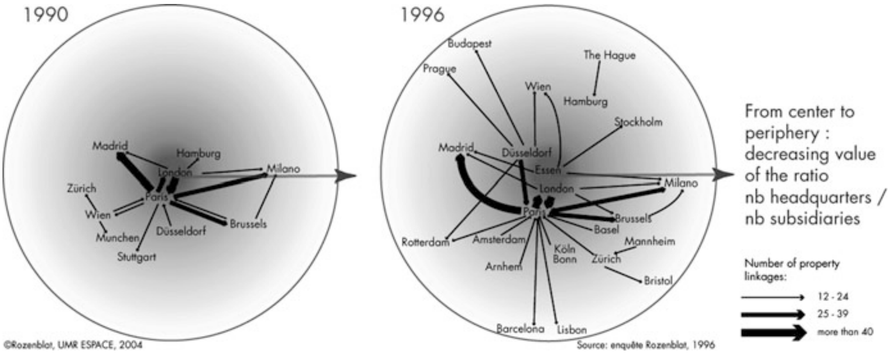

Fig. 2.4 Hierarchy of European cities according to their control of multinational firms from 1990 to 1996

positions, such as the node degree (number of links), reachability (distance to all other points), betweenness centrality (number of shortest paths passing through a point), or generalized Strahler index (Auber, Delest, & Chiricota, 2004; Delest & Auber, 2003), measuring how many trees can be built from a node; every measure can be weighted or not (Wasserman & Faust, 1994; Newman, 2003; Brandes & Erlebach, 2005). These indexes are all very useful to compare node positions in a graph or even the position of the same node in different graphs (multiplex graph).

- Dependencies and power: this characteristic is considered when social or economic networks are oriented either reflecting ownership between enterprises, decision-making, or hierarchy. The balance between incoming links (in-degree) and outgoing links (out-degree) can be a measure of such dependencies or power. For example, this method can be used to easily identify cities of power in multinational-firm networks according to the opposition between headquarters and subsidiaries (Fig. 2.4). Links are oriented and the centrality in the graph is calculated based on the share of the number of headquarters (representing the out-degree) relative to the number of subsidiaries (in-degree). Between 1990 and 1996, the graph has spread all over Europe, particularly areas like southern and eastern Europe. London, with a high share of headquarters/subsidiaries, is the most central, with many American headquarters controlling subsidiaries in the continent. However, Paris seems to be much more connected to other larger European cities.

  Also, one can identify dual positions in which some cities are only linked to one other. According to Nystuen and Dacey's methodology (1961), one can build a conceptual hierarchy with the highest link of each city going to a bigger city. All of these links create some "regional systems". Therefore, a hierarchy can also emerge from non-oriented links according to weighted dependencies. Figure 2.5 shows this construction applied to connections among European cities using complete graphs built inside each firm of a sample of 100 groups in 1996 (Fig. 2.5). The first link of the majority of the analyzed European cities is oriented to Paris, the most connected city according to this kind of graph of firms.

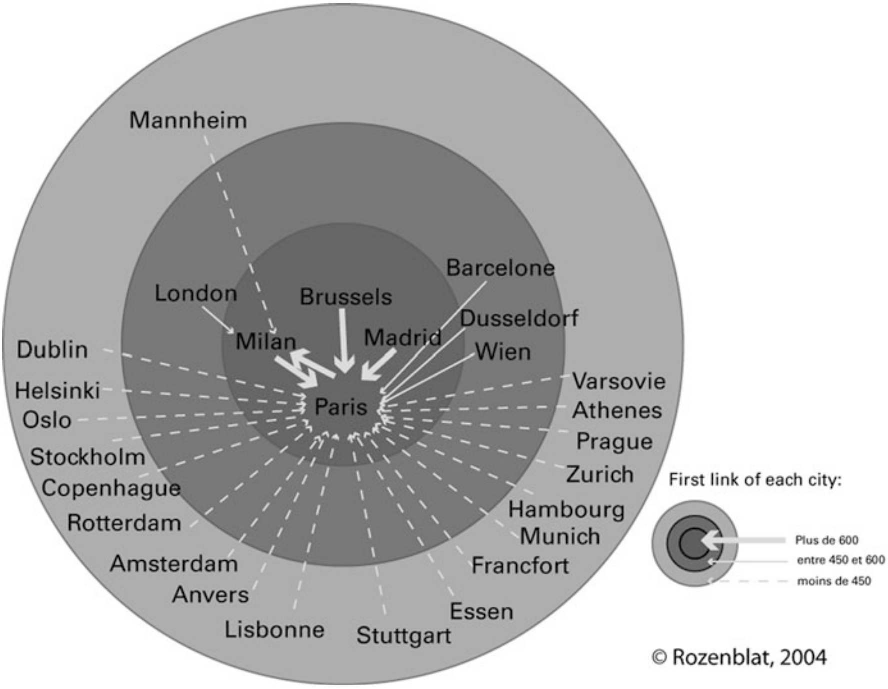

Fig. 2.5 Hierarchy of European cities according to their positions in multinational firms in 1996

- Equivalence and structural equivalence: organizational structure is viewed as a pattern of relations among positions. White, Boorman, and Breiger (1976) and Burt (2000) have developed positional theories of structural equivalence. According to Monge and Contractor (2003, p. 19), this theory "argues that people maintain attitudes, values, and beliefs consistent with their organizational positions irrespective of the amount of communication that they have with others in their organizational networks". From a geographical perspective, we could argue that places like cities are formed by tangled and overlapped social, economic and institutional networks that also put them in equivalent positions. For example, cities of the same country are equivalent with respect to their political national capital in many ways, from hierarchical administration to hierarchical economy and culture. In contrast, national capitals are in structural equivalence with their respective national urban systems, although some national networks are more hierarchical than others.

Bridge cities can be identified by confronting the weighted degree and betweenness centrality of each city at every level (Barrat, Barthélémy, & Vespignani, 2005; Guimerà, Mossa, Turtschi, & Amaral, 2005). In fact, degree and betweenness centrality are very correlated, although they have different natures: local (for degree) and global (for betweenness centrality). However, a low degree with a high betweenness centrality especially shows the role of bridges between clusters (Fig. 2.6 left), and the threshold to apply these measures must

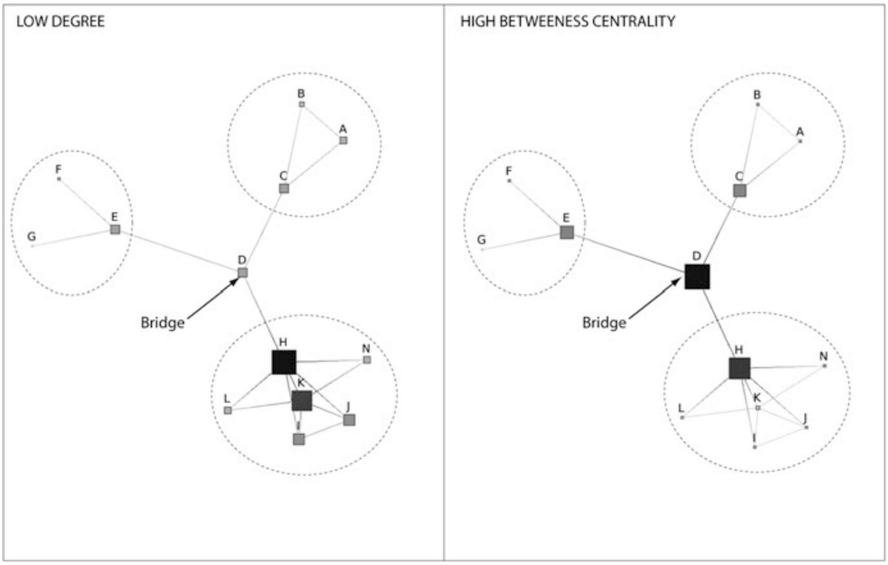

Fig. 2.6 Identification of bridges

be carefully selected to properly identify these bridges (Fig. 2.6 right). We can extend this approach to test all kinds of confrontations of local and global measures.

Individuals or organizations acting as bridges (or connectors) can override the "structural holes", strengthening the entire "social capital" but primarily their own capital (Burt, 2000, 2005). These bridges have a very strong strategic centrality even if they have a small number of links (Guimerà et al., 2005). A city can form a "bridge" between several cities when it is located at the interface between different groups or clusters or between different units (e.g., as a relay between a country's national cities and abroad or between a continent and the rest of the world).

In dynamic terms, such urban placements require high flexibility in networks, strong adaptability of cities and reactivity of the network actors. In contrast, a hierarchy that is too strong between nodes freezes the system but leaves individuals excluded from any network. The limitations of networks between what is integrated and not integrated are highly constitutive of the networks' operation and evolution (Barabási, 2003).

2.4.3 *Hierarchies of Spatial Groups of Cities*

If we assume that interaction implies interdependency, then groups of cities that exchange more together than with others are more dependent upon each other. Such cities constitute groups that can be defined in different ways (as explained below).

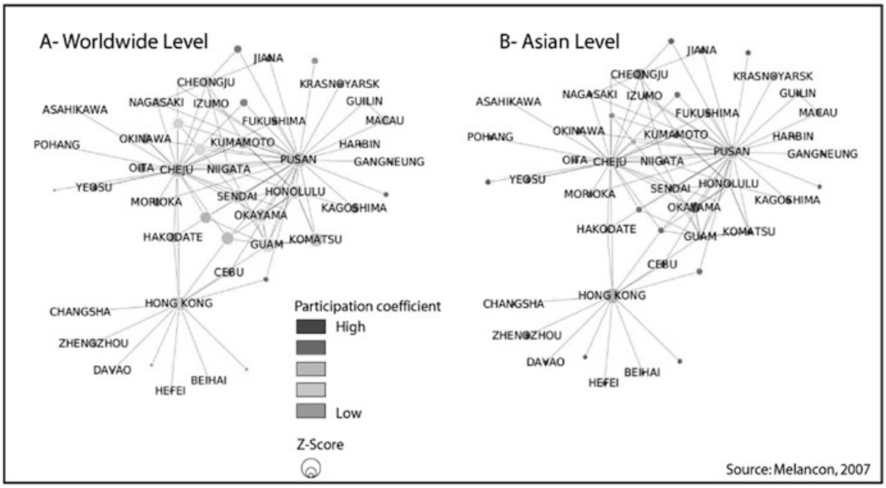

Fig. 2.7 Identification of hubs based on contribution indexes

Whatever method of classification is used, these groups imply some relative closure due in part to the property of transitivity, as previously discussed. In other cases, the network organizes into a star-shaped structure built around a central node that acts as a hub connecting the whole group to the outside world. This phenomenon can be tracked by measuring the relative density or "cohesion" of a group. As in classical classifications, some nodes (like cities) contribute more than other nodes to the cohesion of their groups, which may be seen as the "contribution" of each point to its group. Conversely, each city can also have links going out to the group, calling for a measure of the "participation" of a node in other groups in the network, as explored by (Guimerà et al., 2005). Contribution and participation indexes can be measured as individual shares in one node to one group or the opposite (details are discussed in the next chapter).

These indexes can help identify hubs in networks The role of hubs is often concentrated in or between particular communities. Guimerà et al. (2005) presented a z-score and "participation coefficient" of nodes that can be extended to take edge weights into account. The z-score of a node measures how many of the node's connections are devoted to its own cluster, while a node's participation coefficient measures how much its connections cover all of the other clusters in the network. Because we cluster the graph into a hierarchy of subgraphs, we can moreover measure these indices at every level and study how the indices vary down the hierarchy of clusters. Again, the full definition of these measures is delayed until the next chapter.

The figure below provides a good illustration (Fig. 2.7). The nodes have been sized according to their z-score (internal connections) and colored according to their participation coefficient (external connections). For example, Hong-Kong has a greater role at the worldwide level than at the Asian level.

Looking at node contribution and node participation as measures of interactions between nodes and groups and computing entropy help to provide a global view of the overall dynamics of a network. The significance of these entropy indexes could be interpreted as usual for entropy as signifying the degree of information contained in each group or information for each node (Lin, 1999; Shannon, 1948). With greater information included inside a node or group, the node or group's resilience and capability to renew are greater. Therefore, maximum entropy corresponds to a great variety of links for each node (balanced participation in many groups) or, at the level of clusters, various contributions of the nodes forming each group (and not only one in the case of star patterns). This variety contains a high disorder and could be interpreted as the system's high capability to maintain and renew itself (Bailey, 1990; Burt, 2005). This pattern illustrates for a particular node the "strength of weak ties" introduced by (Granovetter, 1973), in which a node has more opportunity for a large number of weak links by relying on differentiated clusters formed by larger links. In those clusters, the vicinities of economic links can develop processes of agglomeration economies or network economies. However, weak links between clusters are a source of diversity, which also produces a savings network, which allows cities both to operate and renew themselves.

It is the coupling between strong and weak links that allows the reproduction of the urban system and its transformations (Guimerà et al., 2005; Uzzi, 1997). We could identify such types of clusters between cities in different kinds of networks (e.g., transport, communication, migrations, multinational companies, etc.), and we could specify for each city the intensity of its membership in a cluster and assess to what extent these clusters correspond to territorial logic (of continents, countries or urban areas) or the logic of economic specialization (cities specialized in the same fields).

Besides diversity, specialization and "closure" are common patterns in networks, according to the general form of "scale-free" laws (see above). The slope index of the "scale-free function" can also constitute a norm used to measure high concentrations (Batty, 2005; Pumain, Paulus, Vacchiani-Marcuzzo, & Lobo, 2006). Then, the scale-free measures of the contributions inside each group could be adopted, but difficulty remains in defining these groups and their relative positions.

2.5 Conclusion

It is essential that our knowledge of all of the properties of these networks of cities be deepened through a multi-level perspective. Identifying, qualifying and measuring each level could better facilitate globalization because, at each level, there are many processes that allow the emergence of urban properties in which "the whole becomes not only more than but very different from the sum of its parts" (Anderson, 1972) (as cited in Lane, 2006).

These methods facilitate the definition and qualification of new properties of spatial resources based on networks, and new spatial groupings then lead to very new approaches in geography. We have to test the contributions of these methods to empirical studies and underline the new questions they bring out.

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Chapter 3
Topological Clustering for Geographical Networks

Jean-François Gleyze

3.1 Introduction

In addition to transportation, energy, communications, city and human networks, the study of reticular structures in geography faces problems relative to the size and complexity of the structures. These problems are particularly daunting when considering networks at scales smaller than their usual scale of representation. In this case, the mass of components makes it difficult to understand the network and synthesize related information.

In addition to cartographic tools to generalize maps and make them easier to read at lower scales, tools have been developed to cluster network components and simplify their representation and assessment. These tools stem from graph theory and have been extended to a particular degree in the field of social networks. However, graph theory tools have not been widely applied in geography because spatial organizations cannot be described only by graph structures; they also require specific information to build relevant models.

Nevertheless, to provide useful guidelines to adapt these tools to issues facing geography, this chapter presents an overview of these clustering methods, with particular attention to the criteria of implementation. We illustrate these methods with examples of simple graphs and discuss the possible applications to the study of reticular structures in geography. This discussion reveals that these methods cannot be applied alone in most cases, but that the way they are constructed provides relevant criteria that can be used to develop suitable methods for the geographical context.

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3.2 Definitions and Notations

Building clusters inside a graph requires the identification of structures that fulfill criteria related to graph theory. In that respect, the following paragraphs briefly present the graph theory concepts required to understand the clustering methods (for further information, see Berge, 1973; Bollobás, 1998).

3.2.1 Specific Notions of Graph Theory

A subgraph (or subgroup) corresponds to the union of a subset of nodes and of the edges linking those nodes.

A subgraph is called "maximal" in relation to a given property if it follows this property, and if every extension of this subgraph in which one or several outer nodes are added leads the graph to no longer follow this property.

Symmetrically, a subgraph is called "minimal" in relation to a given property if it follows this property and if every restriction of this subgraph in which one or several of its nodes are removed leads the graph to no longer follow this property.

A path between two nodes is a sequence of nodes and edges linking those nodes. The length of a path is given by the number of its edges. Two nodes are reachable from each other if there is at least one path between the nodes. The length of the shortest path(s) between two nodes corresponds to the distance between them (cf. Fig. 3.1).

Two nodes are said to be "connected" if there is at least one path between them. The graph is said to be "connected" if each pair of nodes is connected.

Two paths between i and j are independent if and only if they do not share any edges.

The number of independent paths between two nodes i and j corresponds to the minimum number of edges to be removed to disconnect i and j: this number is the connectivity index of the node pair $\{i, j\}$, and it provides information about the robustness of the paths between i and j on the graph (cf. Fig. 3.2).

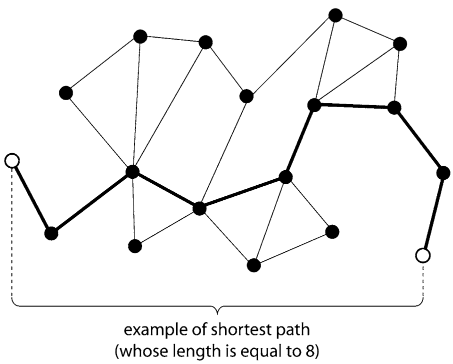

Fig. 3.1 Example of a shortest path on a graph

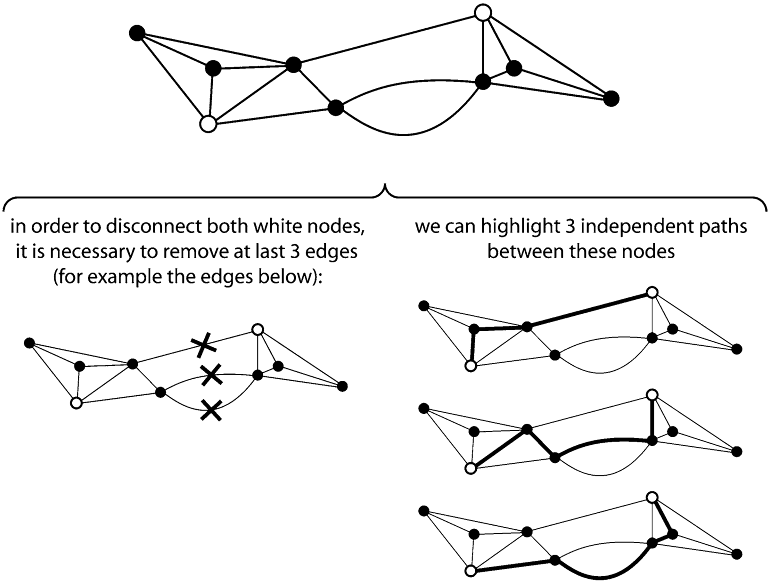

Fig. 3.2 The connectivity concept and its interpretation in terms of independent paths

By extension, the connectivity index of a graph corresponds to the minimum number of edges to be removed to disconnect this graph: as defined, the index is equal to the minimum of the connectivity indexes computed on all the node pairs of the graph.

The minimal number of edge sets or node sets that can be removed to disconnect the graph is called the number of "cut-sets".

In practice, the concepts from graph theory and their applications cannot be directly applied to geography. Studying a geographical network requires contextual adaptations that go beyond the strictly topological network description and integrate factors such as node location, node weighting, and edge values.

Among these factors, graph theory provides tools that take the direction and value of the edges into account: these extensions are important in a geographical context because they help to model the right way to pass through a section on the one hand (for example in road networks with one-way streets or expressways), and the cost of a section on the other hand (for example, the time required to pass through a section).

In the next paragraphs we present ways of integrating edge direction and value into network modeling and later into clustering methods.

3.2.2 *Specific Features of Geographical Networks*

Graph theory includes tools to take into account the possible edge directions (Berge, 1973; Bollobás, 1998). The suitable graphs correspond to "directed" graphs: inside

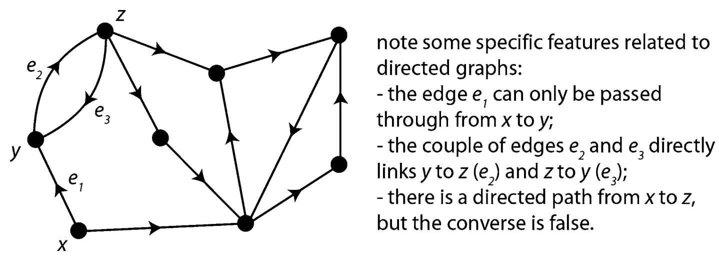

Fig. 3.3 Example of directed graph

these graphs, the edges are directed from an initial node to a final node. This modeling helps to represent asymmetric relationships in sociology ("I appreciate sb's company") and to consider the direction of a section of an infrastructure network (cf. Fig. 3.3). In this representation, the two-way sections have to be modeled by two edges opposite from each other.

Taking the possible impact of edge direction into account affects the meaning of the relationships between nodes. In this connection, edge directions may be integrated in several ways depending on the context of the study:

- a tie between two nodes x and y may be considered valid if either both edges $x \rightarrow y$ and $y \rightarrow x$ exist or if at least one of these edges exists;
- a connection between two nodes x and y may be assessed through both the shortest paths $x \rightarrow y$ and $y \rightarrow x$ or through the shortest path computed on the graph without taking edge direction into account.

In practice, the interpretation of edge direction depends on the type of network under study and on the meaning of the relationship between two nodes within a network. For example, within the context of risk, it is relevant to allow for two-way circulation on one-way sections because it may provide relief. This reasoning cannot be extended to air transport networks in which directed edges correspond to flights from one airport to another: for such graphs it is essential to take edge direction into account for path computation.

Graph theory is also a useful way to improve network modeling by taking the possible lengths or costs of sections into account (Berge, 1973; Bollobás, 1998). The operation consists of "valuating" edges by a scalar: from then on, the path lengths are no longer measured by the number of edges but by the total value of their edges (cf. Fig. 3.4).

As for edge orientation, edge values may be integrated in several ways:

- a direct link between two nodes x and y may depend on an additional condition related to the edge value (for example, the tie is considered valid if there is an edge linking both nodes and if its value is lower than a given threshold);
- in the same way, the path from x to y may be considered valid if its total length is below a given threshold.

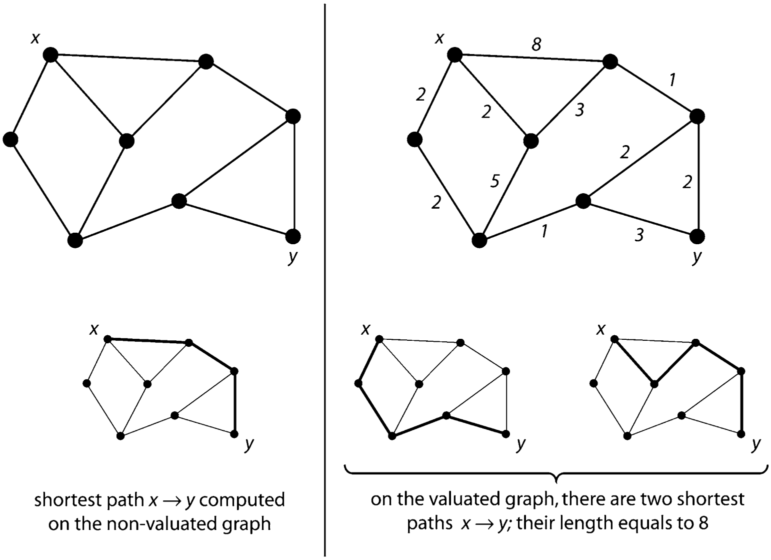

Fig. 3.4 Examples of a non-valuated graph (*left*) and a valuated graph (*right*) – impact of edge values on the computation of shortest paths

In practice, the interpretation of edge value depends on the meaning of the relationship between two nodes. Choosing a threshold (such that every edge with a greater value is considered unavailable) may be relevant for issues where the "metric" closeness is a main condition within the context of the study, such that nodes have to be topologically and geometrically well-connected.

Based on these notions and extensions of graph theory, we now propose to discuss the meaning of a clustering operation inside a graph and its possible expressions in terms of graph analysis.

3.3 Identifying Cohesive Subgroups Inside a Graph

Clustering operations inside a graph aim to gather strongly connected nodes according to criteria on the presence and nature of ties between those nodes.

Secondly, these operations may lead to the replacement of the identified groups with clustered nodes to produce a simplified representation of the graph (cf. Fig. 3.5). Nevertheless, this simplification represents a topic of research in that it also requires simplification of the edges and the component attributes (values, weightings, structural information such as paths, etc.).

Graph theory provides several mathematical tools to carry out node clustering within a graph. These tools have been widely formalized and developed in sociology

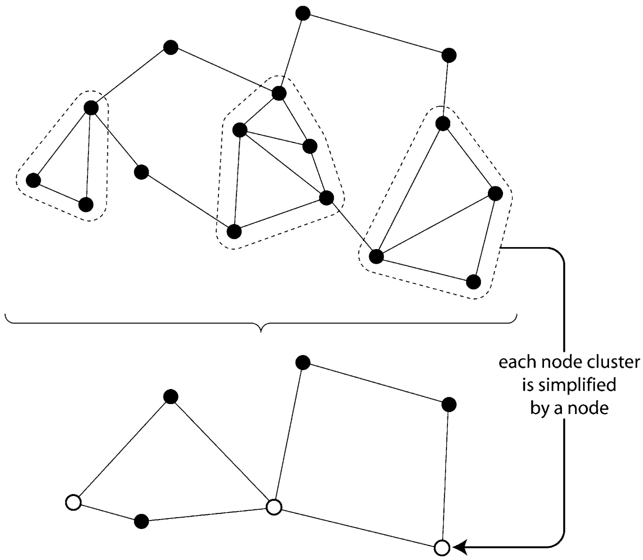

Fig. 3.5 Example of graph simplification by node clustering

because this research field needs graphs to model sets of people and the relationships between them. Within these “social graphs”, the nodes and edges represent the individuals and the relationships that they maintain. These relationships may have different natures and concerns:

- individual relationships (e.g., “I have made sb’s acquaintance”) and group relationships (“I work in the same company as sb”);
- similarity relationships (“I speak the same language as sb”) and dissimilarity relationships (“I was not born in the same country as sb”);
- symmetric relationships (“I am related to sb”) and asymmetric relationships (“I appreciate sb’s company”);
- binary relationships (“I am indebted to sb”) and quantitative (or “valuated”) relationships (“I owe sb x euros”).

In such graphs, a relationship is basically modeled by an edge between the nodes related to the individuals involved in the relationship. When considering group relationships, the edges are drawn between each pair of individuals stemming from the group.

However, some types of relationships demand more complex modeling:

- asymmetrical relationships require work with directed graphs, i.e., with graphs in which each edge connects an initial node to a final node;
- quantitative relationships need to value the edges.

These models need to adapt the methods of analysis by considering the directions and values of edges.

The clustering tools stemming from graph theory help to highlight the similarities between the individuals of a social graph, taking into account the relationships they maintain based on several criteria.

The different clustering methods presented in this chapter are based on the research work of Wasserman and Faust (1994) and Moody and White (2003), and we discuss those works from a geographical perspective.

3.3.1 *The Cohesion Concept*

The following clustering methods are based on the concept of "cohesion" between the "members", i.e., individuals, of the same subgroup.

The Petit Robert French dictionary defines cohesion as:

- the strength that brings together the parts of a material substance;
- the feature of a set whose parts are united, matched.

This definition is very close to the meaning of cohesion in graph theory as applied to sociology, as it defines subgroups of individuals who are strongly united by the relationships between them.

It is quite important to distinguish the cohesion concept from the adhesion concept related to structures centered on a node. Such structures are characterized by the convergence of many ties towards a "leader", node and therefore are strongly dependent on the status of this node. For this reason, "adhesive" structures are fragile because they can easily be affected by acting on this node.

On the contrary, "cohesive" structures are characterized by many independent ties that unite their members.[1] Groups with stronger cohesion are more difficult to split.

Finally, the group cohesion is affected by the arrangement of ties within the group. Groups with stronger inner ties exhibit a better ability to hold together.

3.3.2 *Qualitative Elements to Identify Cohesive Structures*

The structure of a group is best held together when all its members are linked in pairs. Such a structure corresponds to the "clique" notion of graph theory, but is rarely observed because the lack of a single tie is enough to "downgrade" this structure. However, the criterion of edge "exhaustiveness" specific to cliques can be relaxed and lead to more convincing clustering methods that remain operational.

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[1] The contrast between cohesive and adhesive structures appears in the etymology of these words. On the one hand, the words cohesion, colleague, and companion refer to notions of equality or numerous connections; on the other hand, the words adhesion, adversary, and administrator refer to notions of centrality or reference Moody & White (2003).

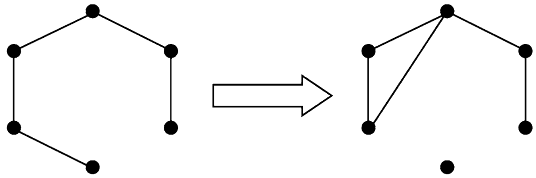

Fig. 3.6 The edge density is not sufficient to describe the cohesion of a group (From Moody and White (2003))

The nodes of a group may form a cohesive structure without pair linkages if there is a sufficient number of relationships symbolized by the edges: in this respect, cohesion is compared to the ease of reaching one node from another, i.e., to their "reachability" (this notion is connected to the notion of accessibility in geography).

Another criterion is the association between the group cohesion and the edge density (or volume) inside the group. Although this parallel at first seems acceptable, this characterization is actually inadequate: the linear structure and its slightly modified version in Fig. 3.6 show that the node reachability can differ widely for constant density.

Although the edge density does not constitute an exclusive indicator to characterize cohesion, the edge layout should be uniform to prevent the group from splitting. If the layout is not uniform, the subgroups with lower edge densities may be more vulnerable, as slight changes may split them more easily.

In this way, a third set of clustering methods demands that conditions regarding the node adjacency be fulfilled inside the subgroups: these criteria are based on the node "degree".

In terms of adjacency, it can be relevant to take into account not only the edges inside the group (these "intra-group" edges should have the highest possible density) but also the edges linking the group nodes with outer nodes (these "inter-group" edges should have the lowest possible density).

In a more formal way, it is possible to build subgroups, not by gathering nodes together, but by identifying the sets of edges that separate them from each other. To that end, it seems worthwhile to take advantage of the structural weakness of these sets with low densities. Then, these sets become small sets of edges whose removal splits the graph. This approach matches well with the whole area of graph theory devoted to the "cut-sets".

Based on these qualitative elements, we present the clustering methods and their possible applications in geography according to the following notions:

- the edge exhaustiveness;
- the closeness or reachability of nodes inside the subgroup;

- the degree of the subgroup nodes;
- the comparison between intra- and inter-group edges;
- the identification of cut-sets.

3.4 Methods for Identifying Subgroups Inside a Graph – Guidelines for Clustering Geographical Networks

3.4.1 Subgroups Built from the Edge-Exhaustiveness Criterion

The most direct clustering method consists of picking out the subgroups where the nodes are directly linked in pairs: this criterion corresponds to the clique notion of graph theory.

A clique is formally a maximal complete subgroup of at least three nodes. In other words, each node pair of a clique is materialized by an edge, and it is not possible to find an outer node that would be linked at each node of the clique (cf. Fig. 3.7).

By definition, the notion of cliques is restrictive for subgroup definition. The lack of a single tie between two nodes of a potential clique prevents clique formation. In practice, cliques are extremely rare inside wide networks, and they are generally very small: for that reason, this notion has to be extended to highlight larger but less cohesive structures.

3.4.2 Subgroups Built from the Reachability Criterion

The reachability notion is a useful extension to the clique notion. Reachability is particularly relevant when studying information networks: in this case, the issue often consists in identifying subgroups where information can be quickly transmitted between nodes. Therefore, the nodes do not have to be adjacent to each other, as they do in a clique (exhaustiveness criterion), but they do have to be close to each other in terms of shortest path length (reachability criterion).

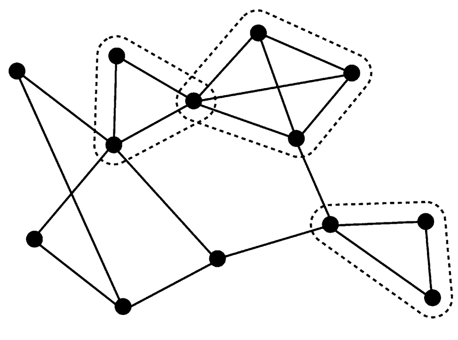

Fig. 3.7 Identification of cliques inside a graph (For this example, we note that the same node can be part of several cliques)

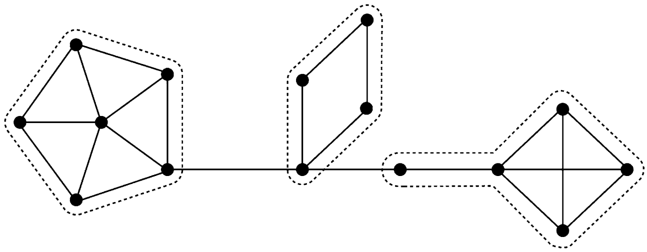

Fig. 3.8 Examples of 2-cliques

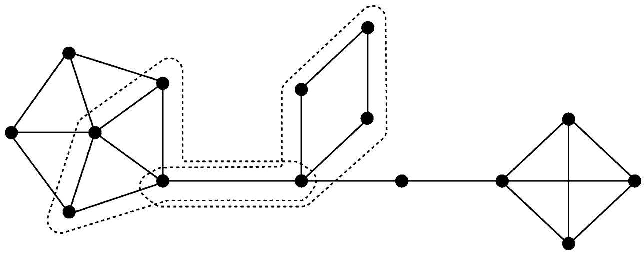

Fig. 3.9 The graph of the Fig. 3.8 also contains two 2-cliques that are difficult to identify at first sight

In this connection, the *n*-clique is defined as a maximal subgraph in which each pair of nodes is no more than n edges apart (the shortest path may pass through the outer edges). For this reason, it is impossible[2] to find an outer node that would be distant from each node of this subgraph with a distance less than or equal to *n*.

On the example of the Fig. 3.8, the spatial layout of edges and nodes shows three obvious 2-cliques.

However, these are not the only 2-cliques of this graph: in Fig. 3.9 we have identified two other 2-cliques, straddling two of the previously identified 2-cliques.

In this connection, reachability appears to be an extension of edge exhaustiveness insofar as the node closeness is under control (this criterion no longer concerns the ties between nodes, but rather the shortest path length).

For example, such a criterion is realistic and relevant in geography for accessibility issues. The need to cluster nodes based on the condition that they are "close enough" to each other amounts to selecting zones in which the shortest paths are shorter than a given threshold.

[2] As defined, a *n*-clique may have a diameter greater than n because the shortest paths between its nodes may pass through the outer edges of the *n*-clique. Nevertheless, there are variants of this clustering method that control the subgroup diameter. Subgroups extracted by such methods are called "*n*-clans" and "*n*-clubs" (for further information, see Moody & White, 2003; Wasserman & Faust, 1994).

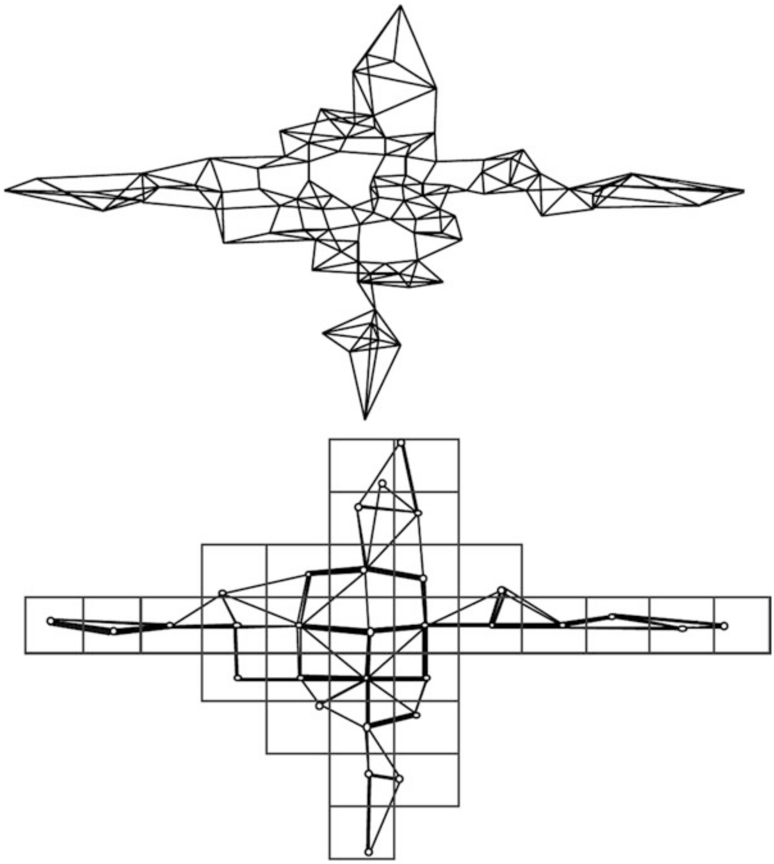

Fig. 3.10 A large social network and its simplification by a clustering method based on a reachability criterion (From Levine (2009))

Levine (2009) uses this principle to simplify a large social network with nodes that are widely spread out over the territory. According to the fact that n-cliques may overlap each other, this author proposes to cluster distinct sets of nodes that he selects inside the different cells of a grid (cf. Fig. 3.10).

In this application, the reachability is used to gather nodes that are close to each other, but some open-ended questions remain, such as the reachability of nodes inside clusters (although they are included in a cell, two nodes of the same cluster may be very far from each other if the shortest path between them passes through other cells) or the relevance of the grid in the clustering process.

From a mathematical viewpoint, the reachability criterion does not necessarily involve a high edge density inside the n-clique: actually, n-cliques may show star-shaped structures as in Fig. 3.9.

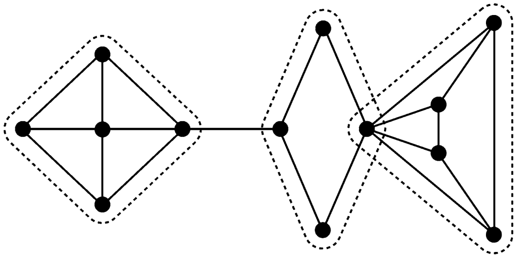

Fig. 3.11 Examples of 2-plexes

The following criterion helps to reject such structures by controlling the minimum number of ties between the subgroup nodes.

3.4.3 Subgroups Built from the Node Degree Criterion

In a subgroup built from node degree criteria, the nodes have to be adjacent to a "relatively high" number of other nodes.

In this respect, such subgroups are built according to the same rule as cliques (each node has to be directly linked to other nodes) but with weaker conditions (each node has to be directly linked to a minimum number of nodes).

This notion seems to be an interesting way to comprehend subgroup vulnerability: vulnerability occurs when the relationships between nodes are not sufficiently redundant, so that removing some target edges causes nodes disconnections. It turns out that *n*-cliques are not robust enough in the sense that their structure may be easily broken by the removal of a single node (a star-shaped structure is a 2-clique and is vulnerable to the removal of the central node).

In contrast, *k*-plexes are more robust subgroups because they are built so that each node has a "relatively high" adjacency number.

A *k*-plex is defined as a maximal subgroup where each node is adjacent to every other node of the subgroup except for *k* nodes at most.[3]

In that way, we have identified three 2-plexes on the graph of Fig. 3.11. In these 2-plexes of five nodes, the nodes are adjacent to 3 (or more) other nodes of the 2-plex. In other words, inside the subgroup built from the 2-plex nodes, the nodes have a degree greater than or equal to 3: the criterion specific to the k-plex is explicit here.

A clustering method based on a degree criterion has been used by Gleyze (2009, September 4–8) to identify groups of mutually supportive countries in the Eurovision Song Contest. In this study, Gleyze first determines which pairs of

[3]Subgroups with a similar criterion can also be built by considering the minimum number of adjacencies (rather than the maximum number of "non-adjacencies"), which we define as the *k*-core. A *k*-core is then a maximal subgroup of n nodes where each node is adjacent to at least *k* other nodes (Moody & White, 2003; Wasserman & Faust, 1994).

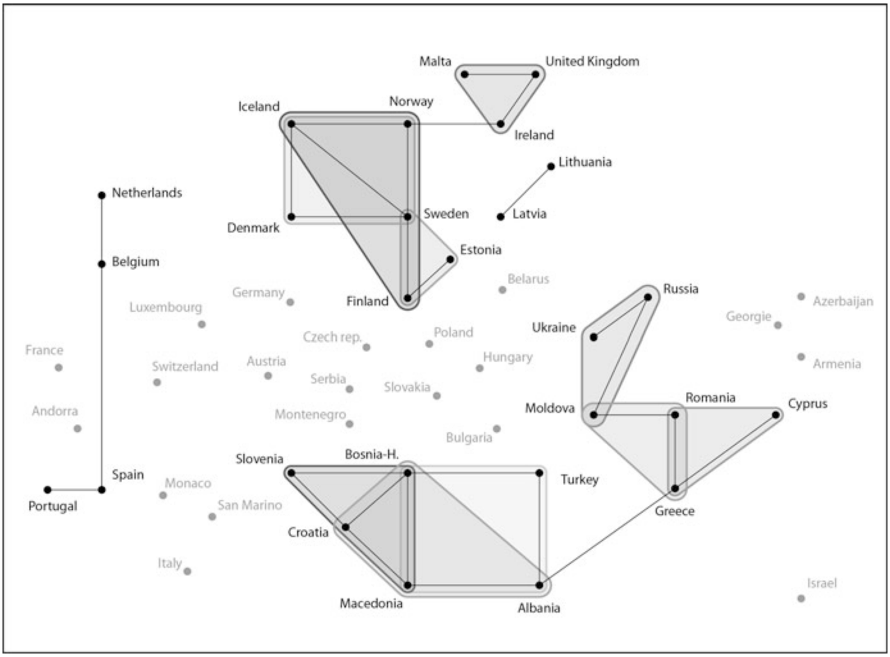

Fig. 3.12 Clusters of countries swapping over-votes between each other in the Eurovision Song Contest between 1993 and 2008 (From Gleyze (2009, September 4–8)) (Note: all the over-votes were taken into account in the cluster computation, but to make the figure more legible, only the reciprocal over-votes are represented here (the edges correspond to reciprocal over-votes between pairs of countries and the clusters are highlighted by *bold lines*))

countries voter performers show an abnormal tendency to produce a high number of votes. Then, he considers the country graph of such relations (called "over-votes"). In this graph, the number of cliques (4) seems to be low compared with the quantity and concentration of nodes (49) and over-votes (135). To detect larger structures, Gleyze suggests lightening the exhaustiveness criterion. In that respect, he defines a cluster as a set of nodes so that the over-vote density is not necessarily equal to 1, but must be higher than three quarters. In compensation, he demands that two degree criteria be verified:

- each country of a cluster must give and receive at least one over-vote from another country of the cluster,
- there must be at least one over-vote between each pair of countries in the cluster.

The Fig. 3.12 shows the country clusters highlighted by this method. While only four cliques were identified at first, these degree criteria allow for the detection of larger cohesive structures and their possible interactions.

Finally, the clustering methods based on the degree criterion guarantee the redundancy of relations and thus strong cohesion among subgroup nodes. In the mathematical definition, the parameter k corresponds to the tolerance (in terms of lack of ties) inside the subgroup in comparison to the maximal cohesion theoretically observed inside cliques. In the geographical application shown in Fig. 3.12, this criterion has been adjusted with the edge-density and two other rules relating to the adjacent edges of each node inside the cluster.

3.4.4 Subgroups Built by Comparing Intra- and Inter-Group Edges

The previous criteria are based on the properties of inner subgroup ties. Indeed, members in cohesive social network groups are closer to each other than to outer members.

Therefore, to identify a cohesive subgroup inside a graph, it is relevant to consider:

- not only the density of edges inside the subgroup (as we did with exhaustiveness, reachability and degree criteria),
- but also the intensities and the comparative frequencies of intra- and inter-group ties.

Lambda-sets are subgroups built from this second criterion. For such subgroups, cohesion is linked to the notion of connectivity: the identified subgroups must be difficult to disconnect by edge removal. Thus, lambda sets are maximal subgraphs for which it is harder to disconnect an inner node pair than a pair made up of an inner node and an outer node.

In other words, the connectivity index of inner node pairs must be greater than the same index computed for pairs composed of an inner node and an outer node (cf. Fig. 3.13).

The computational methods used to identify lambda-sets are difficult to implement. However, the criterion based on the comparison between inner and outer ties may be relevant for graphs whose clusters:

- may be made up of nodes that are not close to each other (actually, this criterion does not depend on degree or reachability criteria),
- and need to be disjoint (as they are defined, lambda-sets do not overlap each other unless they are included in each other).

Thus, Amiel, Melançon, and Rozenblat (2005) use a similar method to identify clusters of international airports, given that the airports of a given cluster have to be better connected to each other than to other airports. With this method, the authors aim to explain how air relations are organized and to highlight their structures at different scales (from global to local).

In practice, Amiel et al. build a graph of the air relations (on this graph, the nodes represent the airports and the edges correspond to air relations between airports). On this graph, they consider each edge and determine whether it can be part of a cluster.

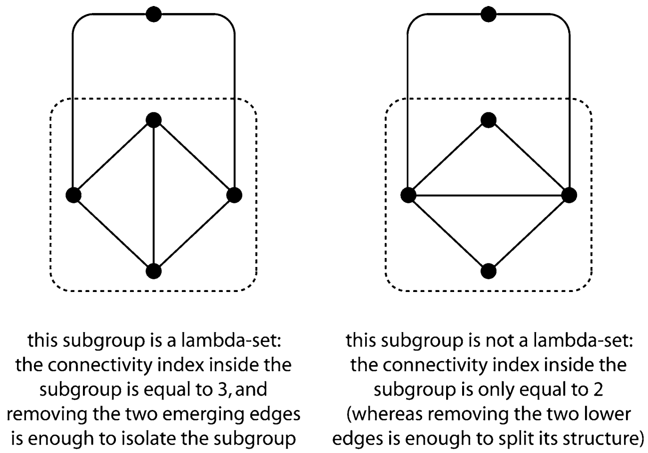

Fig. 3.13 Illustration of the lambda-set notion: the local weakening of a lambda-set (here by decreasing the degree of some nodes) can lead to a "downgrade" of the set

For this analysis, they compare the sets of nodes that are adjacent to each end of the edge. If these sets overlap each other enough (in comparison to a given threshold), then the edge is considered an inner-edge. Finally, the sets of inner edges delimit several clusters according to a criterion based on an inner/outer edge comparison.

Figure 3.14 shows the Tokyo cluster identified with this method (for a threshold equal to 1/2).

3.4.5 Subgroups Built from Cut-Sets

As previously mentioned, the notion of connectivity is linked with the minimal cut-set notion.

Moody and White (2003) propose to use these notions to identify cohesive subgroups inside a graph, not by comparing intra- and inter-group connectivity indexes, but by gradually splitting the graph around its cut-sets.

This "cohesive blocking" method is recursive: for a given graph, it aims to identify the minimal cut-set, pick out subgraphs on both sides of this cut-set, and then repeat this process on these subgraphs.

Figure 3.15 is 1-connected: the minimal connectivity index computed on its node pairs is equal to 1 (additionally, this graph can be disconnected by removing only one node).

By applying the "cohesive blocking" method, we identify two subgroups on both sides of this critical node. In the same way, these subgroups are split around their cut-sets. The new subgroups have connectivity indexes equal to 2 and 3.

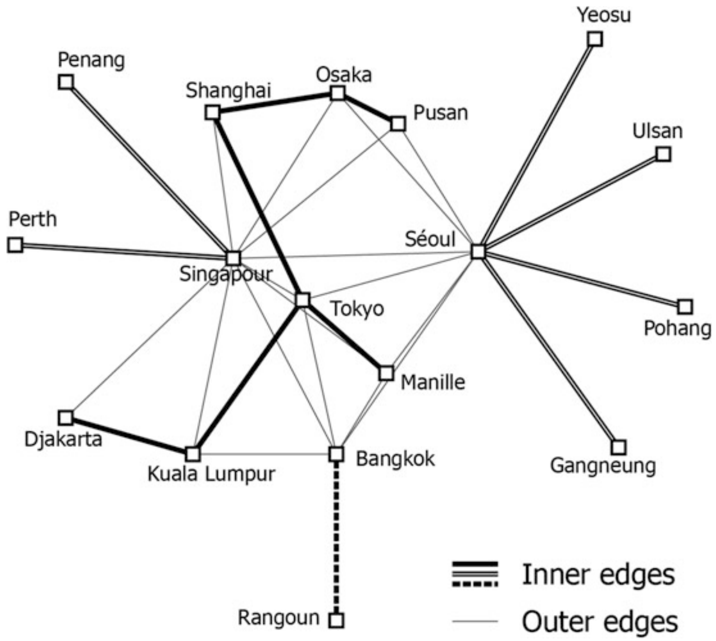

Fig. 3.14 Inner and outer edges identified around Tokyo on the air relations graph – the set of airports linked by bold ties represents the Tokyo cluster (From Amiel et al. (2005)) (Color figure online)

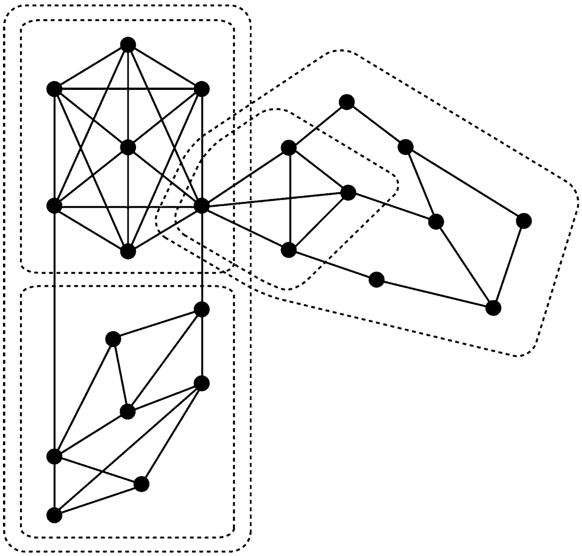

Fig. 3.15 Illustration of the "cohesive blocking" method (From Moody and White (2003))

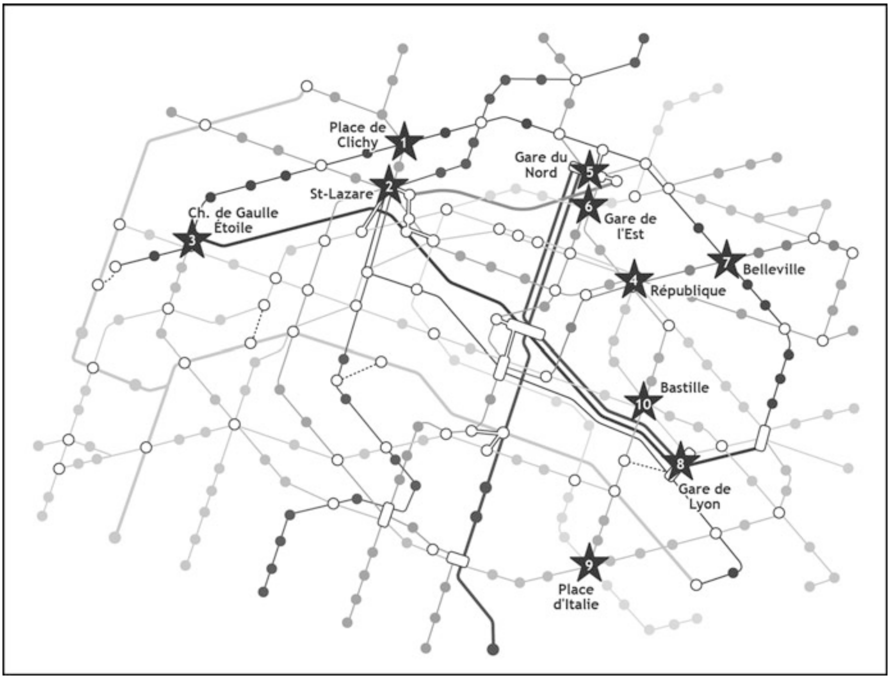

Fig. 3.16 Stations of the Parisian Metro network whose successive removal leads to the greatest reduction in mean accessibility (From Gleyze (2005))

This method finally helps to hierarchically segment the graph into increasingly cohesive subgroups.

The connectivity notion rarely appears in geographical studies as reticular structures are often robust: actually, transportation, energy and communications networks contain several redundant ties and are not considered to be systems that could be gradually disconnected.

There is an exception to this fact: when analyzing risks, it may be relevant to identify the most fragile points in the network. However, the edge density of geographical networks is so high that it is not possible to identify clusters by successively damaging such points. In fact, these networks are almost never disconnected, but some paths become so long that they could be considered as disconnected.

Nevertheless, Gleyze (2005) proposes to identify the node of a transportation network whose removal would lead to the greatest decrease in the mean accessibility inside the network. Then, he considers the network deprived of this node, identifies the node in this network whose damage would exert the greatest effect on the mean accessibility, removes this node, and so on.

Figure 3.16 shows the succession of the "most fragile" nodes of the Parisian Metro network.

Finally, the clustering methods based on cut-sets cannot be directly applied to geographical issues because of the high edge-density of geographical networks. However, a criterion based on network weakness may indicate the components that are likely to segment the network in the same way as cut-sets. For that reason, this criterion has to be considered as a segmentation method instead of a clustering method.

3.5 Conclusion

Graph theory provides clustering methods that help to simplify networks into cohesive subgroups, i.e., into subgroups in which nodes are close to each other and are difficult to disconnect. These methods depend on criteria whose implementation may lead to splits of various sizes and natures. This review is not exhaustive; nevertheless, it is representative of the main topological criteria that are commonly used to build cohesive subgroups (cf. Fig. 3.17).

These clustering methods fit with three main ways to comprehend the relationship between two nodes of a graph:

- according to the exhaustiveness and degree criteria, the relationship is assessed in view of the presence or absence of an edge between these nodes;
- according to the reachability criterion, the relationship is assessed in view of the connection quality, i.e., the length of the best path linking these nodes;
- finally, according to the inter-/intra-group and connectivity criteria, the relationship is assessed in view of the robustness of the connection, i.e., of the

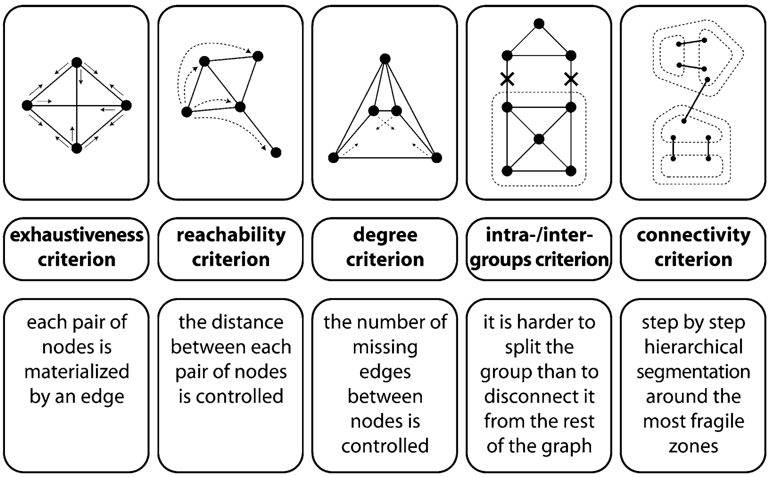

Fig. 3.17 Main topological clustering criteria

maintenance of at least one path between these nodes when some network components happen to be unavailable.

These criteria are exclusively topological because they are based on the presence of edges, the connection quality or the connection robustness between node pairs. Nevertheless, graph theory provides extensions that integrate the edge directions and values, and geography itself provides suitable models that help to take the specific features of infrastructure networks into account.

From then on, the clustering criteria become relevant within an application context because they provide a topological framework within which network simplifying methods can be contextually adapted. However, this approach leaves several issues unaddressed. These issues need to be considered based on the meaning of the topological clustering within the context of the geographical study: How can cluster quality be assessed? How can an index be computed for a simplified network? How can nodes belonging to several clusters be managed? How is a path on a network affected by its simplification? Is it possible to simplify a network that has already been simplified?

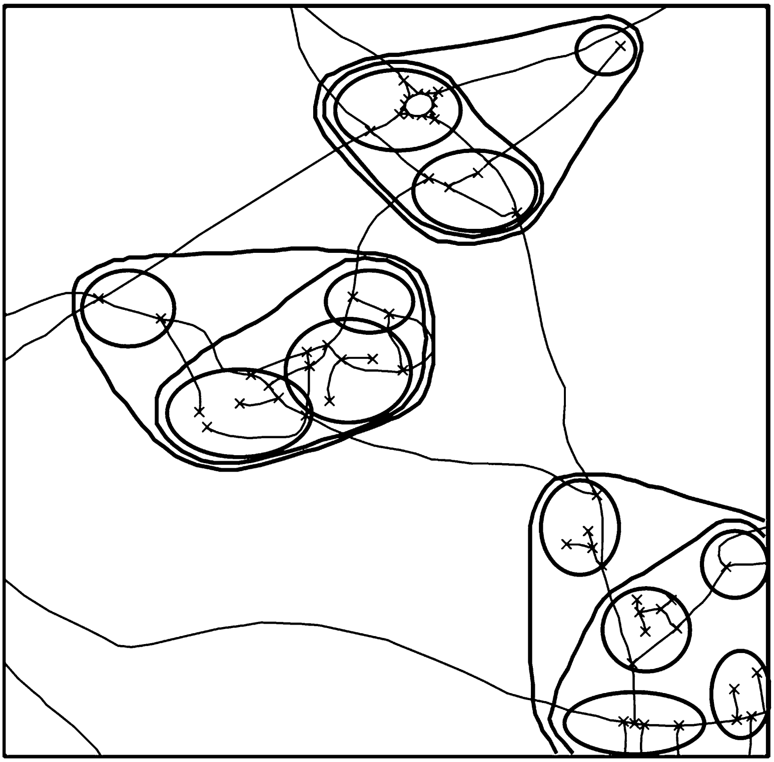

Fig. 3.18 Clustering on road networks for simplification of junctions from Mackechnie and Mackaness (1999)

These different ways of comprehending the relationship between two nodes finally influence the choice of the clustering criterion used to study a network. In that respect, the geographical examples presented in this chapter often adapt the clustering criterion to the context of the study.

Several criteria may be adapted and mixed to provide a relevant clustering method. For example, MacKechnie and Mackaness (1999) propose to simplify a cartographic representation of a network by sequential clustering of nodes that are closest to each other (cf. Fig. 3.18).

In this geographical application, Mackechnie and Mackaness finally use a similar criterion:

- with the definition of a *n*-clique,
- and with the hierarchical approach relating to cut-sets (except that components are progressively gathered together instead of being separated).

Ultimately, they build a method that is relevant for identifying possible spatial clusters according to the level of observation.

In addition, it is important to underline that these research directions are not exhaustive. Actually, they depend on the notion of cohesion, but within some contexts it may be relevant to consider other clustering criteria:

- the adhesion notion: adhesive structures are characterized by the convergence of ties towards a "leader" node and are representative of local hierarchies within the network;
- the similarity notion: the associated structures contain similar nodes considering the relationships they maintain with the rest of the network (Wasserman & Faust, 1994).

Finally, if the study of a geographical network is strongly dependent on the context, application of a clustering method requires the accurate identification and interpretation of the topological criteria that affect this operation.

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Chapter 4
Theoretical Models of Time-Space: The Role of Transport Networks in the Shrinking and Shrivelling of Geographical Space

Alain L'Hostis

4.1 Introduction

Understanding the distance between places is a fundamental task for the geographer, while the representation of distances constitutes the primary function of cartography. This is why a time-distance representation is a critical tool for the contemporary geographer. Among the types of maps introduced to represent time-space, anamorphoses were supplemented with time-space relief cartography in the 1990s. In one aspect, globalization has been made possible primarily through a reduction in time-distances, which are allowable by high travel speeds, particularly through the development of air transportation. However, the metropolitanization process, which is seen as the urban counterpart of globalization, is deeply associated with the development of air connection platforms. Both phenomena are intrinsically linked with the formation of distance, specifically with time-distances.

The purpose of this chapter is to present cartographic models of time-space and discuss their theoretical meaning for geography. The first step is to show a set of solutions for the cartographical representations of distances, which are transformed by different means of transportation. In the second step, we will discuss the relations between these cartographical solutions and the theoretical geographical discourse on time-space, which is structured around classical theoretical models.

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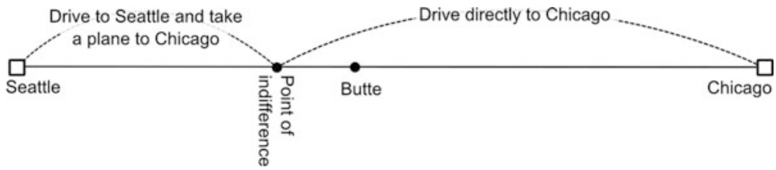

Fig. 4.1 The phenomenon of spatial inversion

4.1.1 Transport Networks Create Distance: A Cartographic Problem

To understand the present global space, it is necessary to emphasize the major role played by high travel speeds in the structuring of metropolitan spaces. These high travel speeds have initiated the development of communications on a global scale. However, high travel speeds also control a dramatic variety of places.

While this high-speed movement highlights the importance of global communication, the secondary networks and spaces remain present in the interstices. A key point in the formation of global time-distances is the fact that these secondary networks are obsolete, when compared to the main high-speed networks.

How can this complicated set of networks and relations in space be represented? To answer this question, a broader perspective of the representation of distances must be considered. In this field, Bunge has stated that two methods are available: "representing complicated distances on simple maps or representing simple distances on complicated maps" (Bunge, 1962).

In his classical example of the complicated relations in space generated by contemporary transportation, Bunge considers the movements from intermediary space to higher level cities with a trip from a location in Montana to the city of Chicago (Fig. 4.1). In this example, the use of the transport modes of cars and planes, implies that the shortest path in time-space takes a completely different shape beyond and after a particular point of space. Departing from Butte would mean driving directly to Chicago, while starting from a location that is closer to the Pacific Coast involves a trip by car to Seattle, followed by a flight. This phenomenon of spatial inversion that follows intuitive logic from a transportation perspective provokes a disturbance in the order of proximities. With regard to Cauvins's formalism (1984), although the Rocky Mountains are located between Seattle and Chicago in chorotaxic space, which is the normal geographic space, their position in functional space is different. In the transport space, Seattle stands between the Rocky Mountains and the Great Lakes.

The identification of the phenomenon of spatial inversion constitutes a key explanation of the research for new representations of time-space that would render this complicated set of distances. Allowing for the representation of distances that would be simpler to read would certainly complicate the map.

From this perspective, time-space anamorphic cartography is the first application in which one moves the locations to represent time-distances more effectively. An example is given by Shimizu, showing the contraction of Japan due to the development of the high-speed train networks between 1962 and 1992 (Shimizu, 1992). In the field of the representation of distances, anamorphosis aligns with the type of cartography defined by Bunge as simpler distances on a complicated map. The two elements of information on time-distances can be found from such a representation: the overall space contraction and the local deformations produced by high-speed lines. If the new transport networks had been characterized by homogeneity and anisotropy, the shape of the external borders of the country would have remained unchanged, and only size would have been reduced. All of the distortions from the normal and conventional shape of Japan indicate directions privileged by the shape of the networks. The literature on networks has abundantly expressed the idea that modern transport provokes heterogeneity in space (Castells, 1996; Dupuy, 1991; Graham & Marvin, 2001; Knowles, 2006).

However, this model is subject to limitations. The major criticism of the application of anamorphosis to the representation of distances is the fact that if two locations, such as two cities, are becoming closer due to a new transport link, this does not mean that the space between the cities is also growing in accessibility. Toll roads are examples of the "tunnel effect" of some infrastructures where the limited access points reduce the accessibility growth to a set of subspaces and are not distributed evenly along the line (F. Plassard, 1976). This phenomenon is even more pronounced in the case of the high-speed rail (Mathis, 2007; Murayama, 1994) and is one of the major characteristics of air transportation (Haggett, 2001). Providing an illustration of this limitation, the phenomenon of spatial inversion cannot be read from the anamorphic map because of the principle of the preservation of the order of proximities, which can be found in most methods developed in the literature (Clark, 1999; Kotoh, 2001; Shimizu, 1992; Spiekermann & Wegener, 1994).

Displacing the locations on the map is not the only way in which distances can be represented. The idea of drawing transport lines between places in such a way that different distances are shown was introduced in the 1980s (H. Plassard & Routhier, 1987; Tobler, 1997). In the example proposed by Tobler, the location of cities and network nodes remains unchanged, when compared to their normal cartographic position. The length of the roads between the nodes is displayed in the form of a spring: the intensity of the tension indicating the sinuousness of roads unevenly distributed in the mountainous area in western Colorado. In this model, one can obtain the information on the difficulty of linking two places by observing the visual length of the links. The notion of visual length was introduced (L'Hostis, 2003) to describe the capacity of a map reader in extracting the information on the length of a route from the analysis of the path's shape. A straight segment can be converted in kilometers through the direct use of the scale, while a sinuous curve indicates a longer road. This principle is used in the spring map to express the idea of privileged and handicapped directions (Fig. 4.2).

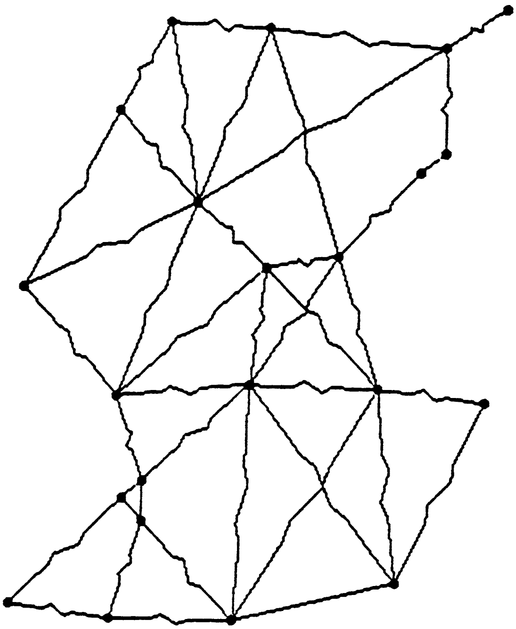

Fig. 4.2 Spring map of roads in western Colorado

The spring map model can indicate the shortest directions in space. A non-Euclidean representation by design, it presents the idea that the shortest paths often differ from a straight line. In this perspective, it constitutes a possible proposal to call for non-Euclidean geography (Golledge & Hubert, 1982; Müller, 1982). Recently, but in the same vein, a model has been formulated to introduce a three-dimensional surface that allows for the representation of different speeds in urban spaces (Hyman & Mayhew, 2004).

Sharing a principle of construction similar to that of the spring map, the time-space relief map was introduced in the 1990s (L'Hostis, 1996; L'Hostis, Mathis, & Polombo, 1993; Mathis, 1996). This type of representation preserves the location of places but exploits three-dimensional resources to draw the various speeds and the corresponding time-distances in a multimodal network.

4.1.2 *Air and Road Modes As Major Inter- and Intra-Metropolitan Transport Systems*

Globalization, along with metropolitanization as its urban counterpart, is made possible through the development of efficient, long- and short-haul transportation systems. If metropolises can be defined as urban entities that communicate on a global scale, then the air transportation mode constitutes the primary passenger transportation system associated with globalization (Sassen, 1991; Haggett, 2001).

In addition to the characteristics of metropolises and airport infrastructure, the number of flights and destinations available as well as the air distances are often used as indicators to position cities within the global economy (Grubesic & Zook, 2007). Nevertheless, the development of the air transportation mode from the twentieth century to now has not led to the replacement of slower transport systems. Each transport mode has developed within its own space of predominance, which contains fierce competition in the margins. On the scale of metropolitan space, the road system is considered the major mode of transport, even when regional specificities are stressed. The overall picture of mobility involves two distinct levels: the agglomeration or local level dominated by cars and the long-distance level dominated by air. For a complete analysis, this picture must be enriched marginally with the development of other transport systems, such as urban public transport and high-speed rail, which operate as a complement, rather than a substitution for cars and planes.

L'Hostis proposed considering the simultaneous high-speed and lower-speed transport modes on a continental scale in a single time-space relief cartography (L'Hostis, 2009). This representation is proposed from a different angle of view (Fig. 4.3). While the typical 30° was used in almost all previous time-space cartographies (L'Hostis, 1996; L'Hostis et al., 1993; Mathis, 1996), this map adopts a 45° angle of view. As the differential of speed for each subspace reaches a ratio greater than 6, this angle highlights the dichotomy of time-spaces, which occurs between the top level high-speed network and the common lower speed non-metropolitanized space.

In the USA, the air and road transport systems create a complicated time-space that the relief cartography helps to understand and describe.

After developing cartographic solutions to the problems of distance, we now interpret the theoretical background of this cartography, relating it to one of the most fundamental tasks of the geographer: understanding space and distance.

4.1.3 The Theoretical Models of Time-Space, from Shrinking to Shrivelling

In geography, there are several theoretical models elaborated to understand time-space. These models consider the movements of contraction or shrinking, convergence, divergence and crumpling or shrivelling. The rhetoric of world contraction can be considered a fundamental observation. Early references from the ancient Greeks reveal that they perceived the evolution of vessel techniques at the time-scale of the life of a human being and linked it to the reduction of distance between places in the Mediterranean Sea (Abler, Janelle, Philbrick, & Sommer, 1975; Braudel, 1979). In the nineteenth century, maps of now classical French geography depicted the contraction of the national territory with improvements in their land transport, while German cartographers mapped the improvements in maritime transport on a global scale, showing the reduction in travel times between Europe and the rest of

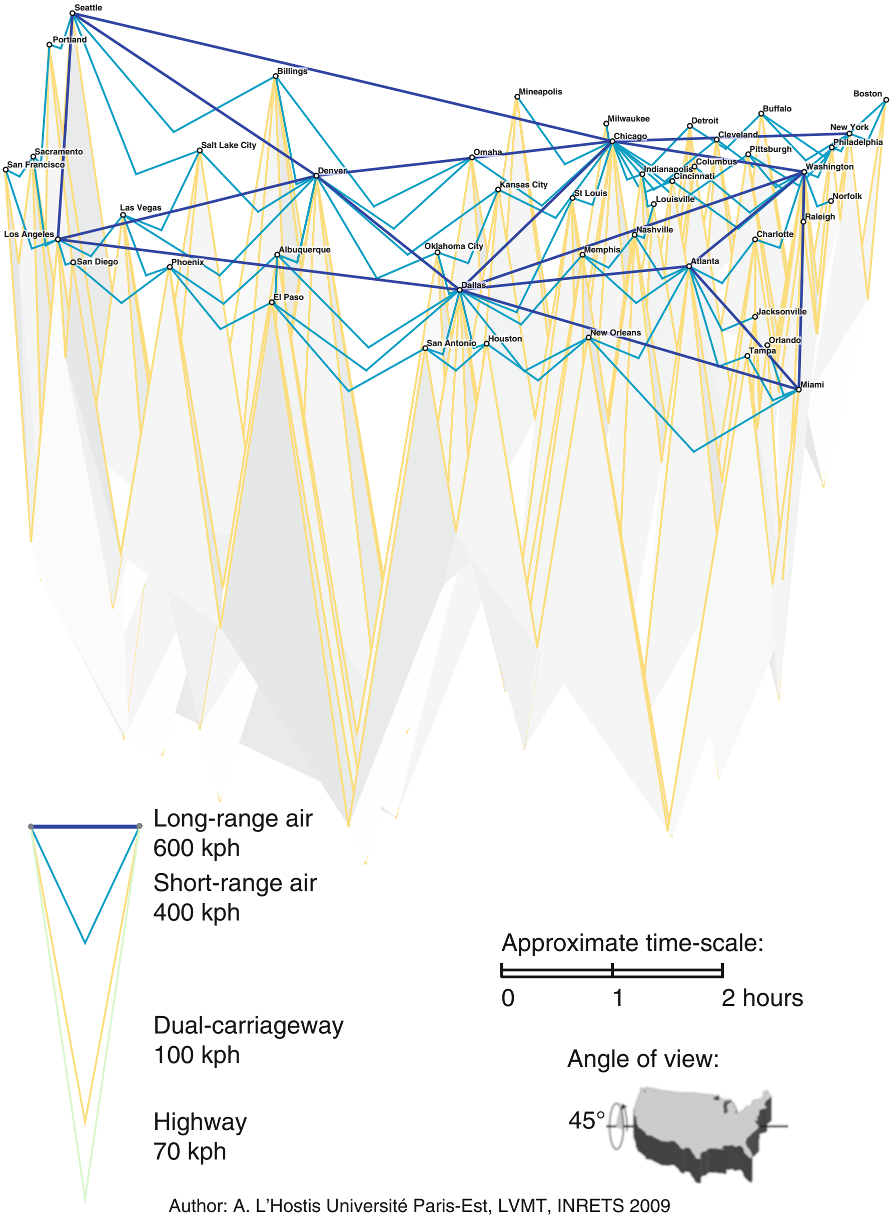

Fig. 4.3 High-speed by air versus lower speed by land: The shrivelling USA

the world (Brunet, 1987). Recently, in the domain of theoretical geography, Forer has developed the principle of time-space contraction (Forer, 1978).

Nevertheless, prominent criticisms of the contraction model have been made by Kirsch stating that "space is not "shrinking" but must rather be perpetually recast"

(Kirsch, 1995). According to Kirsch, the evolution of time-space cannot be seen as a simple contraction or shrinking process. Various disagreements with the uniform contraction idea can be found in several geographers' works on cartographical developments (Abler et al., 1975; Boggs, 1941; Haggett, 1990). More recently, Knowles uses the expression of a "shrunken but misshapen world" to describe the present time-space where contraction is all but uniform (Knowles, 2006). The abandonment of commercial supersonic flight, the development of congestion and the increasing concern about security in the air transportation system are the cause of contradictory movements implying both convergence and divergence in time-space.

The notion of time-space convergence was introduced (Janelle, 1968; Janelle & Gillespie, 2004) to show that larger cities benefited more than smaller cities from the contraction of time-space, which resulted from the development of faster modes of transportation. For Janelle, the modernization of transport systems is seen as a factor of concentration in urban agglomerations. Throughout history, increased transport speeds have benefited larger cities more than smaller settlements. According to Christaller's theory of urban hierarchy, large cities are more dispersed in space than smaller ones. Two large neighboring cities will be separated by a much longer distance, than any two smaller neighboring cities. Janelle demonstrated that the increase in speed produces a stronger effect on the time-space contraction of long distances than on short distances. The evolution of the transportation systems speed provides an advantage to the larger cities, rather than the smaller ones, which is in agreement with the literature on metropolitanization. For Knowles, the identification of privileged places in the process of space contraction is still an idea that must be demonstrated to challenge the misrepresentations of uniform time-space shrinkage (Knowles, 2006).

Recently, the literature on globalization has adopted the principle of fast communication and transportation on a global scale as its base (Sassen, 1991; Smith & Timberlake, 2002; Taylor, 2004). Global transport systems are solely responsible for making the present movement of globalization and the unprecedented concentration of population in major metropolises possible.

The initial discussion on the three-dimensional model presented here considered the terrestrial relief as the space of reference. The expressions of time-space peaks and time-space valleys referred to the relative position of the portions of space in the representation. In the time-space deformation, following the introduction of the high-speed train system within French national space (L'Hostis et al., 1993), the development of a new high-speed tangential axis was seen as a way to fill up the valleys created from the introduction of a differential in transport speeds, combined with a star shape in the network. These initial contributions emphasized the analogy with terrestrial relief.

Later, the idea of a time-space 'crumpling' was introduced to develop a metaphor (L'Hostis, 2000) to represent European space deformed by the high-speed rail network. The image developed is the deformation of a shrivelled sheet of paper, which is an idea of the three-dimensional treatment of a plane. The metaphor refers to a shortening of some distances while preserving the initial geographical surface. The metaphor of 'crumpling' opposes the two spaces of high and low speeds and suggests a three-dimensional geometric construction coherent with the concept behind the representation. It also proposes a rather negative image, with the crumpled surface observed as a degradation of the ideal unaltered flat plane. A positive perspective can be established when the crumpled shape, being more compact than the flat surface, is considered because it allows for shorter paths between locations. The crumpling metaphor gives an evocative image of the poor treatment reserved for interstitial spaces but is not as expressive of the global contraction of geographical space, given the increases in speed.

It is relevant to associate these reflections on the representation of geographic time-space with some recent developments in theoretical physics: The astrophysicist Luminet describes the shape of the universe as crumpled around the idea of multiple folding due to time-space deformation, according to the theory of general relativity (Luminet, 2001). Even while establishing relations between completely different fields should be made with caution (a use of common words is not sufficient to validate a comparison), it is apparent that both systems of representation are tightly linked to the identification of a maximum speed. Indeed, the speed of light is one of the three fundamental constants in physics. Astrophysicists have to work with the existence of a maximum speed, which is the speed of light on the universal scale, while geographers have to take into account the maximum speed of transport provided by the air transportation mode to understand terrestrial time-space. To better understand space, both reflections seem to require building complicated representations that divert radically from common Euclidean geometry.

In a different field, psycho-analysts have been studying crumpled spaces (Diener, 2008) to understand the links realized in the time-space of dreams, where the associations of ideas lead to direct relations between locations that can be very distant in time-space. In reference to the astrophysicist Luminet's work, a crumpled space is defined as "welded on itself by several points" and can establish these types of connections (Diener). The analogy goes much further: In the geographic space, fast transport systems directly link remote locations, advocating for the development of crumpled time-space cartography, while in the time-space of dreams, direct connections between remote locations constitutes an essential property. The movement of crumpling generates new connections and new proximities that reflect both the properties of geographical space and the time-space of dreams.

In the evolution of the discourse produced on the time-space relief, the following step explores a different type of metaphor based on the idea of shrivelling. The first use of the word must be credited to Tobler through his commentary on the L'Hostis-Mathis image, when he stated that "the world is shrivelling as it shrinks" (Tobler, 1999). We move from an image of the shape of an inanimate entity or artifact, such as the crumpling of a sheet of paper, to a principle of natural evolution of a living organism, such as the shrivelling of a fruit. This shrivelling expresses the idea of contraction with the deformation of an envelope; i.e., the volume decreases while the external envelope keeps its initial surface.

The strength of the metaphor lies in the combination and the linking of two complementary movements of both the contraction and deformation of the surface.

It is the reduction of the volume due to a loss of substance that provokes the deformation of the skin of the fruit. In geographic terms, it is then possible to explain the complicated shape of the map from global contraction due to the high speeds of transportation. The model generates forces of contraction along air routes that apply to high-speed nodes, such as metropolises. As L'Hostis proposed (2009), "high speeds and metropolitanization make the world shrivel as it shrinks" would then be a reformulation of Tobler's statement.

4.2 Conclusion

To conclude this chapter we will discuss a social dimension of time-space that can be understood from the analysis of time-space relief cartography.

4.2.1 A Social Space in Maps: "It Took Me One Hour to Get There"

Let's consider terminal T2 at the Roissy-Charles-de-Gaulle Airport near Paris. Several people inside the terminal may state "it took me one hour to get there". This includes the airline travelers at 600 km/h, the high-speed train travelers at an average of 250 km/h, as well as the airport employees that went to work by car through the congested Paris urban region at an average of 20 km/h and those who came by public transportation at 10 km/h from neighborhoods around the airport. Each person took 1 h to arrive there, but each moved at a different speed, with a profoundly differing kinesthetic experience (Hall, 1966).

The first person belongs to the global network; they occupy the Higher Metropolitan Jobs market, whose concentration is one of the most revealing markers of metropolitanization (Rozenblat & Cicille, 2003). They progress in the space of horizontal relations between metropolises, which is the space of globalization. Their time-space is the top level network space in the relief cartography.

The second person belongs to a multi-polarized urban space, which is made possible by the "High-Speed Train web" that links the French cities where those living there are "neighbours of one of the rare global cities" (Viard, 2008).

The third person belongs to the local or slow network. They live inside the time-space abysses located around the high-speed nodes. They may pass members of the two other categories, but they do not obtain access to high-speed transportation. Their time-space has a steep slope. They live in the folds of the crumpled time-space. Their time-space is nearly orthogonal to that of the metropolitan workers.

The time-space crumpling produces time-distances that coexist and renders the propagation of movement at differing speeds, with differing means of transportation.

Building a representation of contemporary time-space requires building a synthesis of these distinct spaces within these distinct time-spaces. This is the purpose of time-space relief cartography.

4.2.2 The Contribution of Cartography to the Models of Time-Space

In this chapter, we have discussed several models of cartographical representation for the problem of distances produced by different means of transportation. This is a problem of fundamental interest for the geographer. In this section, anamorphosis, spring maps and crumpled relief maps are discussed. In a second step we have analyzed the relations between these cartographical solutions and the general discourse on time-space in geography. Complex and sometimes contradictory phenomena occur in time-space, and each cartographical model is able to account for parts of these phenomena. Time-space relief cartography produces an image associated with metaphors, linking it to the crumpling of a sheet of paper and to the shrivelling of a fruit. This discussion leads to the astrophysicist's conceptions and to recent developments in psycho-analysis. Finally, consideration is made for the social dimension of time-space; thus, time-space relief cartography is seen as a representation of the encounter between socially distinct spaces in nodal points located inside metropolises.

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Part II
Tools for Networks Analysis

Chapter 5
Structural Analysis of Networks

Guy Melançon and Céline Rozenblat

5.1 Introduction

Discovering patterns in a network, understanding how information flows between the regions of the network, and being able to locate these regions are central issues in a number of scientific areas or application domains. Previous chapters encouraged the use of graph theoretical concepts to capture notions related to geography, such as *reticularity* (Chap. 5.3), *reachability*, *accessibility* (Chap. 5.4) and *cohesion* (Chaps. 5.2 and 5.3). Such notions actually apply to other fields and, in fact, graph theory now plays a key role in the study of complex systems. Studying the structure of a graph can reveal deep insights about the phenomenon it models.

In this chapter, we adopt a more quantitative perspective and introduce a series of measures used to typify the roles of nodes in a network, ultimately allowing the location of regions of interest. Notions such as node reachability and group cohesion will be revisited, and node metrics that can help quantify these notions will be discussed.

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5.2 Measuring Reachability

Roughly speaking, the most easily reachable entities in a network are those sitting at a minimum distance from all others. This informal definition calls for a precise definition of what is understood as the *distance* between any two nodes in a network. We first establish the notation that will be used throughout this chapter and the rest of the book.

A graph $G = (V, E)$ is a pair where V is the set of *nodes* in the graph and E is its set of *edges*. Formally speaking, the set E is defined as a subset of the Cartesian product $V \times V$; that is, an edge $e = (u, v)$ is an ordered pair of nodes in V. Note that this definition implicitly assigns a *direction* to the edges. The particular case where E always simultaneously contains the pairs (u, v) and (v, u) allows us to neglect the edge direction, as we can alternatively represent edges as unordered pairs $\{u, v\}$. This chapter will only be concerned with undirected graphs.

A *path* in a graph can be described as a sequence of nodes u_0, u_1, ..., u_k, where pairs $\{u_i, u_{i+1}\}$ each form an edge in E.[1] (A similar definition can be given for directed graphs.) The notion of paths between nodes is central to connectivity: a graph is connected if for any two nodes $u, v \in V$, there exists a path from u to v. Equivalently, a graph is connected is there is a node from which any other node can be reached.

The special case where u_0 coincides with u_k is called a *cycle*. Given that all nodes are distinct (except possibly for u_0 and u_k), we say that the path (cycle) is *elementary*. The *length* of a path is its number of edges. Thus, the *distance* between any two nodes in V is the length of the shortest path connecting them. The distance between u and v in G is denoted as $d_G(u, v)$; if a path between u and v does not exist, we set $d_G(u, v) = \infty$. Note that the latter case only happens when the graph is disconnected. Also note that the graph theoretical distance $d_G(\cdot, \cdot)$ is a distance in the pure mathematical sense: it is always positive and satisfies $d_G(u, u) = 0$, it is symmetric ($d_G(u, v) = d_G(v, u)$), and it obeys the triangular inequality ($d_G(u, v) \leq d_G(u, w) + d_G(w, v)$).

The neighbors of a node u are the nodes sitting at distance 1 from u. The neighborhood of u, denoted as $N_G(u)$, thus equals $N_G(u) = \{v \in V | d_G(u, v) = 1\}$, and we have $|N_G(u)| = d_G(u)$. The neighborhood can be extended to the set of distance-k neighbors denoted as $N_G^{(k)}(u)$, which is the set of nodes sitting at a distance of at most k from a node, namely $N_G^{(k)}(u) = \{v \in V | d_G(u, v) \leq k\}$.

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[1]Strictly speaking, this requires that the graph does not have multiple edges, which is the case we consider here. Otherwise, paths should specify which edges are followed along the path.

5.2.1 Distances and Closeness

Although reachability essentially relies on the *existence* of paths between nodes, one can attempt to provide a measure of *how easily* a node $u \in V$ can be reached in G – with the idea that longer paths require more effort to be traversed. Thus, the reachability of a node can be expressed in terms of graph distances.

The metrics we are about to describe use the graph theoretical distance to infer the properties of nodes and ultimately indicate how/where information flows in the graph. The rationale underlying all these metrics is that nodes sitting close to most other nodes have the easiest access to information; here, ease is measured in terms of distances.

$$s_G(u) = \sum_{v \in V} d_G(u,v) \tag{5.1}$$

The metric in Eq. (5.1) was introduced by Harary (1959) as the *status* of a node (in a graph). Observe that this metric is integer valued and can take any positive value (and even $S_G(u) = \infty$ can occur when G is disconnected). Beauchamp (1965) (although often cited through Sabidussi, 1966) later suggested computing the inverse ratio, which is currently called the *closeness centrality* of a node:

$$C_G(u) = \frac{1}{\sum_{v \in V} d_G(u,v)}. \tag{5.2}$$

Note that $C_G(u) \in [0,1]$ and that $C_G(u) > 0$ when G is connected. Additionally, $C_G(u) \leq \frac{1}{d_G(u)}$; the equality $C_G(u) = 1$ can only occur in the very special case of a two node graph.

An alternate definition is the *eccentricity* of a node $e_G(u)$ (see Hage & Harary, 1995), with the idea that central nodes are those having minimal eccentricity because they sit relatively close to all other nodes in the graph:

$$e_G(u) = \max_{v \in V} d_G(u,v). \tag{5.3}$$

Note, however, that the eccentricity of nodes does not lie in a bounded interval, which makes it difficult to compare nodes of different graphs. *Node centrality* (see Hage & Harary, 1995) overcomes this problem by taking the inverse ratio $1/e_G(u)$. The *diameter* of a graph is defined as the maximum eccentricity:

$$diam(G) = \max_{u,v \in V} d_G(u,v) = \max_{u \in V} e_G(u). \tag{5.4}$$

The *average distance* in a graph is also often used as an indicator of the graph structure:

$$\frac{1}{\frac{|V|(|V|-1)}{2}} \sum_{u,v \in V} d_G(u,v). \tag{5.5}$$

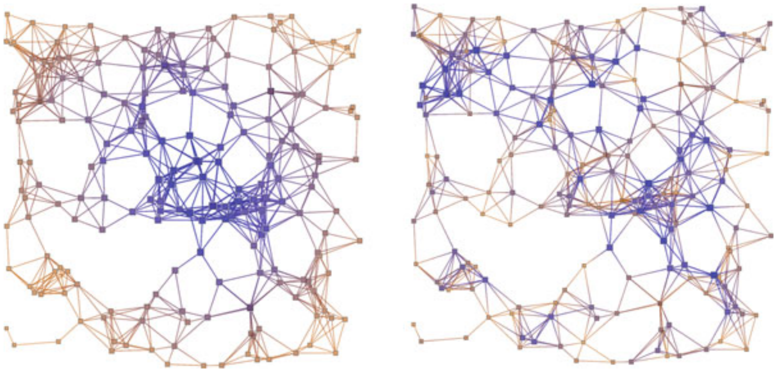

Fig. 5.1 The figure shows how values of the (*left*) Beauchamp Eq. (5.2) and (*right*) integration Eq. (5.6) distribute over nodes of a typical small world graph. Note how the Beauchamp reachability acts as a global measure, whereas the integration metric reveals local features. The node color changes from *light orange* to *purple* as the values increase. The node size also correlates with the node values (Color figure online)

Several authors have proposed variations to attempt to measure reachability; all of these variations use the distances between nodes as a basic component. Valente and Foreman (1998), for instance, define the *integration metric* as:

$$I_G(u) = \frac{\sum_{v \in V} \frac{1}{d_G(u,v)}}{|V|-1}. \tag{5.6}$$

Just as with Beauchamp's reachability metric, the integration metric lies in the bounded interval $[0,1]$. At first glance, one may think that these metrics actually compare or even correlate with each other. Figure 5.1 shows that this is not the case and illustrates how Beauchamp's closeness centrality is a global measure, unlike integration, which acts as a local indicator of the degree to which a node "integrates" in its close-by neighborhood. It is true, however, that the closeness centrality correlates well with eccentricity.

Dangalchev (2006) recently proposed exponentially altering distances before computing the same sum $\sum_{v \in V} 2^{-d_G(u,v)}$. Surprisingly, Dangalchev's residual closeness strongly correlates with Beauchamps's closeness centrality; this correlation indicates that the geometric transform has a "globalization effect" on the distances. Note also that Dangalchev's centrality can be computed even when the graph is disconnected as $2^{-d_G(u,v)} = 0$ if $d_G(u,v) = \infty$.

5.2.2 Shortest Paths

Other authors designed measures that capture the degree to which a node is central in connecting the other elements of a network. This is somewhat different from

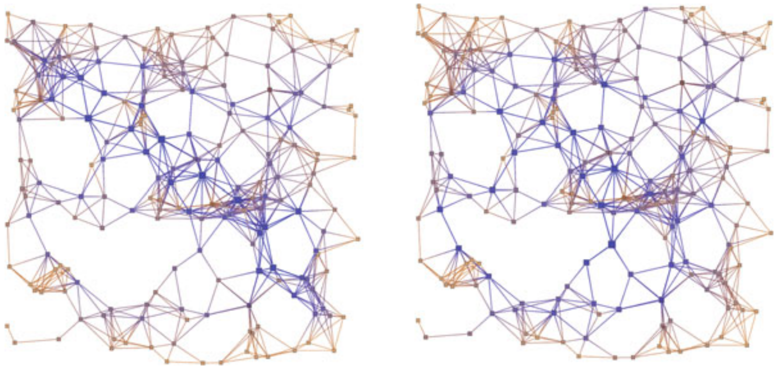

Fig. 5.2 The figure shows how values of the (*left*) stress centralities Eq. (5.7) and (*right*) betweenness Eq. (5.8) are distributed over the nodes of a typical small world graph. Note how both metrics compare well. The node color changes from *light orange* to *purple* as the values increase. The node size also correlates with the node values (Color figure online)

all distance-based metrics described in the preceding paragraph. In fact, distances between nodes do not fully describe *how* nodes are connected together and do not explicitly indicate whether actors have an essential role in distributing information through the network. Roughly speaking, focusing on the notion of *paths*, we aim to identify nodes that play an essential role in making information available to others, as opposed to the preceding paragraph, in which we tried to identify nodes that had easy access to information. That being said, distance-based and/or shortest path-based metrics can nevertheless be correlated, as we shall describe.

More precisely, let σ_{vw} denote the number of shortest paths connecting two nodes v and w. We set $\sigma_{vv} = 1$ by convention. This number may be greater than '1': imagine a cycle of size $2n$ for which this number is equal to 2 when nodes sit at distance n (that is, when they are one diameter away from each other). Let us also write $\sigma_{vw}(u)$ for the number of shortest paths connecting v and w *and* going through u (this number may be equal to 0). Shimbel (1953) defined the *stress centrality* of a node as:

$$S_G(u) = \sum_{v,w \in V} \sigma_{vw}(u). \tag{5.7}$$

Anthonisse (1971) and Freeman (1979) independently considered a ratio involving both $\sigma_{vw}(u)$ and σ_{vw}, which is now known as a node's *betweenness centrality*:

$$B_G(u) = \sum_{v,w \in V} \frac{\sigma_{vw}(u)}{\sigma_{vw}}. \tag{5.8}$$

Figure 5.2 shows both metrics mapped in terms of color and node size. As can be observed, these two variations correlate well, which can be confirmed, for instance, by examining the histogram of values.

A useful exercise is to compute distance-based and shortest paths metrics on the same graph and compare the results. As we have argued earlier, we can consider these metrics as belonging to different classes. Distance-based metrics highlight nodes having easy access to information, while shortest path metrics identify nodes playing a central role in distributing information. As such, both classes of metrics will indicate nodes involved in both roles: those sitting at the center will presumably play a role in distributing information, while efficient broadcaster nodes should not sit at the periphery. This exercise can be performed by visually comparing the colormaps in Figs. 5.1 and 5.2.

5.2.3 Group Cohesion

As emphasized above, singular nodes can embody specific roles in terms of reachability and/or the distribution of information through the network. As for the other nodes, although they do not have decisive impacts as individual entities, they might collectively contribute to the overall network structure. What is usually meant here is that the network organizes into tighter subgroups and that, in a sense, the whole network divides into "communities", a term coined by Newman (2001), see also Newman (2003, 2006), interacting with each other.

We seek to identify the *community structure* of a network: find the subgroups and observe how they interact. Being able to identify these communities is an issue that differs somewhat from the questions we addressed in previous sections. More precisely, the perimeter of a community cannot be deduced based on the role of a single node but rather from the overall properties of a subset of nodes. We shall see, however, how these two perspectives act dually and relate to each other.

Watts and Strogatz (1998) had introduced the *clustering index* of nodes in a graph as an index measuring the overall connectivity between the neighbors of a node u:

$$c_G(u) = \frac{e(N_G(u), N_G(u))}{\binom{|N_G(u)|}{2}} \tag{5.9}$$

where $e(A,B)$ is the number of edges connecting the nodes in set A to nodes in set B. The expression $\binom{k}{2}$ denotes the binomial coefficient, which incidentally computes the maximum number of edges that can exist in a graph with k nodes. That is, the index $c_G(u)$ roughly computes the probability that any two neighbors of u are connected. The *clustering index of a graph* then equals the average value of its nodes $c(G) = \frac{\sum_u c_G(u)}{|V|}$.

Until Watts and Strogatz started studying *small world networks*, the only available graph model was that defined by Erdős and Rényi (1959, 1960). The Erdős-Rényi model includes the following characteristics: a set of n nodes is given; edges are then added independently between node pairs following a random procedure (heads or tails, for instance). These graphs can be shown to have a rather

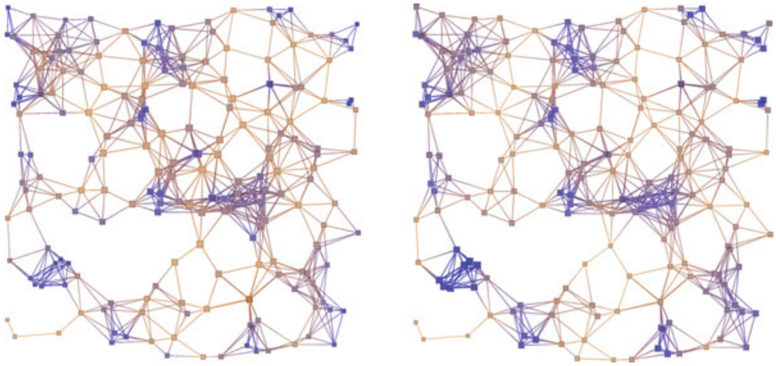

Fig. 5.3 The figure shows how values of the clustering index (*left*) and Jaccard index (*right*) are distributed over the nodes/edges of a typical small world graph. Note how both metrics act locally, as opposed to the metrics in Fig. 5.1 or Fig. 5.2. The node color changes from *light orange* to *purple* as the values increase. The node size also correlates with the node values (Color figure online)

low average distance (see Eq. 5.5) between nodes. However, nodes do not split into distinct communities because the connections are uniformly distributed among the nodes.[2] In other words, the clustering coefficient of an Erdős-Renyi graph can be expected to be somewhat small.

Inspired by the popular saying "It's a small world", Watts and Strogatz developed different graph models that showed characteristics similar to those of the real world networks observed by Milgram (1967). More precisely, a graph is said to be small world if its clustering coefficient is high while the average distance between nodes is low when compared to the values of random Erdős-Renyi graphs with the same number of nodes and edges.

The clustering index does just what it is expected to do, as it indicates just how well connected is the neighborhood of a node u; the clustering index can thus be presented as a *cohesion metric*. Another approach is to focus instead on edges and consider how many common neighbors that the end nodes of an edge $e = \{u, v\}$ have:

$$J_G(e) = \frac{|N_G(u) \cap N_G(v)|}{|N_G(u) \cup N_G(v)|} \tag{5.10}$$

The metric in Eq. (5.10) was first introduced by Jaccard (1901), who studied the similarity between floral species. However, the Jaccard index can be computed on sets and can thus be used to compare any type of attribute-based data (Fig. 5.3). Also note that, when applied to neighbor sets $N_G(u)$, the numerator actually computes the number of triads (cycle of length 3) in a graph G going through an edge e.

[2]This being said, a random Erdős-Rényi graph might not be necessarily connected. For more details, see Bollobás (1985).

This idea converges with that of Granovetter, in which triads are a key component in social cohesion (Granovetter, 1973). Other edge metrics that were proposed much later were designed to achieve similar goals (see Sallaberry & Melançon, 2008 for more details).

The Jaccard index has a useful interpretation in terms of group cohesion. Note that when an edge $e = \{u, v\}$ connects two distinct neighborhoods $N_G(u) \cap N_G(v) = \emptyset$, we have $J_G(e) = 0$. That is, the Jaccard index seems capable of locating regions where communities break apart. In the same line of reasoning, one may expect the clustering coefficient to help locate such transition areas in networks.

The two metrics we have described so far are *local*, meaning that the value assigned to a node or edge is computed by examining neighboring nodes and/or edges. Two other types of metrics can be defined to capture community structures. A well-known and widely used metric that has recently attracted the attention of a wide audience through the fertile work of Newman et al. (Clauset, Newman, & Moore, 2004; Girvan & Newman, 2002; Newman, 2001, 2006) is the betweenness centrality metric *extended to the edges* of a graph. Recall that the betweenness centrality Eq. (5.8) is defined in terms of the number of shortest paths going through a node (or edge). That is, an edge with a high betweenness centrality can be expected to act as a *bridge* between communities. Burt (2005) also highlights high centrality edges as bridges passing through structural holes in the network. Bridges have been exploited as a central component for breaking down a graph into communities (see, for instance, Amiel, Melançon, & Rozenblat, 2005; Auber, Chiricota, Jourdan, & Melançon, 2003; Clauset et al., 2004; Girvan & Newman, 2002).

5.3 Community Dynamics

Finding cohesive subgroups or communities in a network helps obtain a better understanding of how network entities interact. When performing a visual inspection or exploration of a network, one will typically compute communities and then build a simpler graph, the "quotient graph", from the community structure. More precisely, let $G = (V, E)$ be a graph and $\mathbf{C}$ be a partition $\mathbf{C} = (C_1, \ldots, C_k)$ where $C_i \subset V$ are distinct subsets ($C_i \cap C_j = \emptyset$ when $i \neq j$) covering $V = \cup_{i=1,\ldots,k} C_i$.

Then, we can form the quotient graph $G/\mathbf{C}$ with vertices $\{C_1, \ldots, C_k\}$, where edges connect C_i and C_j when there is at least one edge $e = \{u, v\}$ connecting two nodes $u \in C_i$ and $v \in C_j$. Fig. 5.4 illustrates this construction. Each box shows the subgraph contained in a cluster, which is shown as a metanode. Metanodes are connected according to the edges between the nodes they contain.

Providing an overview of all existing graph clustering is beyond the scope of this book. The interested reader should see Brandes, Gaertler, and Wagner (2007) and Schaeffer (2007), for instance. Here, we shall limit our discussion to a few popular clustering strategies that rely on network indices (see Amiel et al., 2005; Auber et al., 2003; Clauset et al., 2004; Girvan & Newman, 2002). As mentioned earlier, centrality indices can be used to identify the bottleneck edges in networks. Hence,

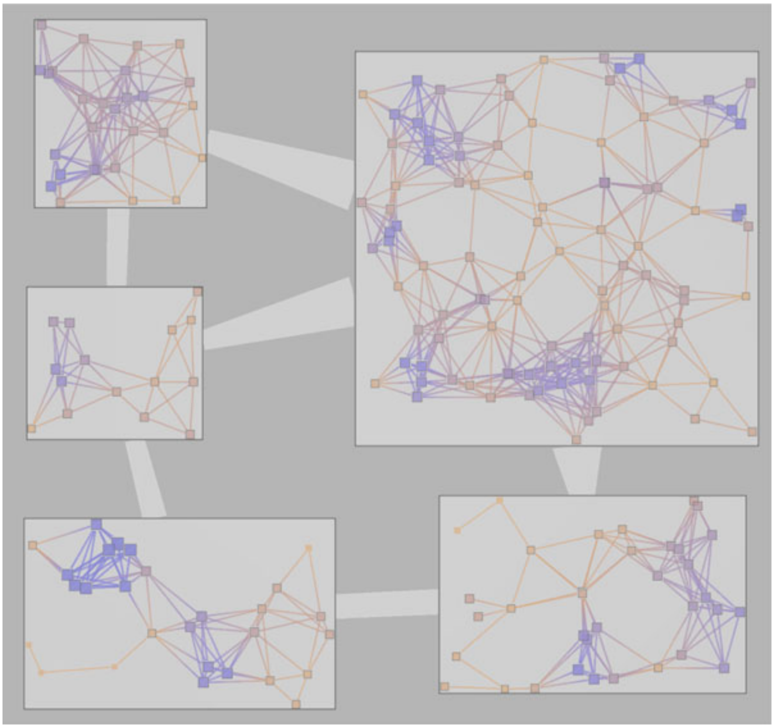

Fig. 5.4 A quotient graph consists of metanodes that themselves contain subgraphs. Links between metanodes consist of the edges connecting the nodes in the underlying subgraphs. This quotient graph is built from the graphs shown in the previous figures

bridges (edges with low centrality values) can be temporarily discarded, turning the graph into disconnected components that all appear as communities and defined clusters. The quotient graph can thus be formed where metanodes connect through bridges. Note that this procedure can be repeated at will on each community to provide a multilevel decomposition of the original graph, as suggested in Fig. 5.5.

The procedure described here proceeds in a top-down manner, further decomposing communities into sub-communities. Other algorithms proceed in a bottom-up manner and build super-communities from smaller subgroups.

A number of questions can be addressed once a graph has been decomposed into communities. Note that in the visual representation of a quotient graph (Figs. 5.4 and 5.5), all edges connecting members of two distinct communities are abstracted as a single higher-level edge. It is interesting, however, to study how clusters exchange through their members. To this end, Guimerá, Mossa, Turtschi, and Amaral (2005) introduced what they call the *participation coefficient* of a node. Before giving a formal definition for this coefficient, we need to introduce some notation. Recall that $d_G(v)$ denotes the degree of a node in a graph G (simply written as $d(v)$ when G is clear from context). Now, we denote as $d_{C_i}(v)$ the degree of a node in a cluster

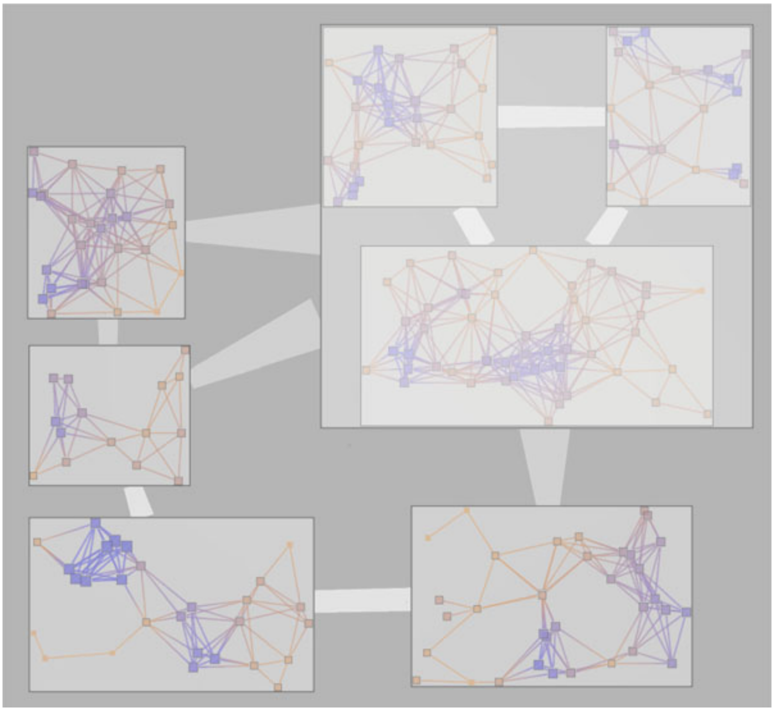

Fig. 5.5 A multilevel quotient graph is one where higher level clusters are themselves decomposed into sub-communities. The upper right cluster in Fig. 5.4 has been further decomposed into three sub-communities

C_i. That is, $d_{C_i}(v)$ equals the number of neighbors the node v has in cluster C_i, i.e., $d(v) = \sum_{i=1,\ldots,k} d_{C_i}(v)$. The participation coefficient of a node $v \in V$ is defined as:

$$p(v) = 1 - \sum_{C_i \in \mathbf{C}} \left(\frac{d_{C_i}(v)}{d_G(v)}\right)^2 \tag{5.11}$$

Note that $p(v) = 0$ exactly when v has all its neighbors in the same cluster, meaning that the participation of v in the overall community structure concentrates on a single subgroup, which is most likely the one it belongs to. Conversely, $p(v)$ is minimized when its neighbors are uniformly distributed over all clusters. The participation coefficient of a node compares with *Shannon's entropy* (Shannon, 1948):

$$H(v) = \sum_{C_i \in \mathbf{C}} \frac{d_{C_i}(v)}{d_G(v)} \log\left(\frac{d_{C_i}(v)}{d_G(v)}\right) \tag{5.12}$$

Note that both of these coefficients (and those defined below) allow for straightforward generalizations to weighted graphs. Similarly, Burt also introduced the *hierarchy index* of a node (see Burt, 2005). The participation coefficient, like Shannon's entropy and Burt's index, can be used to evaluate the nodes' participation in the overall network dynamics.

In Eq. (5.11), we may distinguish the term involving node v and consider the quantity

$$\frac{d_{C_i}(v)}{d_G(v)}$$

as the *representation* of node v within its cluster C_i. Similarly, we can define the *contribution* of a node v to its class as:

$$\frac{d_{C_i}(v)}{\sum_{u \in C_i} d_{C_i}(u)}$$

These indices have proven to be useful and complementary to Guimera's participation coefficient and z-score (Guimerà et al., 2005) when analyzing community dynamics.

5.4 Conclusion

This chapter surveyed a number of nodes and edges metrics, echoing the notions explored in the previous chapter, and implicitly classified these metrics into a taxonomy. Local metrics only rely on neighbor information and can usually be computed efficiently. Distance-based metrics typically require traversing the graph and computing all node distances. Centrality measures rely on the shortest paths between nodes.

All of these types of metrics can help identify densely connected subgroups by either assessing the local edge density, such as with the Jaccard index for edges Eq. (5.10), evaluating the node clustering index Eq. (5.9), or identifying the nodes or edges acting as bottleneck routes or points in the network. These bottleneck elements can then be used to split the network into subgroups and capture its community structure. The last metrics we described apply to clustered graphs and aim to measure the degree to which a node interacts with other clusters in the network. Examples showing how these metrics can be used to analyze networks shall be discussed at length in the forthcoming chapters.

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Chapter 6
Graph Visualization For Geography

Antoine Lambert, Romain Bourqui, and David Auber

6.1 Introduction

Network analysis is usually performed with combinatorial measures such as those presented in Chap. 5 or traditional statistical tools such as principal component analysis. However, it is extremely difficult for some patterns, even with these powerful approaches, and the results of these methods can be difficult to interpret without an appropriate representation.

The purpose of this chapter is to present methods for the automatic drawing of networks, which is a complex field that can raise several intractable problems related to graph theory. However, for the purpose of geographic network analysis, there are two main approaches that are sufficiently general for use in this application. The first method is the so-called force-directed approach that uses a physical analogy to construct a model network where the Euclidean distances are very similar to the distances in the actual network. The second method creates an abstract network that reduces the visual complexity of the representation. Because the geographic positions of the network elements can provide crucial information, one specific approach relates the topology of the network to the geographical positions. Then, the flow map layout technique can be applied to emphasize high level patterns in that network.

The remainder of this chapter is structured as follows. Section 6.2 reviews some related work on general graph drawing methods and, in particular, force-directed approaches. In Sect. 6.3, we present the compound graph visualization technique. We next explain how node positions can be taken into account and high level patterns can be highlighted in Sect. 6.3.1. Finally, we draw our conclusions in Sect. 6.5.

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6.2 General Graph Drawing Method

The most frequently used approach for laying out general graphs is the so-called force-directed method that uses particles and attractive forces to model the nodes and their edges in a network, respectively. The algorithm creates a physical system and simulates its evolution to a state of equilibrium. Figure 6.1 shows a representation of a physical system that models nodes with particles and their edges with springs.

That method has become increasingly popular in recent years because it presents some interesting advantages. First, the physical analogy is easy to understand for practitioners without a background in graph theory. Thus, it generates visualizations of graphs that can be shared and presented to large audiences. Second, the naive implementation of this algorithm is straightforward, and one can easily modify it and make customized versions to meet particular needs. Finally, this method generates drawings that are visually pleasant, structurally significant and usually better optimized than those obtained with other graph drawing algorithms.

When using this naïve approach (e.g., Eades, 1984; Frick, Ludwig, & Mehldau, 1995; Fruchterman & Reingold, 1991), system convergence is quite slow and this method is not useful for large datasets. Recent force-directed algorithms overcome this limitation by making a trade-off between time efficiency and aesthetic criteria (e.g., Gajer & Kobourov, 2002; Hachul & Junger, 2005; Lauther, 2007). In this section, we first present the main classical force-directed algorithms and then explain how to improve the time complexity of such algorithms.

6.2.1 Force Directed Drawing

In 1984, Eades introduced the first algorithm based on the use of a force system. His algorithm is initialized by placing the nodes at random positions. Then, at each round, each node is moved in the direction of the attractive (springs) and repulsive forces (nodes). After several rounds, the system automatically converges to equilibrium. The bottlenecks of this approach are the force computation complexity and, in some cases, the system can oscillate and never reach equilibrium. Several

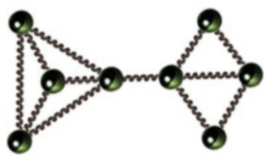


Fig. 6.1 Example of a physical system built using particles and springs to represent the nodes and their edges, respectively. Particles create repulsive forces while springs create attractive forces between particles

improvements have been proposed. Even if these methods do not scale to large datasets, they guarantee the convergence of the system.

All force-based algorithms follow the same concept, and algorithm 1 summarizes the four main steps of these methods. In the following, we compare three of the most commonly used implementations for each step of the algorithm (Eades, 1984; Frick et al., 1995; Fruchterman & Reingold, 1991).

```
Data: A graph
Result: A force directed layout
Calculate Initial Position (CIP)
while not equilibrium do
    Compute Attractive/Repulsive Forces (CARF)
    Compute Displacement Vector (CDV)
    Move Nodes (MN)
end
```

Force-directed algorithms can be summarized in four steps. CIP initializes the system before running the simulation, CARF implements the interaction rules of the system, CDV manages convergence of the system and MN applies the result to the system.

Eades (1984):

To speed up the convergence of the system Eades (1984) proposed replacing the Hooke's forces or Hooke's law with his own force model where P_u is the coordinates of a node u, $\overrightarrow{p_u p_v}$ is the unit vector co-directional with $\overrightarrow{P_u P_v}$, $dist(u,v)$ is the norm of $\overrightarrow{P_u P_v}$, l is the ideal length of an edge (i.e., spring), and c_{att}, c_{rep} are two constants that define the strength of the spring. Attractive and repulsive forces are given by the following formulas:

$$f_{att}(u,v) = c_{att} \cdot \log\left(\frac{dist(u,v)}{length}\right) \cdot \overrightarrow{p_u p_v} \tag{6.1}$$

$$f_{rep}(u,v) = \frac{c_{rep}}{dist(u,v)^2} \cdot \overrightarrow{p_v p_u} \tag{6.2}$$

and the total force exerted on a node u is as follows:

$$f_{total}(u) = \sum_{(u,v)\in E} f_{att}(u,v) + \sum_{(u,v)\notin E} f_{rep}(u,v) \tag{6.3}$$

Note that the repulsive forces are computed between all pairs of non-neighbor nodes. Because the MN phase is performed in a synchronous way, i.e., all nodes are moved at the same time, Eades' method used a constant $\delta \in [0,1]$ to limit the movements of a nodes. The displacement vector is computed as follows:

$$disp(u) = \delta \cdot f_{total}(u) \tag{6.4}$$

Fruchterman and Reingold (1991):

The force system was then modified to reach equilibrium with fewer iterations. This is achieved by using a quadratic force model:

$$f_{att}(u,v) = \frac{dist(u,v)^2}{length} \cdot \overrightarrow{p_u p_v} \tag{6.5}$$

$$f_{rep}(u,v) = c_{rep} \cdot \frac{length^2}{dist(u,v)} \cdot \overrightarrow{p_v p_u} \tag{6.6}$$

and the total force exerted on node u is as follows:

$$f_{total}(u) = \sum_{(u,v)\in E} f_{att}(u,v) + \sum_{v\in V, v\neq u} f_{rep}(u,v) \tag{6.7}$$

Note that in Fruchterman and Reingold's algorithm, the repulsive forces are computed between all pair of nodes. To optimize the time computation, Fruchterman and Reingold use a grid that helps to approximate the repulsive forces and a decreasing function δ that bounds the movements of the nodes (during the CDV step):

$$disp(u) = \delta(iteration\_number) \cdot f_{total}(u) \tag{6.8}$$

where

$$\delta : [1..maxIterations] \to [0,1]$$
$$itNumber \to \delta(itNumber)$$

is a decreasing function. The extent to which the algorithm restricts the node movements increases with the number of times the algorithm has iterated, which improves the convergence of the algorithm.

GEM by Frick et al. (1995):

In this article, the authors give their own force model:

$$f_{att}(u,v) = \frac{dist(u,v)^2}{length \cdot \Phi(u)} \cdot \overrightarrow{p_u p_v} \tag{6.9}$$

where $\Phi(u) = 1 + \frac{\deg_G(u)}{2}$.

$$f_{rep}(u,v) = c_{rep} \cdot \frac{length^2}{dist(u,v)} \cdot \overrightarrow{p_v p_u} \tag{6.10}$$

and the total force exerted on node u is as follows:

$$f_{total}(u) = \sum_{(u,v)\in E} f_{att}(u,v) + \sum_{v\in V, v\neq u} f_{rep}(u,v) + f_{gravity}(u) + f_{random}(u) \qquad (6.11)$$

The force-directed approach determines the node positions by minimizing the total energy of the system. However, the solution is usually sub-optimal and the algorithm finds a local minima. Frick et al. (1995) added a random force in an attempt to overcome that problem. Frick et al. also introduced a new displacement scheme (CDV phase) in which the δ function is defined for each node of the network:

$$\begin{aligned} \delta : V[1..maxIterations] &\to [0,1] \\ (u, itNumber) &\to \delta(u, itNumber) \end{aligned}$$

Again, the more the algorithm has iterated, the more the nodes movements are restricted. This function also decreases when the node rotates and/or oscillates around a point, which allows the algorithm to converge faster.

6.2.2 Fast Force Directed Drawing

To reduce the computation times, particular nodes are extracted from the network. These nodes must be as "central" as possible because they will represent the whole graph. This process is repeated until the set of elected nodes is small enough to be quickly drawn, typically several dozen nodes. This results in a hierarchy of sets of elected nodes, from the highest set that contains only a few nodes to the lowest set that contains all of the nodes from the original network. Let $S_0, S_1, \ldots, S_k$ be these sets of elected nodes, then $S_0 \supset S_1 \supset \ldots \supset S_k$ and $S_0 = V$. Each set of elected nodes is then drawn in a top-down manner, i.e., from S_k to S_0, using a classical force-directed algorithm (see Sect. 6.2.1). To reduce the computation time, when drawing the set S_i, only nodes not contained in S_{i+1} are taken into account so that each node is embedded only once.

In the following section, we present a more detailed description of GRIP (Gajer & Kobourov, 2002; Gajer, Goodrich, & Kobourov, 2004), one of the most popular fast force-directed algorithm.

GRIP: Graph dRawing with Intelligent Placement (Gajer & Kobourov, 2002; Gajer et al., 2004):

The GRIP algorithm consists of two main steps: an extraction step and a drawing step.

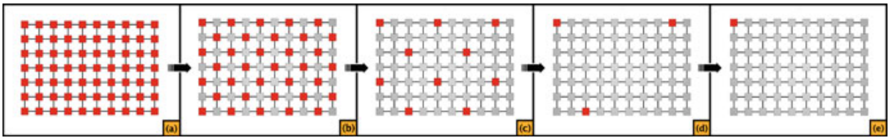


Fig. 6.2 (**a**) Example of a graph containing 70 nodes and 123 edges; (**b**) Maximal set S_1 of nodes at distance at least 2 is shown in *red*; (**c**) Maximal set S_2 of nodes at a distance at least $2^2 = 4$ is shown in *red*; (**d**) Maximal set S_3 of nodes at a distance at least $2^3 = 8$ is shown in *red*; (**e**) Maximal set S_4 of nodes at a distance at least $2^4 = 16$ is shown in *red* (Color figure online)

Extraction Step:

The first step of the GRIP algorithm computes a *Maximal Independent Set Filtration* (MISF) $\mathcal{V}$ of the set of vertices V of G. The filtration, $\mathcal{V}$, is defined as follows: $\mathcal{V} = S_0, S_1, \ldots, S_k$ where $S_0 \supset S_1 \supset \ldots \supset S_k \supset \emptyset$, $S_0 = V$ and $\forall i, 0 < i \leq k, S_i$ is a maximal subset of S_{i+1} such that for all pairs of vertices u, v of S_i, the graph distance between u and v is greater or equal to 2^i. The idea is to extract the nodes at a distance of at least 2 to represent the whole graph, then to extract the nodes at a distance of at least 4 to represent the nodes at a distance of 2, and so on until the set of elected nodes contains at most 3 nodes as shown in Fig. 6.2. This process makes it possible to compute sets of elected nodes that are well-distributed in the network.

Drawing Step:

During the second step of the GRIP algorithm (Gajer & Kobourov, 2002; Gajer et al., 2004), the process first places nodes of S_k and then each filtration set $S_{k-1}, s_{k-2}, \ldots, S_0$. For each level, the placement is split into two phases: an "intelligent" initial placement (i.e., nodes are placed closed to their final positions), and then a refinement phase that uses a force-directed algorithm (either the Kamada-Kawai (1989) or the Fruchterman-Reingold (1991) algorithm).

Intelligent Initial Placement:

For the smallest set S_k, the authors consider that S_k contains exactly 3 nodes. (If this is not the case, then the nodes of S_{k-1} are included in S_k). Let u_1, u_2 and u_3 be the three nodes of S_k, which are laid out on a triangle as follows:

$$dist_{\mathbb{R}}(u_1, u_2) = dist_G(u_1, u_2)$$
$$dist_{\mathbb{R}}(u_1, u_3) = dist_G(u_1, u_3)$$
$$dist_{\mathbb{R}}(u_2, u_3) = dist_G(u_2, u_3)$$

where $dist_{\mathbb{R}}(u, v)$ is the Euclidean distance between u and v and $dist_G(u, v)$ is the theoretical graph distance between them.

Table 6.1 Comparison of computation times based on our networks in seconds

	AT 2000	AT 2004	US migration	Daily migrations
# nodes / # edges	1,525 / 16,434	1,767 / 19,353	1,716 / 9,775	1,181 / 10,829
GEM (s)	251.1	384.9	291.5	105.8
GRIP (s)	1.5	2.2	1.1	1.3

For every other level i, $0 \leq i < k$, let u be a vertex of S_i, and v_1, v_2 and v_3 be the three closest and already placed neighbors of u. The authors lay out u at the barycenter of v_1, v_2 and v_3 that is evaluated from the graph distances between u and the three neighbors.

Refinement:

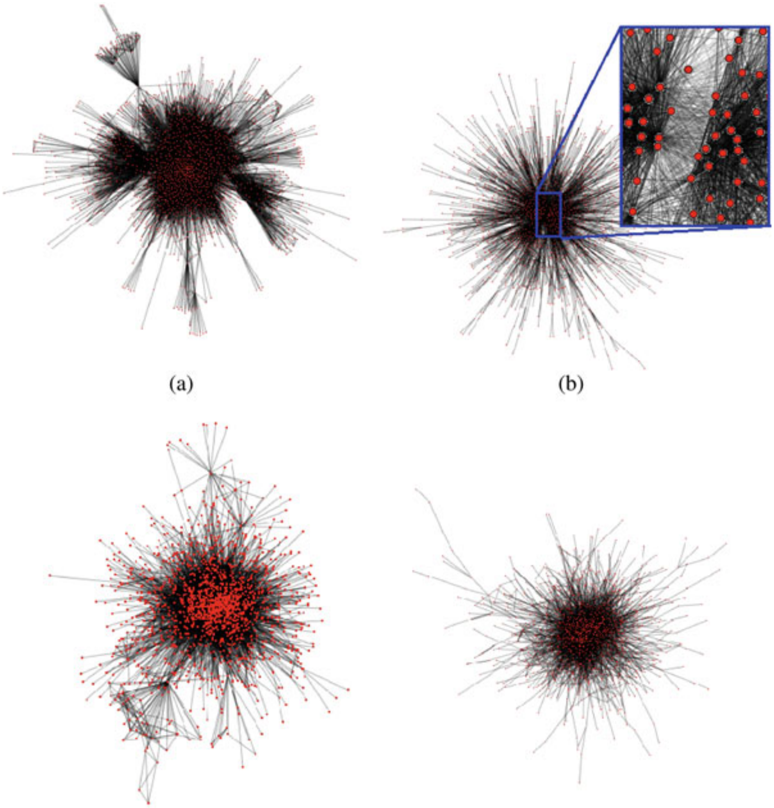
To refine the placement, the authors use force-directed algorithms. For each level i, $1 \leq i < k$, they use the well-known Kamada-Kawai algorithm (1989). This algorithm takes into account the graph distances in the computation of the forces. And, for the last filtering set S_0, computing all graph distances would take too much time and/or memory space, so they apply the Fruchtermann and Reingold algorithm (1991), which uses only Euclidean distances (see Sect. 6.2.1). To further improve the computation time, the forces applied to a vertex v of S_i include only the interactions between v and its closest neighbors in S_i.

6.2.3 Results Comparison

In this section, we compare two well-known force-directed approaches in terms of their computation time and drawing quality.

Table 6.1 shows the computation times obtained with GRIP (Gajer & Kobourov, 2002; Gajer et al., 2004) and GEM (Frick et al., 1995), a fast force-directed algorithm and a classical force-directed algorithm, respectively. These networks are 2000 and 2004 international air interconnections, US migrations and French daily migrations. Using GRIP improves the computation times by a factor of more than 100. This approach handles large networks (in this example, up to more than 1,500 nodes and 25,000 edges). The gap between the force-directed and fast force-directed approaches is even wider when drawing networks containing hundreds of thousands of elements.

Figure 6.3 shows drawings of 2004 international air interconnections and French daily migrations networks by GEM (Frick et al., 1995) and GRIP (Gajer & Kobourov, 2002; Gajer et al., 2004). When looking carefully at these results, one can see that the drawings obtained with GEM emphasize more information than



(a) (b) (c) (d)

Fig. 6.3 Drawings obtained from 2004 international interconnections and US migration networks by: (**a**, **b**) GEM (Frick et al., 1995) and (**c**, **d**) GRIP (Gajer & Kobourov, 2002; Gajer et al., 2004)

those from GRIP. For instance, in Fig. 6.3b, one can see two large components that split the US migration networks into two regions while no such phenomenon is observed in Fig. 6.3d. Actually, these two regions correspond to groups of western and eastern states of the United States.

When dealing with reasonable size networks (several hundred or thousand elements), it seems that the classical force-directed approaches are preferable to the fast force-directed ones, because they offer better results in terms of aesthetic criteria and they emphasize more information. On the contrary, when dealing with large networks, one should use fast force-directed algorithms because they offer much better computation times.

6.3 Compound Representation

To find an algorithm that gives good results (in term of computation time, aesthetic criteria and information emphasized) for arbitrary networks is a very difficult problem. One of the most popular approaches to drawing such general graphs, namely the force-directed approach, which produces visually pleasant and structurally significant results (e.g., Frick et al., 1995; Fruchterman & Reingold, 1991; Gajer & Kobourov, 2002; Hachul & Junger, 2005; Lauther, 2007).

Even if fast graph layout algorithms can scale up to thousands of elements, two important issues still remain: cluttering and slow rendering. The clutter (node-node overlaps, node-edge overlaps and edge-edge crossings) increases with the size and complexity of the graph, resulting in unreadable visualizations. Additionally, displaying a large number of elements may lead to slow rendering and thereby hinder interactive exploration. Therefore, both cluttering and slow rendering make the analysis task harder for end-users and must be avoided.

An effective way to reduce the visual complexity of the representation, thereby reducing visual clutter and speeding up the rendering process, is to build an abstraction of the original graph. That abstraction is then displayed on the screen and the user can explore his/her data via a dedicated interactive system that allows the end-user to reduce/increase the level of detail.

6.3.1 Building an Abstraction

To build an abstraction, one usually applies clustering algorithms that group together similar elements of the network (e.g., Auber, Chiricota, Jourdan, & Melançon, 2003; Dongen, 2000; McSherry, 2004; Newman & Girvan, 2004; Schaeffer, 2005). After the first partition of the elements is computed, two options are offered: either refine each cluster by applying the clustering algorithm, or contract each cluster into a single node and apply the clustering algorithm to the resulting graph. If the first partition of a few clusters contains many elements, then the first option should be preferred. On the contrary, if the partition of many clusters contains only a few elements, then the second option will increase the level of abstraction. In Fig. 6.4a, one can see the result of an iterative decomposition of an illustrative network. The network has been first decomposed into three clusters (green, pink and yellow) and then the yellow cluster has been refined and a brown cluster has been found. In Fig. 6.4b, one can see the usual data structure that was used to represent that hierarchical partition of the nodes.

Once the hierarchical partition has been computed, the abstraction of the network (according to that partition) is then built by replacing each cluster of nodes with a single node (called a metanode), replacing all edges linking two of these subsets with a single edge (called a metaedge), and linking the corresponding metanodes. This operation reduces the number of displayed nodes and edges and, therefore,

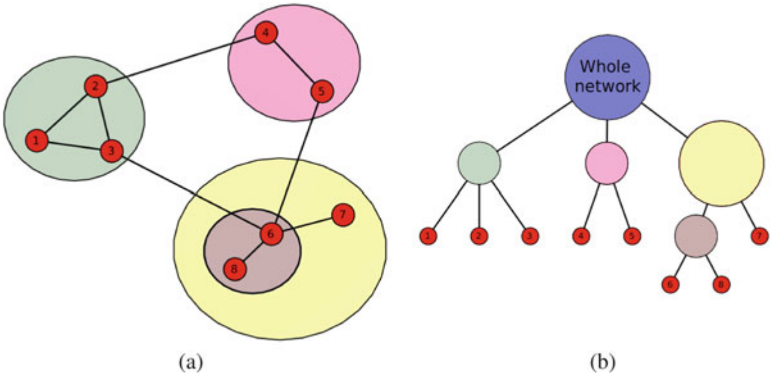


Fig. 6.4 (**a**) Example of a network that has been iteratively decomposed into clusters and sub-clusters. Each of these clusters is shown in a particular color. (**b**) The corresponding data representation where each leaf of the tree represents a node of the network, and an internal node represents a cluster (Color figure online)

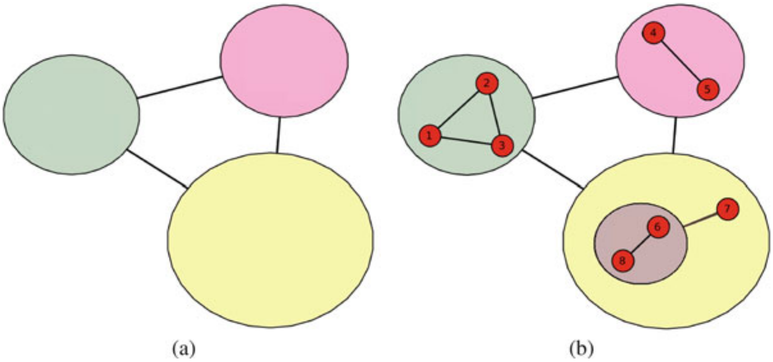


Fig. 6.5 (**a**) Classical compound visualization of the highest level of abstraction of the network shown in Fig. 6.4a; (**b**) corresponding multiscale visualization

reduces the visual clutter and increases the rendering speed. This abstraction is usually called a compound graph, which is associated with the original graph and the partition (see Fig. 6.5). If repeated iteratively, this process allows the construction of abstractions of higher and higher levels.

6.3.2 *Drawing the Abstraction*

After the abstraction has been built, one must draw it in order to present a readable image to the end-user. To draw an abstraction, there exist two strategies called top-down and bottom-up. The top-down strategy consists of first drawing the abstraction at the highest level, and then drawing deeper and deeper clusters in the hierarchy. For instance, applying this strategy to the network of Fig. 6.4a one would first draw the compound graph of the highest level (containing the yellow, the green and the pink metanodes), then draw the compound graph contained in the yellow cluster (containing node "7" and the brown metanode) and finally draw the content of the brown cluster (containing nodes "6" and "8"). The main drawback of that method is that one cannot predict the size of each metanode when drawing a cluster. For instance, when drawing the yellow cluster, one does not know the size of the brown metanode. To overcome this problem, the bottom-up strategy first draws the deepest clusters and then draws clusters at lower and lower levels. In Fig. 6.4a, the brown cluster would be drawn before the yellow one, and the size of the brown metanode can therefore be determined before drawing the yellow cluster.

Some particular tools (Abello, van Ham, & Krishnan, 2006; Archambault, Munzner, & Auber, 2007, 2008) that focus on the visualization of very large graphs (even those graphs that are too large to fit in memory) support on-demand drawing to quickly give the user a first picture of the data. Only the highest level of abstraction is displayed, and on-demand clusters can be drawn in a top-down manner. However, because these tools use the top-down strategy, metanodes sizes in the representation do not necessarily correspond to the number of elements they represent.

6.3.3 Compound Visualization Methods

In this section, we present the two compound visualization methods that we call classical and multiscale compound visualization methods.

In the classical compound visualization, the metanodes appear opaque. Figure 6.5 shows an example of classical compound visualization corresponding to the highest level of abstraction of the network of Fig. 6.4. One of the first interactive classical compound visualization techniques, developed by Schaffer et al. (1996), shows the effectiveness of using graph clustering and compound visualization when exploring large networks. To enable exploration, the authors introduce a variable zoom method that consists of using a combination of a metanode expansion (or contraction) and a geometrical fish-eye. While this interaction (Schaffer et al., 1996) only allows the expansion of a single metanode, van Ham and van Wijk (2004) proposed a method to define the desired level of abstraction.

In contrast to classical compound visualization, multiscale compound visualization displays both the original graph and the whole hierarchical partition in a single view. This is done by filling the "interior" of each metanode (that represents a cluster) with a drawing of the highest level of abstraction (i.e., the compound graph of the sub-hierarchy). For instance, in Fig. 6.5b, the interior of the green metanode is filled with a drawing of the compound graph corresponding to the top level of the subtree rooted on the green node, here a graph with three vertices and edges. And the interior of the yellow metanode is filled with an abstraction of the subgraph it represents, here a compound graph containing the brown metanode and

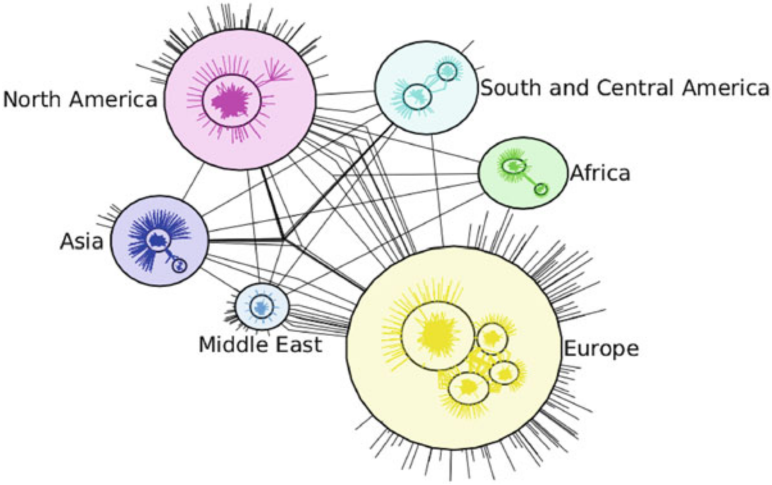


Fig. 6.6 Multiscale compound visualization of 2000 international air traffic network clustered according to continents and then to subnetwork density

node "7". The ability of this method to display both abstracted inter-cluster and intra-cluster relationships has been shown in numerous work (Auber et al., 2003; Balzer & Deussen, 2007; Eades & Feng, 1996; Huang & Eades, 1999).

6.3.4 *Example Based the 2000 International Air Traffic Network*

In this section, we present some results that we obtained by analyzing the international 2000 air traffic network.

Figure 6.6 shows a multiscale compound visualization of the 2000 international air traffic network. In this representation, the first partition has been computed according to geographical regions and then each cluster has been refined using a clustering algorithm. That view of the network allows one to visualize intra-region relationships while having an overview of inter-region ones.

However, the representation in Fig. 6.6 does not allow one to identify the central airports (or hubs) of the network. This is mainly due to the utilization of geographical positioning of the airports in the clustering process. Figure 6.7 shows another representation of the same network. Connections with fewer than 300,000 passengers have been filtered out to remove "noise" from the data. Indeed, connections having few passengers may lead to inconsistent clusters (usually, clustering algorithms are based on cluster density). When not using the geographical positioning of airports, one can see in Fig. 6.7 that clusters do not necessary correspond to geographical regions of the network. For instance, the main international (e.g., Paris,

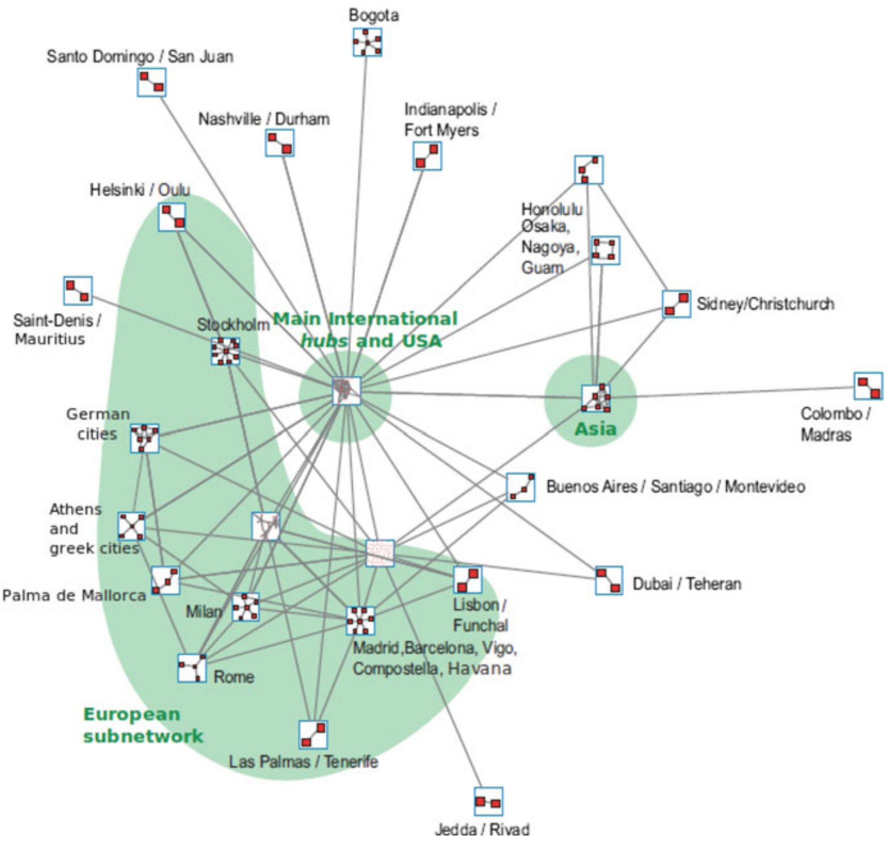


Fig. 6.7 Multiscale compound visualization of the 2000 international air traffic network. Connections with fewer than 300,000 passengers have been removed and the resulting graph clustered using a strength clustering algorithm (Auber et al., 2003) (Image courtesy Amiel, Rozenblat, and Melançon (2005))

London, Frankfurt) and North American airports have been clustered together (cf. Fig. 6.7), because they are highly connected and form one of the main hubs of the network. One can also see that Asian airports have been clustered together and that these airports are sparsely connected to the rest of the network (in Fig 6.7 the “Asia” metanode is linked only to the main hub and to several other clusters).

6.4 Flow Maps Representation Of Graphs

Graph drawing algorithms focus primarily on the computation of node positions and try to achieve various aesthetics in order to provide readable layouts. A major graph drawing aesthetic is edge crossing minimization (di Battista, Eades, Tamassia, &

Tollis, 1998). The effect of this aesthetic on human understanding was demonstrated in previous user studies (Purchase, 1998; Purchase, Cohen, & James, 1995). In some cases, however, graph layout algorithms cannot avoid producing edge cluttering due to high edge density or intrinsic connectivity. This is typical of force-directed layouts that are applied to real world dense graphs: edges connecting close neighbors in the drawing mix with long range edges impair readability or even introduce confusion. The situation is even worse when laying out data using geographical positions. In such cases, the task of identifying flows inside a network is challenging because displaying a large number of connections with lines results in visual clutter. Therefore, reducing the clutter in a graph representation is of utmost importance to the identification of relationships and high-level edge patterns.

Currently, edge bundling techniques are of increasing interest in the graph visualization community. Put under the spotlight by Holten (2006), this technique addresses the issue of reducing edge cluttering in graph drawings by routing edges into bundles. The resulting graph visualization improves the layout readability by uncovering high level edge patterns and emphasizing relationships in relational data. Several rendering techniques have also been proposed in order to improve this type of visualization. In this section, we will focus on the recent and intuitive bundling technique proposed by Lambert, Bourqui, and Auber (2010). This bundling algorithm has the advantages of outperforming the execution times of existing methods and can guarantee that no node-edge overlaps will occur in the drawing. Furthermore, this work introduces a rendering technique that makes it possible to perceive bundle density while preserving edge colors.

The remainder of this section is structured as follows: Sect. 6.4.1 reviews related work on edge bundling methods. In Sect. 6.4.2, we present the bundling algorithm of Lambert et al., while Sect. 6.4.3 refers to rendering techniques that can be applied to enhance edge bundling visualization.

6.4.1 Previous Work

Phan, Ling, Yeh, and Hanrahan (2005) present a flow map layout technique based on geometrical node clustering. Edges are routed along the hierarchy tree branches. This idea has also been used by Holten (2006) to enhance relationships in hierarchical (and relational) data. The main drawback of both methods is that the edges are routed by using a hierarchy tree that can be restrictive in the general case.

Gansner, Koren, and North (2005) give an improved circular layout algorithm where the edges are routed on either the outer face or the inner face of the circle. Edges routed inside the circle are bundled using an edge clustering algorithm that tries to optimize area utilization. Another edge clustering method is given by Cui, Zhou, Qu, Wong, and Li (2008). In this paper, they propose a geometric approach to create bundles of edges. They build a control mesh based on user interaction or a Delaunay triangulation. The mesh is then used to compute regions where edges should be merged. Then, a clustering algorithm based on the orientation of edges is used to merge the edges. A post processing step is applied to reduce the effect of "zigzag" edges.

Recently, Holten & Wijk (2009) introduced a force-directed heuristic to bundle edges and, therefore, to unclutter a representation of a graph where the node positions are fixed. In this heuristic, dummy nodes are inserted in order to split edges into segments. A similarity measure between edges is computed to determine which of the dummy nodes should interact. Dummy nodes of any two interacting edges are linked by inserting dummy edges. Bundles are obtained by running a force-directed algorithm while preserving the positions of the original nodes.

6.4.2 Edge Bundling Method of Lambert et al.

This technique uses edge routing to bundle edges. A grid is computed according to the node positions. This grid is then used to compute the shortest routes for each edge. In the same way that highways attract more drivers than smaller roads, frequently taken paths are used to bundle edges.

Grid Computation

To compute the shortest paths for each original edge, a grid graph is created on which the nodes of the original graph are connected. This grid is computed by discretizing the plane into cells using original node positions.

To obtain a multi-resolution grid graph, one can use a quad tree where the plane is decomposed in four parts until it contains at most one element. Such an approach is efficient in terms of computation time because its complexity is $O(|V| \cdot \log(|V|))$. On one hand, it generates a large grid, and on the other hand, large cells promote horizontal and vertical paths. Voronoi diagrams can also be used to generate the grid graph. In a Voronoi diagram, the cells are regions of the plane in which points of a cell are closer to the cell's site (here, the original nodes) than to any other site. Using classical Voronoi diagram does not guarantee that node edge overlaps will be prevented in the case of non-point size nodes. However, that problem can be easily addressed by using a constrained Voronoi diagram that takes into account the node size. This method generates a small grid graph that can be computed in $O(|V| \cdot \log(|V|))$, but it generates large cells for a sparse region. Due to the routing method used in the next step of the algorithm, these large cells will create large detours. Lambert et al. propose a hybrid algorithm based on both quad trees and Voronoi diagrams. In this algorithm, the quad tree cell sizes are parameterized to generate different levels of clutter reduction. Then, Voronoi diagrams are used to construct the final grid graph. Figure 6.8b shows the grid graph obtained with this hybrid approach. Because the quad tree adds $O(|V|)$ nodes, the $O(|V| \cdot \log(|V|))$ time complexity is preserved. Therefore, the resulting grid graph is of reasonable size.

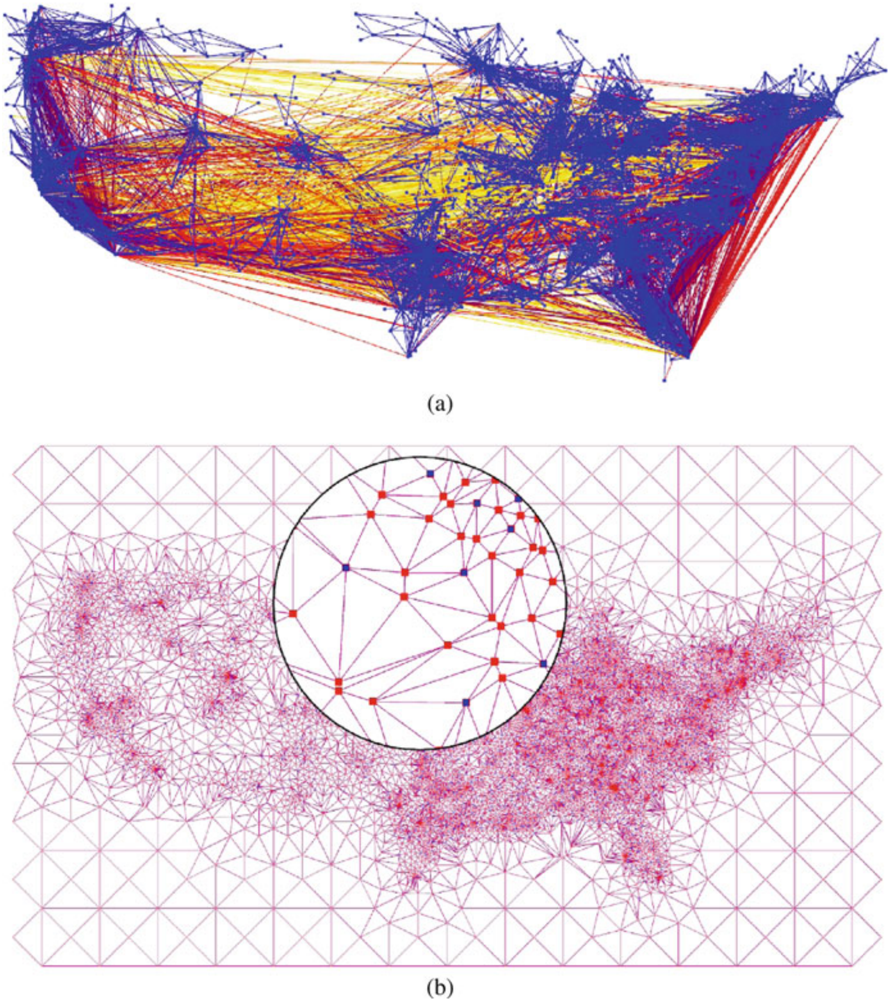


Fig. 6.8 (**a**) Original graph layout before the bundling process. This network represents migrations of workers between major cities in the USA. (**b**) The grid graph created to perform the edge rerouting. *Red nodes* are grid nodes and *blue nodes* are those from the original graph (Color figure online)

Edge Routing

The next step in the method consists of routing edges in the original graph onto the grid obtained in the previous step. A shortest path algorithm could be used directly to perform this operation. However, this method does not guarantee that edges follow the same path and, thus, it creates few bundles. To augment this bundling effect, the metaphor of roads and highways is used. Regular roads that are frequently used are

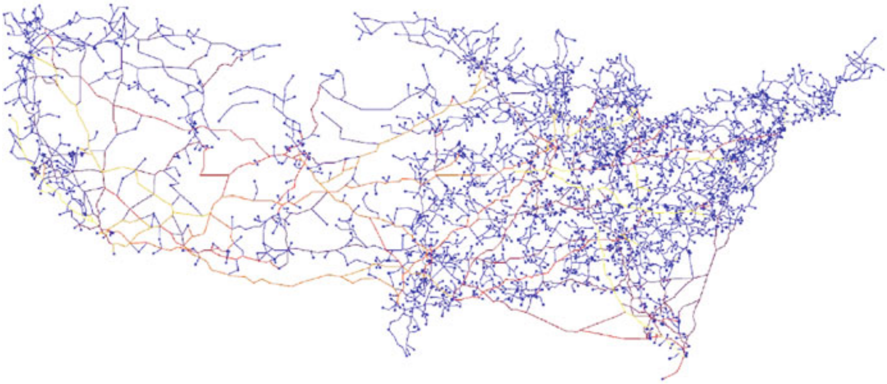


Fig. 6.9 The layout of the graph introduced in Fig. 6.8a after the edge bundling process

transformed into larger ones. This effect is reproduced by first computing all of the shortest paths between linked nodes on the original graph. Then, according to the number of shortest paths through an edge of the grid, the weights of the grid edges are adjusted. Reducing the weight of an edge is equivalent to transforming it into a highway because it is possible to go faster from one point to another. A shortest path for each edge of the original graph is then computed. This adjustment of the weights creates new bundles because the new distance matrix of our graph promotes frequently used edges. To compute the shortest paths, we use the well-known Dijkstra's algorithm (1971), leading to $O(|V_{grid}| \cdot |E_{grid}| + |V_{grid}|^2 \cdot \log(|E_{grid}|))$ time complexity. The result of this edge routing phase is presented in Fig. 6.9.

6.4.3 Enhancing Edge Bundled Graph Visualization

Edge bundled graphs leverage several issues with respect to rendering the graphs on a screen. To obtain an aesthetic drawing and to ease the retrieval of information from the visualization, some rendering methods and visual encodings have been designed specifically for this type of visualization technique. The following summarizes these techniques.

Smoothing Edges with Curves

The main feature common to every edge-bundled graph visualization is the drawing of edges as curves. Indeed, rendering graph edges as curves makes it easier to follow the edges and gives a more visually appealing graph drawing. In 2006, Holten renders bundled edges piecewise with cubic B-splines. By using this type of spline, which provides local control of the curve shape, one can produce distinct

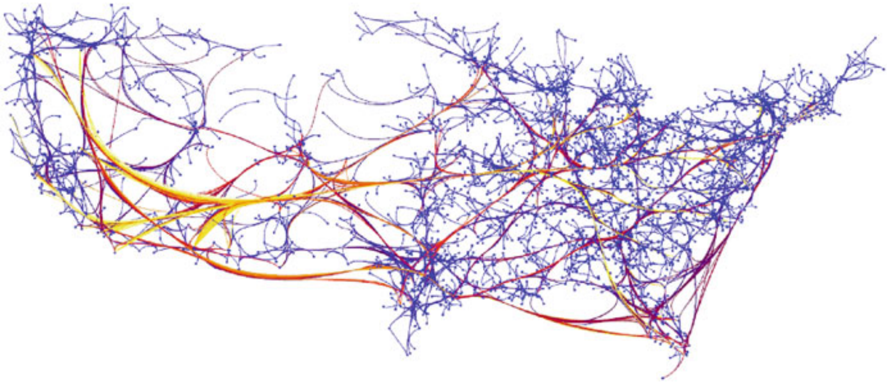


Fig. 6.10 Smoothing the edges of the graph from Fig. 6.9 with Bézier curves

and coherent bundles. Lambert et al. (2010) use this type of spline as well as others such as Bézier curves or Catmull-Rom splines. Another method used by Holten and Wijk (2009) and Cui et al. (2008) is to apply a smoothing technique to the edges that are drawn as polylines in order to morph them into curves. A rendering of the same graph in Fig. 6.9 with edges drawn as Bézier curves is introduced in Fig. 6.10 for visual comparison.

Coloring Edges

Another method to enhance edge-bundled graph visualization is to use edge colors and opacities to encode information. Edge colors are mapped to the directions of the original links (Cui et al., 2008). In a similar technique, edge direction is encoded by an interpolated color gradient running from a fixed color for the source to a fixed color for the target (Holten, 2006). Holten (2006) maps edge opacities to their length where long curves are more transparent than short ones, which prevents short curves from becoming obscured. Cui et al. (2008) use the opacity of each segment of the polyline representing an edge to map the density of the lines overlapping it.

Perceiving Bundle Density

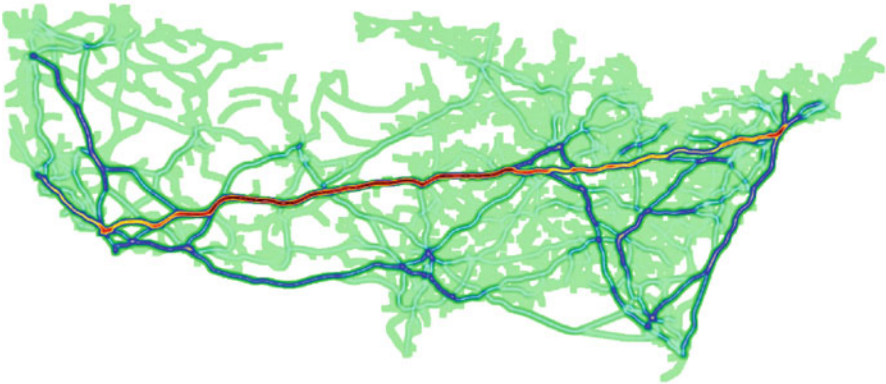
After graph edges have been bundled, some of the bundles share successive bends. Consequently, several edge segments are merged into a single segment and the information about the number of edges contained in a bundle is not readily visible in the drawing. To distinguish strong bundles from weak ones, some techniques have been designed to visually enhance the bundle strength. The first rendering technique for estimating the quantity of merged edge segments is proposed by Holten & Wijk (2009). A GPU-based method is used to compute the amount of overdraw for each pixel in the graph visualization. This value is then used to map pixel colors to a user-defined gradient color scale after the minimum and maximum values of the overdraw have been computed. Lambert et al. (2010) introduce an "edge splatting" technique that allows the viewer to perceive bundle density while preserving edge colors. In a similar manner, the GraphSplatting technique introduced by Liere and Leeuw (2003), a splat field is computed to encode continuous variations in the density of the merged edges. To obtain the splat field, the first step is to compute the number of edges crossing each pixel in the drawing. A GPU-based method (Holten & Wijk, 2009) is used to perform that task. Then, the splat field is generated by convoluting the discrete density values (associated with each pixel) with a Gaussian kernel. The larger the kernel radius and the standard deviation, the more the splat field is smoothed. This splat field can be rendered on a screen in a various ways. After computing the minimum and maximum values of the splat field, one can perform a simple color mapping, for instance. To preserve edge colors, Lambert et al. use a *bump mapping* technique. Bump mapping is a computer graphics technique that allows a rendered surface to appear more realistic without modifying its geometry. Bump mapping adds a per-pixel shading that makes the surface appears bumpy, by changing the surface normals. The color and brightness of each pixel are then altered with respect to these normals by using an illumination algorithm. The final color of a pixel is computed from the light properties and a color map. This color map can correspond to a splat field color mapping or to the original edge colors. By mapping the splatting values to the heights, bundles with high density edges appear taller than others and visually emerge from the layout. Results of this rendering technique can be found in Fig. 6.11.

6.5 Conclusion

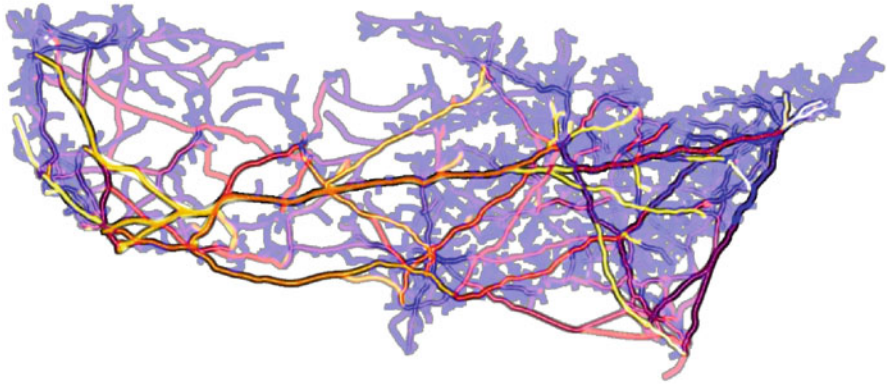
In this chapter, we presented the main methods for the automatic drawing of networks for geographic data visualization. Among these methods, one of the most popular approaches is the force-directed method, which produces visually pleasant and structurally significant results. In that method, nodes are considered as particles and edges represent attractions between these particles. To overcome the computational cost problem of such methods, fast algorithms have been designed to make a trade-off between computation time and aesthetic criteria.

We also presented the compound graph visualization that displays an abstraction of the network. This is achieved by first producing a partition of the nodes using a clustering algorithm. Then, each cluster is collapsed into a single node to build the abstraction. In the case of large and complex data, compound graph visualization allows the reduction of visual clutter in the representation while preserving the rendering speed and, therefore, supporting interactive exploration.

Finally, we reviewed the main flow map layout techniques. In this approach, node positions must be preserved because they can provide information. The main problem is that it thereby creates many edge crossings that clutter the representation.



(a)



(b)

Fig. 6.11 Perceiving bundles densities with a bump mapping rendering technique. Edges are rendered as cubic B-splines. (**a**) A splat field color mapping is used as a color map. (**b**) Original edge colors are used as a color map (Color figure online)

To remove this clutter and to emphasize high-level edge patterns, the edges are routed and grouped into bundles. Finally, rendering techniques such as bump mapping are used to illustrate bundle densities.

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Chapter 7
Exploring Hierarchies Using the DAGMap

Pierre-Yves Koenig

7.1 Introduction

Hierarchical data appears naturally in many applications. In their simplest form, hierarchies are trees. Tree structures, such as classifications (for instance, geolocalization classifies continent, country, states or region), phylogenetic trees, and company organization charts, are but a few examples. In richer hierarchical organizations, cross links allow elements to belong to several non-distinct classes. Inheritance relations of classes in object oriented programming is a typical example. Classifying concepts extracted from documents, for instance, can sometimes require concepts to be "duplicated", depending on the possible interpretations. The "network" concept, for example, can refer to both social network analysis and low level computer hardware. Additionally, both concepts may be required to index a collection of documents. Such a classification naturally leads to the construction of a directed acyclic graph (a *DAG*).

In a DAG, nodes are ordered using *ancestor/child relationships* just as with trees, with the exception that nodes may have multiple parents. Nodes without ancestors are called *source* nodes, while those without any children are called *sinks*.

The case study we shall explore in this chapter is made up of companies linked to one another through subsidiary links, i.e., company c_1 is linked to company c_2 if c_2 is a subsidiary of c_1. Clearly, this graph structure is a DAG: subsidiaries themselves have subsidiaries and a subsidiary may be held by several "ancestor" companies. The dataset also collects attributes measuring how much of a subsidiary is held

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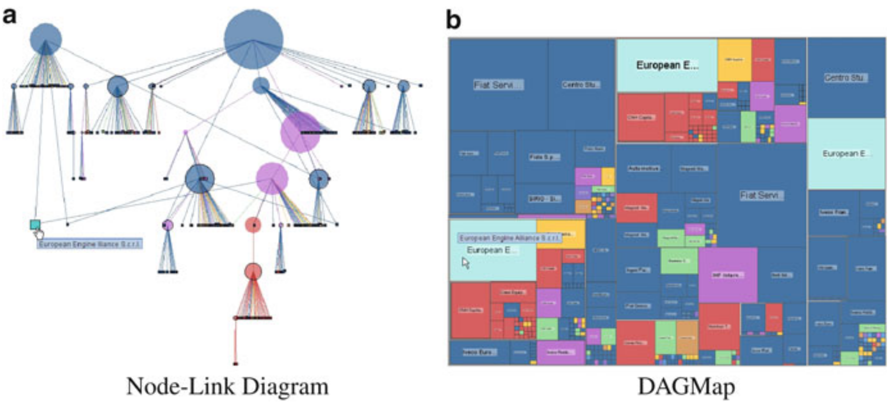

Fig. 7.1 (**a**) Traditional Sugiyama node-link layout. (**b**) Corresponding DAGMap view of a DAG. The node size and color correspond to node attributes such as the companies' assets and the location of headquarters (color figure online)

by each of its parent companies. Image (a) in Fig. 7.1a shows a part of a DAG describing links between companies and their subsidiaries. The node (and link) color and map size correspond to different attributes that can be computed from the DAG (see Sect. 7.3).

Natural questions emerge when studying data modeled by DAGs. The level of a node v in the DAG roughly corresponds to how "general" the node is. More precisely, the level can correspond to how much of the DAG the node spans, or how many nodes can be accessed going downwards from v. For companies, the node level corresponds to the degree to which a company controls its subsidiaries (and subsidiaries of its subsidiaries, etc.). This is even more the case when one takes into account edge or node attributes, such as a company's assets. In our case, the DAG structure also reveals the extent to which two (or more) companies' strategies or interests overlap over a set of subsidiaries. We have developed a technique that combines a node-link view with the DAG, explicitly showing links between companies and visually indicating where a company is located in the whole hierarchy. However, this type of view is not optimal for showing and comparing node attributes. We have thus designed a DAGMap view, which constructs a TreeMap (Shneiderman, 1992) from a DAG, in order to emphasize node attributes, such as the total capital of a company, making it easy to compare companies based on attributes. Color coding semantic attributes, such as the country (or region) for the company's headquarters, has been shown to be efficient in helping geographers study how companies build strategies to avoid taxes, compete or collaborate with others. For instance, the DAGMap view facilitates identifying small subsidiaries as "tax havens", while the node-link view helps clarify how small subsidiaries link to ancestor companies or other subsidiaries.

The remainder of the chapter is organized as follows. We first present related work, followed by a description of our case study, motivating the use of the combined DAGMap and node-link layout. We then provide details on how the DAGMap is computed from the DAG. Returning to our case study, we explain how the node-link and DAGMap views are linked through user interaction.

7.2 Related Work

7.2.1 Node Link Diagram

A node-link diagram is an intuitive representation of a hierarchical dataset. Each element of the dataset is represented as a node, and relationships between elements are represented as edges linking two nodes. Tree hierarchies have been widely explored, and different types of layout algorithms have been proposed. Figure 7.2 shows different representations of the same hierarchy using several algorithms.

These algorithms can be extended to a directed acyclic graph. When drawing a DAG, source nodes are often placed at the top and are said to have level 0. The level of a node is then set to the length of the longest path connecting the node to a source node. In this process, we make sure that all of the edges are directed downwards (see Fig. 7.1a).

Tree layout algorithms (see di Battista, Eades, Tamassia, & Tollis, 1998) draw internal nodes as well as leaf nodes, thus explicitly showing the relative positions of the nodes in the tree. These properties also remain the same for the layout of the DAGs (Eades & Sugiyama, 1990).

The quality and readability of these node-link representations are usually measured in terms of the ability of the representations to avoid edge crossings (see Gutwenger & Mutzel., 2004, for instance). Node-link diagrams are useful for representing DAGs but are less efficient when the representation involves semantic information in terms of node sizes and colors. Indeed, even when drawing DAGs with nodes of equal sizes, layers must be kept sufficiently apart to ensure that the diagram is readable.

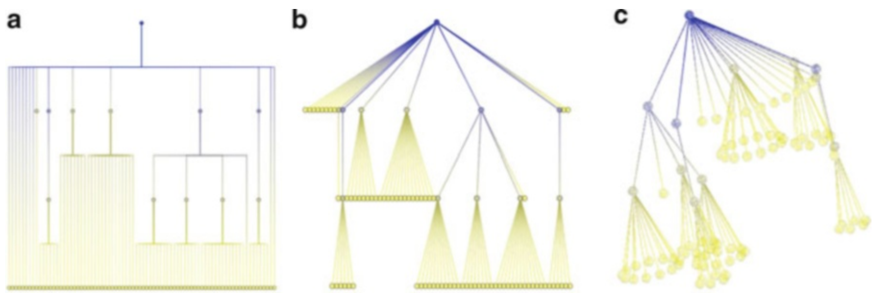

Fig. 7.2 Different layouts of the same hierarchy using different algorithms. (**a**) Dendogram. (**b**) Walker (Reingold & Tilford, 1981; Walker, 1990). (**c**) Cone tree (Carriere & Kazman, 1995)

Additional space is obviously required when dealing with nodes of various sizes. Edge readability requires that layers be kept apart and that horizontal edges be avoided. Even with medium-sized DAGs, overlapping neighboring nodes can only be avoided at the price of a bad aspect ratio. Consequently, the identification of color or size patterns is difficult because nodes stemming from a common ancestor are placed in rows. Note that this is also true for the standard node-link representations of trees because in both cases, the layout is partly devoted to the encoding of the structure of the graph (dominance relations), leaving empty screen space between layers.

7.2.2 Space-Filling Approaches

Space-filling approaches (Shneiderman, 1992) were a solution to the visualization of trees with node attributes at the price of illustrating less structure. Treemaps are a visualization technique for presenting hierarchical information for two-dimensional displays (Shneiderman, 1992). TreeMaps follow a space-filling approach, mapping the leaf nodes of a tree onto contiguous areas in a plane, with several graphical cues reflecting attributes in the data. The area itself can be computed by taking the attributes into account. The internal nodes of the tree are only apparent through nesting and encode several attributes through node size or color.

This space-filling strategy radically differs from classical node-link representations for trees (see di Battista et al., 1998), where much care is taken with the relative node position, reflecting the structure of the hierarchy, as opposed to semantics in the data (leaf nodes).

The commercial success and adoption of TreeMaps in several domains of application corroborates the usability of TreeMaps. Improved interactivity (Chintalapani, Plaisant, & Shneiderman, 2004) and versatility (Vliegen, van Wijk, & van der Linden, 2006) often make TreeMaps an obvious choice for designing visualization systems for hierarchical data.

Many improvements on the original TreeMap representation have been suggested (Bruls, Huizing, & van Wijk, 2000; van Wijk & van de Wetering, 1999). In the original TreeMap algorithm, the display is cut into alternating directions parallel to the X-axis and Y-axis. The resulting drawings (see Fig. 7.3) seem to make it difficult for users to compare two cells in the TreeMap. The TreeMap cells end up being long, thin slices, which are difficult to read both in terms of shape and color.

In the “Squarified” TreeMap layout, the authors attempt to keep the ratio between width and height of the rectangle close to 1 (a square). Large square areas are easier to compare with each other (see Fig. 7.4a). Likewise, in Voronoï TreeMaps (Balzer & Deussen, 2005), cells are represented by polygons rather than by rectangles. Two polygons are easier to compare with each other (polygons are closer to circles and two circles are easier to compare with each other) (see Fig. 7.4c).

Other techniques focus on the perception of the TreeMap structure. In (van Wijk & van de Wetering, 1999), the authors draw cushions over cells to highlight

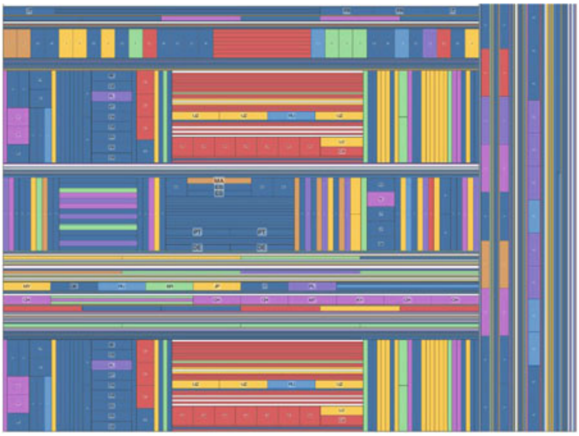

Fig. 7.3 Shneiderman TreeMap algorithm

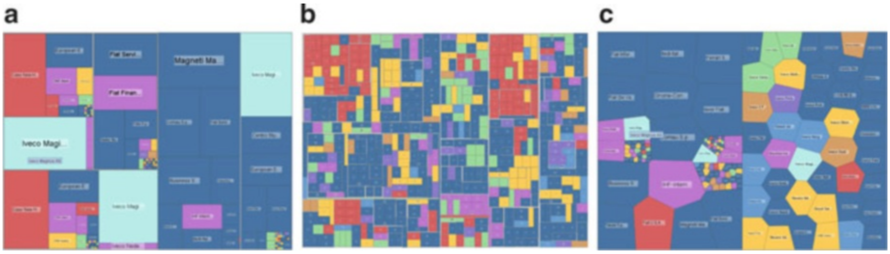

Fig. 7.4 Different layouts of the same hierarchy using different algorithms. (**a**) Squarified (Bruls et al., 2000). (**b**) Ordered (Bederson et al., 2002). (**c**) Voronoi TreeMap (Balzer & Deussen, 2005)

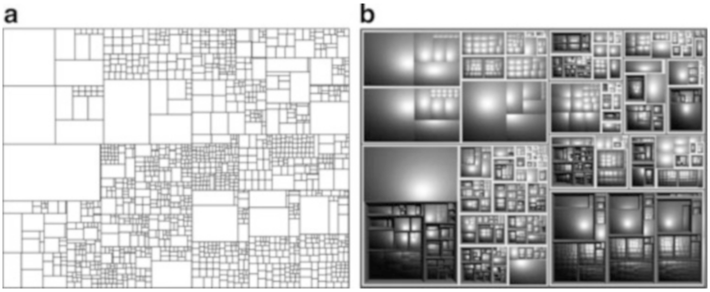

Fig. 7.5 Use of the gap and cushion to emphasize hierarchical structure. (**a**) The basic algorithm computes the plain underlying cell structure. (**b**) The TreeMap is augmented with a cushion effect to enhance the nesting structure

the hierarchy (see Fig. 7.5b). Gaps between cells can also be added. As shown in (Wattenberg & Fisher, 2003), gaps play a very important role in the human perception of levels. Adding gaps between cells in the TreeMap can better illustrate different hierarchical levels (see Fig. 7.6a). In (Lü & Fogarty, 2008), offsets illustrate the relationships between elements as an alternative to nesting (see Fig. 7.6b).

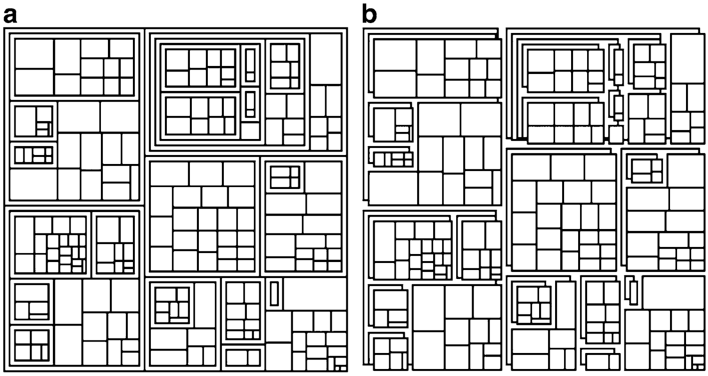

Fig. 7.6 Use of the gap and cushion to emphasize hierarchical structure. (**a**) Extra space is inserted between cells to make the nesting structure apparent. (**b**) The cushion effect is computed using a small shift of cells

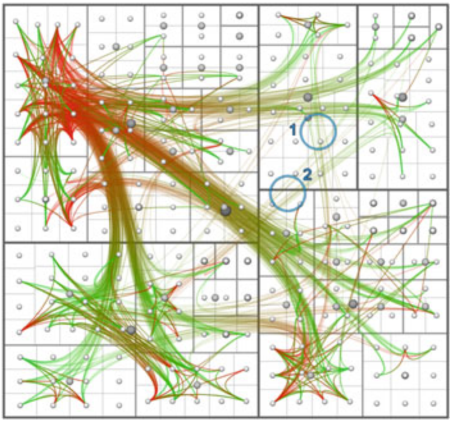

Fig. 7.7 Edge bundling

7.2.3 Combined Views

Fekete et al. have extended TreeMaps to general graphs (Fekete, Wang, Dang, Aris, & Plaisant, 2003) by extracting a spanning tree from the graph and then drawing edges over the TreeMap. Incidentally, Holten's edge bundling technique (Holten, 2006) can be used to improve the readability of this technique (Fig. 7.7).

We believe our approach is an improvement over previous techniques for visualizing hierarchical data (DAGs) for two reasons. First, in our case, edges do not connect two arbitrary cells but correspond to inheritance relationships that incorporate specific meaning. Users should refer to the Sugiyama layout to understand inheritance relationships and the level of companies before returning to the Treemap to view the attributes. Frequently, users switch between these two views to obtain a complete understanding of the system.

Linked highlighting enables structures in the Sugiyama layout to be easily identified at a glance. Consulting the Sugiyama layout orients the user in the DAG because spatial position is used to encode the node position and the level in the hierarchy. Simply drawing DAG edges on the treemap view obscures the level and the position of the structure in the hierarchy.

Second, extracting a spanning tree biases an arbitrary subtree of the DAG, randomly assigning the subtree more to one owner company than another owner company. However, a subtree can only be chosen by using information obtained from exploring and visualizing the datasets.

The DAGMap indeed lays out useful and complementary information on different parts of the screen while linking corresponding cells through user interaction. In a sense, unfolding the DAG along with our visualization system provides a framework for exploring any hypothesis.

7.3 Case Study

Part of this work was completed in collaboration with geographers in the National French Research Program SPANGEO[1]. Some data were obtained from the Orbis database maintained by the Bureau van Dijk office[2], and some of the data were manually collected. The full dataset encompasses approximately 140,000 companies, which emerge as subsidiaries of 597 main companies that cover numerous industrial sectors. Companies (and subsidiaries) are linked to one another by approximately 250,000 links. However, geographers are not interested in studying the full dataset but would rather focus on specific sectors of activity (NACE code). Alternatively, a part of the DAG that corresponds to selected major companies (source nodes) can be computed and explored separately. In this case study, we consider a DAG that spans the subsidiaries of a major European car manufacturer.

The visualization helps geographers determine how companies follow territorial logics or, in contrast, develop their activities based on other concerns. Strategies differ from one group to another. For example, Peugeot's organization is completely different from that of Renault. However, strategies also differ between sectors. Food companies tend to sell their products locally. The car industry is organized differently, producing parts in lower-cost countries, assembling the cars in another country, and shipping the vehicles to wherever markets exist. The picture becomes even more complex when companies expand their activities over several industrial sectors. Typically, a company will develop subsidiaries in the financial sector that manages financial flows generated by the overall activity of the company. Consequently, commercial and financial strategies intertwine over several industrial sectors.

[1] See the URL s4.parisgeo.cnrs.fr/spangeo/spangeo.htm

[2] See the URL www.bvdep.com/en/orbis.html

The combined DAGMap and node-link visualization provide an efficient exploratory device in order to develop an overview of these phenomena. Figure 7.1b shows the DAGMap view of subsidiaries in the car industry for the Fiat international group. Cells have been colored according to whether subsidiaries are in Europe (blue to dark blue is used to indicate that a company belongs to one of the 15 founding European countries), Asia (yellow), North America (orange), South America (green) or Africa (gray). This color coding was designed with the help of geographers. The geographers assigned a special color code for subsidiaries that are suspected tax havens (magenta). The DAGMap relies on a squarified treemap algorithm (Bruls et al., 2000), where the cell size corresponds to the amount of company assets.

The DAGMap does not simply encode a tree but actually encodes a DAG. This translates into being able to determine, in the treemap itself, if a subsidiary depends on a single ancestor company or is held by more than one of the competing companies. By clicking on a cell, the user can readily see whether the underlying element encompasses other cells in the treemap. This visual feedback provides a quick measure of the presence of a subsidiary in the network and aids with analyzing company strategies. This is the case for the subsidiary "Centro Studi sui Sistemi di Trasporto" (CSST for short), which depends on both "Iveco S.p.A." and "Fiat Auto Holdings B.V." Examining the node link diagram, we indeed see that CSST sits between these two companies. Moreover, we observe that "Fiat Auto Holdings B.V." does not hold its CSST subsidiary directly but rather through "Fiat Auto S.p.A.". We do not wish to draw any conclusions about the relationships between these companies and their subsidiaries. We rather wish to draw attention to the utility of this combined view, as was reported to us during our interviews with geographers.

7.4 DAGMaps: Extending TreeMaps to Directed Acyclic Graphs (DAGS)

Treemaps appear to be an excellent alternative to the traditional (node-link) layout for trees (Shneiderman, 1992), emphasizing the attributes of leaf nodes as opposed to the relative position of nodes in the tree. The DAGMap we describe here aims to do the same for DAGs.

We now explain how to adapt the basic TreeMap algorithm to address DAGs. Roughly speaking, the DAG is unfolded into a tree by duplicating nodes wherever necessary. Thus, a node v with multiple parents is duplicated as many times as necessary so that each parent has its own copy of v. In formal terms, let $G = (V, E)$ be a DAG. Given a node $v \in V$, let $F(v)$ denote the parents of v in G. In other words, $F(v) = \{u \in V | (u, v) \in E\}$. Now, assume that the subgraph H induced by the set of descendant nodes of $v \in V$ (nodes accessible by going downwards from v, including v itself) is a *tree*. For each parent $u \in F(v)$, we clone the subtree H and attach it below u. In doing so, the nodes $u \in F(v)$ now have distinct descendants (as far as v is concerned) (see Fig. 7.8). Performing this transformation

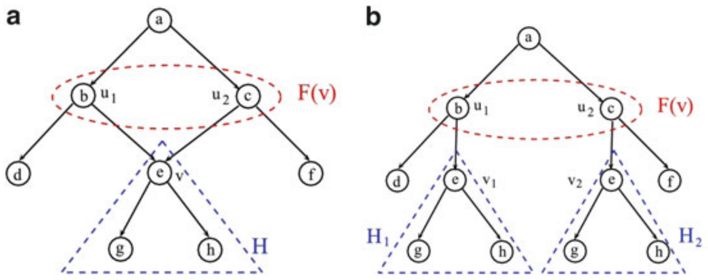

Fig. 7.8 A tree is obtained from a DAG by duplicating nodes (and labels) with multiple ancestors. (**a**) Two sibling nodes share a common subgraph. (**b**) The subgraph is duplicated to recover a tree structure

(denote $\mathscr{T}$) bottom-up from the sink nodes to the sources will eventually produce a tree $T = \mathscr{T}(G)$.

Conversely, let $T = (V,E)$ be a tree where the nodes have labels, that is, T comes equipped with the label $\lambda : V \to \mathscr{L}$. If two nodes $u, v \in V$ in T have equal labels $\lambda(u) = \lambda(v)$, then the subtrees $T_u = (V_u, E_u)$, $T_v = (V_v, E_v)$ extending from u and v are isomorphic (the subtrees have the same tree structure) and the corresponding nodes have equal labels. Thus, a bijective correspondence $\phi : V_u \to V_v$ satisfies $\lambda(x) = \lambda(\phi(x))$ for all $x \in V_u$. There is also a correspondence for preserving edges: (x,y) is an edge in E_u if and only if $(\phi(x), \phi(y))$ is an edge in E_v. We can then define on T an equivalence relation for nodes where $u \equiv v \iff \lambda(u) = \lambda(v)$. The quotient set $V/\equiv$ can then be equipped with a graph structure G, where the classes $[u]$, $[v]$ connect (in G) if two nodes $x \in [u], y \in [v]$ connect in T. As can be easily seen, the graph computed from T is a DAG and the previous unfolding process unfolds G back into T (see Fig. 7.8).

This bijective correspondence must be implemented in order to track user interaction on the DAGMap and to map the user interaction back to the original DAG (or over the Sugiyama layout when synchronizing views).

The TreeMap algorithm proceeds recursively, dividing the cell associated with a node into sub-cells for each of the child nodes, ordering the child nodes $u_1, \ldots, u_k$ according to their number of leaf nodes (in $T_{u_1}, \ldots, T_{u_k}$). This also holds true with the DAGMap: the number of sink nodes accessible from node u (in G) equals the number of leaf nodes in the subtree T_u (in $T = \mathscr{T}(G)$). Consequently, cells with greater area are placed in the top left part of the TreeMap because companies with many subsidiaries are expected to have greater assets.

7.5 Exploring the Hierarchy: Coordinating DAGMaps with the Classical Sugiyama Layout

We explain below that using a DAGMap alone is not sufficient to explore the entire hierarchy of companies and subsidiaries. The exploration focuses on the discovery

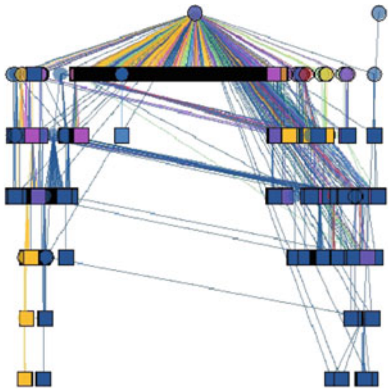

Fig. 7.9 The DAG shown here describes the links between Nestlé and its subsidiaries. Although the DAG is sparse, the node-link diagram obscures the distribution of subsidiaries over world regions and the ways in which higher level companies control lower level subsidiaries

of different commercial strategies and companies and their relationship to the territory. Note that the visual exploration only represents a first step toward a full explanation of such phenomena. Typically, users try to build hypotheses by combining standard (text-based) exploration with Google searches. Users subsequently return to the classical node-link visualization with questions in mind, iterating a sense-making loop (Thomas & Cook, 2006) by engaging in various intellectual postures (from wild guesses to strong and documented assertions).

The complexity of the analysis, however, is partly due to needing to quickly perceive the level and place of a node in the hierarchy, while simultaneously visualizing attributes such as a company's assets and locality (country/continent)[3]. Simply mapping a company's assets and territorial membership using node size and color in a traditional layout (image (a) in Fig. 7.1) proved to be inefficient because the node areas could not be easily compared.

The traditional layout displays at least twice as much visual information as the DAGMap (because ancestor nodes are mapped onto colored disks as well) or edge crossings and occlusions. Notice also that there is a lot of free space with a Sugiyama layout, as is the case with almost all node-link layouts. Consequently, displaying all of the nodes needed to report companies' assets requires much more space than using TreeMaps and argues against a visualization based solely on a Sugiyama layout.

Our experience with end-users clearly indicates the need to visualize the hierarchical structure directly on the DagMap. To this end, we enable the user to visualize how ancestor nodes cover cells in the DagMap, i.e., the user can actually define a "strip" that contains all of the elements at a given level in the tree (which come from the expanded DAG). In this way, the user can visualize the dependence of elements on ancestors.

[3]In fact, the original data are not exactly a DAG: there may indeed be links from a subsidiary controlling part of an ancestor company, thus introducing cycles into the network of links. However, this only happens exceptionally and cycles are considered marginal by our expert users, who actually discarded them.

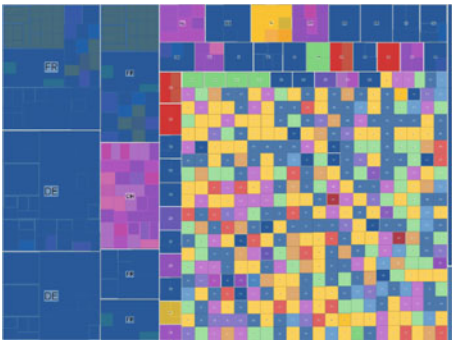

Fig. 7.10 Locating patterns in node attributes (*color*/*area*) is easier with the DagMap. By overlaying higher level cells on the DAGMap, hypotheses can be constructed on the potential management strategies of higher level companies (color figure online)

Even when the DAG is sparse, the node-link diagram in Fig. 7.9 cannot be used to analyze the distribution of subsidiaries over the regions of the world, or the ways in which higher level companies control lower level subsidiaries. The computation and interaction with the strip is designed to overcome this difficulty.

The strip is visualized using alpha values, by overlaying subsidiary cells by ancestor cells (Fig. 7.11). The mix of colors naturally indicates whether subsidiaries are controlled by mid-level companies residing in the same region of the world, or whether control is concentrated toward headquarters. When colors were mixed, indicating that subsidiaries from different parts of the world were all controlled through the same mother company, users suspected that the organization of companies relied on by-product logic (as opposed to territorial logic).

By varying the strip height, the user obtains information about the attributes of the ancestor cells and the size of their neighborhood. This functionality is helpful when combined with color variation. Color coding was shown to be useful with our test data, where the subsidiaries under the control of a suspected tax haven company were highlighted (purple colored cells), as shown in Fig. 7.10. In other situations, geographers could directly see that the South American and/or Asian subsidiaries occupying the lowest level of the hierarchy were controlled by European headquarters. Compare, for instance, the left side of the DagMap in Figs. 7.1b, 7.12, and 7.13.

7.6 Conclusion

In this chapter, we presented the DAGMap as an extension of TreeMaps to directed acyclic graphs or general hierarchies. The DAGMaps, together with the interactions we described, were designed with the help of geographers. Our case study showed that this combined view was particularly well-suited to our tasks. This was not only because the dataset was intrinsically encoded as a DAG but also due to the geographers' need for a visualization technique that astutely combines both the data attributes and hierarchical structure into a single view. The technique and the tool

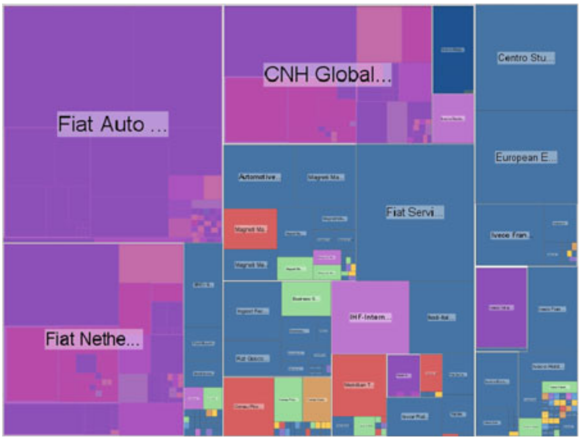

Fig. 7.11 The DAGMap shown here is obtained from that in Fig. 7.1b, using the "strip" (Fig. 7.12). The nesting of subsidiaries is revealed by visualizing the mother companies overlaying the subsidiaries. Additionally, the *color code* indicates that these subsidiaries are held by a mother company, which is suspected to be a tax haven (Fiat Netherland, *bottom left*; CNH Global, *center row*) (color figure online)

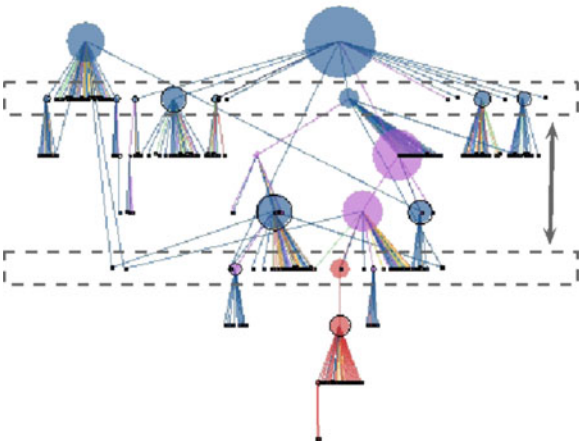

Fig. 7.12 The user can define a strip positioned at a certain level in the tree (the unfolded DAG) and can visualize the strip on the DAGMap with superimposed colored cells. Varying the height of the strip provides direct visual feedback on the DAGMap (color figure online)

were designed with expert geographers who were able to informally evaluate our prototype.

By exploring the Fiat dataset with the combined DAGMap-Sugiyama visualization, we were able to observe (and confirm) different strategies that have already been identified by Porter (Porter, 1986): these strategies have been developed on a continental level with Fiat, which most likely obeys a "car culture" differentiation. Additionally, (Fiat) Europe appears to traditionally control the hierarchy, while emergent South American countries occupy lower levels, thus confirming a classical center-periphery schema (Porter).

Further analysis is needed to confirm the following results of the DAGMap-Sugiyama visualization: the lower levels of the hierarchy obey a global model, which may be linked to the development of the "world car", explaining why

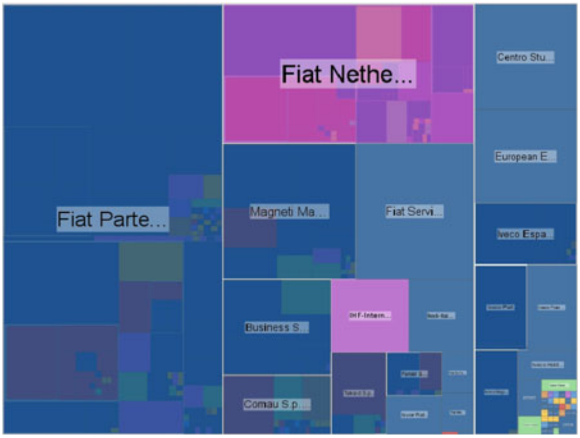

Fig. 7.13 The same DAGMap as in Fig. 7.1b, where the "strip" has a greater height. The *color code* indicates that the tax havens on the left of Fig. 7.11, themselves being subsidiaries of higher level companies, are actually held by mother companies that are all located in Europe. Thus, there may be a strategy on the part of European companies to control globalized subsidiaries through "tax haven" subsidiaries (color figure online)

subsidiaries from different world regions end up in the same DAGMap cell. Conversely, higher levels of the hierarchy represent the concentration of control on European soil, revealing a pyramidal logic in the entire structure: headquarters at the top of the pyramid, which relies on financial subsidiaries (2nd level) right above a market structured by cultural (continental) differences (3rd level, mainly involving European firms) and finally, an undifferentiated "world car" market at the bottom spread over emergent countries.

Different extensions of this technique have been proposed for dealing with larger hierarchies (Koenig, 2007). Using focus+context techniques, the user can explore the data using a specific interactor.

We also formally evaluated the combined DAGMap-Sugiyama technique versus the Sugiyama technique alone and the DAGMap alone. The evaluation showed that the DAGMap-Sugiyama visualization did not produce the best results but represented the best compromise between the number of interactions and the task completion time.

Our DAGMap visualization corresponds to a single view point showing low level details. Currently, there is no animated transition when the view point changes. In future work, an animated transition between two points of view in the DAGMap will be designed.

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Part III
Empirical Studies of Spatial Multilevel Networks

Chapter 8
Ports in a World Maritime System: A Multilevel Analysis

César Ducruet

8.1 Introduction

Contemporary sea transport carries approximately 90 % of the world trade volume. Despite this enormous importance, very little attention has been paid to the spatial organization of maritime networks throughout transport geography. Extensive research has been performed on air transport and other land-based networks; in the latter, urban centrality is the chief concern, whereas seaports are often considered aberrant cases and of peripheral interest because of a predominantly continental conception of urban and economic geography.

The aim of this chapter is to further understand the relative position of seaports within a world maritime system formed by the circulation of containerships. A global database of daily vessel movements allows for the study of the individual network attributes of seaports. Such a study will shed new light on the relationship between the individual network attributes of seaports and the classical indicators of throughput volume. In addition, this research applies clustering methodologies to the world graph to reveal the functional regions in which ports are embedded, while also evaluating the respective importance of geographical proximity and economical linkages.

The remainder of this chapter is organized as follows: The first section reviews the lack of network analysis on maritime networks throughout port geography and economics. It also provides some possible explanations for the lack of significant research in this area and some key directions for potential improvements. The second section introduces the data and the methodology together with some preliminary results of port rankings and a visualization of the world graph in 1996

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C. Rozenblat and G. Melançon (eds.), *Methods for Multilevel Analysis and Visualisation of Geographical Networks*, Methodos Series 11, DOI 10.1007/978-94-007-6677-8_8,

and 2006. Based on these preliminary results, the third section provides a multilevel analysis based on the application of strength clustering. The conclusion presents implications for policy decisions and some possibilities for further research.

8.2 The Network Analysis of Maritime Transport

8.2.1 A Lack of Network Analysis on Maritime Transport

Transport geographers have faced many obstacles in the study of maritime networks. One obstacle is contextual. Recent technological innovations in maritime transport that displace port functions from urban areas have eroded the importance of maritime transport in public representations. While these circumstances have likely reinforced the influence of the central place theory as stated by Bird (1970), they have paradoxically renewed scholars' interest in the transformation of sea transport itself, notably through its impact on port development (Slack, 1993). Shipping networks have become more footloose, partly due to shrinking transport costs and reduced trade barriers in general (Clark, Dollar, & Micco, 2004) but also due to the capacity of shipping lines to reorganize their networks globally with increased bargaining power and to integrate land transport through vertical integration (Robinson, 2002). However, the spatial complexity realized by such changes worldwide seems to have discouraged scholars from mapping the new organization of sea transport. Instead, port and maritime specialists have concentrated their efforts on the changes occurring within ports (Slack & Frémont, 2005), between ports of a given region (Ducruet, Roussin, & Jo, 2009), and across port hinterlands (Notteboom & Rodrigue, 2005), where various actors intervene in a territorial context that is more visible than across the oceans. In addition, containerization has permitted the integration of maritime transport with land-based logistics through the actions of giant companies (Robinson, 2002), while the land leg has remained the most expensive portion and has witnessed the most concentrated scholarly efforts. Therefore, the dynamics occurring across the maritime space between ports are not well known, although the current evolution may lead us toward an "ultimate system of maritime transportation [...] whereby every port node can theoretically be linked to every other port node" (Bird, 1984, p. 26).

A second obstacle in the current study of maritime networks is economic and technical. Detailed data on maritime traffic between ports are often difficult to obtain because of their rarity and their very high cost. Thus, most port and maritime specialists use aggregated measures of port throughput for comparative analysis (e.g., traffic volume, growth, and concentration) because these are simplified and easily accessible measures that indirectly analyze the spatial changes in sea transport such as the impact of port selection and the hub-and-spoke strategies of ocean carriers. Some researchers have used data from meteorological offices to obtain a snapshot of the worldwide location of sea-going vessels (Brocard, Joly, & Steck, 1995), while others have used manually encoded and computed paper-based sources to capture the sequences of port calls by vessel and by company (Joly, 1999). Recent research has used more easily accessible data derived from the annually published *Containerisation International Yearbooks*. These data sources provide information about the regular services of the world's main shipping lines, which permits the mapping of their geographical coverage by port or by region, as measured by the Weekly Containerized Transport Capacity (Frémont & Soppé, 2005). However, the lack of available software other than classic Geographical Information Systems (GIS) prevented any innovations in the visualization and analysis of large maritime networks.

In the context of continuous growth, increased spatial complexity, and the widening power of global alliances and shipping lines around the world, the utilization of new visualization and analytical tools becomes necessary. However, such an effort cannot ignore the specific issues in maritime transport with regard to the other transportation networks.

8.2.2 The Specificities of Maritime Transport

Despite the rapid success of air transport for commercial use, maritime transport has retained a very important role supporting, and even enhancing, globalization (Frémont, 2005). From the 1960s onward, containerization has facilitated the regional and global integration of transport and value chains (Robinson, 2002). Of course, this integration has been made possible in a context of lowering trade barriers and geopolitical stabilization after the decolonization of the then-Third World and the collapse of the socialist block, resulting in higher freedom of circulation, lower transport costs, and continuous growth. Even the Soviet Union increased its domestic share of maritime transport from 2 to 9 %, not only for geopolitical purposes (e.g., supporting distant brother countries such as Cuba) but also to enlarge its commercial power in response to Western imperialism (Vigarié, 1995).

These evolutions have provided shipping lines the liberty to invest heavily in new technologies, and the regular and dramatic increase in vessel sizes is proof of their success, as reflected in the enormous amount of literature on this subject in maritime and port studies. One key aspect of global transportation by sea is the evolution from trade support (demand-driven) to trade stimulation (offer-driven). This means that shipping lines have become proactive by providing efficient door-to-door services across oceans over ever-longer distances and also across continents through the integration of terminal and logistics operations, notwithstanding the role of shippers, forwarders, and intermodal operators in ensuring the space-time continuum of freight flows (Ducruet & Van Der Horst, 2009).

The implications for ports are enormous and varied. Ports are bound to waterside locations where physical conditions are increasingly important due to growing vessel sizes (e.g., 14–15 m of maximal quay depth are required for large containerships). In addition, the technological revolution in sea transport (i.e., containerization) has provoked a drastic selection of ports capable of planning new terminals equipped with modern and costly cargo-handling facilities (Slack, 1985). Given the aforementioned freedom of circulation, shipping networks have become increasingly footloose, selecting ports based on various factors such as centrality and intermediacy (Fleming & Hayuth, 1994). Centrality refers to the landward position of the port with regard to hinterlands, markets, and intermodal arrangements, while intermediacy corresponds to the seaward position, facilitating the implementation of hub-and-spoke strategies with other ports. Such dynamics have fostered competition among neighboring ports, resulting in traffic concentrations at a few load centers and hub ports and traffic dispersion due to diseconomies of scale and the preference of ocean carriers for brand new facilities created on greenfield sites (Slack, 1999).

Thus, our traditional conception of port-development processes has radically changed in the last few decades (Olivier & Slack, 2006). While ports and supply chains are "terminalized" by ocean carriers and terminal operators acquiring global portfolios (Slack, 2007), the factors contributing to port growth or decline seem to have shifted in the hands of the shipping lines. No longer is proximity to a market or a densely occupied hinterland sufficient to explain the distribution of traffic along a maritime range, although it is clear that despite a few exceptions for terminals built in the "desert" for transshipment purposes, most of the world's container traffic is concentrated within large urban agglomerations, and this trend is actually increasing (Ducruet, 2008b)[1]. For instance, Europe's largest container ports tend to be located as close as possible to the megalopolis ranging from London to Milan; the northern European range is a perfect example of high port concentration near Europe's core economic region (i.e., the Rhine). Nevertheless, the maritime component of port evolution has gained unprecedented importance. The focus of this chapter is to determine new ways of measuring and comparing this importance worldwide.

8.2.3 Possible Improvements

Two main approaches in the literature on ports and maritime transport are essential to an understanding of the positioning of ports in shipping networks.

Functions and performance of seaports

The first approach is concerned with the geographical functions of ports. Depending on the quality of their insertion into maritime networks, container ports can be

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[1] Ducruet (2008a) calculated that the proportion of world container traffic at ports located in urban areas of over one million inhabitants has increased from 66 % in 1980 to 77 % in 2005. Of course, these increases are influenced by the inclusion of many hub ports for which transshipment traffic is counted twice, such as in Singapore, Hong Kong, and Busan.

defined as global pivots, load centers, regional ports and minor ports (Bichou & Gray, 2005; De Langen, Van der Lugt, & Eenhuizen, 2002). This typology is rarely verified empirically because of the complexity of liner networks. As explained by De Langen et al. (2002), four main factors contribute to this complexity: the continuous increase in traffic volume, the increase in the number of connected ports, the increase in vessel sizes, and the increase in the spatial freedom of ocean carriers. However, as the authors argue, "the role of different ports in maritime networks has not been documented, nor has a precise typology that would allow for such a precise exercise been proposed" (De Langen et al., p. 3).

An indirect analysis of ports' insertion into maritime networks through empirical case studies is more feasible. For instance, research has been performed on the distribution of seaborne connections of ports of Australia, the United Kingdom, and France on various scales (Bird, 1969; Britton, 1965; Von Schirach-Szmigiel, 1973). These studies have been complemented by analyses of the number of vessel calls as a proxy for maritime performance in the United States (Lago et al., 2001 cited in De Langen et al., 2002) and worldwide, combined with other port and urban indicators (Ducruet, 2008b). As mentioned above, relevant data sources and analytical tools to measure more complex realities based on large maritime networks are lacking.

In fact, the relative position of ports within a given maritime system is analyzed either theoretically, through the definitions of hub functions, centrality, and intermediacy (Fleming, 2000; Fleming & Hayuth, 1994) and the formulation of port-concentration models within a port system, or empirically through the analysis of traffic distribution and concentration (Ducruet et al., 2009). However, the latter analyses are based on aggregated individual measures (e.g., port throughputs) that hide the extent to which ports that handle similar traffic may, in fact, be very different in terms of seaborne connections and their positions in the networks in terms of vulnerability. One good example is Frémont's (2005) mapping of the global port network of Maersk, the world's main liner shipping company; however, it does not include references to the changes in local performance resulting from global insertion.

Port regions and port systems

Another approach attempts to position ports within a precise port region or maritime region. Despite the lack of clarity over the definition of such terms[2], these studies are similar in that they give more importance to the architecture of the maritime networks, where ports are only one aspect. An original insight inspired from

[2] Ducruet et al. (2009) differentiates between the maritime façade (coastal alignment of ports), the port region (the inland area smaller than the hinterland but wider than the port city where the port activities influence the economic structure), the port range (the coastal system of interdependent ports), the port network (the portfolio distribution of a given carrier), and the port system (interconnection of ports by shipping networks within a given area).

maritime history is proposed by Westerdahl (1996), who examines how maritime itineraries shape functional regions in Scandinavia and Europe in the early Middle Ages. In a similar vein but based on the application of network algorithms, Joly (1999) proposed a worldwide analysis of maritime linkages among main regions, resulting in the calculation of estimated port throughputs based on vessel movements. Other specific studies of liner networks cover specific regional areas such as the North Atlantic (Helmick, 1994), the Caribbean (McCalla, Slack, & Comtois, 2005; Veenstra, Mulder, & Sels, 2005; Wilmsmeier & Hoffmann, 2008), the Mediterranean (Cisic, Komadina, & Hlaca, 2007), and the relative position of North Korean ports in Northeast Asia (Ducruet, 2008a). While such studies clearly focus on port performance and maritime network design, notably visualizing the situation of ports in such networks, they do not have a multi-level approach, and they rarely relate network attributes with port performance[3].

Despite their fundamental legacy in clarifying our understanding of contemporary shipping and port development, two main weaknesses can be highlighted in such studies. First, the regional scale in which ports are studied is often defined arbitrarily; this argument is defended by Slack (1999) in his study on the evolution of containerization in the North Atlantic. Therefore, the regional areas within which different ports share privileged linkages are taken for granted and are not well-studied. Second, individual measures of port performance rarely include different levels of observation, from the local to the global, although it is recognized that contemporary ports are better compared through their ability to connect scales rather than through their traffic volume rankings (De Roo, 1994). It seems that those objectives – definition of regional areas and individual measures – strongly require an engagement as indicated by current research on social network analysis and small worlds.

8.3 Structure of the World Maritime System

8.3.1 Data Source and Methodology

Three main data sources exist for the analysis of maritime networks from a graph perspective. The previously mentioned *Containerisation International Yearbooks* offer an overview of the main service schedules of the world's shipping lines,

[3]This statement should not ignore that some authors point to specific situations in which a relationship is established between performance and network design. For instance, Lago et al. (2001) note that last ports of call attract more cargo on average because of transit time advantages; Notteboom (2006) specifies that upstream ports generate more cargo throughputs because ocean carriers compensate for the deviation between distance and time; Ducruet (2008a) finds that ports situated within larger urban regions often have a higher share of long-distance connections in their traffic. The main problem underscored in this chapter is the lack of systematic empirical verification, especially on a global scale.

Table 8.1 Overview of the maritime database

	1996	2006
No. ports	975	1,240
No. countries	157	173
No. vessels movements	176,439	390,740
No. vessels	1,759	3,973
No. operators	497	720
Total slot capacity (TEUs)	3,352,849	9,590,309
Total deadweight capacity (DWTs)	50,644,151	130,742,023
Share world fleet (% containerships)	91.52	98.33
Share world fleet (% TEUs)	92.15	97.91
Share world fleet (% DWTs)	6.23	12.54

Source: calculated by the author based on LMIU and UNCTAD

together with the fleet capacity of the companies by vessel. Although such information would permit the building of a world graph of inter-port linkages and has the advantage of a cheaper cost compared to other sources, it necessitates large amounts of manual data encoding. Another problem is the lack of coverage on local and regional services and the probable mismatch with effective ports of call.

Two other sources provide numeric information on effective vessel movements. First, the French ship broker Barry Rogliano Salles through its branch company AXS Marine maintains the Alphaliner database on container vessel movements. Second, the source used in this chapter is derived from Lloyd's Marine Intelligence Unit (LMIU), a service of Lloyd's, the world leader in maritime insurance and shipping information based in London. This data source is selected because of its wide coverage of the world fleet (98 % TEUs[4] in 2006), as seen in Table 8.1. The data also include ship operators' names and daily ports of call (previous, current, and next), thus allowing for many measurements by link and by port.

A fundamental reflection is necessary about the way vessel movements should be computed to address issues of port performance and port regions. Several aspects deserve careful attention:

- *Weight and frequency of linkages*: Many vessel movements of different capacities pass through the same links within a given period of time. Therefore, edges can be weighted according to the total traffic (the sum of all vessel capacities), the number of vessels, the number of calls, or by ratios such as the average vessel capacity, the weekly average number of calls, etc. In this study, we retain the total traffic realized by the overall circulation of vessels within 1 year in 1996 and 2006. The same applies to vertices (ports) that can be weighted and compared based on their total capacity circulated.

[4]Twenty-Foot Equivalent Unit (TEU): a normalized measure of container traffic and vessel capacity referring to the number of 20-foot container boxes. Vessel capacities can also be measured in deadweight tonnage (DWT) or "commercial capacity".

- *Canals, straits, strategic passages*: The original data contain several places that are not container ports or even seaports, such as canals (Panama, Suez), straits (Gibraltar, Dover, Dardanelles, Messina), channels (Yucatan), and other passage points at which the vessel reported a call (e.g., Tarifa and Cape Finisterre on the Iberian peninsula; Skaw in Denmark; Brixham in the UK). While such "nodes" are part of the effective movement of vessels, they do not account for port commercial operations, nor are they part of voluntarily selected logistics routes or transport chains. Because almost all pendulum services pass through the Panama and Suez canals, their centrality in the graph would go beyond those of the biggest commercial ports. Thus, they were omitted from the data[5].
- *Direct or indirect inter-port connections*: An analysis based on direct connections would imply a simplification of the reality of shipping networks. Although direct connections provide useful insights into the way ports are related to their close neighbors, liner networks are built upon a majority of indirect calls. Line-bundling and hub-and-spoke[6] are the most common services provided by ocean carriers willing to extend their influence across trading areas and continents. Thus, vessels are operated through rotating patterns that make an analysis based on indirect linkages more relevant. In addition, direct linkages may deprive some ports of their true foreland extent: a direct degree of 2 may hide an indirect degree of 30 if the port is connected to wide international logistics chains.

The methodology for building the graph consists of retrieving for each port all its direct and indirect connections through the circulation of each vessel during 1 year, regardless of the exact time of the connection. This enables Rotterdam to be connected with Tokyo, although in reality, those two ports are not directly connected by a single voyage; usually, pendulum services run for 3 weeks between Europe and Asia through the Suez Canal, including many intermediate calls. In the end, every vessel's circulation creates a complete graph in which all ports are fully interconnected. The resulting world graph is therefore a combination of all individual vessels' complete graphs.

[5]Other nodes that are commercial ports such as Istanbul (Turkey) and Port Said (Egypt) were also omitted because of their enormous number of calls compared to their actual traffic. Their proximity to important strategic passages has caused them to be reported by many vessels, although not every call represents a commercial operation at the terminals. Other cases include Brunsbuttel (Germany), a port at the mouth of the Elbe River, whose calls were attributed to Hamburg, the actual destination. Finally, some terminals have been merged in the data with their representative port, such as Port Botany and Sydney (Australia).

[6]The hub service is a combination of line-bundling and local services centralized upon one main transshipment center. A mother vessel calls at a transshipment hub where containers can be transferred to another mother vessel (i.e., interchange) or to a feeder vessel that carries out the rest of the local or regional service (Brocard et al., 1995). There are a few round-the-world (RTW) services where ships are bigger. Other services are pendulum services such as Europe-Asia and local services such as Rotterdam-United Kingdom. Line-bundling services often connect different global regions while hub-and-spoke services are more intra-regional.

Table 8.2 Topological characteristics of the world maritime network, 1996–2006

				Direct links		Indirect links	
	Measure	Description	Calculation	1996	2006	1996	2006
e	Length	Number of edges	Sum	6,322	9,493	29,251	51,054
v	Population	Number of vertices	Sum	975	1,240	975	1,240
k	Cyclomatic number	Number of independent cycles	$e-v+p$	5,347	8,253	28,676	49,814
α	Alpha	Lattice degree	$k/\frac{v(v-1)}{2}$	0.011	0.010	0.011	0.010
β	Beta	Degree of graph complexity	$\frac{e}{v}$	6.484	7.655	30.001	41.172
γ	Gamma	Global connectivity	$e/\frac{v(v-1)}{2}$	0.013	0.012	0.061	0.066
C	Connectivity degree	Observed vs. optimal connectivity	$\frac{v(v-1)}{2}/e$	75.106	80.920	16.232	15.046

Source: calculated by the author based on LMIU and Joly (1999)

8.3.2 *Topological Characteristics and Geographical Structure*

The resulting graphs are characterized by a high complexity (Table 8.2). The high cyclomatic number, where p is the number of separated components, indicates a high connexity of the graph. The higher the connexity, the more accessible is a node from all other nodes. The connexity has increased between 1996 and 2006, and it is always higher for indirect links because of a higher density of inter-port relations. However, the lattice levels are relatively low, most likely due to the hierarchical nature of the network. The global connectivity is also low, but it is higher for indirect links, for the reasons cited above. In terms of complexity level, the high values for non-planar graphs indicate a very complex pattern. Notably, the growth rate of the number of ports connected is 27 %, but the maritime links grew 64 % over the same period, resulting in a denser network. This is most likely an effect of the factors cited by De Langen et al. (2002) on the current evolution of container networks. The observed connectivity (c) has increased for direct links but has decreased for indirect links, where it is significantly lower. All these facts indicate that the graph of indirect links is denser and more complex due to the richness of inter-port relations, taking into account the overall circulation of vessels instead of direct inter-port links, which tend to break the continuum of shipping.

The structure of the graph can also be analyzed based on the relationship between the number of ports and the number of connections (i.e., maritime degree). The results presented in Fig. 8.1 indicate that the organization of liner networks corresponds to a scale-free network that is defined by a power-law distribution. A few ports dominate the network by their high number of connections, while a majority of the other ports have only limited connections. Some exceptions in

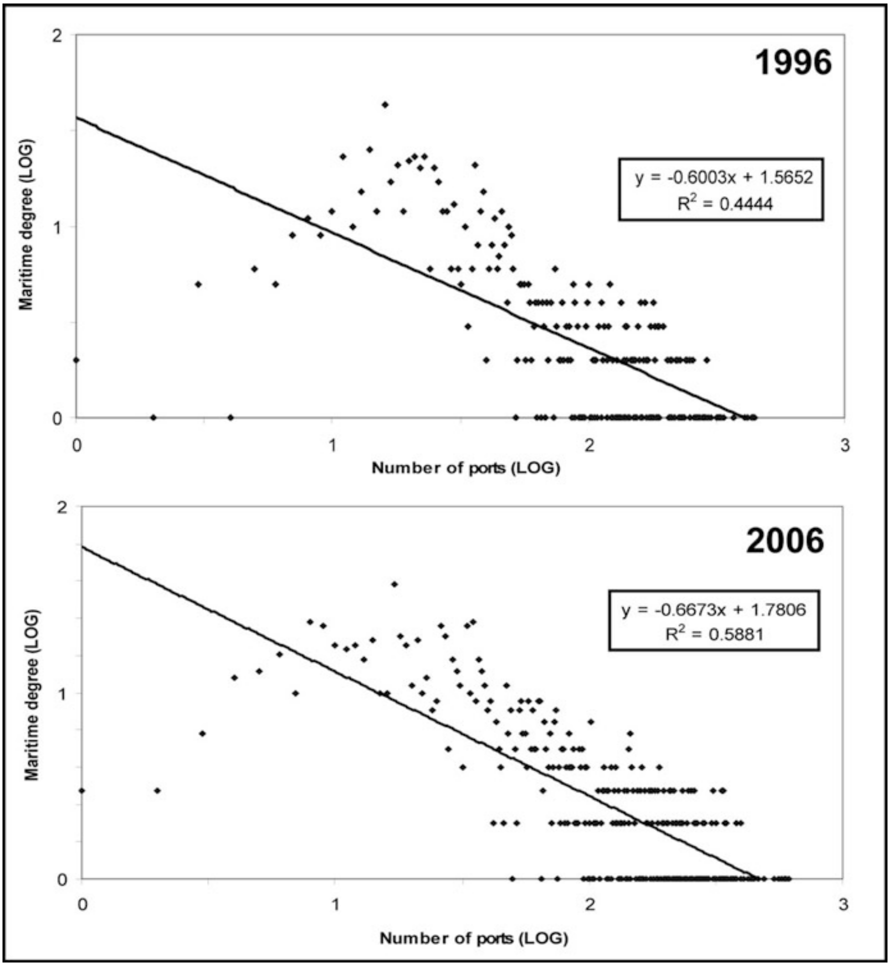

Fig. 8.1 Scale-free dimension of the world maritime network, 1996–2006 (Source: calculated by the author based on LMIU)

the figures – a few ports having the fewest connections – are explained by the methodology of data collection: only twelve ports are not very well-connected to the rest of the network in both years. In terms of evolution, we note that the slope of the line and the coefficient have increased from 1996 to 2006, highlighting a concentration of the network. This result most likely stems from the rationalization of carrier services, notably through the implementation of hub strategies throughout the world.

The spatial structure is observable through TULIP software based on the ports' betweenness centrality that is the sum by port of all their positions on their shortest paths. This measure is equivalent to a level of relative accessibility within the graph.

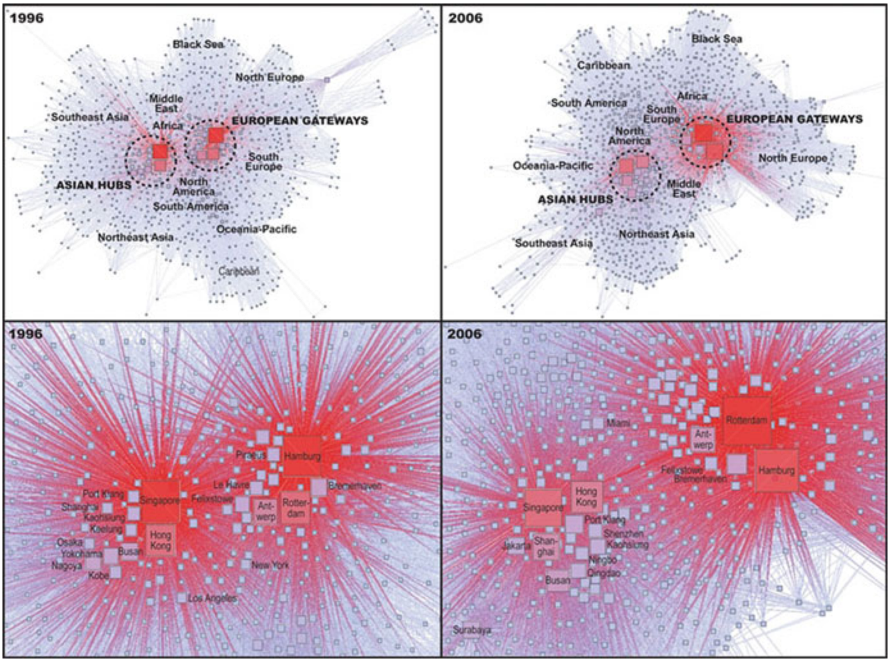

Fig. 8.2 Visualization of the world maritime system, 2006 (Source: realized by the author based on LMIU and TULIP)

Although it does not correspond to the daily preoccupations of port authorities or carriers, it helps to distinguish the positioning of ports in the overall pattern of circulations on various scales. A Gem-Frick layout is applied to situate the most central ports in the center and the least central ports in the periphery (Fig. 8.1).

The results confirm that very few ports dominate the hierarchy of centrality: “European gateways” (Rotterdam, Hamburg, Antwerp, and Bremerhaven as the northern range) and “Asian hubs” (Singapore, Hong Kong, Shanghai, and Busan as the Asian corridor). Despite the lower score of Asian hubs in general compared with the most central European ports (Rotterdam and Hamburg), we see many more Asian ports with a relatively high centrality: Port Klang (Malaysia), Jakarta and Surabaya (Indonesia), Kaohsiung (Taiwan), and Shenzhen, Ningbo and Qingdao (China). Thus, the measure of betweenness centrality seems to provide more advantage to hub ports upon which numerous smaller ports depend. Scandinavia and the British Isles tend to depend on Rotterdam and Hamburg, while Southeast and Northeast Asia tend to depend on their respective Asian hubs. In comparison, ports that usually rank high in traffic volume such as New York or Yokohama have a limited centrality. Outside the two cores of the system, only Miami scores high, most likely because of its strategic position as a hub between the Caribbean and the North Atlantic regions (Fig. 8.2).

The geographical dimension of the system is also apparent when examining the position of the ports and the region to which they belong. Despite the borderless crossing of multiple services and circulations allowed by indirect linkages, a strong spatial proximity characterizes the graph. The two large clusters are separated by Middle Eastern ports and Mediterranean ports (the Europe-Asia route), while other regions are logically distributed around their respective cores: the Black Sea, Scandinavia, and Africa for European gateways; Asia, Pacific and the Americas for Asian hubs. Although this global snapshot of the geographical structure does not account for a precise distinction among spatial and functional proximities, it demonstrates that the organization of the world maritime system is fundamentally geographical in scope. More advanced methods of clustering allow for a better investigation of possible hidden sub-structures in the global graph.

8.4 Multilevel Analysis of Port Performance

8.4.1 Comparison of Ports' Network Attributes

Two measures are compared with the performance of container ports (Table 8.3). The maritime degree is the total number of connections, as described above; here, the maritime degree is distinguished between direct and indirect numbers. The level of hub dependence corresponds to the traffic share (% TEUs) of the biggest connection in total port traffic. It highlights the extent to which a given port depends on another port for the distribution of its traffic: the more dependent a given port is, the more vulnerable it is in the system.

There is a close relationship between the direct degree and throughput in 2006: Singapore (210) and Hong Kong (193) have the largest throughput and the highest degree. Thus, larger ports are those that deploy a wider set of connections. This indicates that in general, network attributes closely follow (or explain) traffic hierarchies. Gateway or hub functions do not necessarily influence the results. However, specific locational factors may have an influence; for example, Guangzhou (Pearl River Delta) has a lower degree as explained by a combination of its upstream position – constraining the accessibility for large containerships – and its proximity to the major ports of Hong Kong and Shenzhen. The traffic and the degree are also very much interrelated in their evolution: their respective growth rates each have a coefficient of 0.83, with Shenzhen (China) at the top of the dynamic. We also see that ports in advanced economies tend to stabilize and rationalize (e.g., decreased degree) their position in the network, while ports in developing and emerging economies see their position improving quickly by catching-up.

Indirect connections show a somewhat more distinct pattern than that of direct connections. Singapore (591), Hong Kong (612) and Shanghai (569) have much fewer worldwide connections than Shenzhen (1,224). This measure is therefore better related with the actual foreland (i.e., commercial relations) of the port. Shenzhen is known as the world's factory; it has welcomed direct calls from global

Table 8.3 Throughput volumes and network attributes of the world's 30 main container ports

Rank in 2006	Port	Container throughput (000s TEU)		Maritime degree				Hub dependence (% TEU)			
				Indirect links		Direct links		Indirect links		Direct links	
		2006	1996	2006	1996	2006	1996	2006	1996	2006	1996
1	Singapore	24,792	12,943	591	439	210	154	11.5	6.5	21.1	32.3
2	Hong Kong	23,230	13,460	612	407	193	132	8.0	5.7	15.6	30.5
3	Shanghai	21,710	1,930	569	235	185	63	9.9	7.4	18.3	33.5
4	Shenzhen	18,468	1,032	1,224	103	177	30	6.8	6.3	50.0	52.5
5	Busan	12,030	4,725	502	328	180	110	8.8	6.7	13.4	19.7
6	Kaohsiung	9,774	5,063	456	294	127	90	13.9	7.1	31.2	40.9
7	Rotterdam	9,690	4,935	622	433	145	137	5.4	5.1	24.3	20.3
8	Dubai	8,923	2,247	394	233	143	55	8.8	4.9	17.3	18.3
9	Hamburg	8,861	3,054	874	443	123	117	8.1	6.6	25.6	27.7
10	Los Angeles	8,469	2,682	287	241	56	63	8.3	6.7	25.6	33.4
11	Qingdao	7,702	810	445	142	100	28	8.6	6.6	22.6	30.1
12	Long Beach	7,290	3,007	317	–	46	–	10.5	–	27.1	–
13	Ningbo	7,068	–	434	70	101	14	11.0	8.7	32.0	34.4
14	Antwerp	7,018	2,653	548	416	96	101	5.0	4.8	32.3	18.6
15	Guangzhou	6,600	–	236	50	31	14	13.0	8.6	41.2	53.8
16	Port Klang	6,320	1,409	473	264	134	54	15.0	7.1	27.3	62.4
17	Xingang	5,900	800	357	151	54	42	12.6	6.9	31.9	28.3
18	New York	5,092	2,269	324	300	75	63	4.6	4.5	15.3	28.1
19	Tanjung Pelepas	4,770	–	340	–	74	–	8.6	–	16.1	–
20	Bremerhaven	4,450	1,543	433	324	92	57	10.1	6.2	22.4	34.9
21	Laem Chabang	4,123	820	313	166	60	25	14.2	7.2	29.9	34.1
22	Xiamen	4,019	400	392	86	74	20	15.0	7.0	35.2	36.9
23	Tokyo	3,665	2,311	330	208	74	51	9.3	7.3	18.7	14.9
24	Jawaharlal Nehru	3,298	423	343	149	50	20	10.3	4.4	16.7	23.5
25	Algeciras	3,245	1,307	370	247	104	62	4.6	5.0	28.7	40.5
26	Dalian	3,212	–	340	113	69	24	9.0	6.4	24.0	19.5
27	Yokohama	3,200	2,334	389	318	100	86	10.1	6.5	17.2	19.5
28	Colombo	3,079	1,356	381	258	63	51	9.3	5.8	20.3	40.2
29	Felixstowe	3,000	2,042	415	369	64	86	8.0	6.0	28.0	21.5
30	Jeddah	2,964	827	341	256	59	41	8.2	5.6	43.7	45.4

Source: Calculated by author based on LMIU and Containerisation International

shipping lines since 1998 (Wang, 1998). Here, gateway and hub functions create noticeable discrepancies along the hierarchy. For instance, European gateway ports such as Hamburg, Rotterdam, Antwerp, and Felixstowe all enjoy wider global connections than ports of equivalent throughput. Gateway ports are more likely to drain vast hinterlands and thus to connect with a variety of overseas markets. In comparison, hub ports have a simplified foreland because of narrowed hinterlands. The relationship between the respective growth rates of traffic and indirect degree remains quite significant with a coefficient of 0.74.

In terms of hub dependence, the direct vulnerability of some ports despite their large throughput is evident. The traffic share of one direct link reveals a higher vulnerability for Shenzhen (50 %), Kaohsiung (31 %), Guangzhou (41 %), Xingang (32 %), Laem Chabang (30 %), Xiamen (35 %), and Jeddah (43 %). This is because many Asian ports depend on another hub for accessing the rest of the system, although the case of Kaohsiung is highly political, with the obligation of connecting Hong Kong instead of mainland Chinese ports across the straits. Hub ports and gateway ports have a more even spread of traffic connections, as seen with New York (15 %) and Busan (13 %). European gateway ports have intermediate values of approximately 25 % due to the existence of port systems such as the North European range from Le Havre to Hamburg. Local strategies of port development also greatly impact the level of hub dependence. The important drop for Port Klang (−35 %) clearly reflects successful relief from the dominance of neighboring Singapore following Malaysian government support for gateway development. In comparison, Shenzhen and Guangzhou could not significantly decrease their dependence on the Hong Kong hub, nor could Ningbo reduce its dependence on Shanghai.

For indirect hub dependence, the highest values in 2006 are for Asian ports because of the unavoidable concentration of circulation at a neighboring hub such as Kaohsiung (14 %) with Hong Kong and Port Klang (15 %) and Laem Chabang (14 %) with Singapore. Continental gateways such as New York and Antwerp have the lowest hub dependence – approximately 5 % – for the reasons cited above, but some western interregional hubs such as Algeciras also have low hub dependence. Due to the comparatively limited importance of hinterlands in Asia, more interactions among Asian ports tend to increase their reciprocal interdependency and connectivity. Western ports function more as gateways linking the hinterland with the foreland, with less inter-port corridors. Thus, the indirect hub dependence can be seen as an indicator of logistics chain diversity through the importance of hinterland coverage.

8.4.2 The Clustering of Port Regions

In this section of the analysis, we use strength clustering to highlight possible “small worlds” in the graph. However, there are inherent limitations in using such methods because the maritime global network is a scale-free network and not a small-world network. Small worlds or “communities” – here, port regions – exist less in scale-free networks because of their very hierarchical dimensions: every node is in some way dominated by a “star” or “hub”, making the formation of relatively independent groups of ports enjoying preferential relations difficult. We apply strength clustering on both the structure of the network itself (links without weight) and on the weighted graph (weight in TEUs, i.e., sum of circulated capacities) to verify the impact of traffic volume on small-world formation. Such an analysis will help to answer two sets of questions:

- *Multilevel maritime regions*: What are the tributary areas of the world’s largest ports? Are they regionally specialized? What is the respective role of geographical proximity and carrier decisions to re-route their services based on economic factors (time and cost)? Are there resilient historical trade patterns still visible?

- *Multilevel maritime dynamics*: How do such strongly interconnected groups of ports evolve over time, given that carrier strategies and port competition profoundly modified the structure of shipping networks in the 1990s?

In 1996, there is some correspondence between the results from the weighted analysis and the non-weighted analysis. For instance, Hamburg appears as a key node in each analysis, although the two clusters are distinguished by the number of ports contained and by the location of those ports. In the non-weighted cluster, Hamburg and Rotterdam stand out as the two most central ports of a predominantly European cluster (Scandinavia, South Europe), while only Belawan and Jakarta (Indonesia) are included from outside Europe. In the weighted cluster, Hamburg also has a dominance of its European counterparts (Iberian Peninsula, North), of which many are similar to the non-weighted cluster, including Jakarta. Some important ports that were not included in the non-weighted cluster are Port Klang (Malaysia) and Keelung (Taiwan). Thus, it can be argued that weighted clusters underscore important corridors on a global level (Europe-Asia), while non-weighted clusters are better related to the neighboring architecture of a port's network (Europe) (Fig. 8.3).

Conversely, the geographical affinity of some central ports does not change much from the non-weighted to the weighted clusters. Amsterdam (with Ymuiden) is the center of a non-weighted cluster with a majority of Latin American ports and two Australian ports. It also appears in a weighted cluster alongside many Latin American ports, although in a less central position, due to the inclusion of large gateways such as Santos (Brazil) and Buenos Aires and some Oceania ports (e.g., Fremantle, Auckland). Therefore, taking into account the weight of the links does not necessarily disturb the pattern. However, some very central ports such as Nagoya (Japan) and Southampton (UK) that have a strong position in some non-weighted clusters are not part of any weighted cluster, most likely because of their lower weight in the network. In addition, some very central ports in some clusters have a relatively low rank in the usual port rankings: Dakar (Senegal), Damietta (Egypt), and Szczecin (Poland), while others are strategic places for carriers to develop gateway strategies, such as Hampton Roads in the United States (Starr, 1994).

In 2006, all clusters show a somewhat stronger geographical coherence than in 1996. For instance, the non-weighted cluster centered on Antwerp includes some major European gateways (e.g., Rotterdam, Hamburg) together with a series of Latin American ports, which highlights the importance of maintained transatlantic ties. This is also the case with the non-weighted cluster centered on La Guaira (Venezuela) linking Western Europe (Genoa, Liverpool) with North Africa (Morocco) and several Latin American ports. The two other non-weighted clusters also reveal interesting patterns. The cluster centered on the rapidly growing Black Sea port of Constantza (Romania) is mostly intraregional, as it concentrates mostly other North or South European ports. Conversely, the cluster centered on Ashdod

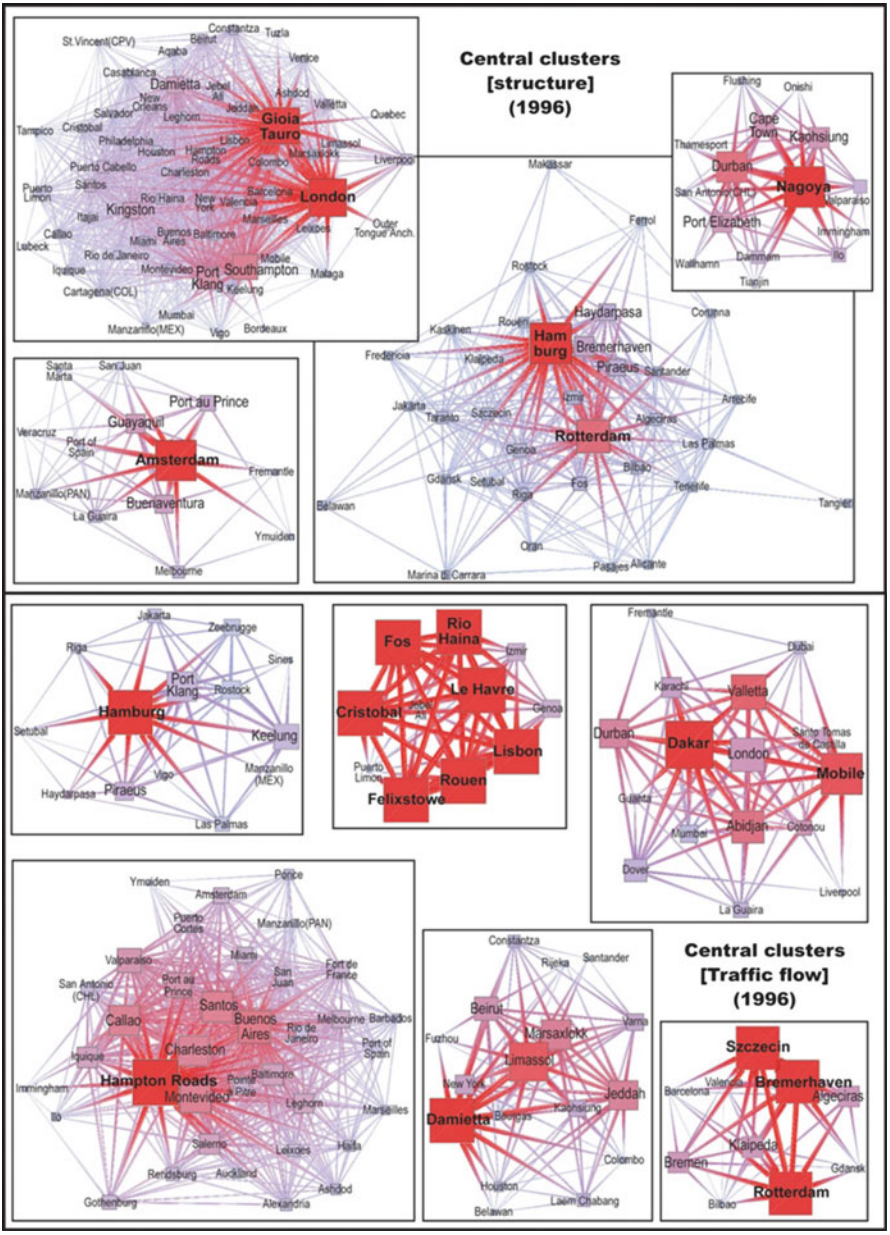

Fig. 8.3 Central clusters in the world maritime system, 1996 (Source: realized by the author based on LMIU and TULIP)

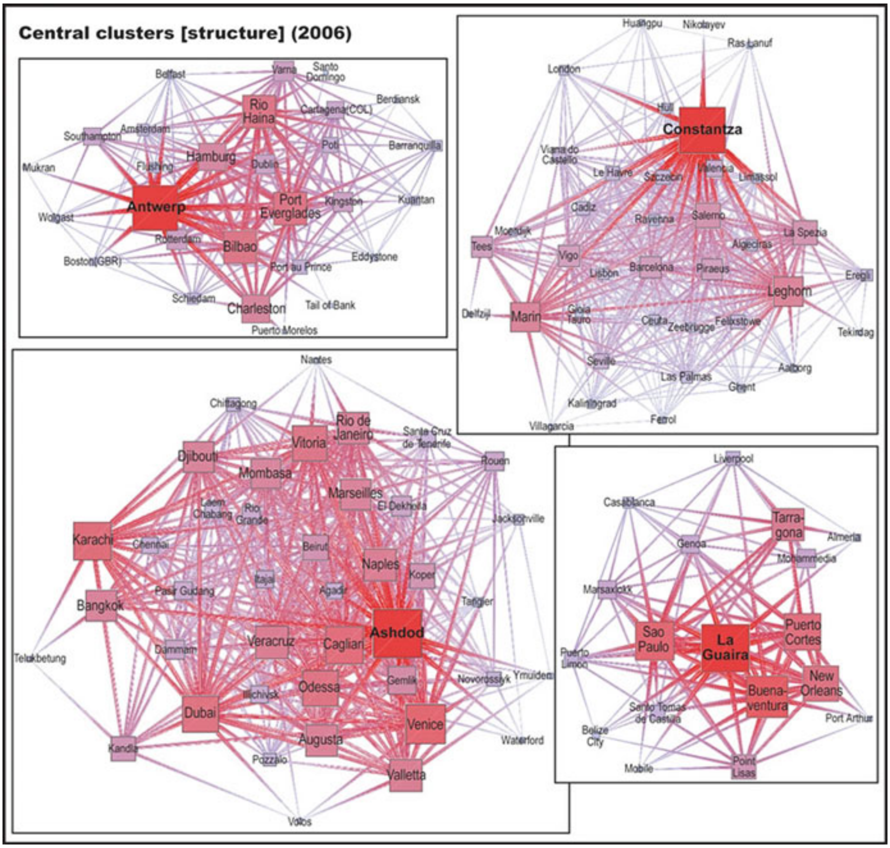

Fig. 8.4 Central clusters in the world maritime system, 2006 (continued) (Source: realized by the author based on LMIU and TULIP)

(Israel) is more diverse geographically, but one can notice a spatial continuity from Southeast Asia (Bangkok) to Brazil (Rio Grande, Itajai) across the Middle Eastern, Mediterranean, and North African ports. Only a few exceptions deviate from this corridor of ports (Fig. 8.4).

The very important role of the geographical and historical continuum becomes clear with weighted clusters. A Northeast Asian cluster centered on Yokohama interestingly connects some outer ports; a “Latin” cluster centered on Cartagena (Colombia) primarily gathers South European and Latin American ports; another cluster centered on Antwerp is predominantly European with some US Gulf Coast ports; and finally, a cluster centered on Dakar gathers a mix of African and Asian ports. The evolution between 1996 and 2006 for weighted clusters shows some permanency, with a majority of Iberian Peninsula / Latin American / Northeast Asia / European ports differently represented within a few central clusters.

8.5 Conclusion

This chapter has for the first time applied a multilevel analysis to maritime transport and, in particular, to liner-shipping networks formed by the daily circulation of container vessels on a global level. What can be learned from such an attempt? First, we confirm that liner shipping is characterized by high complexity, while the network properties of seaports interestingly are in line with the usual port hierarchies provided by economic intelligence and earlier academic studies on port performance. Second, the clustering methodology applied to the world graph of direct and indirect inter-port links, with or without traffic, provides a rather unusual combinations of ports that do not correspond to our vision of the world delineated by political and cultural criteria.

Thus, retrieving the inherent functional, spatial, economic – and perhaps accidental – logic of each cluster would necessitate enormous efforts of data checking from the raw dataset itself. What should port specialists understand from the results? Some clusters are not easy to "define" because they do not exactly overlap with the usually defined geographical areas or systems in port geography, such as port ranges and hub-port regions. For instance, Yokohama appears as the most central port in a Northeast Asian cluster, whereas all indications in the literature are that Busan (South Korea) has the strongest position in this region as a hub. This is perhaps where the methodology follows a somewhat different direction than the mainstream literature: hub ports (i.e., stars) where many links converge have a relatively lesser importance in the results because instead of forming – or belonging to – small worlds, they tend to create hierarchy and polarity in the system.

However, there are very positive lessons to learn from the application of such methods to liner shipping for port and maritime geography. Despite the "automatic" dimension of clustering, strong coherence is found in a number of clusters where either geographic or commercial/cultural logic dominates, as seen with transatlantic groupings or South-South groupings. Surprisingly, we did not find many clusters including the biggest ports of the Triade as altogether dominant poles of a global system (e.g., North America, Western Europe, and East Asia). This indicates that the world maritime system is regionally polarized but not globally polarized: some corridors link different regions through a complex mix of pendulum, round-the-world, and other line-bundling services, while intraregional services tend to be most concentrated on a few ports. This confirms that liner shipping does not exactly overlap with trade routes: the hub strategies of global ocean carriers have rerouted the dominant flows toward many hub ports in the Caribbean, the Mediterranean, and Asia as a whole, for the aforementioned reasons. Perhaps further research focused on finding a better match between the world economic system and the world maritime system would "delete" such hub ports from the map. Thus, the question is as follows: which ports are more hubs than others? Unfortunately, the answer or the methodology to answer is not yet available in the literature.

Further research should follow several key directions to improve the analysis. First, selecting only a category of vessels of a certain size would allow for the results to be refined: vessels over 2,000 TEUs often operate on longer-distance services (e.g., pendulum, round-the-world), while lighter vessels tend to operate on intraregional services (e.g., barging, feeder). The present analysis has mixed together different sizes of vessels, which in the end may have blurred the geographical logic behind the vessel movements. Second, because liner shipping is operated as a scale-free network – whether it is analyzed through direct or indirect linkages – it would be interesting to make use of other types of vessels carrying commodities such as bulks or general cargo, for which hub-and-spoke strategies do not apply. Therefore, bulk and general cargo shipping tend to overlap better with trade routes and commercial patterns. Third, as mentioned above, excluding hub ports from the analysis would permit a better appreciation of the trade continuum among ports of the world and possibly provide better results in terms of clustering and small-world analysis.

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Chapter 9
Comparing Multilevel Clustering Methods on Weighted Graphs: The Case of Worldwide Air Passenger Traffic 2000–2004

Céline Rozenblat, Guy Melançon, Romain Bourqui, and David Auber

9.1 Introduction

Worldwide deregulation of air transport began in 1978 and came to fruition in 2008, and the re-organization of flows and companies since 1978 is one of the main subjects of air transport network studies. Hubs and spokes are re-shaping the entire network in national and multinational contexts and shrinking international and national links. Thus, each city with specific activities, such as business, research or tourism, develops its own strategies to maximize accessibility from the relative position with the goal of strengthening its economic base. Diagnostics for cities increase the need to study the properties and dynamics of cities, which can be considered nodes in the entire network of flows.

The study of air traffic networks involves large flow matrices. A useful approach to understanding the structure of networks and the evolution of this structure is to search for the highest subgroup densities in a graph, assuming that the graph is neither random nor homogeneous (Barabasi & Albers, 1998; Watts & Strogatz, 1998). Then, clusters of the most connected city airports encapsulate the entire network structure underlying highly inter-connected groups of cities. Different approaches from this perspective were recently developed by physicists (Brandes, 2001; Newman, 2004; Newman & Girvan, 2004). In air transportation in particular, air traffic networks have been used by different network clustering methodologies as a case study (Guimerà, Mossa, Turtschi, & Amaral, 2005; Sales-Pardo et al.,

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2007) or to test the network properties (Colizza, Barrat, Barthelemy, & Vespignani, 2006). The procedure in these studies for identifying the advantages of a method that analyzes or clusters an air transportation network, in terms of static and dynamic properties, is not clear.

The aim of this paper is to compare different clustering methods for an air transport network to evaluate the ability of these methods to reveal hidden structures. Consequently, we first discuss the properties of the air traffic network (Sect. 9.2). Next, we present recent contributions to clustering approaches (Sect. 9.3). We then test and compare different methodologies using the same dataset (Sect. 9.4). The paper concludes with the results of the comparison of the methods used and describes future research directions.

9.2 Complex Logics of World Air Network Organization

The organizational characteristics of the world air network are perceived through its shape (i.e., the topology of the graph and the weight of the exchanges), which has been produced by the activity of economic actors and policies that have evolved largely over the past 10 years.

9.2.1 Principal Traffic of the World Air Network

Assuming that the strength of links between cities is reflected in annual passenger traffic, the network is obviously concentrated around a small number of dominant cities. The 49 connections of more than two million passengers per year (in 2000) connect only 41 cities (including 23 cities in the United States). Paradoxically, the connections that comprise the highest passenger traffic are the shortest ones (in terms of average distance). The most frequented connections are Pusan – Seoul (more than six million passengers), Fort Lauderdale – New York, Hong Kong – Taipei, Chicago – New York, New York – Orlando, Los Angeles – New York and Boston – New York (all having more than five million passengers). The highest ranked European connection, Dublin – London, is in 13th place (with four million passengers), followed by Barcelona – Madrid (three, nine million) in 15th place. On the whole, of the 49 connections of more than two million passengers, 32 connect cities in the United States, 10 connect cities in Europe, and 6 connect Asian cities. London – New York is the only major transcontinental connection in this group (ranked 12th with four, two million passengers).

Connections with more than one million passengers extend this world coverage slightly, but they increase the density of already well-served zones. Notice that no Latin American city appears in this major world subnetwork. The highest-ranked connection for this region is Buenos Aires – Santiago (850,000 passengers per year), followed by Buenos Aires – Sao Paulo (725,000 passengers per year).

9.2.2 Effects of Deregulation on the Forms of Networks

One could assume that this world concentration results from gravitating logics, where the richest and most populated cities of the planet interact more intensely, being closer to each other. However, the application of the gravitational model to air passenger traffic reveals the ineffectiveness of Euclidean space-time (Amiel, 2003) on the overall network structure. The current organization of world air traffic results from various deregulatory processes. Indeed, with the advent of deregulation in 1978 in the United States, which then spread across the world in 1993, plane routes no longer depend only on the exchange capacities of the places being connected or on the "technological" limits of the apparatuses.

Other processes contribute to the structure and organization of air exchanges:

- *economic competition between companies or partnerships within* "alliances", of which the most well-known are Sky TEAM, Star Alliance and One World. These alliances organize the division of air networks between various companies and offer more destinations to passengers. The economic logic of these alliances develops consumer loyalty through various programs providing specific advantages (such as guaranteed reservations, seat choice, and frequent-flyer programs);
- governorship within each company, which centers activities on air courses and higher added-value activity sectors. Another type of governorship is produced by company mergers, which create groups on an international scale that are able to maintain a strong position in a greater number of markets;
- development of airports and definition of hubs and spokes through agreements between companies and airports to concentrate decreased traffic or average traffic ranges to supply long-distance routes more regularly. The major factors in a company's choice of airport are dedicated piers, reserved departure gates, the number of takeoffs and increased landings.

Thus, the exchanges are actually organized in a reticular form where companies charge for airport stops, redistributing passengers according to partnership agreements between companies and between airports and companies. From any place in the world, one stops at different airports to connect to the dominant network, which in turn leads to stops at other airports to reach the desired destination. Thus, many airports function as successive relays between every city on the planet, and the great intercontinental exchanges simply reinforce the dominant network.

The network structure, which was hitherto subject to the will of the cities and countries, is founded on supervised company strategies. For the most part, companies are private, and their networks are organized to be as powerful and profitable as possible, even to the detriment of a territorial homogeneous service routes. Companies have fewer national loyalties (even if company's national history still appears in its current structure), so the routes planned by companies cross national borders and create a new transnational structuring of equivalent territories (i.e., those connected to the same focal point or hub). Thus, the territorial logics that prevailed prior to deregulation are becoming obsolete, and new territorialities are emerging.

The objective of our approach is to emphasize these "new reticular territories", which are defined by an inter-connected overhead grid that divides the world into various levels of road service through mandatory stops in some hubs. The star-like form of the networks, a consequence of deregulation of the air industry, supports the emergence of a system comprising multiple air platforms. The dynamic space of the center-periphery type is reinforced in these networks. With the emergence of secondary centers (Seoul, Fort Lauderdale) (Amiel, 2005), the great centers have often become more powerful (New York, London, Chicago, Paris).

9.2.3 "Small World" Form of the Air Network

Thus, the world air network has specific "small world" properties. It is necessary, for example, to take 15 different flights to go from Mount Pleasant (in the Falkland Islands) to Wasu (New Guinea): this is the largest short path in the world air network (Guimerà et al., 2005). We can now see how "small worlds" are created in this network. In fact, a high degree of connectivity exists between selected airports so that short paths can be found between airports, but there are also numerous peripheral airports that are very far from the entire network.

In particular, the different continents of the world are especially "coherent" in the sense that airport traffic can create some very strong intertwined systems of exchanges compared to sparser inter-continental links.

9.3 Clustering Methods for Air Transport Network

The methodologies applied to the air traffic network can be classified into three families:

(a) Q value methods maximizing internal densities within groups;
(b) methods based on the Betweenness centrality index;
(c) common neighbors methods, including Jaccard or strength methods.

These methods are described below in the context of non-weighted graphs (classical cases) and in the context of weighted graphs that we have developed.

9.3.1 The Q Value Method

The Q value method was developed by Newman (2004). Given a graph $G = (V,E)$, let $C = \{C_1, C_2, \ldots, C_p\}$ denote the partitioning of this graph into *clusters* $C_1, C_2, \ldots, C_p$. Also let $|V|, |E|$ denote the number of nodes and edges in G, $|E(Ci)|$ denote the number of edges with extremities in the cluster C_i, and $|E(Ci,*)|$ denote the number of edges with at least one extremity in the cluster C_i.

The *modularity measure* Q of the decomposition C is defined as $Q = \sum_{1 \leq i \leq p} Q(C_i)$ where $Q(C_i) = \frac{|E(C_i)|}{|E|} - \left(\frac{|E(Ci,*)|}{|E|}\right)^2$.

The weighting of the edges of a graph by a weight function $\omega : E \to \mathbb{R}$ can be accounted for by setting $Q(C_i) = \frac{\sum_{e \in E(C_i)} \omega(e)}{\sum_{e \in E} \omega(e)} - \left(\frac{\sum_{e \in E(Ci,*)} \omega(e)}{\sum_{e \in E} \omega(e)}\right)^2$.

The modularity value $Q(C)$ is used to judge the relevance and efficiency of a decomposition in finding "natural clusters". In particular, when C' is obtained from a decomposition C by merging two clusters C_i, C_j, the modularity values $Q(C)$ and $Q(C')$ can be used to judge whether the decomposition C' is "better" than C (with respect to Q). Let $\Delta_{i,j}Q = Q(C') - Q(C)$ denote the increase in Q of this merging operation on clusters C_i and C_j (which may be negative).

Newman's method is agglomerative, i.e., we begin with a decomposition C such that clusters correspond to singleton sets containing a single node; larger clusters are then formed by aggregating smaller ones.

1. Begin with a decomposition $C = (C_1, C_2, \ldots, C_{|V|})$, where each cluster C_i contains a single node (and conversely, each node is included in a cluster).
2. Find the two clusters C_i, C_j with the largest $\Delta_{i,j}Q$ values; merge these two clusters.
3. Step 2 is repeated until a single cluster decomposition $C = (V)$ (containing all nodes) is reached.
4. Return to the decomposition produced from a cut in the aggregation tree that maximizes Q (i.e., the best cut in terms of Q).

Step 3 requires some explanation. The merging process may be described by a tree to denote which clusters are merged and how clusters are nested. Each cluster occupies a given level, depending on how far the cluster is from the root cluster $C = (V)$. A *cut* is obtained by selecting all the clusters at a given depth, for example, d. The tree structure is designed such that clusters of a cut induce a decomposition $C = (C_1, C_2, \ldots)$. Step 3 thus consists of selecting the cut with the maximum modularity among all possible cuts.

9.3.2 The Betweenness Centrality Method

The betweenness centrality method was developed by Newman and Girvan (2004) based on edge betweenness centrality (see Brandes, 2001).

Let $G = (V, E)$ be a weighted graph: for the example considered, an integer attribute is assigned to the edges that correspond to passenger traffic. We then compute the weight of an edge by taking the inverse of the number of passengers. Low weights correspond to a smaller "distance" between the nodes. The weights may then be used to compute weights for paths in the graph by summing the weights of the edges along a path. The (weighted) betweenness centrality metric of an edge e represents the number of weighted shortest paths containing this edge. A low $BC(e)$ value suggests that e is likely to be in a community, whereas a high $BC(e)$ value suggests that e is a mandatory passageway connecting distinct communities.

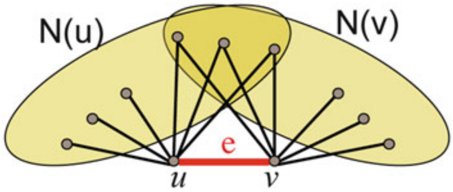

Fig. 9.1 Neighborhoods in the Jaccard method

In contrast to Newman's modularity method, the betweenness centrality method is *divisive*. The process starts with a decomposition containing a single cluster $C = (V)$ that is split into smaller clusters by removing edges before iterating on the newly created clusters.

1. Begin with a single cluster decomposition $C = (V)$.
   (a) Compute betweenness centrality on the edges.
   (b) Remove the edge with the maximum value. If edge removal disconnects a cluster into two smaller clusters, then update the decomposition.
2. Repeat steps 1(a) and 1(b) until there are no more edges to remove.
3. Return the decomposition induced by a cut in the aggregation tree that maximizes Q (i.e., the best cut in terms of Q).

This divisive process may be again encoded using a binary tree to indicate the nesting of the clusters. Additionally, the edge removal operation requires that the betweenness centrality of the remaining edges be updated.

9.3.3 *The Neighbors Method*

The Jaccard and strength methods were developed by Auber, Chiricota, Jourdan, and Melançon (2003) based on the extension of a metric designed by Jaccard (1901), which was later generalized to weighted networks (Amiel, Rozenblat, & Melançon, 2005).

The (weighted) "Jaccard metric" of an edge represents the (weighted) neighborhood similarity of the extremities of the edge. Assume that we are given a weight function on both nodes and edges, i.e., we are given the values $\omega(v)$ and $\omega(e)$ for all nodes $v \in V$ and edges $e \in E$ of a graph $G = (V, E)$. In our example, the weight of a node would typically be the passenger traffic going through that node.

Let $\omega(v)$ denote the weight of the node v (passenger traffic going through node v). Recall that $N(v)$ and $N(u)$ denote the neighborhoods of v and u, respectively, in G (see Fig. 9.1).

The weighted "Jaccard metric" of an edge $e = (u, v)$ is $jac(e) = \frac{\sum_{n \in N(u) \cap N(v)} \omega(n)}{\sum_{n \in N(u) \cup N(v)} \omega(n)}$. A high $jac(e)$ value suggests that e is likely to be in a community. The Jaccard method is also a divisive method that maximizes Q.

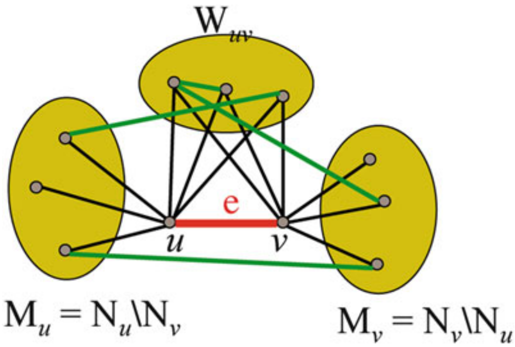

Fig. 9.2 Neighborhoods in the (Auber et al., 2003) strength clustering method

W_{uv} are the common neighbors of u and v, $M_u = N_u \setminus N_v$ are neighbors of u but not neighbors of v, and $M_v = N_v \setminus N_u$ are neighbors of v but not neighbors of u (Fig. 9.2).

For this operation, a ratio is calculated based on the number of cycles of length 3 involving an edge e:

$$\gamma_3(e) = \frac{|W_{uv}|}{|M_u| + |W_{uv}| + |M_v|}$$

A similar ratio can be defined for cycles of length 4:

$$\gamma_4(e) = s(M_u, W_{uv}) + s(M_v, W_{uv}) + s(M_u, M_v) + s(W_{uv}, W_{uv})$$

The strength index is then the sum of both indices $\Sigma(e) = \gamma_3(e) + \gamma_4(e)$.

Once again, the operation is a divisive method that maximizes Q. A quality measure is used to neglect edges with low strength values (Fig. 9.3).

This metric completes Burt's network constraint, which measures how much an actor is constrained by its direct neighborhood (Burt, 2000, 2005). In both cases, edges with low values are expected to act as bridges between tighter communities.

9.4 Comparison of Hierarchical Network Analyses

The three methods were compared by constructing datasets to describe the flow of air transport passengers between cities, based on data from ENAC (French National School of civil aviation). This data source adds national and airport sources to the classical OAG source (Official Airline Guide) for completeness. We also aggregated airports by city to reconstruct the actual traffic of each city.

Clustering using the Weighted Quality Measure for the international air-traffic network, whether non-valued (Guimerà et al., 2005) or valued, demonstrates that groups of cities are geographically organized by continents (Fig. 9.4).

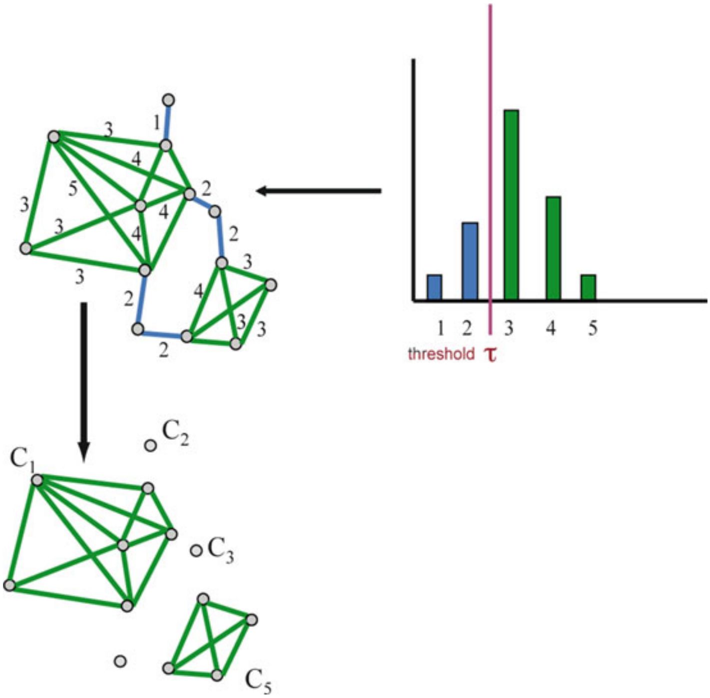

Fig. 9.3 The divisive approach of the (Auber et al., 2003) strength clustering method

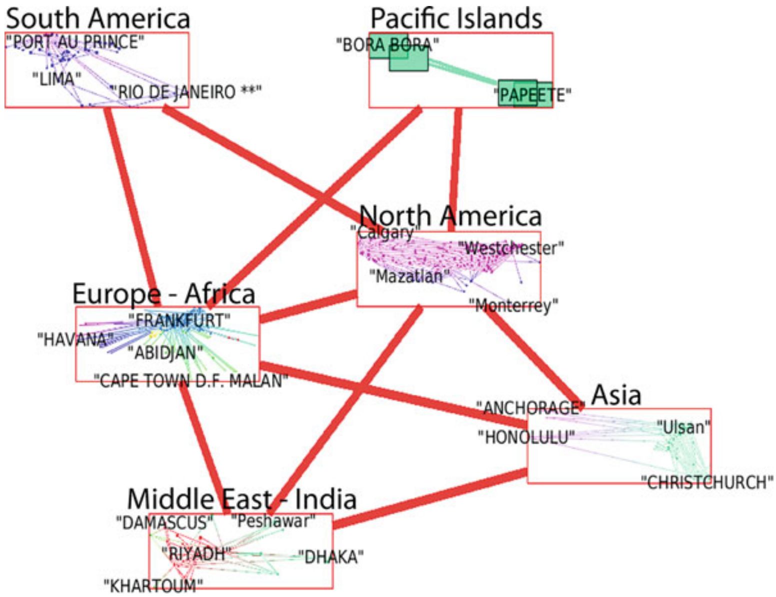

Fig. 9.4 Clustering of Worldwide air traffic using the Weighted Quality Measure Q

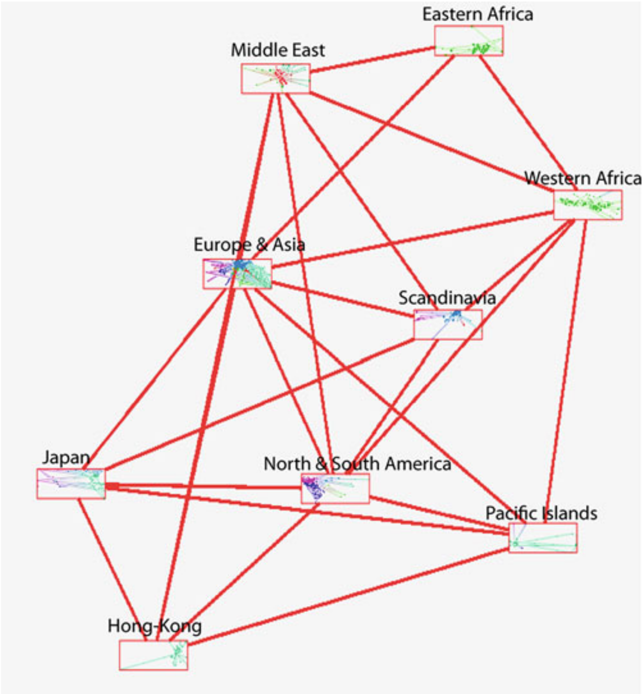

Fig. 9.5 Clustering of worldwide air traffic using betweenness centrality

Clustering using Betweenness Centrality also emphasizes the geographical proximity between cities but introduces three main changes:

1. Some continents are included in the same clusters, such as North and South America, Europe and Asia;
2. These continental groups also include non-continental cities. For example, Jerusalem and Aqaba are included in the Scandinavian group;
3. Other locally centered clusters emerge, such as Hong Kong or Japan (Fig. 9.5).

Clustering using the strength index was implemented via a multi-level approach, fragmenting each cluster into several denser clusters that were subsequently fragmented until the individual nodes were reached (Amiel et al., 2005). At the highest level of world air traffic (Fig. 9.6), the network is organized around a central component called the "principal worldwide hubs". A star topology spreads around this component, emphasizing the role of the intercontinental hubs. Small cores are strongly inter-connected at the same level as this central component. Among these cores, sub-networks with continental logic appear, as is the case with Europe and Asia. This general organization can be specified by descending the levels in the graph. Applying the decomposition algorithm to each component iteratively isolates the levels from the connected network, starting at the most general level and proceeding to the encased sub-graphs of levels 2, 3, etc.

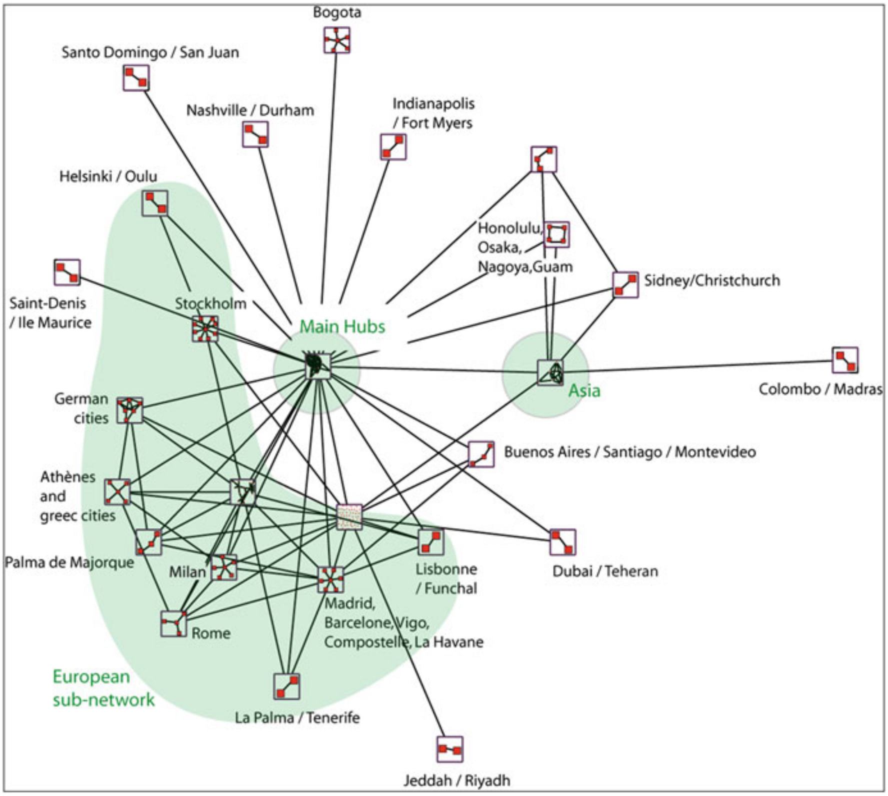

Fig. 9.6 Clustering of worldwide air traffic using the strength index

The cities forming the "principal worldwide hubs" group are American and European (Fig. 9.7). Examining the second, finer level of this area of the graph reveals European hubs such as Paris, London and Frankfurt, as well as the principal American hubs such as New York, Los Angeles, Houston and Miami. These American hubs are dissociated for two principal reasons:

- American hubs are the continental entrances for connections arriving from Europe;
- The majority of American hubs are chosen by large American companies, such as Delta Airlines in Miami or American Airlines in New York (Vowles, 2000).

An American sub-network is dissociated in the center, which can be specified at a third level. In fact, the American territorial extent creates a more complex air organization than does Europe. Indeed, air is the fastest and most effective means of transportation in the United States. This level mainly consists of American cities, but three European cities appear to be particularly connected to these cities: Amsterdam, Dublin and Manchester. This European presence can be explained by the bilateral agreements and alliances between companies, in particular Continental Airlines, which is present at all three airports.

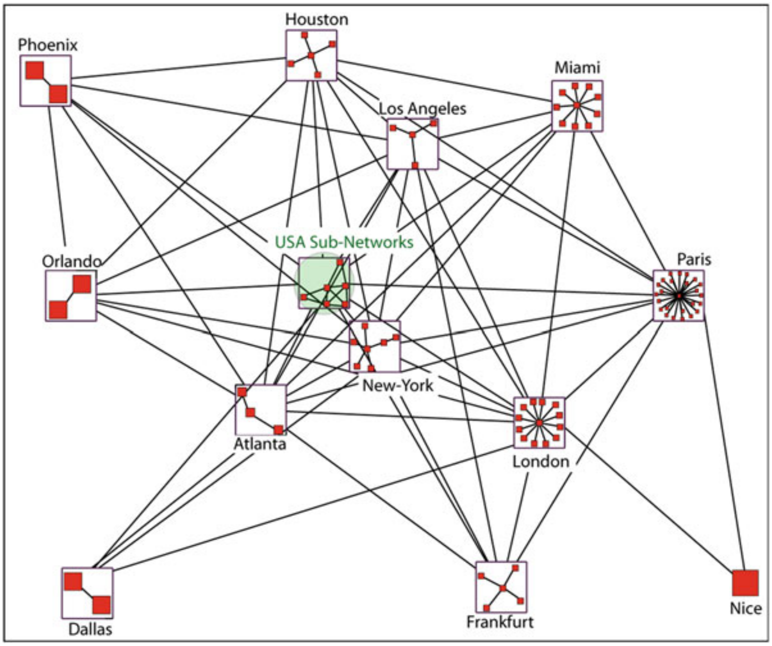

Fig. 9.7 Clustering of worldwide air traffic: focus on main hubs

The central component of the third level of the graph can also be divided into two lower levels, i.e., a fifth level is introduced (Fig. 9.7). This fifth level represents the local organization of the center and the western North American area. These are secondary areas, which are very dependent on the connections between them and are, at the same time, deeply "embedded" in the American hub system (levels 2 and 3) that is dominant at the world level (level 1). The strong connections between the secondary American cities and the world level arise from the characteristic organization of American airspace, which has been hierarchical, from very early on, in terms of three main hub categories:

- traditional "gateways" (Los Angeles, Chicago, Boston, and San Francisco);
- principal hubs (Philadelphia, Atlanta, Houston, and Dallas); and
- secondary hubs (Minneapolis, Denver, Phoenix, Cincinnati, St Louis, Tampa, and Las Vegas) (Connor, 2003; Weber & Williams, 2001).

This hierarchical organization integrates American secondary cities particularly well into the world air network.

The position of all these cities is thus at the core of air world traffic. The encapsulated shape of these graphs shows a highly integrated system, primarily on the part of the United States territory.

In comparison to the North American system, the Asian and European systems appear less integrated into the world system. However, while the European cities are

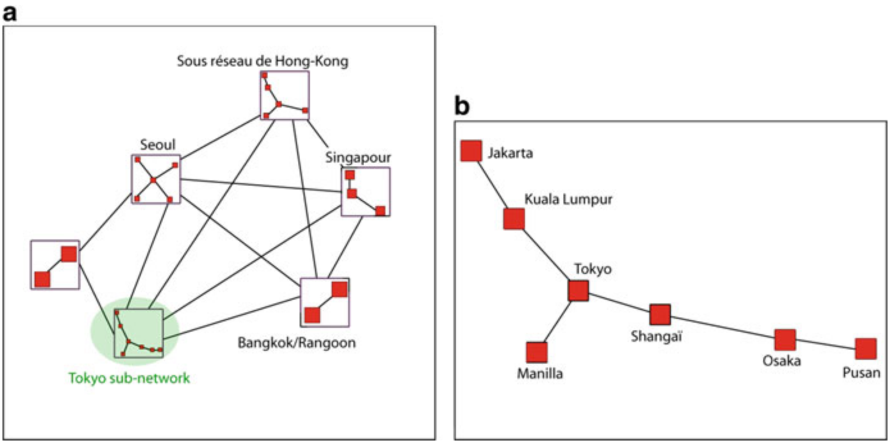

Fig. 9.8 Clustering of Worldwide air traffic: focus on Asian cluster

not well-integrated into the system, with the hubs displaying a burst structure in the form of various subgroups, the Asian system is very connected and forms a group with whole market share (Fig. 9.8).

The Asian system can be broken down at a second level (Fig. 9.8a). In particular, this system is organized around two poles, Hong Kong and Tokyo. Decomposition at a third level, around the Tokyo pole, shows an international system that is strongly integrated around the Japanese capital: the system spans Jakarta to Pusan while passing through Shanghai (Fig. 9.8b). The insularity of the Asian area partly justifies the strong integration of the regional network. Moreover, the potential and the demand for air transport in Asia involve increasingly strong competition between airports and cities (Park, 2003).

At the other end of the spectrum, the European system appears to be less well-integrated from Stockholm to Lisbon, undoubtedly because of the complex history of the airspace burst structure. Indeed, national companies, under pressure from the states, organized hubs for each large European capital. It was only with the deregulation of the European skies in 1993 that the management experience of the European air routes was transferred to private airlines (Burghouwt, Hakfoort, & Ritsema van Eck, 2003). Despite the efforts of the European Community to build a coherent airspace, great competition still exists between the principal European hubs, such as London, Paris, Frankfurt and Amsterdam (Graham, 1998).

Some cities, although strongly dependent on the major hubs or the two non-intermitting systems, have few connections between hubs. This is the case for cities in Latin America such as Bogota, Buenos Aires, and Santiago and for cities in the Middle East such as Dubai, Tehran, Jeddah, and Riyadh. There is intense traffic between the large South American capitals and the central network because the majority of the exchanges are with the international network, starting exclusively from the large capitals. These capitals have reproduced the traffic resulting from the neo-liberal policies of airspace openings, producing a star distribution network around the hub and spokes system (Lipovich, 2002).

9.5 Conclusion

The organization of the air transport network represented here reveals an interesting process of spatial integration. The networks are articulated around a central core, consisting of principal hubs where the arrangement of "reticular territories" distinguishes the three organizing zonal sets of the world economy: the United States, Europe and Asia. In the United States, structures are hierarchical, and the various territories are perfectly integrated with each other. Europe is an example of an airspace with very little organization and low levels of hierarchy: there is a multitude of airports and relations at the same level without a single organizing influence, as in the United States. One may assume that this phenomenon will attenuate over the next few years with the new European transportation policy (in particular, through the implementation of the White Paper on the "European transport policy by 2010: the hour of choices").

Attention should be given to the influence of Asian airspace. Indeed, Asia is the area currently showing the greatest growth in air transport. It will be necessary to closely follow the evolution of the Asian sector because one may assume that the principal worldwide hubs group will soon integrate with airports such as Tokyo, Hong Kong and Singapore.

Economies, markets and the internal reorganizations of airline companies are factors supplementing these tendencies. Power transfer from states to private companies is leaving airspace less divided and consequently more inclined toward competitiveness logics. Thus, private strategies have become the dominant organizing influence for the "reticular territories" of air transport. The only regulatory authorities in this system are the international air organizations (IATA, ICAO). With air transport being one of the most competitive sectors in the world, one must expect constant evolution of its networks and an increasingly complex organization of the reticular territories.

From a methodological point of view, the comparison of clustering methods can be classified into two types of final results:

- results that include a large number of geographically proximal areas but do not highlight the hubs in the network;
- results that highlight the denser parts of the networks and the hubs. These methods are interesting but represent the star shapes of the networks very poorly.

Repeating the clustering methods with different datasets shows that neither of these types of methods is satisfying in terms of the processes that need to be delineated: the methods do not operate on the same order or with similar weights. Thus, these types of exploratory methods are limited and could be supplemented in the future by more data-driven methods and the selection of different steps depending on the initial assumptions. These types of data-driven methods were first tested on commuter networks (see Chap. 11) and could be automated to test these methods on different datasets. Thus, the field of clustering is in progress and is open to many future research directions.

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Chapter 10
Multilevel Analysis of Corporations Networks: A Comparison Between Agro-Food and Automobile Strategies for Urban Development

Charles Bohan and Bérengère Gautier

10.1 Introduction

The integration of territories is one of the major objectives of the convergence policies that Europe encourages in order to stabilize its borders and make them safer. In the Mediterranean region, as well as in Central and Eastern Europe, states use the structural funds that they provide for development to support policies that make the territories more attractive to multinational firms. By diffusing capital, information and expertise on a worldwide scale, firms became the principal driving force of development processes in the European Neighborhood Policies.

Most of the current studies on the economic integration of territories is based on the scale of national economies. However, in the context of the international division of labor and of the internationalization of the exchanges under the impulse of the NTIC, companies develop networks based on complementary and localized territorial competences, such as the local factors of attractivity and the faculty of networking production processes. Then, the networks of multinational firms seek locations that can enable them to achieve economies of scale and economies of networks (Doz, Santos, & Williamson, 2001; Rozenblat, 2004; Veltz, 2000). It is necessary to integrate this reticular dimension of the integration of cities in globalization. On the transnational scale, the firms stimulate economies of agglomeration (localization, urbanization and economies of scale) for cities and create original developments within each of them, thus reinforcing their position within the system

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of cities (Camagni, 1996; Rozenblat, 2004, 2010). The relationship between the networks of firms and the system of cities seems relevant for understanding this global/local articulation and the developments, which result from the interaction of intra-urban and inter-urban processes.

At the global scale, we distinguish two major types of organization strategies: a market-oriented organization (horizontal strategy) and a production-oriented organization (vertical strategy) (Porter, 1986). The market-oriented organization is based on a network of subsidiaries that are established within large areas of mass consumption and production and that adapt to the specific assets of local markets and of labor markets. This strategy is often planned on a continental scale and is observed in free trade areas. A production-oriented strategy exploits the specializations of various geographical areas in order to establish a different stage of its production in each area, based on its comparative advantages (Veltz, 2000). Such a strategy is responsible for the international division of labor. However, firms do not rigorously apply these two organization patterns, and a majority of large firms combine these two aspects, mixing strategies of production and geographical organization (Michalet, 1999; Rozenblat, 2004; Veltz, 1998).

Their strategies are organized in a three-dimensional system that is formed by the economic system to which each firm belongs, its governance or system by which the company is governed, and the territories in which it is embedded. The economic system corresponds to the external environment of the firm (Francfort, Osty, Sainsaulieu, & Uhalde, 1995). "This environment is based on more or less monopolistic competition, the technological projections and cycles of the products, imbalances between supply and demand (gone, price), of the fluctuations of the products value" (Rozenblat, 2004, p. 29). Within the economic system, the position of the invested firms and territories are constantly redefined. The governance of the firm is "the whole of the strategies and objectives of the companies that make it up, the human means and materials, which it implements, its organizational architecture, and its own managerial culture" (Rozenblat, 2004, p. 13). Taking an international perspective, the governance of the firm determines the relationships among its various establishments: it introduces hierarchical and functional relationships between territories. Within this system, the territory becomes a dynamic object, and it is therefore important to articulate the global and local dimensions in which each territory and each firm fits.

The economic literature on the agro-food and automobile sectors reveals that multinational companies in the agro-food sector rely more on market-oriented strategies, while multinational firms in the automotive industry primarily seek locations that minimize their production costs. The networks of multinational firms of the agro-food industry should therefore reinforce the existing urban hierarchies. Conversely, according to cost minimization strategies, the firms of the automobile sector develop their strategies on a worldwide scale. Such strategies should therefore be based on urban specializations that allow them to achieve important economies of networks by complementarities between locations. Thus, they play a larger role in the international division of labor.

To highlight the role of each economic sector in the integration of territories, we would like to demonstrate the role of each of these economic strategies in the articulation of the network of cities. In the first part of this paper, we will describe the governance of six multinational firms, starting from their individual network of filiations. From this individual firm network, we will collect measurements for each firm. These data enable us to compare individual networks of firms and to observe their strategies. In a second section, we will produce a visualization of the cities' networks based on the aggregation of the subsidiary networks of the firms. This stage enables us to observe their territorial strategies and to replace each city in the context of the global strategies of the firms. Finally, we compare our results for the automotive and agro-food sectors by comparing the cities' networks as formed by the main companies. Such graphs enable us to visualize and to compare the sector's strategies according to their inter- and intra-urban dimensions. This comparison will allow us to identify the intra-urban links that form the basis of the influence that each city has in the automobile and agro-food networks of cities.

10.2 Constraints of Economic Sector and Firm Governance

10.2.1 Two Economic Sectors

Up until now, international research on urban systems has been very difficult because of the lack of data relating to networks (Rozenblat & Pumain, 1993; Veltz, 2000). The ORBIS database (Bureau Van Dijk), which was created in 2003, however, now allows analysis of information on companies at a global scale (company names, location, level and nature of filiations, turnover, number of employees, etc.). Before explaining our procedure for analysis and visualization, we will provide an overview of the companies that we have selected to allow a comparative analysis. We have chosen to study 6 multinational firms in two different sectors: the agro-food industry and the motor industry.

10.2.1.1 Agro-Food Industry

The agro-food industry is a diversified economic sector that encompasses myriad sub-sectors (meats, dairy products, cereals, wine and spirits, milk, water, etc.), where small companies interact with large companies. Through the study of multinational firms in the agro-food industry, we focus on these "giant" enterprises. These enterprises are a product of the agro-industrial model, which has been growing since the beginning of the century, and is based on a model of mass consumption. The agro-industrial model of production is described as "specialized, concentrated, financialized and in the process of globalization" (Rastoin, 2000). However, food

Table 10.1 Selected firms in the agro-food industry

	City headquarter	Date of incorporation	Turnover billions US$	Number of employees
Nestlé SA	Vevey (Switzerland)	1866	69,709	250,000
Unilever Group	Rotterdam, London	1930	46,801	212,000
Kraft Foods	Chicago	1903	29,531	97,850

remains strongly anchored in cultural practices, which slows down the export of the model of Western food consumption. The ability of a firm to adapt to each mass consumption area constitutes an important factor of competitiveness for firms in a highly competitive sector. This sector is dominated by three multinational corporations (Table 10.1).

Nestlé S.A

Nestlé S.A, founded in 1866 in Switzerland, is the leading global agro-food company. With 250,000 employees throughout the world, distributed in 104 countries, the firm generates 70 billion dollars in sales each year. The firm acquired leadership in the sectors of water, ice cream, and baby food as a result of its innovation, which is the main competitive advantage of the firm. Nestlé has a strong policy of repurchasing local brands, allowing it to acquire local expertise and providing great adaptability in the international markets.

Unilever Group

Unilever was created in 1930 by an association between the Dutch margarine company UNI and the English soap manufacturer Lever Group Bothers Ltd. Since then, the group has had a bicephalous management, with Unilever PLC in the United Kingdom and Unilever NV in the Netherlands, and has diversified income due to its presence in both the hygiene and food markets. Consequently, Unilever profits from an important list of brands, which has allowed the company to establish in 106 countries and to become the second leader of the agro-food industry. The firm has acquired leadership in margarine, tea and olive oil.

Kraft Foods

In 1903, Kraft foods was just a creamery located in Chicago. The store opened its first cheese factory in 1914. The firm was then developed by a series of acquisitions and has acquired leadership in the sectors of coffee, chocolate, snacks and cookies.

Table 10.2 Selected firms in the motor industry

	City headquarter	Date of incorporation	Turnover millions US$	Number of employees
Toyota MC	Japan, Toyota city	1937	186,177	285,977
Peugeot SA	France, Paris	1890	83,193	211,700
Fiat S.p.A	Italy, Torino	1899	57,965	173,695

10.2.1.2 Motor Industry

On the economic scene, the motor industry is a tightening oligopoly, increasingly prone to fusions/acquisitions (F&A) with repurchases and alliances, and comprises only 14 main manufacturers (up to one billion sales per year, OICA, 2010). The industry is characterized by an extremely competitive climate at the international level, though there can be strong cooperation in local markets (Co-opetition model) where joint ventures are frequent (Toyota/Peugeot Citroen Automobile (TPCA), PSA/FIAT SevelNord, etc.).

We have chosen three multinational groups from the motor industry that have clearly differentiated strategies (Table 10.2). Toyota, PSA and FIAT have completely different modes of governance, based on their own histories and corporate cultures as well as their strategic choice of investments and localizations throughout their development.

Toyota Motor Corporation

Toyota Motor Corporation is now the world's leading car manufacturer, ahead of General Motors, in terms of sales (OICA, 2010). However, the group has only recently become the world's leading producer in terms of produced car units. Toyota is a very diversified group, whose activities range far beyond the sale of automobiles. Toyota produces automobile parts, components and accessories for its own needs and for other manufacturers. The strategy of Toyota is unique compared to its competitors in terms of production and locations. The group was first internationalized in the United States and then in China and other countries of Southeast Asia. Toyota has 52 assembly plants in 27 countries.

PSA Peugeot-Citroën

Peugeot-Citroen Group PSA is the second largest European car manufacturer. PSA is the result of the fusion of two French brands, which occurred in 1976. PSA's governance is characterized by its strong centralization in terms of locations and in terms of distribution of capacity to subsidiary companies. The group is engaged in the design, development, production and sale of private cars, commercial vehicles, scooters and motorcycles. The operations of the company include the bank PSA Finance, a transport and logistics group (Gefco) and Faurécia, which is the most important European equipment supplier. The market of PSA is primarily in Europe, but the firm has a strong presence in Latin America and operates in Africa, Asia Pacific and other parts of the world. PSA operates through five principal divisions: cars, automobile equipment (Faurécia), transport and logistics (Gefco), finance and other activities.

Fiat S.p.A

The Italian firm Fiat produces and sells commercial and agricultural vehicles, as well as construction equipment. The group also produces engines and transmissions, automobile components, metallurgical products and systems of production for its own needs and for sales to third parties. However, the group has some other interests such as press and communication. Fiat operates mainly in Europe and North America by means of an important network of subsidiary companies. Fiat has 12 operational sectors: Fiat Auto; agricultural and construction equipment (Box New Holland CNH); trucks (Iveco), component cars (Magneti Marrelli); systems of production (Comau); Ferrari; metallurgical products (Teskid); services (Business solutions); Maserati; editions and communication (Itedi); Fiat powertrain technologies and other companies. Fiat holds and uses 11 assembly plants (6 in Italy, 1 in each of Poland, Brazil, Argentina, India and Serbia) and participates in joint ventures with other car manufacturers.

Our analysis of the strategies of multinational firms largely focuses on the reticular field of firms' networks. Creating graphs makes it possible to compile a mass of information (labels) and allows a novel visualization of a city's place in the firm's network. Our analysis is comparative so that we can examine the way the various economic strategies articulate the territorial properties of the world's cities.

10.2.2 Comparison of Individual Firm's Networks

To connect the various components of a firm, we initially create graphs of individual corporate networks. The method consists of representing filiations of the companies, starting from their financial relationships. In a hierarchical way, these graphs are produced from the database ORBIS (Bureau Van Dijk) and are supplemented with information from firms' annual reports. These graphs enable us to observe the distribution of the financial relationships between each element of the multinational firm. Hereafter (Figs. 10.1 and 10.2), the nodes represent the companies and the edges denote the ownership relationships among them. We used the metric of betweenness centrality to highlight the centrality of each subsidiary in the governance of each group.

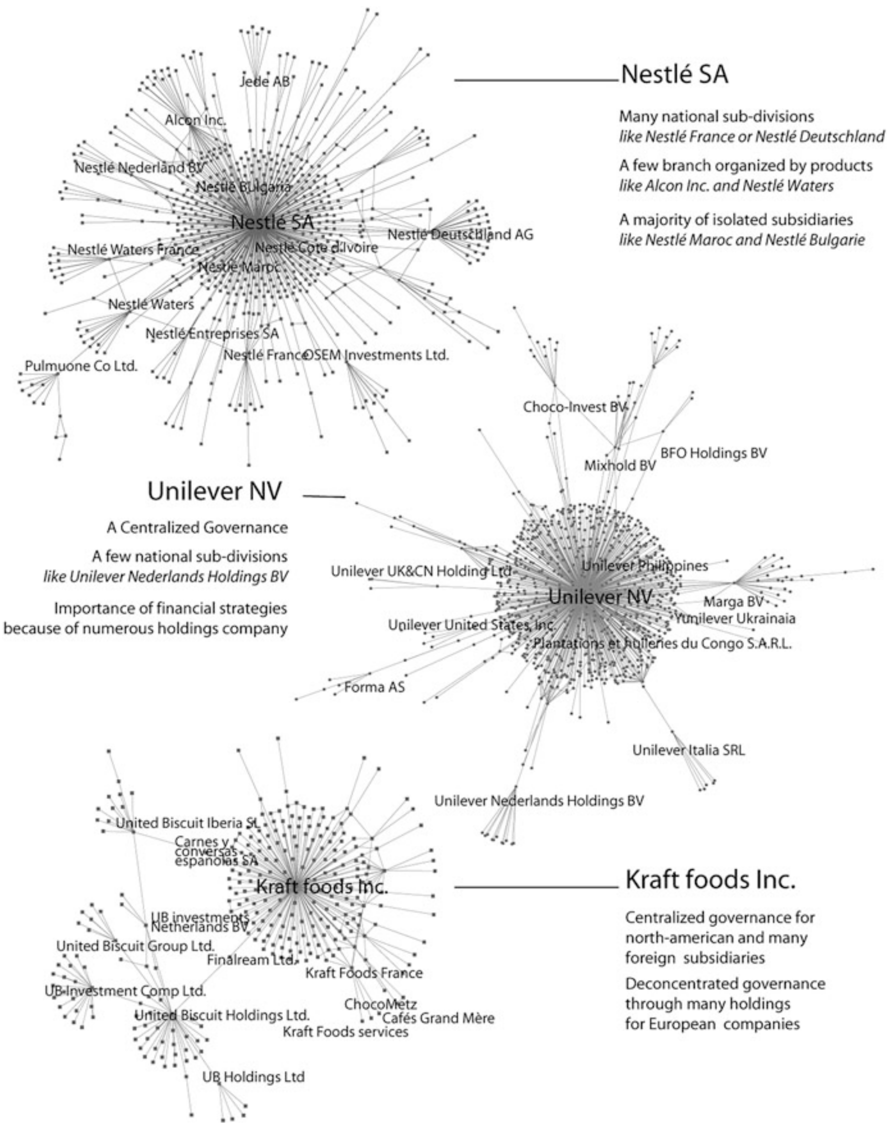

Fig. 10.1 Corporate governance in the agri-food sector (2005) (Source: ORBIS, 2005 – Gautier B. & SPANGEO @ IAMM, 2007)

10.2.2.1 Governance of Networked Companies

The network of a firm is a complex object, which deserves a graphic visualization tool to allow economists, managers, geographers or others to analyze its structure and evolution or to compare it to other networks. The governance of a firm varies

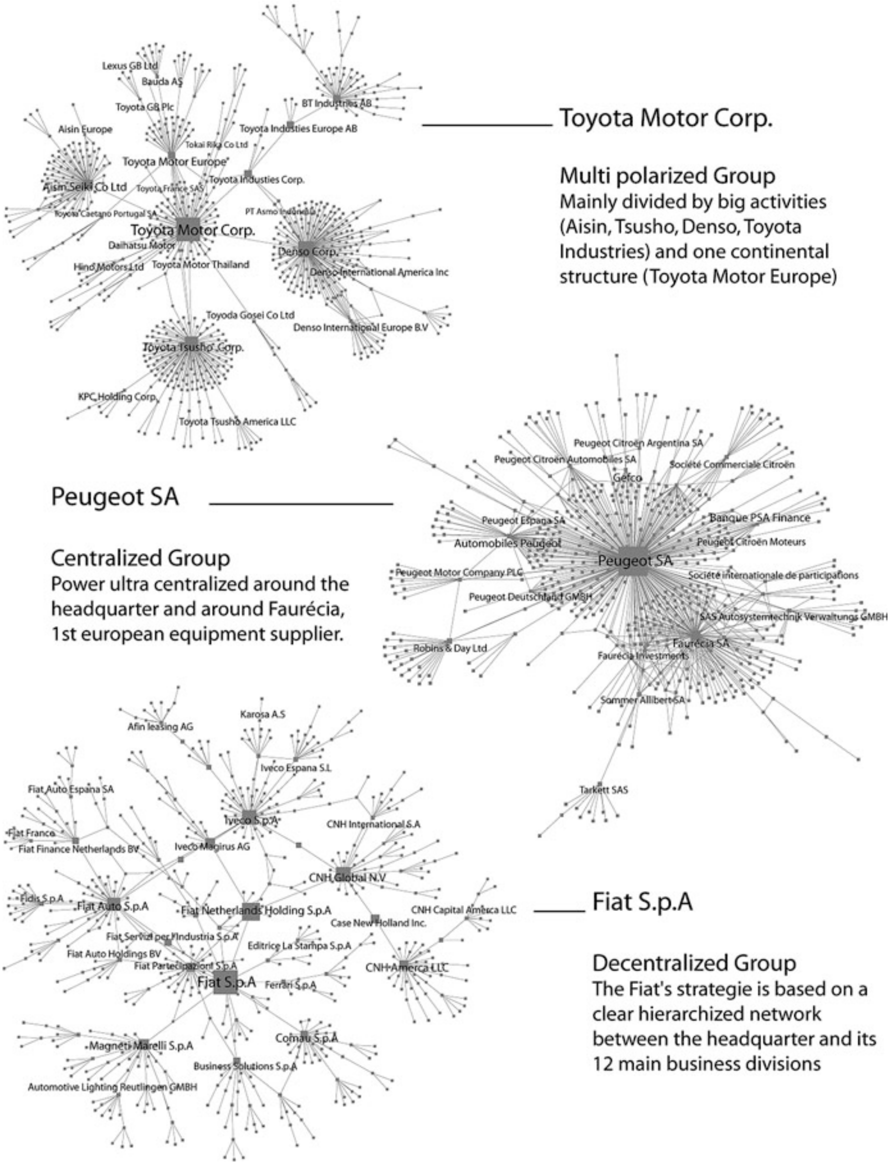

Fig. 10.2 Corporate governance in the automotive sector (2006) (Source: ORBIS, 2006 – Bohan C. @ Cefres, 2007)

according to its history, the corporate culture, its strategic decisions (such as acquisitions), the transfer of credits, and the establishment of subsidiary companies abroad, which modify the way it treats capacities inside its network on a hierarchical basis. Thus, the network of a multinational firm is an object in constant evolution, but we consider the actual shape as the legacy of past actions. The various forms that a network can take reveal the particular strategies according to its organizational structure, its localizations or the control of its capital and employees (Figs. 10.1 and 10.2).

The networks of the multinational food companies studied in this research show a strong centralization of power around the headquarters of Nestlé, Unilever and Kraft Foods (Figs. 10.1 and 10.3), where the headquarters owns an isolated subsidiary in each country. There are some branches organized within national spaces in countries that have a large market size. For example, Nestlé Deutschland AG and Nestlé France SA reflect market-oriented strategies with a strong national dimension. There is thus a strong constraint for national food network deployment, which can be interpreted to result from both a strong constraint related to the various markets in which these firms are located, with a strong cultural embeddedness of food consumption, and a constraint to food commodities that have a short life span, with a relatively low export capacity. All of these constraints on the agro-food sector hinder the internationalization of the groups. Thus, the networks of agrofood companies are highly organized according to geographical area. On the other hand, the motor industry networks present various structures. The power is distributed related to the governance organization and history of the firm. The three selected multinational companies are a good examples of different types of network structure. The Toyota group (Fig. 10.2) is mainly divided into five groups (Denso, Aisin Seiki, Toyota Motor Europe, Toyota Tsusho and BT industries). The headquarters holds five semi-autonomous groups that manage clearly delineated activities. The French group PSA is very centralized, except for its equipment group, Faurécia. The headquarters has quasi-direct control of its subsidiaries. In contrast, the Fiat group is very decentralized into twelve main divisions due to its governance structure and its diversification of activities (from agricultural machines to finance holdings). Even if these networks present different types of structure, the subsidiaries are regrouped around cluster activities. This type of structural organization is characteristic of a typical production-oriented governance.

10.2.2.2 *Betweeness Centrality*: Centrality of the Subsidiaries in the Network

The differences between the shapes of the networks can be evaluated by the distribution of the power inside each of them (measured by betweenness centrality) (Fig. 10.3). This metric was defined by Freeman in 1977 (Freeman, 1977, 1979). Betweenness centrality describes the control exerted by an individual on the interactions between the other actors of the network. The more often an individual is on a path that other individuals must use to communicate, the more central the network is Lazega (1998). To compare the distribution of power in the corporate networks, (we recorded) this metric for all of the subsidiary companies in each corporate network.

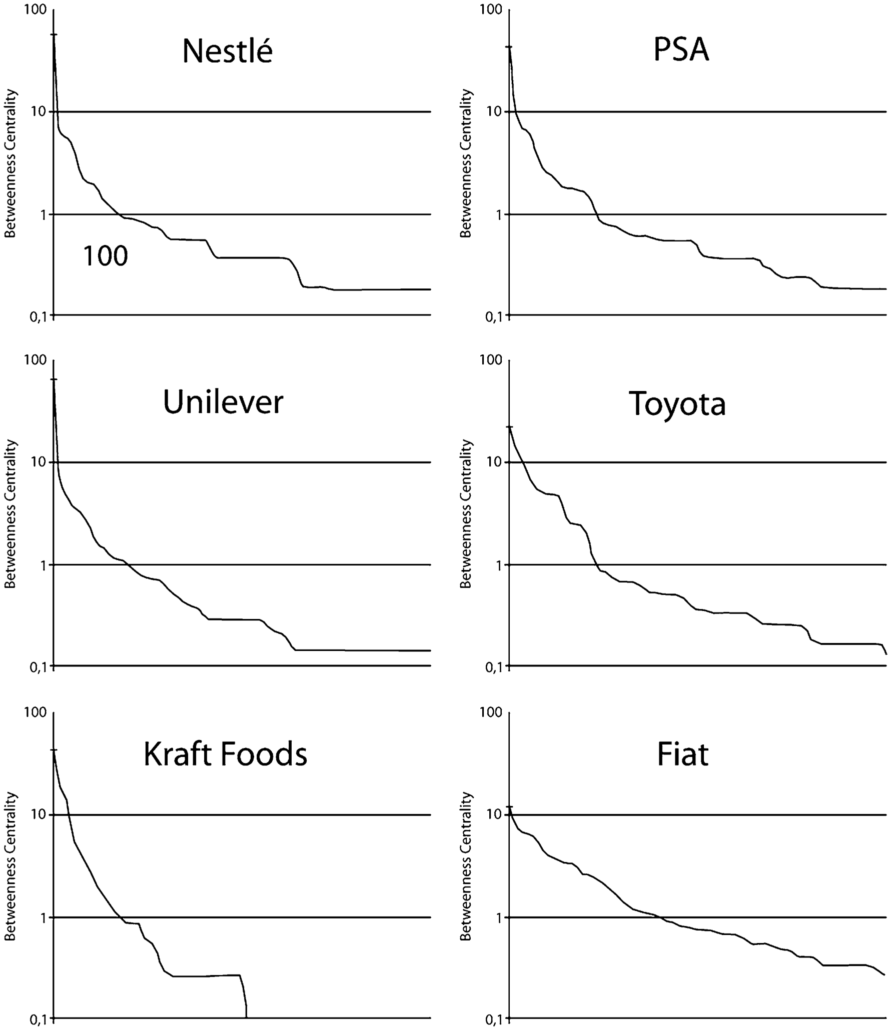

Fig. 10.3 Rank-size betweeness centrality distribution analysis (Source: ORBIS, 2006 – Gautier B., Bohan C. @ IAMM, Cefres, 2007)

These graphics show that the headquarters of the agro-food industry firms are much more centralized than the headquarters of the motor industry firms. Several models of governance are shown through the various graphics. While the agro-food industry presents similar modes of governance with a strong centralization, the strategies vary much more in the motor industry.

The three graphs of agro-food governance generally show similar characteristics, with a strong centralization of headquarters. At the heart of each network, we observe an important group of subsidiaries without any other relationships that bind it to the headquarters. The majority of the subsidiaries belonging to this star formation are in small, often-partitioned national markets (Morocco, Bulgaria, Congo, etc.). Nearby, we notice in each one of these graphs, sub-centers of control corresponding to the following:

- National branches, directing the activity of each subsidiary company in countries or small areas (e.g., Germany, Scandinavia or other countries and regional areas);
- More rarely, branches by product (e.g., Nestle waters, United Biscuit)

The three graphs of governance of the motor industry are different. Fiat and Toyota present strongly decentralized models (respectively, 11.75 and 22.62 % of betweenness centrality held by the headquarters of FIAT and Toyota). These models present branches organized by products at a global scale. These branches have strong connections between each other. On the other hand, PSA and its equipment supplier Faurécia have organized all of their global production around the Parisian headquarters, and hold 53.97 % of the total betweenness centrality of the graph.

Through this sectorial distinction of the governorship modes of the companies, we can distinguish two organizational models:

- An organizational model of agro-food companies, which articulate production-oriented strategies and market-oriented strategies inside each network. The strategies of localization for the subsidiaries mainly follow market dimensions of the territories. The general structure of each of these networks is relatively simple, with a concentration on the most important functions at the top and a weak specialization of the affiliated companies downstream. These mega-structures articulate affiliates involved in micro-strategies that are adapted to the markets, which can be drawn as vertical strategies (global geographical division structure (Dicken, 1992)).
- An organizational model of companies of the motor industry, where the strategies are articulated on a worldwide scale, according to branches organized by products. The networks have diversified morphologies because the strategies of the multinational corporations of the motor industry are complicated on a global scale. The complexity and the diversity of the organizational forms revealed by these graphs, according to a "federal" model (Veltz, 1998), attest to an organization by project, which is accompanied by a strong specialization of subsidiaries (Francfort et al., 1995) (global products division structure (Dicken, 1992)).

A part of the firms' governance is explained by the economic sector to which it belongs. As we can clearly see in these two examples, economic logic drives the governance of a firm depending on the sector. The multinational firms of the agro-food industry usually choose strategies of multi-localization. Indeed, they are constrained by strong market segmentation due to extremely diverse cultural practices. On the other hand, the companies of the automotive sector, compelled by a strong competitive climate at the global level, instead follow a "central logic of the globalization which consists in creating synergies in more and more widened geographical *scales*" (Veltz, 1998, p. 26). The activities within the subsidiary companies will be different: in the agro-food industry, diversified subsidiary companies are adapted to the same regional national markets, whereas in the car industry, subsidiary companies are directly specialized and integrated within a global project. Therefore, the competition between cities is not on the same spatial scale (it is on the regional or national scale in the agro-food industry and on the global scale in the automotive sector).

10.3 Networked Cities Through a Corporate Firm's Network

To ensure their competitiveness, the multinational firms studied in this research divide their activity according to localized territorial skills. These territorialized skills are the result of local networks of cooperation between private and public actors. The local scale allows close relationships between these actors (Storper & Venables, 2004). According to the classic definition of economies of agglomeration (Camagni, 1999; Duranton & Puga, 2004; Ellison & Glaeser, 1997; Henderson, 1988; Hoover, 1937, 1948; Jacobs, 1969; Marshall, 1920; Ohlin, 1933), these effects of proximity allow the companies to realize different kinds of economies:

- Economies of scale, allowing them to increase their productivity;
- Economies of urbanization, related to the collective use of generic services in the heart of the territories (e.g., grid systems, administration and unspecialized services);
- Economies of location, related to the collective use of specific agents (e.g., subcontractors, services, specialized infrastructures).

Economic actors such as multinationals will be based on these economies of agglomeration and will stimulate them, thus reinforcing the capacity and/or the specialization of the territory (Rozenblat, 2004). The company networks use these localized territorial properties and they are articulated in the heart of the network (Doz et al., 2001). The networks of multinationals comprise hierarchical and functional links between territories. Worldwide, the relations between territories follow two simultaneous and articulated plans:

- A hierarchical model that organizes the local market areas, as described by Christaller (1933), which relies more on networks of proximity, facilitated by close markets and regional hierarchies of cities.
- A model of specialization between specialized cities encouraged by long-range relationships defining "economies of archipelagos" (Veltz, 2000).

The approach of the firms' networks, aggregated by cities, highlights the spatial effects of the inherent strategies of the two sectors:

- For the agro-food industry, except for the cities that contain headquarters with broad functions, we observe that most large cities of the large economic regions contain a large number of subsidiaries: Paris and London for Nestlé, London and

Paris for Unilever and London and Amsterdam for Kraft Foods. Furthermore, we notice that the spatial organization of each of these firms creates "cliques" among cities belonging to cohesive economic systems. In every example, the cities belonging to the European Union form a distinct group where the interurban relations are denser than in the remainder of the network. This spatial organization is particularly visible within the group Nestlé (European origin) and to a lesser extent in the governance of the group Kraft Foods (American origin). Worldwide, we observe globally a respect for the urban hierarchy in very different areas of markets.

- On the other hand, the logics of production that we find throughout the automotive sector grant an important place for medium-sized cities: PSA is heavily localized in Coventry or Sarrebruck; Toyota, in the cities of Mjolby and Vantaa; and Fiat, in the cities of Wilmington (which is an international tax haven) and Ulm. More than agglomeration economies, the motor industry requires space and a labor pool.

In the automobile sector, the city to city relationships across national borders (which represent a strong constraint in the agro-food sector) increase the importance of long-range relations, such as Bratislava-Mexico City-Seoul at PSA; Sydney-Kariya-Mjolby-Brussels at Toyota or London-Shanghai-Zedelgem at FIAT. In this production-oriented strategy, relations between specialized cities cross national borders and integrate cities worldwide (Figs. 10.4 and 10.5).

We can thus define various spatial types of organizations:

- Logics of market within the agro-food framework, with relations contained within preset international frameworks. These spatial organizations respect the urban hierarchies and strengthen existing links between cities belonging to the same economic bloc.
- Logics of production of the automotive sector, where the specialized subsidiaries rely on localized territorial skills to strengthen or create relations between distant specialized cities.

According to the economic strategies adopted by the governances of the firms, we see that the firms look for different territorial skills and aim to utilize them in an original way within their network. Now the question is how these different networks affect the territories.

10.4 Competition Between Cities in Corporate Networks

By their choice of location, firms develop and stabilize their competitiveness. They find within territories the useful resources for their development, and through economies of agglomeration, they stimulate those resources. Moreover, economies of agglomeration result from cooperation between economic actors who unite infrastructure and information needs, guaranteeing their competitiveness.

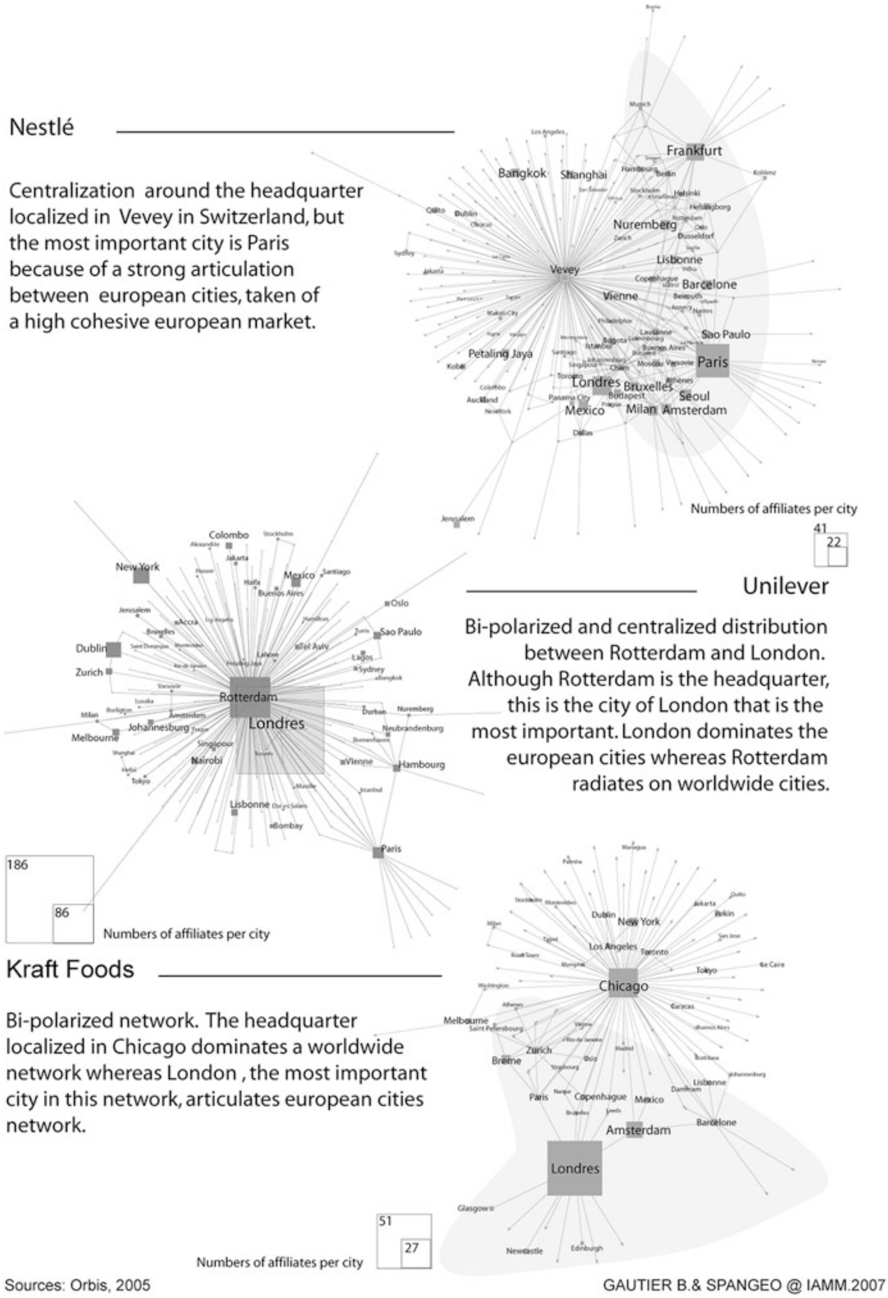

Fig. 10.4 Corporations and their urban networks – agri-food sector (Source: ORBIS, 2005 – Gautier B. & SPANGEO @ IAMM, 2007)

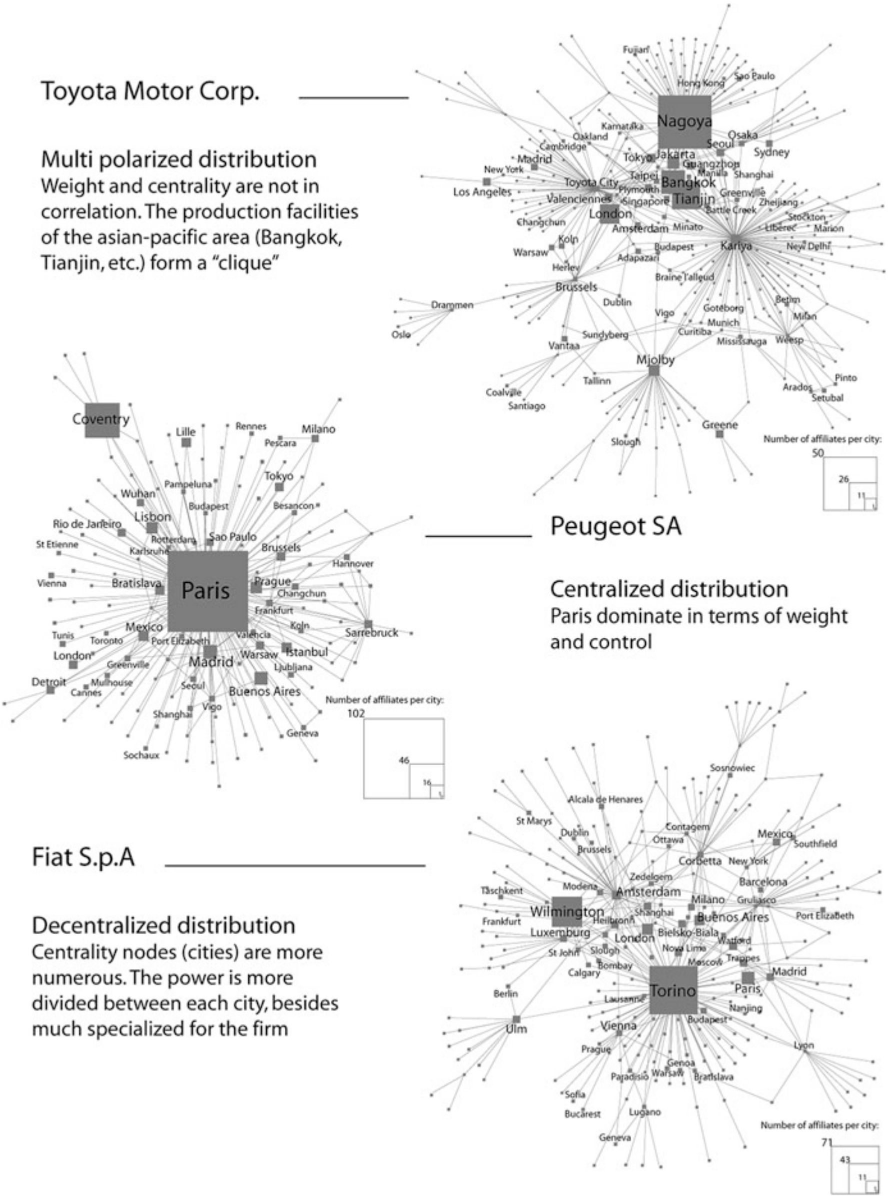

Fig. 10.5 Corporations and their urban networks – automotive sector (Source: ORBIS, 2006 – Bohan C. @ Cefres, 2007)

The territorial embeddedness of the firms assumes a paradoxical aspect: whereas those firms are concurrent on a worldwide scale, they cooperate directly (e.g., resource exchange or exchange of information) or indirectly (e.g., lobbying) within local area networks.

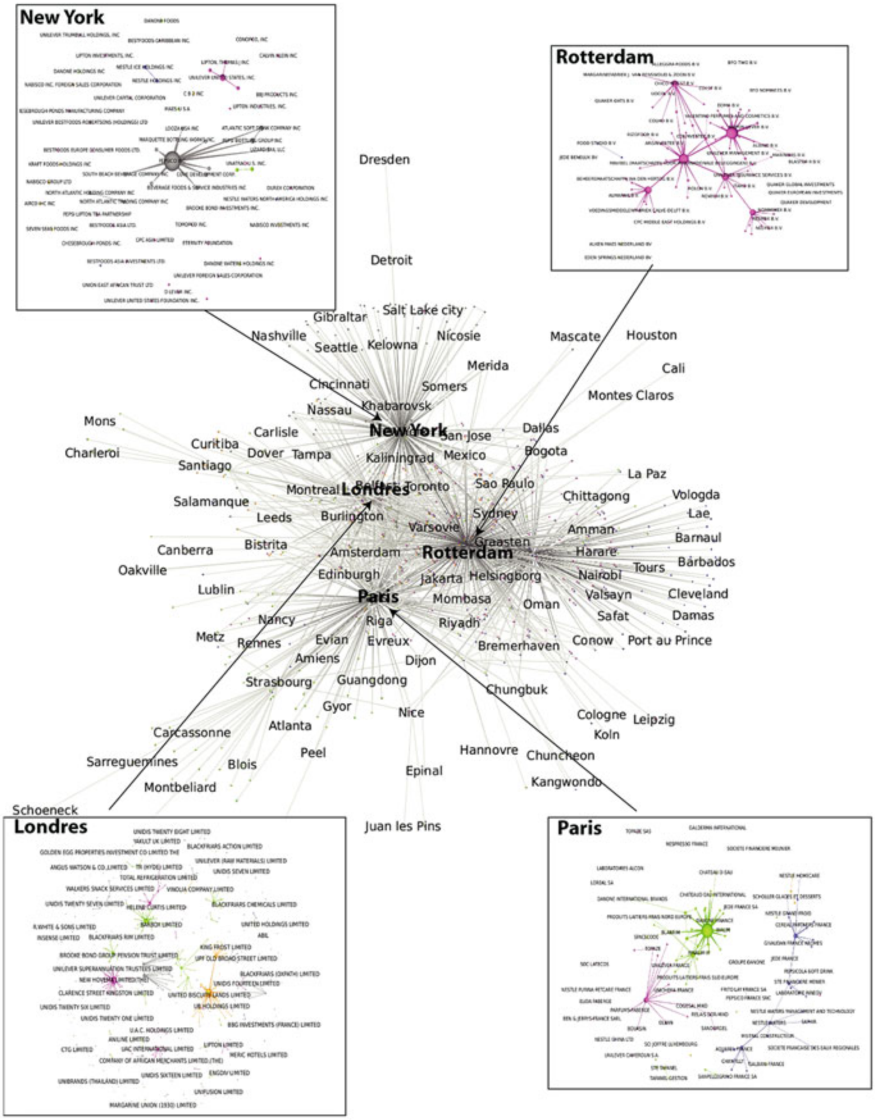

Fig. 10.6 Inter corporate competition through urban areas – urban network formed by Nestlé SA, Unilever, Kraft Foods, PepsiCo and Danone (Source: ORBIS, 2005 – Gautier B. & Rozenblat C. @ SPANGEO, 2007)

To observe this phenomenon, we aggregated all the networks of each economic sector (see Figs. 10.6 and 10.7). Combining the networks of several firms, we finally obtained a single network that represents inter-urban relationships. This kind of graph allows us to visualize not only relations between cities in one particular branch of an industry but also relations within these cities. In this way, every city of the

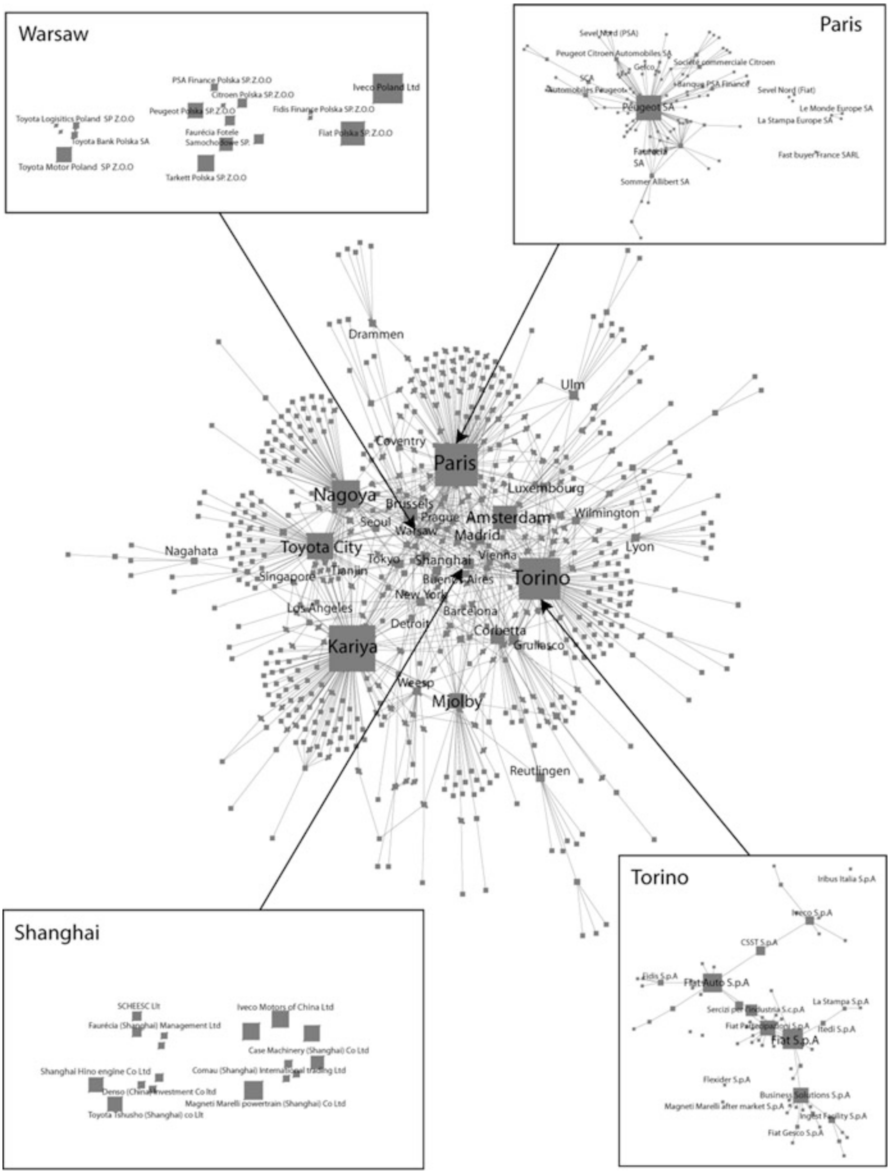

Fig. 10.7 Inter corporate competition through urban areas – urban network formed by Toyota MC, Peugeot SA and Fiat SpA (Source: ORBIS, 2006 – Bohan C. @ Cefres, 2007)

network becomes a cluster displaying every firm localized therein and represents an intra-urban network (Rozenblat, 2010). This operation reveals the main urban framework that firms use to localize their subsidiaries and where multinational companies locate, according to their needs, in terms of row, size and specializations (Pred, 1977; Veltz, 2000).

Table 10.3 Most important cities in each economic sector

Agro-food industry		Motor industry	
City	Nb afiliates	City	Nb afiliates
London	500	Paris	109
Paris	120	Torino	71
Rotterdam	95	Nagoya	50
Mexico city	92	Coventry	46
Edinburgh	81	Wilmington	43
New York	67	London	29
Dublin	56	Buenos Aires	28
Chicago	43	Tianjin	26
Amsterdam	41	Madrid	24
Vitoria	40	Bangkok	24

The inter-urban relations of the motor industry are made on a more global scale than those of the agro-food industry. We explain this pattern through the strong specialization of the territorial resources necessary for the competitiveness of the automotive companies and the close relations of the markets of the agro-food industry. In terms of weight (see Table 10.3), we notice a stronger polarization of the cities for the agro-food industry: London accumulates 500 subsidiaries, which is one-sixth of the total agro-food subsidiary sample used. The position of London in the strategic space of the agro-food sector is largely due to its European position: the city radiates to all of Europe for Kraft Foods, which uses the cultural and linguistic proximity between the United Kingdom and the United States. The city is also a pillar for the Unilever firm, which has a secondary headquarters there that influences all the European cities. Paris is the second city most heavily invested in by the subsidiary companies of the agro-food industry. Paris is the main city in Nestlé's network, because of the cultural proximity between French-speaking Switzerland and France. Paris has regional importance for the European agro-food networks. The weight of the European Union in the agro-food strategies is strong: six of the ten most heavily invested cities belong to the European Union. This result is due to the cohesion and the size of the European market (Figs. 10.8 and 10.9).

The first most heavily invested city in the network of the automotive sector is Paris, which contains 109 subsidiary companies, due to the presence of the PSA headquarters and its surroundings (Fig. 10.6), since PSA centralizes many functions at the top of the hierarchy. It is the same for Torino and Nagoya, respectively second and third most heavily invested cities of the classification. The fourth city is Coventry, a town in the United Kingdom of 305,000 inhabitants (UK census, 2002), which saw the establishment of Rover at the end of the nineteenth century. Since then, 130 industries connected to the automobile sector have settled nearby. This specialization is also visible in Shanghai and Warsaw, with the presence of the three selected firms (Fig. 10.6). Finally, this automobile classification reveals the strong proportion of cities belonging to emergent countries, such as Buenos Aires, Tianjin and Bangkok, which may result from strategies to minimize production costs.

Fig. 10.8 Main cities of the agro-food industry (Nestlé, Unilever, Kraft Foods, Pepsico et Danone) (Source: ORBIS BVD, 2006 – Bohan C. & Gautier B. @ IAMM, Cefres, 2007)

Fig. 10.9 Main cities of the motor industry (Toyota, PSA, Fiat) (Source: ORBIS BVD, 2006 – Bohan C. & Gautier B. @ IAMM, Cefres, 2007)

The heart of the network formed by the firms of the agro-food industry is marked by strong relations between cities benefiting from a powerful market and, more particularly, by the presence of European cities. This model follows a classic economic core/periphery model because it presupposes the existence of agro-food markets. The peripheries are not ignored by these strategies but remain marginal because of their weak cohesion networks. On the other hand, strong relations between distant cities form the heart of the automobile network. The heterogeneous spatial strategy of the motor industry makes it possible to combine the specific advantages of the territories through strategies to minimize costs, due to connections between distant cities. This economic strategy diffuses capital and expertise more widely globally and contributes to an international division of labor by creating competition among cities at a global scale.

Above, we discussed the table of the ten most important cities by sector (Table 10.3). On a global scale, the five largest cities for the agro-food industry are situated in Europe, with a disproportionate ratio in London because it is unambiguously superior for the administrators of this sector. A second pole is distinguishable in North America. New York presents the same advantages as London but on a North American platform. Chicago is the headquarters of Kraft Foods, and Mexico City controls activities for all the Latin America.

For the three firms of the automotive sector, Europe stands out because PSA and Fiat have their primary markets there. In the United States, Wilmington (situated in the tax haven of Delaware, which is between Washington DC and Baltimore) is the American pole of the activities of Fiat. On the Asian side, Nagoya is the most important city for Toyota, which holds numerous production units in Bangkok and Tianjin, near Beijing.

10.5 Conclusion

This spatial and multilevel analysis investigates the economic and spatial dimensions of multinational corporations by placing them in our three-dimensional system, which comprises economic environment, governance, and territory (Porter, 1986; Rozenblat, 2004). These dimensions determine the territorial embeddedness of the firms and the territorial development. Two main types of economic strategies appear: market-oriented strategies for firms of the agro-food industry and production-oriented strategies for the companies of the motor industry.

Thus, we were able to underline the way each branch of industry constrains the organization of the firms, which results from two geographical types of division:

- A geographical division where the localization and the connections between the subsidiaries of the agro-food industry respect the broad outlines of the regional markets;
- A division of labor based on globalization at the world level, placing specialized cities in competition for the companies of the automotive sector. The original aspect of our work is the scale of the inter-urban range. We explain how firms of the agro-food industry tend to gather in the most powerful cities, and how the companies of the automotive sector join in medium-sized and specialized cities.

All of this information allows us to generate some hypotheses on territorial development and to sketch the basis of a typology of the development of territories by the corporate networks. Although this information is incomplete, the typology based on the affiliated networks is able to include the financial links that bind subsidiaries to each other. We know that there are numerous other forms of exchange between subsidiaries (intra-firm business, information, decision-making power, etc.) as developed with the methodology of the global value chain (Gereffi, 2001). All these approaches must be developed on the local scale in order to understand the ways in which these local area networks influence a city at the global level. These analyses must also be conducted with territorial data.

The methodological approach of using networks of individual firms enabled us to cover two different geographical levels of cities, intra-urban and inter-urban scales. The complementarity of the processes occurring at and between these two levels has been analyzed, even if the explanatory processes are not yet demonstrated. Determining those explanatory processes is now a challenge opened by this analytical study.

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Chapter 11
The Capture and Diffusion of Knowledge Spillovers: The Influence of the Position of Cities in a Network

Marie-Noëlle Comin

11.1 Introduction

Cities concentrate economic activities, information, power and people in both quantitative and qualitative ways. Cities are also nodes of complex, interconnected networks. In Europe, the establishment of a large supranational entity has resulted in the multiplication and intensification of the relationships between politically unified countries. The majority of these relationships pass through cities. Studying the complex links that underpin the European system of cities is critical to understanding the interdependencies in the system. Here, the interconnection of European national urban systems is studied by analyzing scientific and technological collaborative-research networks. Such networks make it possible to observe the flow of scientific knowledge within the European system of cities.

In Europe, as in the rest of the world, scientific and technological innovation has acquired increasing strategic importance in economic competition. Such innovation also plays a crucial role in the structure and dynamics of settlement systems: in the emerging "knowledge economy," the major dynamic feature characterizing the evolution of urban systems appears to be competition for the collection of knowledge and innovations. Knowledge spillovers are considered to be both an input and an output of the innovation process. Therefore, understanding how knowledge spillovers flow within European territories is critical to understanding innovation processes in Europe. Contrary to the widespread idea that innovation is indifferent to location, various empirical studies stress the importance of cities as nodes of accumulation, production and diffusion of scientific and technological knowledge (Bouinot, 2004; Castells, 2000; Lever, 1999; Simmie, 2001). Thus, analyzing

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scientific collaborative networks can yield critical insights regarding the wider geography of interactions among European cities.

The study of knowledge flows distinguishes two types of knowledge: codified knowledge and tacit knowledge. Codified knowledge is defined as knowledge that is stated in an explicit form. Explicit knowledge is relatively easily transferable and can be transmitted through information channels and infrastructures. Tacit knowledge is described by Michael Polanyi's famous quotation, "We can know more than we can tell". Hence, tacit knowledge is a non-linguistic and non-numerical form of knowledge that essentially arises from personal experience and skill. Tacit knowledge requires social interaction for transmission and is context specific. Thus, it is difficult to capture, codify and transfer tacit knowledge. Tacit knowledge is recognized as a central component of the "knowledge-based economy." As the key element for effective exploitation of innovative opportunities and abilities, tacit knowledge crucially influences the innovation process. Therefore, many studies focus on this form of knowledge. Generally, studies show that tacit knowledge can be transmitted via collaboration between research centers, training or personnel exchange.

From a geographical perspective, the mechanics of knowledge flows are unclear. Studies commonly state that codified knowledge does not require proximity to be shared and thus can flow easily across long distances. In contrast, tacit knowledge requires proximity to be shared; thus, it is difficult to exchange tacit knowledge over long distances. In reality, the geography of knowledge flows is far more complicated. In addition to geographical proximity, additional types of proximity make it possible to share tacit knowledge at long distances (Comin, 2009). Here, we focus on organizational proximity in analyzing scientific networks between European cities created through collaborative Research and Development (R&D) projects dedicated to converging technologies (Boschma, 2005). Converging technologies result from the merging of nanotechnology, biotechnology, information technology and cognitive science (NBIC). Such technologies are expected to drive the future innovation wave predicted to emerge by 2020 (Nordmann, 2004).

The position of cities in scientific networks highlights the geographic structure of European knowledge creation, which facilitates cities' economic competitiveness in the "knowledge economy". However, a large number of scientific exchanges with other cities does not by itself make a city well positioned in a scientific network. The criteria for judging cities' success also include their ability to ensure the interconnection of national urban systems at the European scale (Rozenblat, 1992, 2004).

The remainder of this paper is divided into three sections. First, the empirical data used to analyze European cities' position in scientific networks are presented. Next, the structure of the European scientific network of cities is described and compared to the structure of the European system of cities in terms of population size. In urban geography, the population of a city is a good indicator of its position in urban systems (Pumain, 1997). Finally, particular attention is paid to the cities that ensure the interconnection of national urban systems. These cities are essential in expanding the spatial dimension of knowledge flows and linking the 27th European national system of cities.

11.2 Sources: From Research Networks to Urban Networks

There are three principal types of indicators for studying scientific flows between cities: (i) patent documents, including references to previous patents (citation). According to Jaffe, Trajtenberg, and Henderson (1993), a patent citing earlier patents reveals knowledge flows between localized inventors. (ii) Co-authorship networks related to joint publication activities indicate close working relationships and potential knowledge flows between localized authors (Matthiessen, Winkel Schwarz, & Find, 2010). The main difficulty with these two indicators is collecting data related to the cities where the innovative actors are located. (iii) Finally, we consider scientific and technological collaborations between organizations engaged in innovation processes (research organizations including public research centers, universities and corporate research centers) within European-funded research and technology development projects (RTDs).

Data were extracted from the EC database CORDIS RTD-PROJECTS (Community Research and Development Information Service) and were drawn from the second to sixth European Framework Programs (FPs) for Research and Technological Development (the first FP is too incomplete to be used). The FPs are 4-year programs initiated in 1984 by the European Union to increase scientific collaboration between European countries.

The CORDIS database provides information about the evolution of European research support from 1986 to 2006. CORDIS data include the actual locations of the organizations involved (not simply the locations of their headquarters). Institutions may have several research centers located in different cities. Therefore, we chose to identify the precise location of each research center (laboratory) involved in NBIC-related projects. We then created urban networks by aggregating CORDIS data at the city level to measure the links that these networks create between cities (Besussi, 2006; Rota, 2008; Rozenblat & Cicille, 2003) These links represent bounds created by scientific collaborations between two cities involved in the same NBIC RTD project. Through these collaborations, cities produce, attract and diffuse knowledge spillovers that encompass the differential evolution of each city in the future innovation wave.

For urban aggregation, we considered cities to be functional urban areas (FUAs) defined in a comparable way throughout Europe (Comin, 2009). Each laboratory appearing in the networks was geographically located and then aggregated to the appropriate urban area.

In total, the urban database includes FUAs with 10,000 or more inhabitants and contains 9,300 research centers located in 800 functional urban areas within 117 countries. Among all functional urban areas in the database, 509 are located in UE 27. Two cities were considered to be connected if their institutions or enterprises had collaborated on at least one project. Here, we focus only on European cities. CORDIS data also make it possible to examine tacit-knowledge flows according to the approach of Candice Stevens (1997), who identified for the journal OECD Observer three main ways in which tacit knowledge can be exchanged: research and development cooperation between the public and private sectors, technology diffusion and personnel movements. We assume that personal contacts exist between people involved in the same European RTD projects because it seems likely that scientists choose collaborators with whom they are acquainted.

11.3 The Distribution of Knowledge Flows Within the European System of Cities

The resulting graph of European scientific-research collaboration networks (Fig. 11.1) has a large number (28,558) of links. How are these links distributed between cities?

First, we can study the whole properties of this network. The connectivity of the graph can be measured using three indices: (i) the density of links in the graph, or the number of links expressed as a proportion of the maximum possible number of links; (ii) the diameter of the graph, or the longest of the shortest paths between all pairs of vertices, which measures the maximal extent of the network; and (iii)

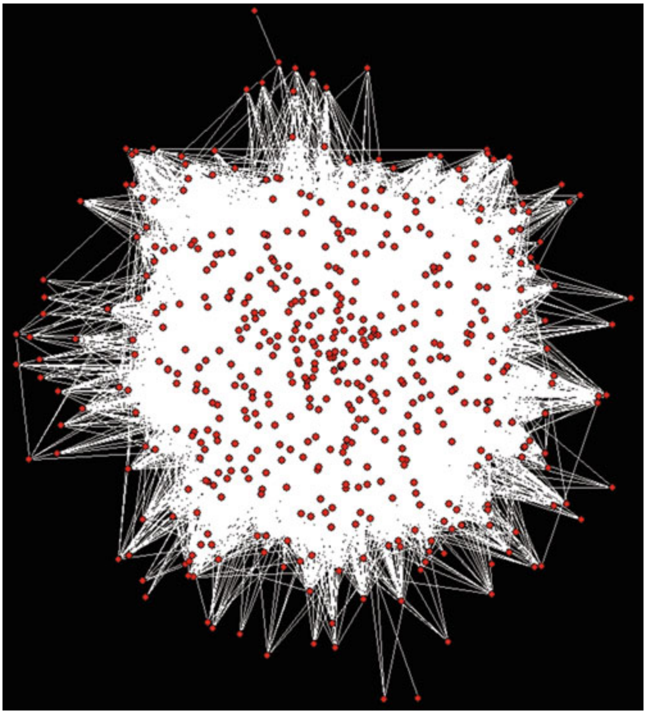

Fig. 11.1 Graph of Research Collaborations in NBIC among European cities, 1986–2006 (Made with Pajek software, Kamada-Kawai layout. Source: NBIC-Euro, Comin, 2009)

Table 11.1 Indices of connectivity

Density	6 %
Diameter	4
Average path length	2

Source: NBIC-Euro, Comin (2009)

the average path length of the graph, which is the average number of intermediate connections between all pairs of vertices.

These three indices (Table 11.1) show that the connectivity of the graph is high: although 22 % of all possible links are present, each city can reach all other cities in an average of two and a maximum of four steps. Thus, the scientific-collaboration network for converging technologies within European cities is strongly connected. These results underline the interdependence of European cities for R&D in converging technologies and provide promising information about the circulation of scientific knowledge between cities.

Nevertheless, knowledge flows are not evenly distributed among European cities. Rather, their patterns of accumulation are strongly affected by the pre-existing population-size structure of the European system of cities (Comin, 2009).

This phenomenon can be illustrated using the indices of centrality developed by L. C. Freeman (1977, 1979) to describe the relative importance of nodes within a network. Two examples can be shown. First, the non-valuated degree centrality of a city is the number of cities connected to it. This index measures the relational activity of a city. Second, the betweenness centrality of a city measures its potential intermediary role within a network: the more often a city occurs on the shortest paths between other cities within the network, the higher is its betweenness centrality. These two indices clearly distinguish the largest European cities from other cities. Indeed, cities of the European megalopolis have large degree centralities (Fig. 11.2). Table 11.2 shows that the 20 cities with the largest degree centralities are also the largest European cities, except for two university cities: Utrecht and Goteborg. The largest European cities, particularly capital cities, also have the largest betweenness centralities (Fig. 11.3).

The structure of the scientific-collaboration network dedicated to converging technologies reveals that European cities exchange knowledge through a classical hierarchical-diffusion pattern (Hägerstrand, 1952).

Moreover, our maps show that certain cities, such as Utrecht and Goteborg, are more central than expected based on their population size. While large cities concentrate the infrastructures that traditionally facilitate material and non-material flows, specialized cities also have important innovation and training capacities. Specialized cities involved in European-funded converging-technologies R&D vary in population size but are well connected to the network. Therefore, their hierarchical positions in the network are much higher than their rankings among European cities in terms of population size . For example, the empirical data analyzed here show that Utrecht, Goteborg and Cambridge are ranked 11th, 19th and 24th, respectively, in terms of degree and 84th, 92nd and 351st, respectively, in terms of population.

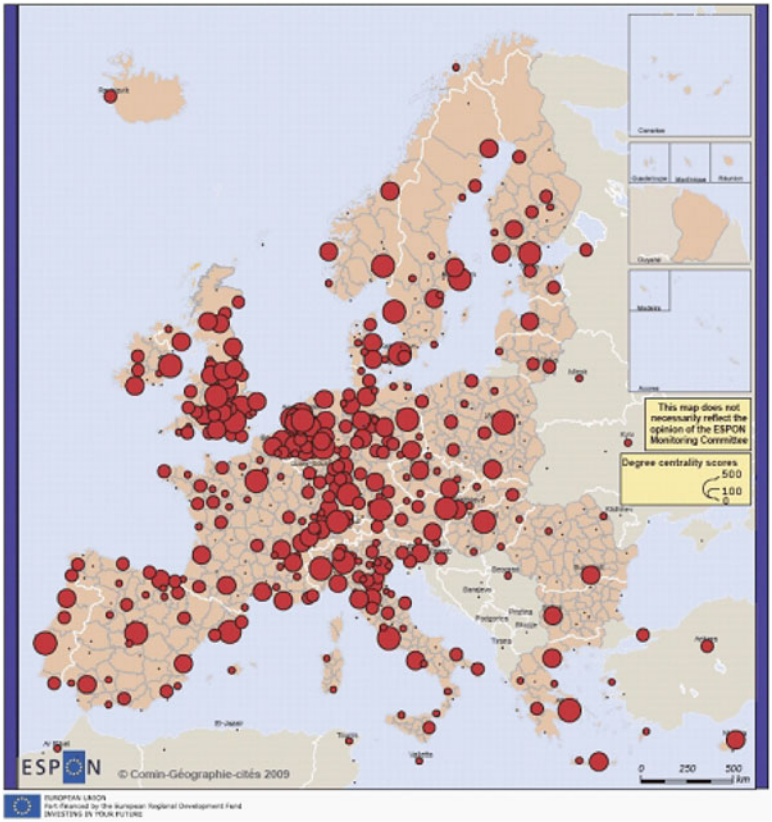

Fig. 11.2 Degree centrality (cumulative over the period 1986–2006)

Table 11.2 The 20 cities with the largest degree centralities (cumulative over the period 1986–2006)

Cities	Degrees	Rank	Cities	Degrees	Rank
Paris	416	1	Utrecht	351	11
London	407	2	Amsterdam	348	12
Athens	396	3	Barcelona	343	13
Madrid	385	4	Lisbon	342	14
Copenhagen	372	5	Munich	342	15
Milan	370	6	Berlin	340	16
Brussels	365	7	Stockholm	338	17
Helsinki	364	8	Stuttgart	337	18
Vienna	362	9	Goteborg	320	19
Rome	358	10	West-Midlands	318	20

Source: NBIC-Euro, Comin (2009)
Note: non-valuated degrees

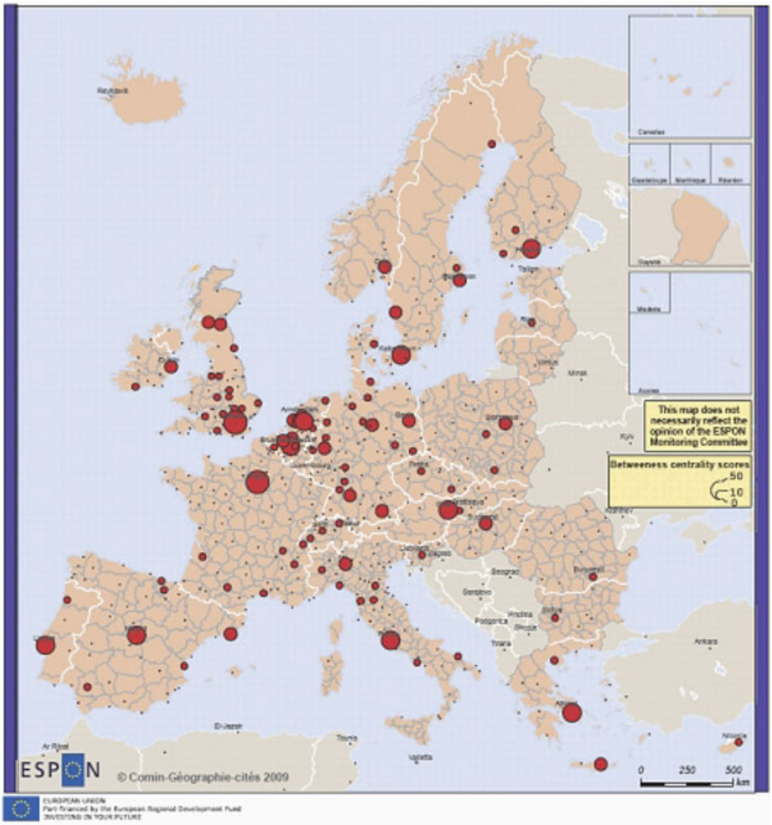

Fig. 11.3 Betweenness centrality (1986–2006)

The simplest way to validate this insight is to calculate the ratio between the number of scientific collaborations (or RTD projects) in a given city and the population of that city. A larger ratio indicates greater specialization of a city in European-funded converging-technologies R&D.

In Fig. 11.4, some small cities appear to have many RTD projects for their population size. These cities are considered to be specialized, as defined above. The most specialized cities are the most renowned university cities, such as Cambridge, Louvain, Oxford and Heidelberg (Table 11.3), because the location factors for R&D in converging technologies depend on the quality of the scientific infrastructure and the presence of a skilled population. These factors tend to favor the most renowned university cities.

As a whole, the structure of the European urban network dedicated to converging technologies is dominated partly by the largest European cities and partly by renowned university cities. We hypothesize that these "hub cities" are essential to the interconnection of national urban systems at the European scale. In the following

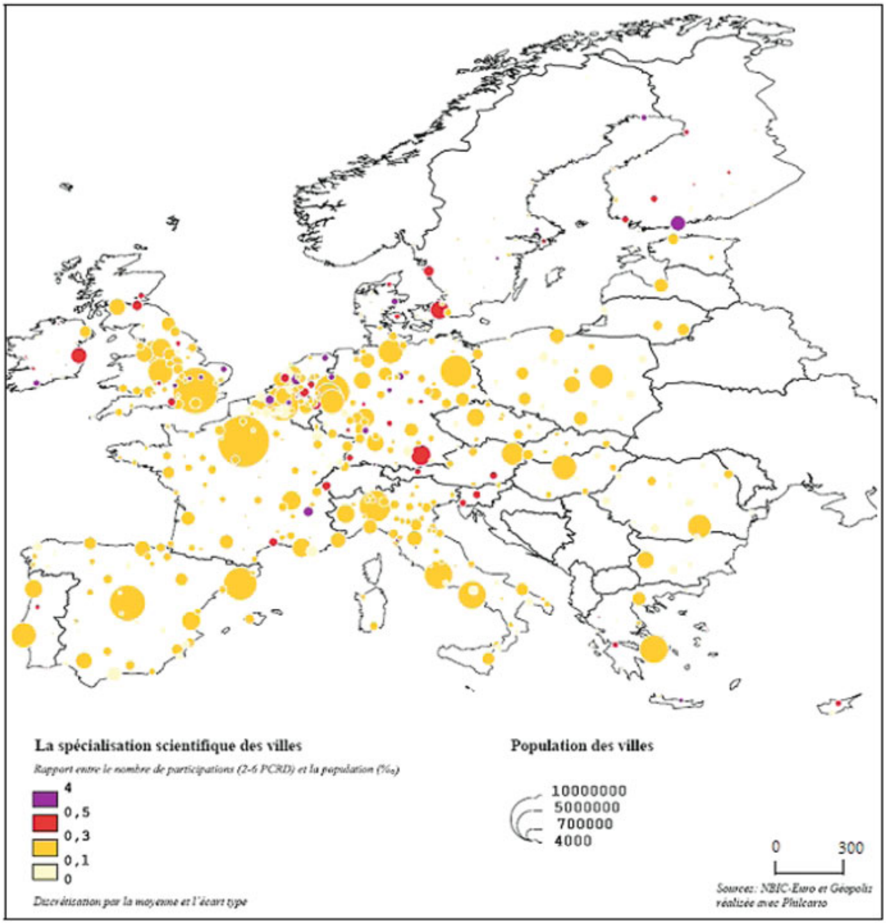

Fig. 11.4 Specialization of European cities in European-funded R&D dedicated to converging technologies

Table 11.3 The most specialized cities in European-funded R&D dedicated to converging technologies

Cities	Number of RTD projects per thousand inhabitants
Lulea	4.02
Cambridge	3.10
Aberystwyth	2.30
Louvain	1.52
Uppsala	1.46
Oxford	1.40
Heidelberg	1

Source: NBIC-Euro, Comin (2009)

section, we will test this hypothesis by distinguishing those cities that act as "relays," ensuring the articulation of scale for knowledge flows between European national urban systems. These cities are known as "relay-cities" (Rozenblat, 1992, 2004).

11.4 Interconnections of European National Urban Systems

To distinguish relay-cities from other European cities, we used the concept of "articulation nodes" from graph theory (Berge, 1958). In a connected graph, such as our scientific-collaboration graph of European cities, a node is an articulation node if the sub-graph obtained by removing it is no longer connected (if removal of the nodes creates disconnect components). Thus, an articulation node is a bottleneck in the graph.

In urban geography, articulation nodes can be interpreted as relay-cities that connect urban systems at different scales: national, European and global. Articulation nodes or relay-cities are crucial vectors for the transmission of knowledge spillovers within the network because they attract diversified knowledge and ensure its circulation among the networked European cities. Moreover, the position of such an intermediary confers a strategic role in controlling the diffusion of knowledge to other European cities: a relay-city may choose to diffuse knowledge among its networked cities or to appropriate knowledge for its own profit.

Our analysis shows that few cities are relay-cities (Fig. 11.5): only 98 cities are structurally positioned as articulation points in the network. Most of these relay-cities connect several components: Copenhagen connects 14 components; Paris connects 11; Athens, Utrecht and Brussels each connect 7; London connects 6; and Vienna, Berlin, Munich, Dublin and Leipzig each connect 5; ...

We assume that a given relay-city tends to act as an interface at a particular scale rather than at all scales (national, European and global). To classify relay-cities according to the scale at which they act as an interface, we chose a factor-analysis approach, principal-components analysis (PCA). A PCA can reveal the latent structure of a set of variables by reducing the attribute space from a large number of variables to a smaller number of factors.

The rows of the data matrix used for PCA represented relay-cities, while the columns contained the number of cities with which each relay-city forms a bridge (i.e., an edge whose deletion increases the number of connected components). These cities were distributed in three modalities (national, European and global) according to their relative locations with respect to the relay-city concerned.

Figure 11.6 presents the first two factors or dimensions of the PCA, which explain 77 % of the total variance. Factor 1 (F1) clarifies the scale at which relay-cities act as interfaces, whereas factor 2 (F2) indicates cities' degree of specialization with respect to this scale of activity.

The majority of relay-cities tend to ensure interconnection at the European scale. However, most of them appear to be diversified, ensuring the interconnection of urban systems at multiple scales. Only Athens and Utrecht act principally as European

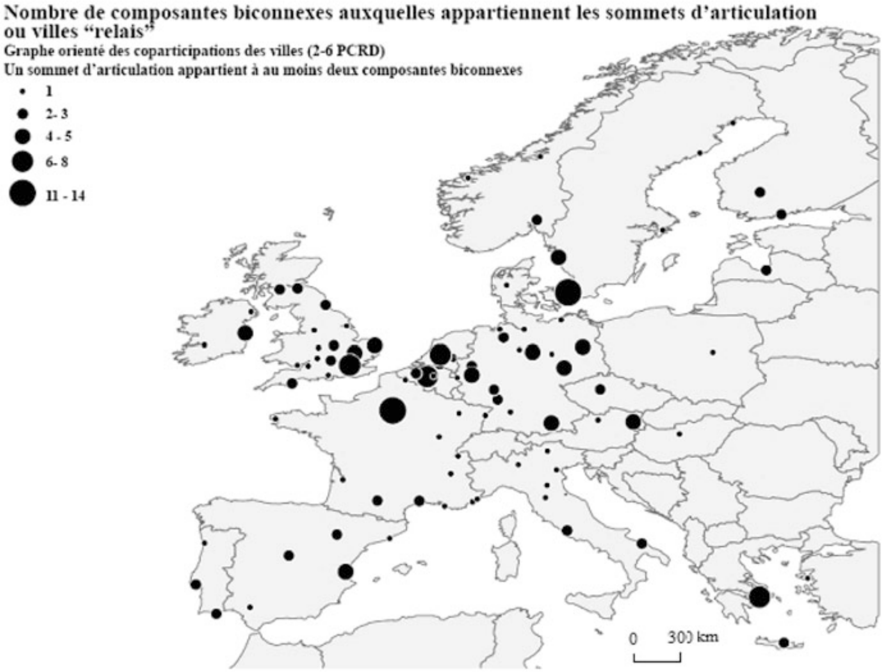

Fig. 11.5 Relay-cities identified as articulation nodes (1986–2006) (Source: NBIC-Euro, Comin, 2009)

interfaces. At the national level, relay-cities tend to be university cities and regional metropolises (e.g., Ålesund, Mytilene, Toulouse, Tampere, Bordeaux and Leipzig) or peripheral European capitals (Helsinki, Dublin, Heraklion and Budapest). Few relay-cities act at the global level; Copenhagen and Paris appear to be strongly specialized for this function, while other large international metropolises, such as Brussels and London, also tend to exercise this function.

11.5 Conclusion

In conclusion, this analysis of networks dedicated to R&D in converging technologies underlines the fact that patterns of accumulation in an urban network of knowledge flow are strongly driven by the pre-existing structure of the system of cities. Thus, the final impact of the knowledge-flow network on the pre-existing structure of the system in which it evolves is rather marginal. However, these results emphasize the trend for larger cities to capture knowledge spillovers, making it possible to predict the strength of the structural hierarchical disparities within the European urban network. This trend prefigures the reinforcement of metropolitan patterns

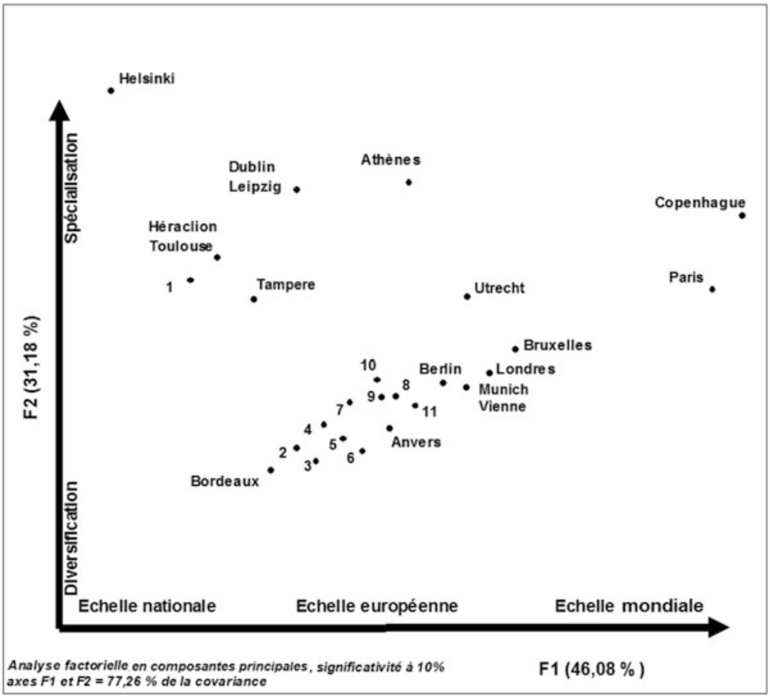

Fig. 11.6 Relay-cities tend to act as interfaces: scale of activity and degree of specialization (Source: NBIC-Euro, Comin, 2009)
1 Ålesund, Barcelone, Budapest, Mytilène, *2* Aachen, Bologne, Brest, Bristol, Cannes, Cheltenham, Florence, Genève, Haïfa, Hambourg, Linz, Louvain, Lulea, Marseille, Nijmegen, Umeå, Varsovie, *3* Arnhem, Belfast, Bergamo, Bolzano, Bremerhaven, Cardiff, Dijon, Grenoble, Hannover, Herning, Kingston, Lille, Limerick, Magdeburg, Manchester, Nancy, Nice, Padoue, Porto, Rostock, Seville, Southampton, Stockholm, Strasbourg, Stuttgart, Trondheim, West-Midlands (Birmingham), *4* Brème, Glasgow, Mannheim, Oxford, Riga, Tilburg, Mayence, *5* Edinburgh, Lisbonne, Madrid, *6* Prague, Essen, Torbay, *7* Bari, Faro, Gand, Leicester, Oslo, *8* Valence (Espagne), *9* Montpellier, Rome, Tyneside (Newcastle), Zaragoza, *10* Brunswick, Cambridge, Cologne, *11* Göteborg, Norwich

within the European urban system through the European-scale integration of cities for R&D activities in the most innovative economic sectors of the present time.

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Chapter 12
Defining Polycentric Urban Areas Through Commuting Cohesion in France

Patrice Tissandier, Trung Tien Phan Quang, and Daniel Archambault

12.1 Introduction

Recent urban processes show two principal ways in which cities are changing. First, at an international and national level, economic assets and power are concentrating in large cities, increasing their population. Second, at a local scale, population and employment is being redistributed, moving away from the urban center and towards the periphery. As a result, urban sprawl develops and polycentric structures materialize. This movement away from the traditional urban structures leads to difficulties in implementing urban management policies. Urban planning based on a halo territory and the actual reticular development of the cities are conflicting goals.

Several studies of daily commuters, all focused on Europe and North America, have been conducted based on methods introduced by Albert and Barrabási' (Patuelli, Reggiani, Gorman, Nijkamp, & Bade, 2007). We can cite, for example, case studies of the Netherlands (Schwanen, Dieleman, & Dijst, 2001, 2002), Germany (Patuelli et al., 2007), France (Aguilera & Mignot, 2004; Berroir, Mathian, & Saint-Julien, 2002; Berroir, Mathian, Saint-Julien, & Sanders, 2004), the United States (Cervero, 1996; Cervero & Wu, 1997; Giuliano & Small, 1991;

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Gordon & Richardson, 1996; Sultana, 2000), Canada (Bourne, 1989) or the comparative study on Stuttgart and Turin (Binder, Haag, & Rabino, 2003). According to these studies, the polycentric structure of major urban areas is now a self-evident truth. A polycentric structure can be defined by the existence of one or several sub-centers in addition to the city center. In our study, the commuters' flows illustrate the existence of these sub-centers, which are seen as a point of attraction for commuters. The aim of our work is to characterize these polycentric structures and to analyze their properties. Therefore, our approach, which is based on the visualization of the network of commuters using graphs and applying a measurement index, is quite different from the approaches used by existing studies.

The analysis of daily commuting patterns, represented as weighted, directed graphs, leads to new measurements and perspectives, potentially assisting in the process of urban planning. The flows of commuters are represented by the edges between places of residence and those of employment, seen as nodes of the graph. Three types of data are added as weights on the edges: the number of commuters that pass between the municipalities; the portion, in percent, of these commuters who are in the working population in their municipality of residence; and the same percentage of these commuters who are in the working population in the municipality of their employment.

In this study, we investigate the home to work commuting patterns among 36,000 French municipalities drawn from the census data for 1975, 1982, 1990 and 1999. For these 4 years, two scales of investigation are developed.

We need to highlight some inconsistencies in this data. First, we do not distinguish between effective and official residences, leading to incongruence between the graphs built on this data and the actual situation. A data cleaning performed at the national level and associated with a coloration of the graph based on its structural properties leads to the delineation of cities through the commuters' flows and is applied in the first stage of this paper.

Second, we show the impact that regional transportation had on the spread of the commuters' network around the French major cities. Comparing the commuters' graphs from four censuses and their cohesion, defined using the average strength index, we highlight the reticular extension of the cities' delineation, their spatial discontinuities and their overlap. At the same time, we show the development of urban sprawl. The number of municipalities connected, directly or indirectly, to a central municipality grows from 1975 to 1999. These municipalities are growing progressively more distant from the city center. However, each municipality is not necessarily either strongly or directly linked to primary city center. We see urban polycentric structures develop through subnetworks that function like subsystems. In this second section, we will apply different indexes to characterize these subcenters. We also explain a method for building a graph that combines the data from the four censuses with the aim of creating an evolving study of the commuters' network.

In the last stage of this paper, we investigate a new approach that considers the commuters' graphs to be scale-free networks. We explain this position by the structure of the commuters' graph: a few important municipalities import a large number of workers every day while the majority of municipalities import very few commuters. For this study, we return to the level of the entire French commuters' network. We apply a recursive algorithm to identify the polycentric structure of the urban areas. Finally, we present a large network evolution analysis.

12.2 Data Cleaning

The census data that is used to construct the commuters' network does not distinguish between the municipality of administrative residence and the municipality of actual residence (Talbot, 2001). Additionally, the respondent may not report a second place of residence in addition to their primary place of residence. These situations, as well as others, raise numerous problems in the visualization of the graphs that are inferred using this data. Several examples from the data acquired in the 1999 census illustrate the types of problems that arise from a lack of information and include the following:

- A total of 45 people commute over 1,000 km every day, essentially the distance between Corsica and the north of France.
- Over 400 people commute over 500 km every day.

To filter out these edges, which are most likely erroneous, most approaches filter out the links with low weight or the links that are distant geographically (Bonnefoy, Pumain, & Rozenblat, 1996; Talbot, 2001). These methods, applied on a French departmental or regional level, provide convincing results. However, the diversity of situations at the national level limits the applicability of these methods. Also, as with many graph problems in geography, we have the problem of selecting a threshold. We need to choose a threshold that depends on the geographic distance between the two municipalities or/and the number of commuters that make the trip on a daily basis.

We choose to apply a gravity model to help distinguish between the edges that represent practical daily commutes with those that, most likely, result from missing census information (Nijkamp, 1975; Pumain, 2001; Sen & Smith, 1995; Shen, 1999). A gravity model stipulates that the attraction between two elements is proportional to their mass P and inversely proportional to the distance d between them.

$$T_{ij} = k\frac{P_i P_j}{d_{ij}}$$

Because we would like to prevent reasonable links from being filtered, we replaced the weight of the municipalities of residence and employment with a specific attribute of the edges, namely the portion of the migrants in the total working population of the municipalities of residence and employment, as described in the introduction.

The gravitational filtering of the graph makes the data appear to be more reasonable. The excessively long commutes have disappeared, which were likely

Fig. 12.1 Graph of commuters for France in 1999 after data "cleaning"

average distances that were imputable to weekly commutes performed by working people who travel home only for the week-end. The reasonable commutes are preserved, as shown in (Fig. 12.1).

After filtering, we apply a coloring that is proportional to a metric value. The value is computed based on the structural properties of the graph. Frequently, we use the strength metric (Auber, Chiricota, Jourdan, & Melançon, 2003; Guimerà, Mossa, Turtschi, & Amaral, 2005) where the edges of low cohesion, or components with less local participation, are given a pale color and the components with high cohesion are given a darker color. These areas of the graph, defined as high cohesion sub-systems, are what we consider to be urban areas.

Our approach differs from the classical approach, which is applied in many countries (see, for example, the French Statistic Institute's definition), where it is assumed that at least *n* % of the active population work in the central locality or agglomeration area (Fig. 12.2a). The classical approach assumes centrifuge flows only occur from the peripheral municipalities to the city center, and it does not take into account any polycentric communities that may arise. Thus, our visualization method, applied to the network of commuters, provides a color to the nodes and edges in such a way that the polycentric sub-systems pop out visually. These sub-systems act like commuter satellites around a city center (Fig. 12.2b). This network approach is congruent with a polycentric model and allows for the cities to be directly or indirectly linked to their center (Fig. 12.2).

When the filtering stage is complete, we next work at the urban areas level. We illustrate the polycentric structure of the French urban areas through several examples and present the metrics to characterize this polycentrism.

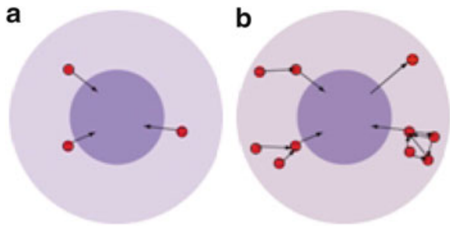

Fig. 12.2 Delineations of urban areas. (**a**) Classical delineation. (**b**) Network delineation

12.3 Characterization of Polycentrism in the French Urban Areas

A polycentric urban area organizes itself around several political, social and financial centers. The commuters' flows illustrate the existence of one or several employment sub-centers, which are seen as points of attraction. Consequently, the commuters' networks can help to illustrate polycentric structure by clarifying how the municipalities contribute to the urban area's polycentrism. In this section, we explain our methodology for defining and visualizing polycentrism through commuting cohesions.

A previous study (Rozenblat & Tissandier, 2007) shows the local polycentric structures but could not take the geographic positions of the cities into account. We fill this gap using the geographic coordinates of municipalities and, to deepen this study, we also choose to realize an evolving network analysis. The aim is, finally, to characterize the polycentric structure of French urban areas but also to underline the formation of sub-centers. So, this work is essentially a dynamic graph visualization problem. Therefore, at the urban area level and using a combined 4 years of census data, we visualize the formation of a polycentric structure by using the cohesions of the cities or by using the weighted connections in terms of the number of commuters between the municipalities.

12.3.1 Metrics Calculated

To illustrate our method, we provide many example networks around cities such as Lyon, Marseille, Lille, Bordeaux and Toulouse. Paris is not presented in this section because the network of commuters around it is very dense. We were not able to render images that were readable using our visualization system, which demonstrates a limitation of our approach.

12.3.1.1 Betweenness Centrality

There are many centrality indices that are based on the set of the shortest paths in a graph. The shortest path betweenness centrality can be viewed as a metric

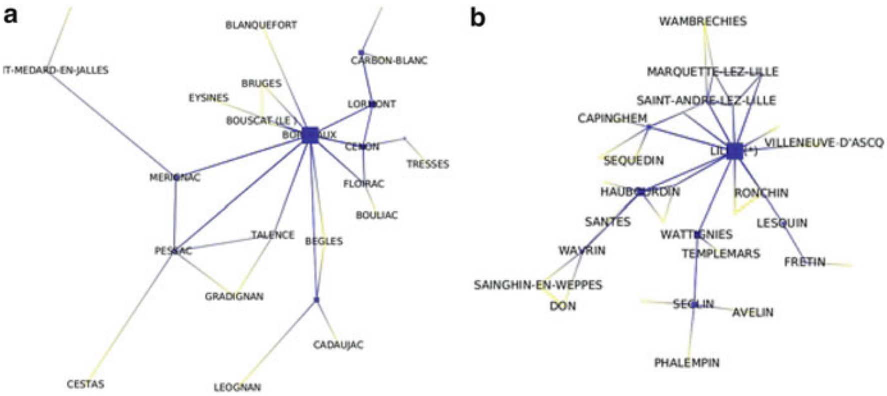

Fig. 12.3 Betweenness centrality index around Bordeaux (**a**) and Lille (**b**), year 1975

to quantify the centrality of a vertex or an edge in a graph. The vertices that appear on many shortest paths have higher betweenness than those that do not. The betweenness centrality (Brandes, 2001) of a vertex is as follows:

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

The value of σ_{st} is the number of shortest paths in the graph between s and t, and $\sigma_{st}(v)$ is the number of shortest paths between s and t that pass through the vertex v. If the value of the betweenness centrality is high, the node is a bridge between components in the graph. Otherwise, the node is part of a densely connected cluster. In the study of the daily network of commuters, the nodes with high betweenness centrality are municipalities that directly receive workers from many other municipalities. Consequently, these nodes are points of convergence for commuters because they are employment centers and major cities in France.

We give edges a color that is based on the following metric: the components with high betweenness centrality are darker colored while the components with low betweenness centrality are lighter colored. The examples of Bordeaux and Lille are developed next (Figs. 12.3, 12.4, 12.5, and 12.6).

12.3.1.2 Strength value

We calculate the strength value (Auber et al., 2003) for each node and edge in the graph. Their average of the strength values enable us to know the cohesion in some sub regions, which in this case are the urban areas. In the following figures, the strength index has been applied in the major French urban areas such as Marseille and Lyon, providing us with a visualization of the high cohesion zones that are a sign of subcenters (Figs. 12.7, 12.8, 12.9, and 12.10).

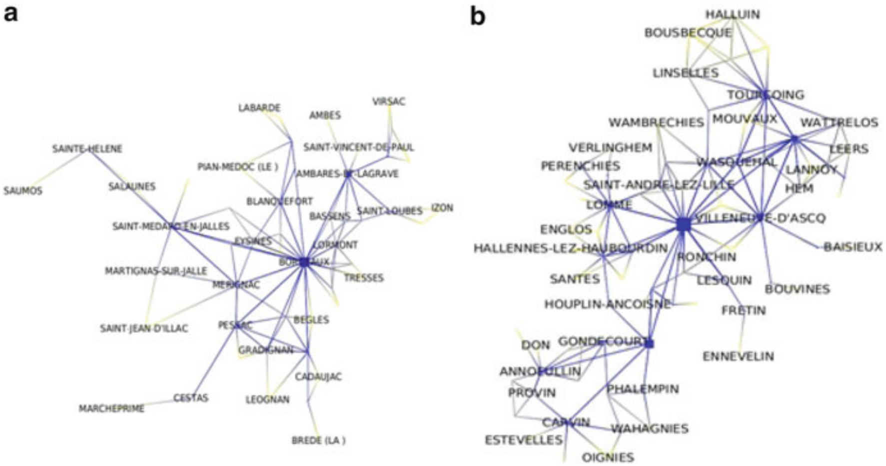

Fig. 12.4 Betweenness centrality index around Bordeaux (**a**) and Lille (**b**), year 1982

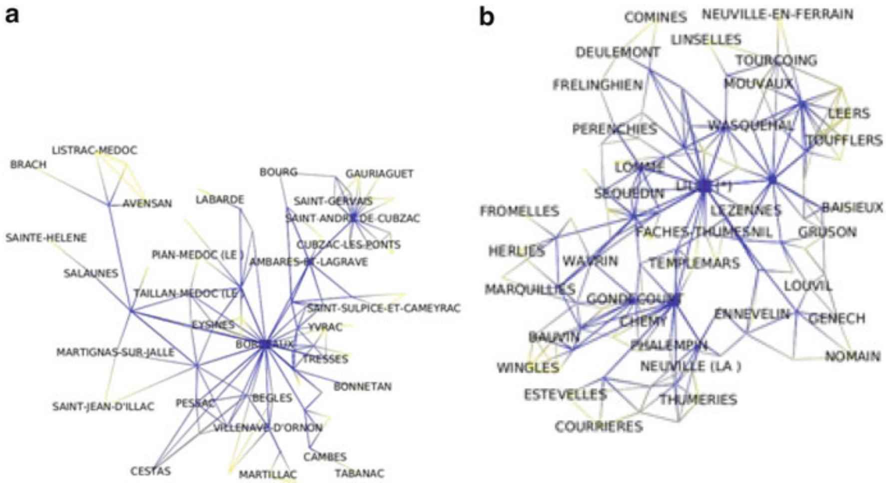

Fig. 12.5 Betweenness centrality index around Bordeaux (**a**) and Lille (**b**), year 1990

In these figures, the strength metric has been applied to the graphs. The color of each edge indicates the connectivity of each region. The areas drawn darker are tightly connected while the areas in pale are loosely connected.

12.3.1.3 Participation Coefficient

The participation coefficient measures the closure of the subnetworks as well as the intensity of the sub-centralities according to the contribution and participation indexes (Melançon et al., 2008). These indexes gauge the contribution of each

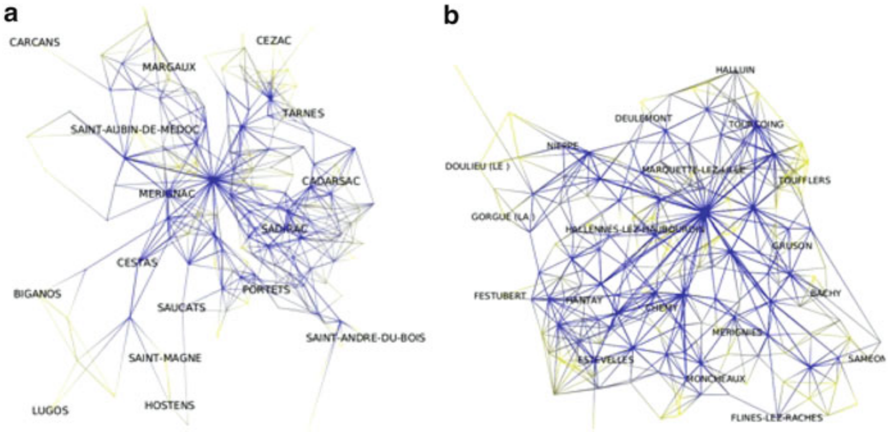

Fig. 12.6 Betweenness centrality index around Bordeaux (**a**) and Lille (**b**), year 1999

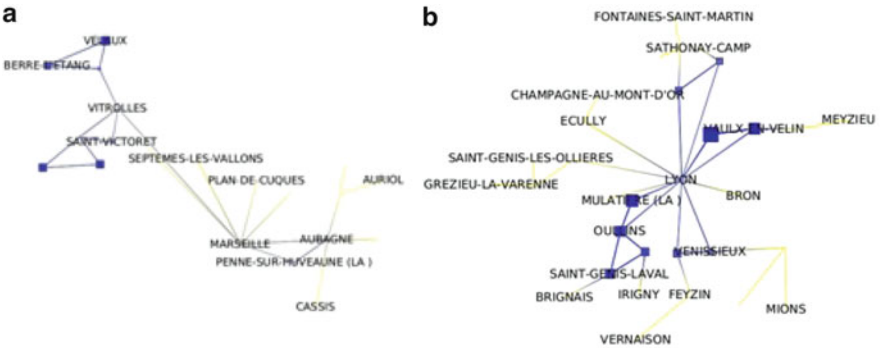

Fig. 12.7 Strength index around Marseille (**a**) and Lyon (**b**), year 1975

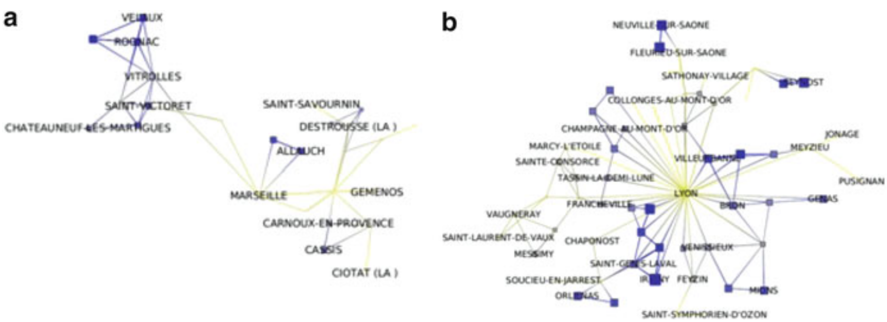

Fig. 12.8 Strength index around Marseille (**a**) and Lyon (**b**), year 1982

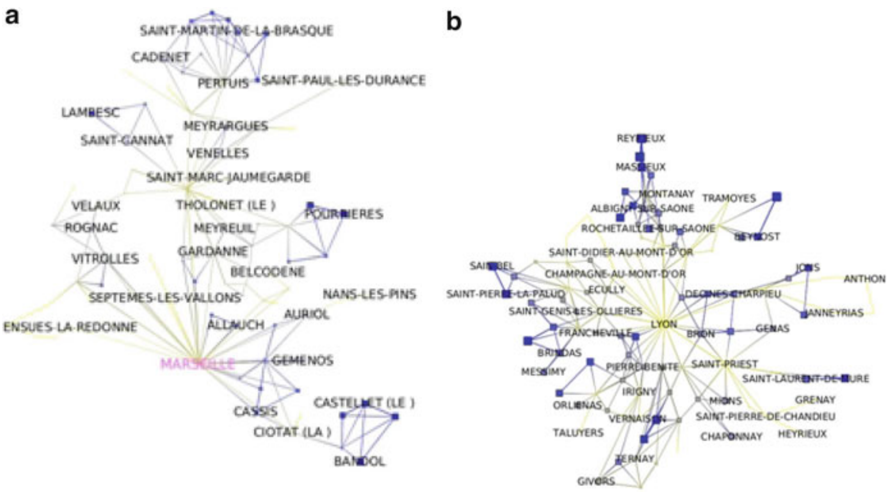

Fig. 12.9 Strength index around Marseille (a) and Lyon (b), year 1990

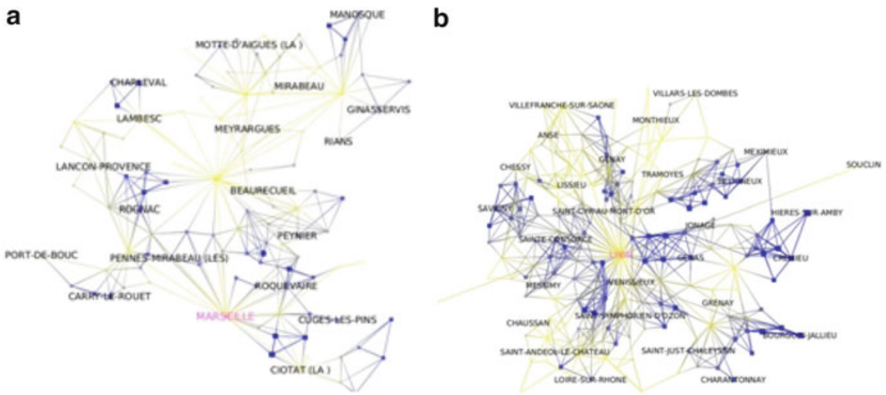

Fig. 12.10 Strength index around Marseille (a) and Lyon (b), year 1999

municipality to the cohesion of a subnetwork by measuring the city's representation in the subnetwork or the number of links that it shares with the cluster.

The participation coefficient can be computed on a directed graph using the incoming or outgoing degrees. The outgoing participation coefficient of a node v can be defined by the following:

$$p^{+}(v) = 1 - \sum_{w \in N_G^{+}(v)} \frac{\omega(v,w)}{d_G^{+}(v)}$$

where $N_G^{+}(v)$ are the outgoing nodes from v, $\omega(v,w)$ is the weight of the edge (v,w), and $d_G^{+}(v)$ is the sum of the weights for the outgoing edges of v. The incoming participation coefficient is similarly defined. The outgoing participation coefficient

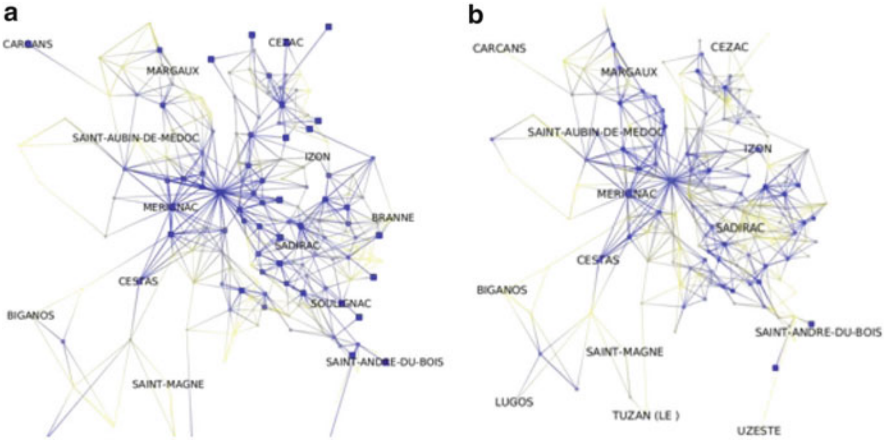

Fig. 12.11 (**a**) The incoming participation coefficient around Bordeaux in 1999. (**b**) The outgoing participation coefficient around Bordeaux in 1999

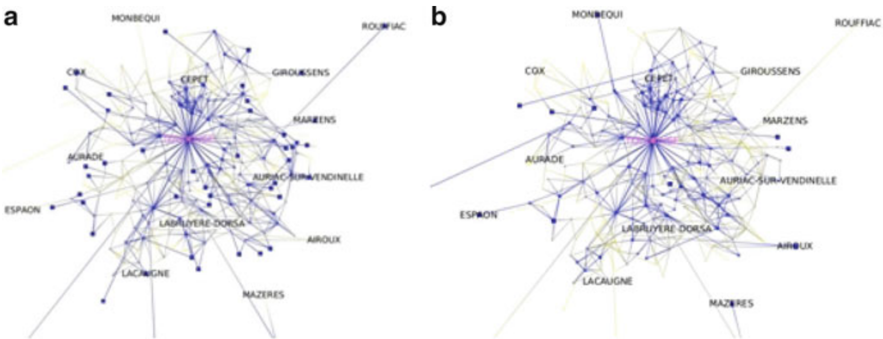

Fig. 12.12 (**a**) The incoming participation coefficient around Toulouse in 1999. (**b**) The outgoing participation coefficient around Toulouse in 1999

should reveal how much a municipality participates in the export of workers, which is another way to understand how much it acts as a residential area that feeds other regions with workers. Conversely, the incoming participation coefficient should reveal how significantly several municipalities act as an attractor, bringing workers into their local employment structure (Figs. 12.11, 12.12, and 12.13).

The above figures, which show smaller cities that contribute to local employment or that send their workers out to urban areas around major cities like Bordeaux, Toulouse, and Lyon have color/size matrices based on the incoming/outgoing participation coefficient.

These examples of major French urban areas illustrate the interdependent processes of urban sprawl and polycentrism while the different indexes applied during this stage lead to the characterization of these phenomena. Urban sprawl is undeniably present in all of the graphs that we show: the number of municipalities

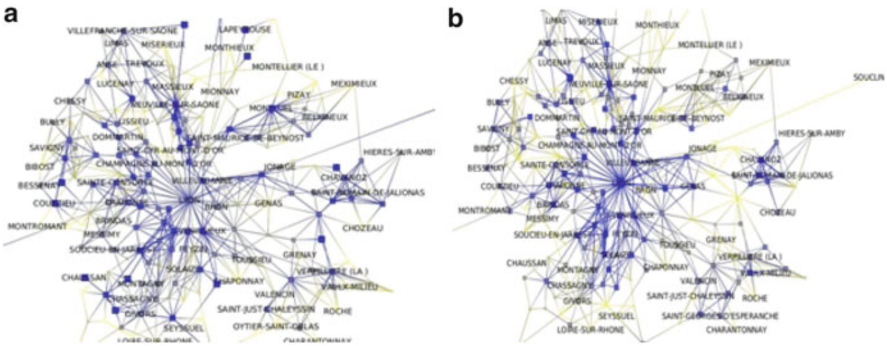

Fig. 12.13 (**a**) The incoming participation coefficient around Lyon in 1999. (**b**) The outgoing participation coefficient around Lyon in 1999

that are connected directly or indirectly with the city center grows during all of these periods. Moreover, these municipalities become more and more geographically distant from the city center over time.

The betweenness centrality index permits the identification of municipalities that polarize the territory and catch workers from many surrounding municipalities. This index illustrates the impact of the major French cities on the commuters' network.

The polycentric structure of the urban areas and its extension is also clearly identifiable through the application of the strength index. The increasing number of subcenters is evident, and their place and weight in the commuters' network also grows. The number of municipalities sending commuters to these subcenters becomes significant and increases the subcenter connectivity. More importantly, the municipalities situated in these subcenters become more tightly connected.

Finally, by applying the participation coefficient, we can characterize two types of municipalities: those who send workers out, defined as residential areas, and those who receive workers, defined as employment centers.

In summary, the commuters network can be characterized by a star topology, highlighted using the betweenness centrality index, with small world properties, illustrated by the strength metric. In the last section of this paper, we investigate this characterization further.

12.3.2 Creating an Egocentric Network of an Urban City On-Demand

In this work, we extracted egocentric networks from the complete data for all four census years to create a local view around a city of interest. The egocentric network of a city in graph G is defined as the subgraph of G induced by the nodes of the graph that are situated near, in a topological sense, the city of interest. The extraction is useful for finding local properties associated with a particular city. We had defined some terms that will be used when creating these egocentric networks.

Given **commuter data** for year D_i (this data includes the number of commuters between a pair of cities and the name and geographic position of each city), a commuter network $G_i(U_i, V_i)$ is defined where

- A node U_i is a city. Cities are mapped to their geographic coordinates. As a consequence, the relative position of the nodes reproduces the geography.
- An edge V_i connects two towns if they exchange commuters.

Given the set of commuter networks over all 4 years (G_1, G_2, G_3, G_4), the union of these graphs, $G(U,V)$, is defined as

$$U = \bigcup_i U_i \qquad V = \bigcup_i V_i$$

Therefore, G is also a network.

If C is the commuter data for 1 year, $C = Table(t_i, t_j, n)$ where t_i is the town of residence, t_j is the town of the workplace, and n is the number of commuters that pass between the towns. Let us denote $linkij$ as the weighted edge between t_i and t_j.

Path(t, length) is a ordered sequence of cities starting at t such that a link exists between the adjacent towns in the sequence, and the sequence is a given length.

Given a city, a number of paths of the distance length exist in the commuter data C for a given year. This data can be filtered where D = Filter(C) with ti in Path(t,length) or tj in Path(t,length). Next, we format all 4 years of our data, using the Tulip[7] framework, into a single file with all of the attributes available: the number of commuters for each year on all edges (a weight of 0 is entered if the edge did not exist for a given year); the geographic positions for each city; and the city names. The city names will be used as an identifier, and, as such, we must ensure that the names do not vary from census to census.

Building a visualization inside of the urban areas as delineated in the first stage can be achieved using a series of Tulip plugins (Auber, 2003). During this study, we choose to work on the major cities of France such as Bordeaux or Lyon. To begin, we work on the union of all 4 years between 1975 and 1999. Therefore, each edge in this graph has a collection of four weights.

All of the nodes that lie on a path of length less than or equal to three are included. A path length of at most three was chosen because the graph is densely connected. All of the cities of distance three or smaller from the query city are included. We could have used the weighted distance from the city center, but that remains for future work. The nodes and the edges of this graph were stocked in a vector for efficiency reasons. This city-centric view of the data can help the geographers to reason about the polycentric structures around a given city.

The next step is to filter the data, at several scales, around the regional and departmental levels surrounding the capitals. In the process of creating a graph on demand by combining all of the edges, we considered that the value of the edge could be positive (if this edge exists in 1 year of data) or negative (if there is no edge). So, imagining that we just need to have a graph in which the edges exist at all times, we could consider the possible values of the edge. We have suggested that it is better to approach the analysis as an extraction from the original network in which the urban area is easier to visualize.

12.4 Commuters Networks as a Scale-Free Network

Previously, we observed that the commuters' network has both a star topology and small world properties. In this section, we explain an approach that exploits these two qualities directly.

A network is said to be scale-free if the distribution of node degrees in the graph follows a power law. More formally, the probability distribution of node degrees, $p(k)$, has the following form:

$$p(k) \sim k^{-\gamma}$$

where k is the node degree and γ is the power law exponent. The principal characteristic of a scale-free network is that a few nodes have many connections while the majority of nodes have very few connections. The commuter network is, for the most part, scale free in nature. A few large cities import a number of workers every day while the vast majority of cities import very few workers. However, not all areas of the graph are scale free and the exponent y still needs to be determined. The areas of the graph that do not have a scale-free structure often correspond to places where polycentric activity occurs in the network.

Figure 12.14a shows the commuter network where the links have been already filtered by the number of commuters. The nodes in this graph are cities and directed edges exist if the cities exchange commuters. In the plot, the y-axis is the node degree and the x-axis is the node index. There are a few nodes with a very high degree, however, most nodes have low degree.

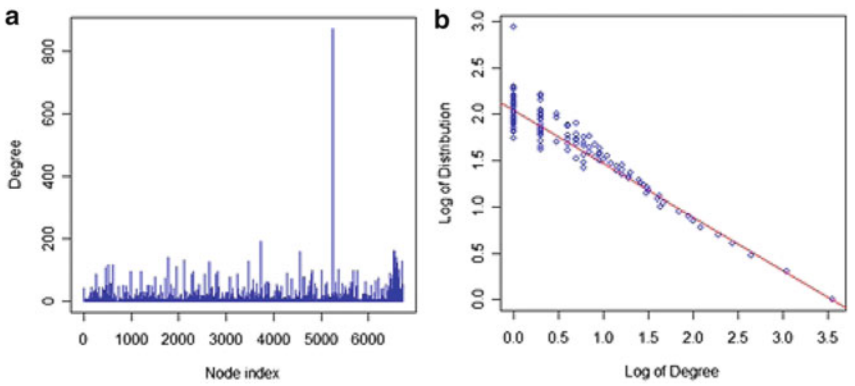

Fig. 12.14 (**a**) Degree distribution in network. (**b**) log-log plot as a straight line in migration network

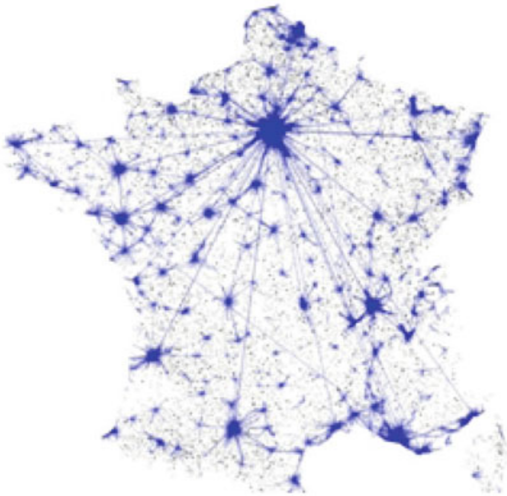

Fig. 12.15 Migration network as scale free

Figure 12.14b shows a plot of the log of the degree versus the log of the frequency of that degree in the graph. If the degree distribution follows a power law, the data should fit a straight line with a slope equal to the exponent y. As shown in the figure, the commuter network appears to fit the power law distribution of degrees.

The high degree nodes in the commuter network often correspond to the major cities in France. Where there exists a central node with a very high degree, we try to detect these major cities and their star topology; the cities around it are often linked to it directly.

We now present a recursive algorithm that helps to illustrate the polycentrism in the commuter networks of France. The algorithm starts by checking to see if the passed graph is scale free. If the graph is scale free, we then decompose the graph into sub graphs using the nodes of highest degree in the network. If the graph is not scale free, the algorithm uses the strength metric to color the edges of the graph. The densely connected areas of the graph are highlighted in dark. Quite often, these areas correspond to the regions of the graph that exhibit polycentric behavior (Figs. 12.15 and 12.16).

12.4.1 Visualizing Polycentric Structures Using the Strength Metric

Although the commuter network for the most part is scale free, at the lower levels of the multi-level decomposition, the graph can exhibit small world properties. Because polycentric phenomena are more densely connected, they are more likely to have small world properties. The strength metric is used to quantify the participation of an edge in a cluster, and therefore, we can use the metric to assess whether or not an edge participates in a strongly connected cluster.

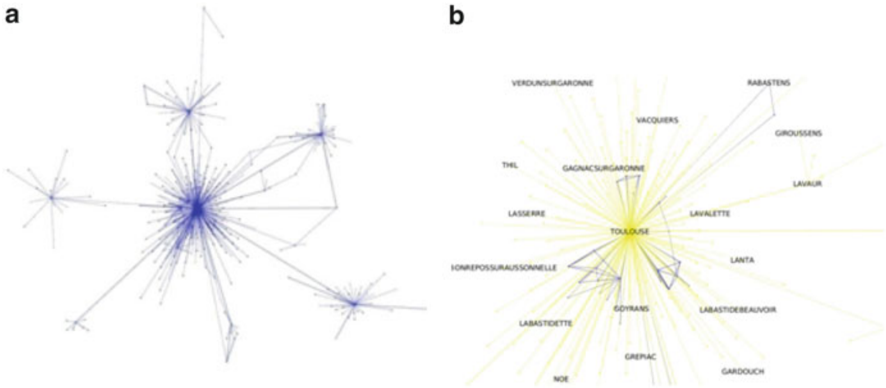

Fig. 12.16 (**a**) Star topology in the scale-free. (**b**) Cohesion on groups in sub-component

12.4.2 Recursive Algorithm for Illustrating Polycentrism in a Network

Step 1 (a) Find the cities that attract the most workers on a daily basis, or the powerful cities in the network. We determine these cities based on their weighted in-degree.
(b) Remove all powerful cities from the network.
(c) For each powerful city, place it back in the network with all of its edges and extract the connected component in which it is contained.
(d) Check whether the connected component has scale free topology. If yes, return to step 1 and recursively decompose this connected component. If not, go to step 2 to illustrate polycentric structure.

Step 2 To illustrate polycentric phenomena in the commuter network, we calculate the strength metric on each edge to determine the areas of high connectivity. Then, using this metric, we color the edges to illustrate the areas of high connectivity. Following figures illustrate polycentric structures around the major cities using darker color. The remaining areas of the graph are colored in pale (Figs. 12.17 and 12.18).

In this example, we illustrate the polycentric structure around "Pays de Montbéliard" in the department of Doubs (Northeast of France). Figure 12.18 shows the subcenter formed around the municipality of Audincourt.

12.5 Conclusion

In this chapter, we analyzed the data from four French national surveys of commuting networks. Because daily commuting patterns provide evidence for polycentric structures situated around urban areas, we have presented visual explorations

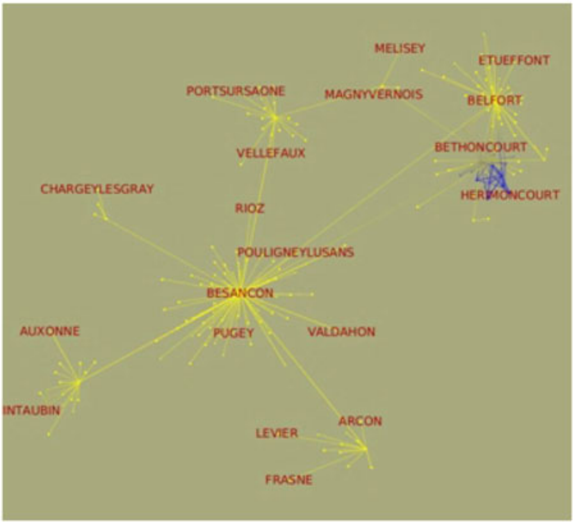

Fig. 12.17 Scale free structure of (star topology) and the structure of the dense sub-graph (zone colored *blue* by applying the strength – density cohesion zone) (color figure online)

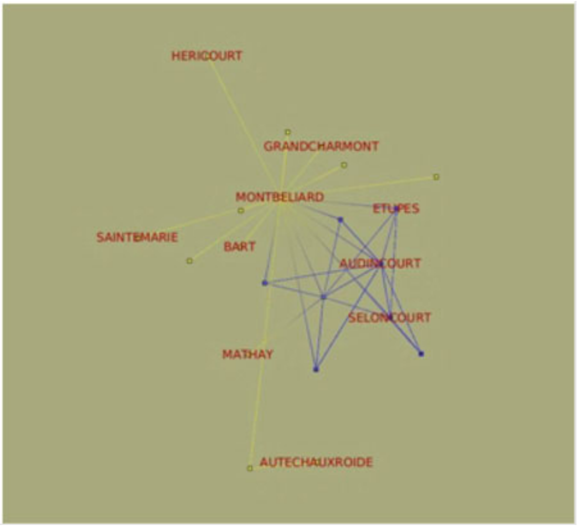

Fig. 12.18 Level of density cohesion zone – image of a polycentric event

of these phenomena. By filtering the data based on a gravity model in the first stage, we visualize the graph based on an accepted definition of polycentrism. Through metrics applied to the examples around Lyon, Marseille, Lille, Toulouse and Bordeaux, we then analyze the topological structure of the graph. The betweenness centrality allows us to locate the major French cities. Their power to attract workers from the surrounding municipalities is seen through the network growth around them. The strength index highlights the polycentric structure of the urban areas. In the examples of Marseille and Lyon, which evolve over time, the polycentric structure not only develops through the creation of new subcenters, but also through additional connectivity at two scales both from inside the municipalities forming the subcenter and from external municipalities. The coefficient of participation identifies where a community is situated in the sending/receiving commuter patterns of the network, characterizing areas as having either a residential or an employment dominant orientation. We also show how to construct a graph that may lead to a way to study network evolution over time. This work helps to demonstrate the impact of urban planning on the residential strategies of the active population inside urban areas.

Finally, based on the results of the second section, we describe a method to decompose the commuter network into its primarily scale-free parts while also highlighting some of its small world structure at a local scale. Our preliminary results demonstrate that a scale-free/small world approach to commuter network analysis is interesting but further investigation is needed.

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Conclusion

Céline Rozenblat and Guy Melançon

This volume explored applications of networks to multilevel, multi-scale and multidimensional aspects of spatial analysis, discussed "complex network" theories and introduced the use of networks to represent the structural aspects of spatial phenomena. With the aid of visual analytics tools, empirical studies of large network samples examined hypotheses regarding the factors influencing the patterns of interactions represented by graphs.

The set of papers included in this volume not only described new analysis and visualisation techniques but also introduced new concepts relevant to geography and more widely for social sciences. Many different networks composed of individual entities were investigated: maritime networks linking ships, knowledge diffusion networks (e.g., scientific networks linking authors), mobility networks (e.g., commuter and airplane passenger traffic), and control networks (e.g., multinational firms' ownership of subsidiaries). In the studies presented in these chapters, networks were aggregated based on territorial attributes to group individual entities into new entities. In these new networks, the interacting entities were places or territorial units, and the individual entities of the original network generated the attributes of the newly formed entities. For example, aggregating companies based on their geographic location produced a set of cities that inherited attributes from the companies located in those cities (Chap. 10).

Using the processes designed to represent society and individuals to represent space has many implications for the analysis and representation of the results. This representation influences the meaning of the geographical interactions observed

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in the social sciences and modifies views regarding the use of the individual networks analysed by sociologists (see Sect. 1 below). This representation transforms geographical space and introduces a new type of visualisation (see Sect. 2) to identify new resources in spatial networks (see Sect. 3). The transposition also identifies the empirical levels of hierarchies (Sect. 4) and cohesive spaces (Sect. 5), which enables interactions between these levels to be investigated (Sect. 6). Many perspectives emerge (Sect. 7) that relate these theoretical and empirical results to other approaches to complexity that employ dynamic models based on individual, as well as global, properties of systems of interactions.

1 Changing the Meaning of Social Networks Through Spatial Interaction

Places and their social components are shaped and transformed by internal and external networks, and conversely, geographical space is a major factor in the transformation of social networks and social entities (Adams, Faust, & Lovasi, 2012). Geography contributes to the understanding of social organisations by determining the impact of geographical and territorial distances on social, economical, cultural and organisational distances. Several contributors to this volume revealed the critical role of geography in identifying the relevant criteria for clustering these networks and the spatial cohesion that reinforces the interactions underlying cohesive territories. Although the concept of "functional territories" in geography (Gottman, 1961; Perroux, 1964) emerged 50 years ago, methods for identifying and understanding the evolution and transformation of these territories have only recently become available.

Just as networks are no longer viewed as random or homogeneous, territorial structures are shaped on spaces that are neither random nor homogeneous. Several issues were addressed – how space and social networks influence each other, the role of distance in linking similar individuals and reinforcing social proximities, and the extent to which networks increase the anisotropy of space. The examples presented in this volume demonstrated that there were two kinds of networks:

- Networks in which space was the major factor in the organisation, such as the slow transportation and daily exchanges of commuters;
- Networks that involved the contribution of other, nonspatial proximities, such as communication, collaborative research, and the global division and coordination of labour; these networks primarily support globalisation and multiscale development.

The second type of network transformed spaces and territories to create new "reticular territories" in which societies' physical space and organisation depended on economic or social distances that made distant spaces closer and neighbour spaces more distant. Examples of the phenomenon provided in this volume were air transportation networks (Chap. 9), and collaboration between researchers (Chap. 11). These two examples illustrated that certain distant cities were highly connected, while other closer cities were less connected. Thus, space and territories are more influenced by the density of networks compared to physical distance.

However, unlike such domains as sociology, the concepts and applications of graph theory could not be directly applied to geography. Studying geographical networks requires conceptual adaptations that extend beyond a strict topological description that focuses on the orientation of the links, weights, positions and attributes of nodes (Sect. 3.4.3). Gleyze argued that the concept of "reachability", which corresponds to the geographical concept of "accessibility", is not necessarily revealed by high density in the graph. Moreover, when networks are aggregated by geographical proximities, non central territories inherit centrality properties, dependencies and powers from institutions as firms, although these properties may not have existed prior to aggregation.

2 Transformation of Space By Networks

Networks create new territory properties by transforming the proximities of spaces. Networks reduce the distance of paths along links that are used to locate individuals based on their relative positions in the network. In Chap. 6, Lambert, Bourqui and Auber detailed general methods of network visualisation for graph layouts based on attractive forces. The process of moving individuals with more interactions closer to each other transforms geographical space into topological space. Network topology may sometimes coincide with geographical distance. However, networks often distort space, and cohesive territories or communities are not based on geographical proximity. The topological proximity of Malta and UK in the Eurovision network provides a typical example (e.g., Gleyze's example of votes for Eurovision songs in Sect. 3.4.3).

In Chap. 4, Alain L'Hostis considered the time-distance relationship and described the spatial inversion phenomenon and the time-space contraction created by transportation networks' selection of a limited number of places. This inversion is difficult to represent by maps, which preserve the order of spatial proximities because they adopt Euclidean principles for representing distance in two dimensions. Abandoning Euclidean space and the rule that the shortest path is represented as a straight line, Alain L'Hostis introduced the "shrivelling" of maps that create new spatial terrain through "time-space" peaks and valleys. This process is similar to the approach adopted in astrophysics, where the space-time of the universe is deformed by general relativity in crumpled spaces (Luminet, 2001). Applied to terrestrial transport, this "crumpling" generates new connections and new proximities that allow new properties of geographical space to emerge. Tunnel effects that reflect the nonaccessibility of the space between two nodes eliminate part of the space between two linked nodes, and geographical distances are no longer symmetrical between places. Space is transformed by conditional relative distance, as well as the new dominating factors of speed and distance evaluation, which creates new centres and peripheries that redistribute the concentration of wealth and resources.

3 New Resources Throughout Networks

Network analysis provides a new perspective for spatial analysis and shifts the focus from how many resources a location possesses to the extent to which resources can be accessed from that location. Thus, privileged places are nodes that access many resources through direct or indirect links and take advantage of other nodes to reach resources they do not possess. These intermediary nodes play new roles in the local or global network because they provide paths for accessing resources. This strategic role implicitly introduces weaknesses into the network as a whole. The network is fragile because reachability depends on these relay nodes and their elimination influences the overall accessibility of the network. Although the nodes themselves are not fragile, their position in the network and the possibility that they might be eliminated makes those nodes fragility sites for the network. In Sect. 3.4.3, Gleyze noted that vulnerability occurs when the relations between nodes are not sufficiently redundant because removing edges causes node disconnection and the fragmentation of clusters. In relation to the issue of vulnerability, Gleyze distinguished between *n*-cliques, *k*-plex and *k*-core methods.

Just as there are fragile nodes, there are also fragile edges. The network becomes a new resource because links become more important than nodes. This feature is important for transportation networks, where power in the network is more and more concentrated in enterprises that manage shipping lines (see Chap. 8) or in primary air traffic lines (see Chap. 9).

Conversely, some links or nodes are highly resilient. Robust economic and financial edges such as the links between London and New York dominate the entire network and connect economies in different domains. The mutual support provided by these different networks increases their strength. Recent physical simulations demonstrate that similar networks are more robust than different networks to the multiple effects of failure (Buldyrev, Parshani, Paul, Stanley, & Havlin, 2010; Parshani, Rozenblat, Ietri, Ducruet, & Havlin, 2010).

4 Hierarchies

Hierarchies naturally appear in various contexts, and spatial geography is no exception (Pumain, 2006). The term itself may refer to an order hierarchy or a structural hierarchy. Hierarchies may be based on organisational structure (e.g., NACE codes classify industrial activity into distinct sectors and subsectors) or may emerge from territorial considerations (e.g., continents are divided into countries that are subdivided into regions and towns). Hierarchies can also emerge from functional dependence, due to the asymmetry of social or economic relations. The various studies presented in this volume refer to hierarchies in different scenarios.

The interactive visualisation DAGMap referred to two different hierarchies, with one governing how subsidiaries organise and the other governing how they distribute over world regions. The two hierarchies were merged into a single visual structure, a TreeMap displaying the organisational hierarchy and colour-coding world regions. Examining how the hierarchy of subsidiaries was globally distributed supported the analysis of patterns reflecting the potential impacts of globalisation. Specific interactions were designed to allow the analyst to navigate through the different levels of the organisational hierarchy and identify colour-coded patterns (see Figs. 7.11 and 7.13).

In Chap. 6, the edge bundling method produced a hierarchy that integrated physical distances and graph topology. Although the goal of the method was to improve the readability of a map, edge bundles also reduced edge cluttering in graphs by routing edges along Bézier curves. Similar to creeks and smaller rivers that flow into a larger stream, the edges were partly merged. The original graph connections were combined into higher-level edges that described overall flows on the map, which created a new hierarchy in the graph by aggregating closely edged segments. This hierarchy of bundles of routes provided an original and novel method for visualising a hierarchy in space.

The order hierarchies present in networks are often used to compare or reveal node roles, as mentioned above. Node degree remains an essential node statistic that captures the overall structure of a network and often reveals the graph's scale-free structure. Although not systematically or explicitly stated in the various studies presented in this volume, most of the networks studied were scale-free. This property is not surprising because places are also hierarchised based on economic dependency. For example, the Christaller model (1933), which is the root of the settlement system, is hierarchised by access to services as well as economic and political functions. Further theoretical research into geographical organisations with different types and scales of hierarchies would be worthwhile (Castells, 1996) and would detect the specific scales that optimally represent a phenomenon's spatial organisation.

5 Detecting Critical Structural "Levels" in Global Organisations

In summary, the methodology adopted in the SPANGEO project consisted in comparing and contrasting the network topology of the regional partitioning of nodes (places). The network's modular and multilevel organisation was based on identifying key nodes or edges that decomposed the network into smaller, denser components. Various connectivity statistics were used to identify the minimal number of edges to eliminate to disconnect the graph. In Chap. 6, Lambert, Bourqui and Auber presented geographically nested and socially nested network dichotomies. The geographical organisation identified the intercontinental links that dominated the air passenger traffic network. Globalisation facilitated the emergence of clusters at the centre of the worldwide network, which emerged as essential links between continents. Because the analysis was driven by the network topology, we were able to detect which parts of the network remained in continental organisations and which parts transcended them.

The present volume revealed how each node of a network participates and contributes to the formation of clusters (Chap. 5). Because a node can participate in more than one cluster, the concepts of "participation" and "contribution" inspired from factor analysis were used to evaluate how each node participated in specific clusters and the extent to which participation in a specific cluster contributed to its internal cohesion. This approach identified several issues:

- The extent to which these procedures could be used to evaluate polycentric structures, such as the commuters described in Chap. 12;
- The extent to which these measures might be described at multiple levels;
- How to introduce fuzzy measures in cluster membership.

Various methods to define clusters were developed by the authors of this volume: DAGMaps, strength clustering, Lambda-sets, and multistep methodologies. Comparisons of different methods of clustering developed for air passenger traffic (in Chap. 9) and commuting (in Chap. 12) did not identify a universal method for detecting the communities comprising different patterns and indicated that clustering is a strategic approach that must be adapted to each specific problem.

Detecting clusters simplified large and complex networks by abstracting cohesive groups and aggregating these groups into higher-level entities to produce smaller, simpler networks. Addressing the issues raised by clustering graphs, Gleyze distinguished two concepts (Chap. 3). The concept of "cohesion" corresponds to the currently popular notion of modularity that is often embodied and measured by edge density. However, other types of clusters that do not qualify as dense subgroups might also be of interest, such as star-shape clusters with the central concept of "reachability". The same network may exhibit different patterns, depending on the level or scale at which it is defined. This heterogeneity of patterns requires new methods to detect the different levels of networks' organisation.

6 Interactions Between Levels

Examining interrelations between organisations at different geographical scales contributes to the understanding of the equilibrium and disequilibrium of territories (Chap. 2). Many social phenomena developed at one level have their root in other levels, and these levels interact. This interaction is illustrated by the subsidiarity of firms, which is produced both by local processes in cities and by their global position (Chap. 10). In Chap. 11, Comin examined relay cities between scales based on the assumption that most components in scientific collaboration networks were intranational and that certain cities linked these components to the structure as a whole. Interactions between levels influenced actors' ability to address each of these levels, and geographical aggregation was important for decision makers. Network patterns made it possible to identify individuals and their interactions, although further research is needed to determine routines and patterns fully.

7 Perspectives

This volume provided an initial exploration of the application of network analysis and visualisation to geography and introduced novel perspectives and new issues to the field. Future work should further this approach through theoretical accounts that link the description of networks to specific processes. For example, in which contexts and at what scales do network patterns, such as stars or clusters, emerge and remain robust and resilient? How are clusters and levels of organisations modified by the evolution of the system as a whole? To what extent does geographical distance contribute to the development of different networks at different scales? Adapting the methods presented in this volume to make them accessible to geographers will allow them to address these issues and many others.

It is worthwhile to review the origin of the project that brought the authors in this volume together. Many problems that were addressed in the present volume had never been fully visualised, and the case studies presented here often involved data sets that had never been fully explored because the data were too extensive to be spatially mapped. The interactive visualisation of graphs provided a means to analyse the entire data set based on the visual analysis and inspection of salient features.

One consequence of this approach was the realisation that physical distances were not central to the analysis, which was based on topological properties of the data sets. This pragmatic approach contrasted physical distances with "social" distances that were measured through the intensity of interactions between entities. This idea is a fundamental principle of network science that parallels similar concepts in the social sciences (Martin, 2009), and this perspective allowed computer scientists to contribute to the data analysis. The present volume documents the value of this type of idea exchange.

The graph visualisation methodology also exploited the central paradigm of "scale", which generated many debates on network hierarchies and the "small world" phenomenon. The constraints imposed by the manipulation of large datasets on standard visualisation displays drove downsizing approaches that transformed large graph structures into hierarchies of smaller subgraphs. Because hierarchies occur as a structural principle in nature (Pumain, 2006), many computational approaches have been successfully applied to these datasets to render the entire data set accessible; in addition, the downsizing process implicitly addressed the concept of data scale. Thus, the computational approaches were relevant to geographers and to social scientists more generally because the concept of scale is central to these fields. Thus, computational approaches based on mathematical features of the data sets provided a paradigm through which both geographers and computer scientists could construct hypotheses. The papers in this volume report the findings and results of SPANGEO project members that exhibit how concepts established through collaboration could generate insightful discoveries.

This new approach to theories of territorial and spatial organisation should strengthen the integration of network analysis into general spatial analysis through the transformation of space by networks and the new resources provided by network hierarchies and levels. To improve understanding of the common and specific properties of spatial networks in empirical studies, network simulations based on small theoretical sets of nodes and subsequently applied to empirical situations should be developed. Exchanges between theoretical studies, empirical studies and simulations should promote progress in this new field.

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