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Networks and geography in the economics of knowledge flows

Mario A. Maggioni · Teodora Erika Uberti

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Abstract This paper reviews the literature dealing with the economic geography of knowledge flows by summarising the most relevant problems and open questions that, according to the authors' view, have been dealt in the past and should be dealt in the future by network analysis in order to model, understand and measure the structure and dynamics of knowledge flows. The interaction between "networks" and "geography" elements within a theoretical, methodological and empirical perspective is discussed throughout the paper by making reference to previous works by the authors and to the established literature. Thus, these references, far from being complete and exhaustive, are instrumental to the achievement of the paper's goal: to demonstrate that "networks" and "geography" are the necessary ingredients for every study of the innovative process at any level of analysis, from individual agent to institution/organization, from the regional to the national and international level.

Keywords Networks · Geography · Social network analysis · Knowledge flows · Innovation

To reconstruct is to collaborate with time gone by, penetrating or modifying its spirit, and carrying it toward a longer future. Thus beneath the stones we find the secret of the springs.
M.Yourcenar, Memoirs of Hadrian

1 Introduction

Aim of this paper is to present a stream of research which has largely developed in the economics (and management) of innovation and in the regional science literature in the last 10/15 years, to discuss the main pros and cons of such a stream and to sketch a sort of research

M. A. Maggioni (✉) · T. E. Uberti
CSCC, DISEIS, Università Cattolica del Sacro Cuore, Milano, Italy
e-mail: mario.maggioni@unicatt.it

T. E. Uberti
e-mail: erika.uberti@unicatt.it

agenda for the next future. In doing this, we will adopt a rather subjective perspective, by referring to previously published (and unpublished) works, as exhibits of the need to mix and merge spatial and network analysis in order to model, understand and measure, the innovative process which is the engine of growth and development of any advanced economy.

Part of this paper originated from a series of lectures and presentations[1] in which it was asked us to summarise in few slides our research of the last 15 years in front of very different audiences. Some of the audiences knew a lot about networks but very little about economics; some of the audiences knew a lot about economics but very little about networks and, above all, most of the audiences thought that networks and geography were two distinct topics with very limited overlapping. Both lectures and presentations (and, hopefully, this paper too) tried to convince the audience (and, as far as the paper is concerned, the reader) that the opposite is true and that networks and geography are the necessary ingredients for the study of the innovative process at any level of analysis, from individual agent to institution/organization, from the regional to the national and international level.

For this reason the paper is a rather peculiar survey since it does not provide a complete coverage of different streams of literature which have dealt with the analysis of network structures and knowledge flows, but it offers a summary of the most important topics which we covered in the past and we are going to address in future research.

The paper is organised as follows. Section 2 presents the recent revival of networks within the economic profession. Section 3 presents different methodologies of data collection. Section 4 deals with the dilemma of networks modality: direction and values of links. Section 5 argues that networks and geography may be considered as two different ways to answer the same questions: "who are my neighbours?" and "why are they relevant?". Section 6 introduces time and evolution in the macro-analysis of networks and presents the comparative static, the longitudinal analysis and the computational simulation approaches. Section 7 addresses the problems associated with the introduction of individual rationality and forward looking expectations in the micro analysis of networks. Section 8 concludes the paper and sketches a research agenda for (the authors and) the profession in the next future.

2 Economics and networks

While Social Network Analysis (NA), originated from the initial intuitions of J.L. Moreno back in the 1930s and 1940s (Moreno 1946), and developed in the 1950s and 1960s in two distinct but intertwined fields of sociology and anthropology, economists were very suspicious about an approach "which did not explicitly include prices and individual incentives in the analysis".[2] As it often happens in the history of economics, the interest raised when networks started to be studied by physicists (Watts and Strogatz 1998; Albert and Barabasi 2002; Newman 2003) and computer scientists (Broder et al. 2000; Daley and Gani 2000) within the so-called "complex systems approach".

In particular these disciplines went back to the original mathematical literature dealing with random graph theory (Erdos and Reny 1959) and introduced in the SNA literature the concept of topology. In other words they defined the architecture of networks, including some static indicators (i.e. degree distribution, clustering coefficient, average path length),

[1] In Milan (2003, 2009), Bologna (2004), Utrecht (2007, 2008), Pécs (2007, 2010), Marseille (2008) and Salerno (2009).

[2] As one senior member of the economics department of the University of Warwick stated to one of the authors in the early 1990s.

and different laws of motions (i.e. random versus preferential attachment) that allowed a comparison between actual networks and benchmark ones (i.e. random networks, scale free networks, small world networks,[3] regular networks, etc.). Hence, even if they did not "include prices and individual incentives", nevertheless they succeeded in building a framework able to describe the structure and evolution of large complex networks, whose statistical properties could easily fit the asymptotic requirements of theoretical models and allows for inference analysis.

In the meantime, by the end of the 1980s[4] game theory had become one of the leading approaches in the economic literature to model agents' behaviour at the micro level and, later, the concept of multiple strategic interactions (both in cooperative and non-cooperative games) was included in the realm of economics.

Thus economics was confronted with a double line of research: a micro perspective studying how the strategic behaviour of agents is influenced by, and in turn influences, the relatively simple structure of a "local" network, and a macro perspective focussing on the statistical regularities of the network as a whole. In this scenario different economists choose their own research path, while a general synthesis was, and it is still, missing. The following sections sketch our own path with unsystematic reference to contiguous pieces of literature.

3 Data sources: primary versus secondary data

Any kind of network analysis (NA) must be based on "relational data", i.e. describing not the characteristics of a single agent but the features of the relations between pairs of agents belonging to a network, hence the need for specific procedures of data collection, treatment and elaboration which are not included in the standard toolkit of both statisticians and economists.

The main issue to be dealt with concerns the boundaries of the population under study and the sampling techniques (Wasserman and Faust 1994; Marsden 2005). Two different procedures have been used to define the boundary of a population in the network analysis of knowledge flows. The first procedure relies on "primary" (or direct) data, where the researcher directly collects relational data though interviews and questionnaires submitted to a number of individuals a/o organizations; the second uses "secondary" (or indirect) attributional data that the researcher adapts in order to perform NA exercises.

The primary data collection strategy is adopted when no ready-to-use database is available to study a specific issue in a given population. The researcher—once identified the geographical borders of the analysis (i.e. an industrial district or a city)—starts by collecting data on the relations of each actor included in the area, through appropriate direct interviews according to a roster-recall methodology (Giuliani 2007; Ter Wal and Boschma 2009). This "direct" procedure consists in a pseudo-snowball sampling in the sense that agents, initially not included in the original population but quoted by interviewed agents, may be added later in the analysis. This procedure works though a multiple steps research design: (i) data are collected at individual level by asking the respondent to identify and/or add *alters* with

[3] We should remind that NA literature was aware about the small world phenomenon, but the perspective followed in the analysis was mainly focussed on the Milgram's six degrees of separation (Milgram 1967). However it was thanks to the mathematical formalisation included in Watts's book (1999) that NA started to propose formal indexes and statistics on this.

[4] In 1989 the journal "Games and Economic Behaviour" was founded and Kreps's "A course in microeconomic theory"—the first graduate level microeconomics textbook to fully integrate game theory into the standard microeconomic literature—was published in Kreps 1990.

whom he/she maintain relations; (ii) *ego*-network of each interviewed agent are created[5]; (iii) the population under analysis is enlarged if additional agents are cited by respondents and these additional agents are interviewed[6]; (iv) all *ego*-networks are transformed into a unique structural network.[7]

The crucial point of the entire procedure consists in the correct design of questions (Giuliani and Bell 2005; Morrison 2008; Ter Wal and Boschma 2009). Each question needs to be designed in such a manner to map both the relation originating from the *ego* to his/her *alters* and also the relation originating from *alter(s)* to the *ego* (Maggioni and Uberti 2009b). The latter is particularly useful when there is no possibility to verify the existence of this relation because the *alter* does not answer the questionnaire, or is not available any longer (i.e. a bankrupted firm). Hence, for instance, in a questionnaire conducted to analyse the productive interactions occurring between firms within an industrial district, it is possible to formulate "mirror" questions such as: "*Which of the following firms have been your customer?*" and "*Which of the following firms have been your supplier?*". The use of "mirror" questions also allows to verify the answers of respondents. Usually the answers to these questionnaires are dichotomic because they map the existence, or not of a link, recording 1 or 0 in the sociomatrix. Hence, when both agents are interviewed and their answers are consistent (i.e. firm i says that firm j is one of its customer and firm j says that firm i is one of its suppliers), a value equal to 2 is recorded in the sum sociomatrix (Maggioni and Uberti 2009b).

When using primary data, the definition of the boundaries of networks is crucial in NA. Exhaustive databases and archives are very uncommon and a choice has to be done either in terms of characteristics (i.e. formal membership) of agents, or in terms of the participation to an event at study, or in terms of social connectedness (Marsden 2005).

It is also possible that the mapping of relations is not complete and excluded some relevant actors (and relations) either because the formal sources of data contain missing information or because the sampling of the actors excluded some "relevant" players, whose presence could reshape the entire network, or because the redemption rate of interviews is particularly low. While in every empirical analysis, this rate is crucial for the statistical significance of the sample, in NA it is even more relevant since the exclusion of few key agents may produce a distorted representation of the whole network and determine biased and unrealistic values of the structural indexes. Having stated the above, any NA researcher should take into account that it is almost impossible to have a complete representation of an actual network (i.e. the identification of all relevant agents plus a redemption rate of 100%).

Finally, while it would be most interesting to study the evolution of a network, it is very difficult (and costly in terms of both time and money) to replicate the study in two significantly distant periods of time. Furthermore it may be the case that a large part of the population included in the initial analysis is no longer present when the subsequent analysis is performed; thus the number of significant comparisons which may be performed is very limited (Ter Wal and Boschma 2009).

[5] Ego-networks are "personal" networks and analyse network composed by a focal agent, (i.e. *ego*) and the set of his/her relations with the *alters* (Wasserman and Faust 1994).

[6] When new actors, i.e. subjects not initially listed in the interview, are cited by the respondents, it is worthwhile to enlarge the interviews and conduct the analysis also for cited *alters*. Of course this enlargement could be very costly and not always possible, for instance when actors are not active any longer or they are located far apart.

[7] There exist several software to manage the transformation of ego-network into whole network (Ucinet, E-net). In Maggioni and Uberti (2009b) an *ad hoc* software, SNAID (Social Network Analysis for Industrial Districts), developed by EGGsist.com was used to transform ego networks and build several large structural networks.

The secondary data collection strategy exploits the availability and accessibility of appropriate "relational" databases. International trade data are naturally relational,[8] defining the country of origin (i.e. the exporting side) and the country of destination (i.e. the importing side), and several international organisations (UN and OECD) provide detailed data on these flows.

Similarly the publication of data concerning the compositions of board of directors of public listed companies, required by law in most countries, allows to exploit the reciprocal influence among firms and people. The availability of such data allowed the diffusion of NA applications to the "interlocking directorates" literature (Galaskiewicz and Marsden 1978; Mizruchi 1996; Davis et al. 2003; Burris 2005).

According to this "indirect" procedure, the main task of the researcher is either to choose the appropriate relational database (and, when relevant, determining the most convenient level of analysis whether individual, or aggregate[9]) or to interpret in a relational way existing database which were originally conceived for attributional purposes.

In the economics of innovation literature, as suggested in Ter Wal and Boschma (2009), patents are a typical example of attributional database which have been recently exploited from a relational perspective so to allow a number of applications of NA.

Traditionally patents are used as attributional measurement of the innovative activity of an agent, organization (firms, university, research centre) or territory (city, province, region, state) since it reveals its innovative marketable output. However each patent could be interpreted from a relational perspective as a "window" on different networks of knowledge flows involved in the innovation process.

A first relational interpretation of patents concerns the mapping of scientific and technological precedents. Through the so called "citation analysis" it is possible to trace how scientific knowledge flows within and across different scientific disciplines and to trace the life cycle of innovations (Jaffe 1983; Hummon and Doreian 1989; Jaffe and Trajtenberg 2002; Verspagen 2005).

A second relational interpretation of patents regards the collaboration among inventors which originate an innovation. Through the so-called "co-patenting analysis", when patents data are aggregated at a given territorial level, it is possible to map the existence of personal and institutional flows of knowledge within the scientific community which determine a relevant part of the innovative performance of a region (Cantner and Graf 2006; Ejermo and Karlsson 2006; Maggioni and Uberti 2007, 2009a).

A third relational interpretation of patents involves the market-led connections between inventors and applicants (or assignees). This last interpretation may be subdivided into two streams: the agent-based "mobility" of inventors approach focuses on the micro-economic explanation of the knowledge spillover phenomenon in terms of the mobility of inventors registering patents with different applicants (Breschi and Lissoni 2003); the region-based "knowledge transfer" approach focuses on the different spatial distribution of inventors and applicants and highlights the spatial patterns of knowledge flows between places where inventions are conceived and places where inventions are commercially exploited, thus investigates the determinants of both knowledge production and utilization (Maggioni et al. 2011b).

Despite its numerous advantages, the indirect approach, suffers from the limitations imposed by the use of secondary information and official databases. With specific reference to knowledge flows, secondary data only refers to official, documented and registered

[8] In fact it is not by chance that one of the first paper on NA economic application is on trade flows (Snyder and Kick 1979).

[9] We should state that one of the most relevant aggregation criterion is the geographical one.

transactions, thus often misses important channel of knowledge transfer simply because they are informal. Further the use of secondary data often restrict the scope of the geographical analysis at administrative levels, while functional areas would better fit the analysis.

4 Treating networks: modes, directions and weights

As stated in Sect. 3, NA deals with relational data which are represented by links between agents (i.e. nodes). Before implementing such a definition, the researcher must tackle a series of methodological problems which concerns the mode of a network, the direction of links and their values. These problems are especially relevant when networks under study regard the structure of knowledge flows.

First of all, the researcher needs to identify the subjects of his/her analysis or, using NA terminology, to define the type, or *mode*, of networks, i.e. the "number of sets of entities on which structural variables are measured" (Wasserman and Faust 1994, p. 35).

In NA there is a basic distinction between *one-mode* networks, where nodes belong to a single set, and contain measurement of relations within the set, from *two-mode* networks, where nodes belong to two sets of social units and contain measurements of a relation from the units in one set to units in the other set (Doreian et al. 2004).

A *one-mode* network may be represented by a squared sociomatrix, of size $n \times n$, where n represents a generic node (i.e. person, firm, institution, region, country), that could potentially establish a relation with any other $n - 1$ nodes. A *two-mode* networks may be represented by a sociomatrix of size $m \times n$, where m identifies a generic node belonging to the first set and n identifies a generic node belonging to the second set (Wasserman and Faust 1994).

Since the classical study by Davis et al. (1941), these networks are often defined as "affiliation networks", because they are the sociometric representations of two dimensional issues such as: people attending events, organizations employing people, justices on a court rendering decisions, and nations belonging to alliances a/o regional trade agreements.

NA techniques allow to transform a *two-mode* network into *one-mode* network where one set of nodes is selected and relations among nodes of the same set are detected through the relations according to the second set. Typical examples of *two-mode* networks applied to the issue of knowledge flows are co-inventorship networks (where inventors are the first mode and patents the second mode). These networks may be easily transformed into *one-mode* networks of inventors, where inventors are nodes and patents are (valued) links between them, if two inventors have worked together to the same patent.

This taxonomy could be easily relaxed when geography is taken into account and data are exploited at the territorial level. The two dimensional characteristic of a *two-mode* network is crucially based on the assumption of non-overlapping modes and this assumption is no longer valid when two distinct sets of agents are geographically grouped into one set of region. In Maggioni et al. (2011b) the relation between inventors and applicants is analysed at NUTS3 regional level (Italian provinces) using a *one-mode* network perspective, since both inventors and applicants are located in the same set of provinces. The different role played by inventors' regions and applicants' regions is captured by the direction of the link: when relations between two regions are symmetrical, there is a reciprocal and balanced knowledge flow between two regions (i.e. there are inventors located in region i inventing for firms located in region j and vice-versa); when there is a strong asymmetry of relations, there is an evidence that different regions play very different roles as producers or users of knowledge and one may assume that a sort of "brain drain" phenomenon—in which inventors located in peripheral areas are inventing for applicants located in core regions—is taking place.

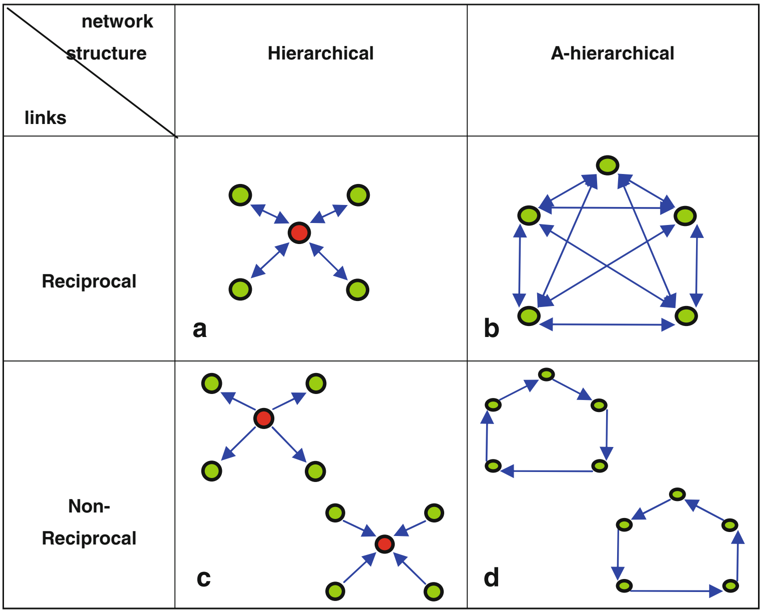

Fig. 1 A taxonomy of knowledge flows within collaborative research networks. *Source:* Maggioni et al. 2011b

This last consideration highlights the relevance of the directions and values of links within a network. When NA is applied to complex networks of knowledge flows, then technical issues relating to directions and values of links become crucial.

The first issue derives from the opaqueness of certain networks of knowledge flows in which (secondary) data on membership are ready available but there is no information on the effective exchange of knowledge. This is certainly the case of joint research networks financed by the EU under the Framework Programmes (FP) which have been extensively studied within this stream of literature (Breschi and Cusmano 2004; Maggioni et al. 2007, 2011b; Scherngell and Barber 2009; Ortega and Aguillo 2010).

Data on research networks financed by the EU within the different FP are publicly available through the CORDIS website[10]; however these data only records the name of the institution and organization financed within collaborative networks programme and, for each institution, the appropriate status of coordinator or participant.

If a researcher is interested in the structure of knowledge flows within a collaborative research network, then different and specific hypotheses on how knowledge effectively flows within the networks must be done. This issue has been explicitly tackled by Maggioni and Uberti (2007) and Maggioni et al. (2011a) in which the following taxonomy based on two dimensions, direction of links and structure of the network, are considered (see Fig. 1).

According to this taxonomy—where, for expositional purposes, we illustrate the case of a very small and simple research network composed by one coordinator and four participants—knowledge may flow in 4 different ways within the same network, hence 4 different relational structures could emerge.

[10] The official web site is available at cordis.europa.eu/home_en.html (European Commission-Cordis 2010).

Firstly ties (i.e. knowledge flows) could be reciprocal and the underlying network structure could be hierarchical if there exists mutual, egalitarian but exclusive ties between coordinator and each participant (Fig. 1a). In this case the network structure is star-like, with a very high centralization value, but symmetry of relations guarantees a mutual exchange of knowledge, that is filtered by the pivotal player.

Differently knowledge could easily flow within the set of agents irrespective of any structural position (Fig. 1b). This structure reflects two facts: the absence of hierarchy within the network (indeed all indexes of centralization have values equal to zero) and no limitations to knowledge flows among all actors. In addition no coordination a/o brokerage of knowledge and information are at play and all agents have equal status of "member".

The assumption on reciprocity of ties could be easily relaxed if we suppose the existence of different levels of knowledge stock between coordinator and participants in terms of emission of knowledge and absorptive capacity, and two structures could emerge according to the existence of hierarchy within the network.

In Fig. 1c, a top-down structure (i.e. from coordinator to participants), or a bottom-up (i.e. from participants to coordinator) structure could be considered if knowledge flows involve an exclusive relation between the coordinator and each single participant as in a star-like structure, but differently from Fig. 1a, there is no mutual and balanced exchange of knowledge between them.

A final network structure is characterised by no reciprocity of links and no hierarchy (Fig. 1d): in this case every member exchanges knowledge locally and exclusively to his/her next neighbour (in right or left direction) neighbour, and a circle-like structure of knowledge flows emerges,[11] where all members are interchangeable and no central node emerges.

The second issue concerns the values of links and the use of binary versus weighted networks. The problem arise when NA is applied to economic datasets in which relational data do not simply refer to the existence/inexistence of a link (which stand for a transfer/exchange of knowledge a/o information a/o resource) between two nodes, but they carry also a quantitative measurement of the intensity of the flows.

In Fig. 2 we represent a taxonomy of links typology: a link value could be binary (B), reflecting the presence or absence of a relation, or weighted (W), if the link presents a value greater than 0; respect to its direction, the link could be undirected (U) if there exist a symmetry of relation, or directed (D), if the direction of the relation is relevant (Fagiolo et al. 2007).

These 4 typologies of network structures could be ranked in ascending order of analytical difficulty of treatments as follows: BUN, BDN, WUN and WDN, but we should stress that while most of the relevant economic applications of NA should be treated as WDN, most of the analysis performed by researchers are based on binary networks (BUN or BDN), through a dichotomisation procedure which is far from being neutral.

Several works by Fagiolo and his coauthors (Fagiolo et al. 2009; Fagiolo 2010; Barigozzi et al. 2010)—despite the fact of being applied to another economic issue: namely the network of international trade—extensively showed that the topological structure of the network is highly sensible to the dichotomisation procedure even when the weakest possible criterion (use a value of 1 in the dichotomised adjacency matrix if the correspondent value in the weighted matrix is strictly greater than zero) is used instead of the average value. A more

11 See Sect. 5 for a discussion on the concept of "geographical" versus "relational" neighbourhood.

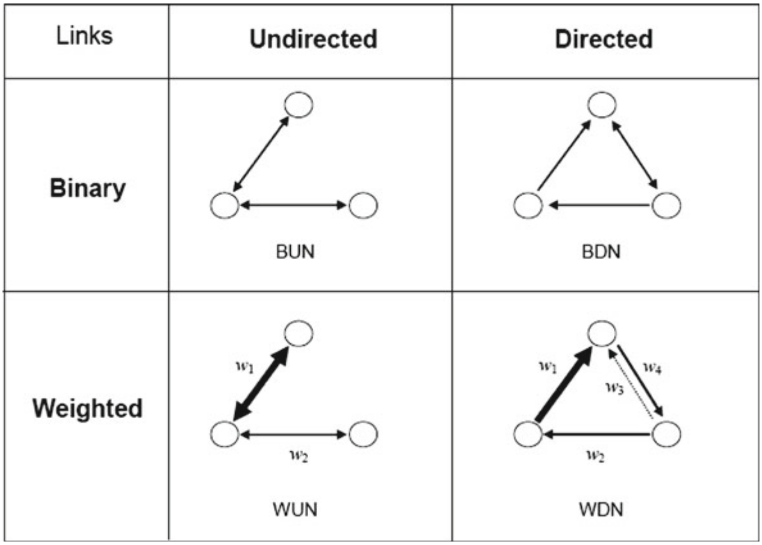

Fig. 2 A taxonomy of networks based on weights and direction of links. *Source:* Fagiolo et al. 2007

correct procedure would imply the performance of a sensitivity analysis on different threshold values before results on dichotomised networks are presented.[12]

The most frequent solution to tackle this problem is to trade off directions against weights of links.[13] In other words it is possible to gain insights on the values of the flows by sacrificing the information on either the direction or the value of links, in order to work on WUN or BDN for which a series of indexes are available.

5 Networks versus geography

This section deals with networks and geography in the analysis of knowledge flows. According to our experience and research history, there are two ways to encompass network and geography: the first puts networks into geography and sees relations as alternative landscapes in which agents act and are conditioned/influenced by the attributional and relational characteristics of their neighbours (thus the definition of neighbourhood becomes crucial); the second puts geography into networks and builds "second level" networks where nodes are geographical (administrative a/o functional) entities.

The fist research strategy sees space as "proximity" and uses spatial econometrics techniques in order to investigate the existence and amplitude of "spatial autocorrelation" phenomena both in the dependent and in the independent variables of a regression model, but allows for different measure of proximity using alternative weights matrices.

The second research strategy sees space as "distance" and assumes that micro behaviours of couplets of actors (at the individual a/o institutional level) are deeply influenced by

[12] This has been performed by Maggioni and Miglierina (1995) when looking at regional innovation systems and Leoncini et al. (1996) when applying input-output and NA techniques to the comparison of the German and Italian technological systems.

[13] In NA literature, there exist also signed ties, assigning positive or negative values to each tie, but we exclude them from this survey since they do not appear in knowledge flows analyses.

unobservable local conditions; thus the need for macro-level network analysis in which "regions" are nodes and gravity models are used to model and test the strength of national and global interactions.

Although for expositional purposes these two strategies have been presented as alternative, in reality they may well be jointly used in order to test the relevance of spatial versus relational neighbourhood effects at the regional level rather than at the individual/institutional one.

In next two paragraphs we detail these different research strategies by referring to several works by the authors dealing with knowledge flows.

5.1 Putting networks into geography (spatial econometrics approach)

In Maggioni et al. (2007) we investigated whether the innovative performance of a region (i.e. the innovative performance of scientists and technologists located in a given region), measured by the number of patent applications, is influenced by "unintended knowledge spillovers" (as mainly argued in the regional science literature.[14]) more than by "intentional knowledge barter exchanges" (as suggested in the economics of innovation literature[15]).

In order to perform such analysis we decided to adapt a "spatial econometric" test based on two alternative weights matrices: one based on "geographical" space; the other based on "relational" space defined in terms of the number of joint research projects that scientists, in a given region, have established with their fellow scientists located in other regions within the 5th EU FP. So, for example, while geography states that Rhone Alpes (F) is close to Piedmont, relations suggests that is closer to Baden Würtemberg (D) and South East (I).

The main methodological problem of this paper concerned the choice of the appropriate weight matrix, a crucial issue in detecting and dealing with the presence of spatial autocorrelation. "Geographical" weight matrices, i.e. matrices that express formally the geographical dependence between couplets of regions, may be built by adopting either a contiguity procedure (where the weights matrix is dichothomic and each cell records 1 when two regions share a border, 0 otherwise) or a distance procedure (where the weights matrix is valued and each cell records the distance among regional centroids.[16]) "Relational" weight matrices, which formally express the relational dependence between couplets of regions, are built on the basis of a relational variable dealing with the science and technology area, but be uncorrelated with the dependent variable.[17] For these reasons we used the participation of institutions, located in the sample of 110 NUTS2 regions, to collaborative research networks financed by the EU 5th FP and we had to solve a complementary problem discussed in Sect. 4 (and illustrated in Fig. 1).

The results showed that although the relevance of spatial autocorrelation was higher when "geographical" weights where used, nevertheless we found also evidence of spatial autocorrelation from a "relational" perspective. However, since the comparison of empirical results obtained using different weight matrices should be taken with care, we decided to perform one additional spatial econometric exercise using another different "spatial" weight matrix

14 See, among the others, Audretsch and Feldman (1996), Gersbach and Schmutzler (1999), Döring and Schnellenbach (2006).

15 See, among others, Breschi and Lissoni (2003) and Moen (2005).

16 In order to test the robustness of our results, we performed the analysis by using both matrices.

17 In the paper the goal was to detect the innovative output of a region measured as the number of patent applications per capita registered by applicants located in any region included.

obtained as a difference between the relational weights matrix and the geographical one.[18] When geography and relations are disentangled as described above, the econometric analysis detected the presence of spatial dependence. In other words, the analysis showed that there was still a "spatial" autocorrelation between "geographically distant" but "relationally near" regions.

5.2 Putting geography into networks (gravity model approach)

A different approach has been followed in Maggioni and Uberti (2009a), in which we investigated the existence of structural difference between 5 different networks of knowledge flows connecting 110 European regions (i.e. digital information exchange transmitted through Internet hyperlinks, EPO co-patent applications, Erasmus students' exchange flows and joint membership in a research networks financed by the EU 5th FP[19]). Here again NUTS2 regions are considered as nodes; however the focus of the analysis is firstly centred on the structural and topological characteristics of the different networks and, secondly, on the role played by distance in shaping the individual knowledge flow linking a couple of regions within a gravity model approach.

It is worth nothing that the relational variables considered in this analysis span the entire spectrum of "relational" aspects of knowledge creation, suggesting alternative ways to detect knowledge trail: from new and immaterial way of information exchange (i.e. Internet hyperlinks), to physical and virtual institution-based interactions built to improve knowledge creation by exchanging mostly codified knowledge (i.e. 5FP Research Networks), to physical and virtual individual-based relationships aimed to develop marketable innovations by exchanging mostly tacit knowledge and know-how (i.e. co-patents applications), to physical movement of people leaving their own region in order to acquire a part of their university education in a foreign institution (i.e. Erasmus students exchange).

In order to "put geography into networks" we decided to analyse these data within a "gravity model" framework, tested using appropriate estimators that take into account the overdispersion of the data. In the original Newton's formulation the gravity law states that every point mass attracts every other point mass with a force which is directly proportional to the product of their masses and inversely proportional to the square of the distance between them. In its international trade version (Tinbergen 1962), the gravity equation predicts that the bilateral trade flow between two countries is directly proportional to the economic sizes (i.e. GDP) of two countries and inversely proportional to their distance.

Since we were modelling interregional knowledge flows embedded within different "media" we decided to enlarge the "traditional" definition of geographical distance including two alternative/complementary concepts: "technological" and "functional" distances. The technological distance measures how different are the technological systems of two regions in terms of innovative capacity (as measured by the Regional Innovation Scoreboard[20]); the functional distance measures how different is the distribution (in terms of industrial sectors) of the manufacturing sector of two regions (and may be considered as a proxy of the regional technological opportunities a/o the absorptive capacities). The results confirmed

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18 By subtracting a geographical contiguity matrix from a relational contiguity matrix we obtain a "purely relational" contiguity matrix which records 1 only for couplets of geographically non-contiguous regions involved in the same collaborative research projects.

19 This issue may generate a number of different network lay-outs according to the representation of how knowledge flows between members of the research networks. Thus, in this paper we examined two extreme representations. More on this point in Sect. 4.

20 Data are available at http://www.proinno-europe.eu/page/regional-innovation-scoreboard.

the validity of the gravity model and showed that geographic, technological and functional distances hinder the transfer of knowledge content (even when flowing through "virtual" infrastructures).[21]

6 Time and networks: studying the evolution of networks

The previous sections, mainly based on our past research activity, describe the relevance of networks for economists, discuss pros and cons of primary versus secondary sources of data, present the issues of modes, direction and weight of links, underline the fundamental interaction of networks and geography for the understanding of knowledge flows but leave two crucial issues unanswered.

The first refers to the process of birth and development of a network, the second concerns the inclusion of individual rationality within the general analytical tools of NA.

Networks, being the results of a series of uncoordinated individual actions and decisions, are not static structures, they change and evolve over time, hence they call for a dynamic analysis.

In the realm of "hard" sciences, the dominant school dealing with networks is the "complex-systems approach" that provides predictions for the evolution of large networks based on stochastic rules on links creation and removal that take into account the features of nodes (i.e. centrality degrees), while neglecting any reference to (economic) individual incentives. "Thus, instead of focusing on understanding the endogenous behaviour of individual agents, the complex-systems approach centers on understanding how the network-formation rules systematically affect the emerging link structure" (Schweitzer et al. 2009, p. 423). In Albert and Barabasi (2002), networks evolution is affected by the so called "Matthew effect", or preferential attachment, for which it holds "the assumption that the likelihood of receiving new edges increases with the node's degree" (Albert and Barabasi 2002, p. 76). According to these class of models, networks are evolving both in terms of addition/removal of edges and nodes respect to the initial network, and these micro changes can redefine the final topology of the network.

In the realm of social sciences, it is possible to identify three different approaches which deals with the study of the evolution of network structures: the *static comparative* approach; the *longitudinal analysis for network analysis* approach, and the *computational simulation* approach

6.1 Static comparative approach

"Classical" applications of NA techniques, with special reference to sociological issues, investigate the evolution of networks mainly applying a *static comparative approach*. In general terms, the theoretical idea is to consider networks as structures evolving in discrete time and to conduct statistical and structural comparison of the same network in different periods of time.[22]

[21] A similar exercise (Maggioni et al. 2007) showed that, in a similar framework, the regional degree centrality in the European collaborative research networks positively influenced the extent of a specific knowledge flow (i.e co-patents).

[22] Several applications of this procedure are applied to networks of trade, see among the others Uberti (1988, 2003), De Benedictis and Tajoli (2009), Maggioni and Uberti (2004), Maggioni et al. (2011b), and Ter Wal (2010a).

In particular this approach can be conducted on three different levels of analysis: changes of the whole network indexes (i.e. density, different centralizations, clustering coefficient, average degree, presence of main components and isolated nodes, etc.), changes of single structural positions of nodes (i.e. measured as different centrality indexes), changes on structural positions of groups of nodes (i.e. cliques, structurally or regularly equivalent groups).

This approach, although very intuitive and easily applicable, has strong limitations since it does not enquire on the determinants of the changes occurring to network structures; it relies on an exogenously determined discretisation of a continuous process (which merely depends on the researcher's decision a/o the availability of data); it is purely descriptive since it does not test any assumption.

A partial possible solution to these limitations implies the use of network indexes as independent variables within an econometric model based on a different temporal configurations of the network and to test whether these coefficients change over time. In Cainelli et al. (2010) some relational variables (i.e. clustering coefficient and the betweenness centrality in the co-authorship networks) are included as regressors in an econometric model aimed at explaining the attributional and relational determinants of the scientific productivity of Italian economists and tested for different time periods.

6.2 Longitudinal analyses (stochastic estimation modelling)

The main scope of this approach is to empirically identify and test those factors that cause the evolutions of networks. Bearing some similarities with panel data procedures, this statistical approach considers data on networks as pooled observations over time periods, with the concern that these observations are not structurally independent.

The main concept behind stochastic estimation modelling is that the change of network structure is related to both current network features and network members characteristics (Stockman and Doreian 1997; Snijders 2005). This methodology is based on so-called stochastic actor-oriented models (and implemented though the SIENA software), in which it is assumed that the network changes continuously as the result of choices made by the individual actors, while the present network structure represents the social context that influences the actors' choices, and changes as a result of them. This approach should allow NA to overcome its typical "case-study approach" and move toward a more general approach where empirical results obtained from several groups can be combined in a meta-analysis or multilevel analysis (Snijders and Baerveldt 2003).

However, due to its recent developments, this procedure has been mainly applied to "pure" sociological issues (i.e. friendship, diffusion of specific behaviours, etc.) and applications to economic databases are still rare.[23] For this reason, in this section we will briefly summarize the main assumptions of this approach in order to highlight possible future applications to the issue at study.

First: since networks change over time, ties are considered states, and not events, i.e. they are not momentary transactions but are characterised by inertia and tend to endure over time. This assumption allows to consider the network as a Markov chain, i.e. "a stochastic process where the probability distribution of future states, given the present state, does not depend on the past states" (Snijders 2009, p. 5). In other words, there is no memory beyond time $t-1$ and this may constitute a limitation when modelling individual a/o institutional behaviour in which long term memory is an essential feature of the decision process.

[23] An exception being Ter Wal (2010b) who applies this technique to co-inventors dynamics in the German biotech industry.

The second assumption refers to the fact that, in each moment in time, only a selected node can: (i) either create a link, (ii) or delete an existing link, (iii) or change its attribute. Thus this approach seems to be suited for the analysis of networks with moderate level of change between subsequent observations with no possibility of modelling radical "innovations/revolutions" happening in a short period of time.

Thirdly, since longitudinal analyses are agent-based models, this implies that each node could unilaterally add, maintain or remove its ties according to its own attributes and to its own knowledge of the network structure. While different matching algorithms are present in the SIENA software to model the possibility of coordination and negotiation among agents as far as the process of establishing a/o severing links is concerned,[24] these are still far from modelling the complexity and variance of mechanisms involved in the real process of links creation and deletion in the different processes of knowledge transfers.

Recently, advances have been made in the methodology (Snijders 2005; Snijders et al. 2010) to allow for a simultaneous analysis of the dynamics of both networks structure and actors' behaviour. In other words it is assumed that while the network changes as a consequence of the actors' behaviour, the individual actor decisions are based on its network position and influenced by the behaviours of his neighbours (Steglich et al. 2005; Snijders et al. 2005). In this case stochastic estimation modelling, as opposed to comparative static analysis, allows for the study of two-way causality between actors attributes and network structure under the headings of "social selection (attributes affect links formation) and social influence (links formation affect attributes)" (Ter Wal 2010b, p. 20).

However since the longitudinal analyses are built on the hypothesis of structural individualism and balance theory, changes in the relational patterns and the individual behaviour of each actor are assumed to be influenced only by its "local context"; therefore limiting the "rationality horizon" of the actors involved.

6.3 Computational simulation approach

The *computational simulation approach* builds "artificial" networks and uses numerical simulation techniques either to identify the best network architecture (*topology*) that allows for the most efficient process of knowledge creation and diffusion; or to study the effects of the individual nodes' decision to use, create, or remove a given link on the network's structure (*evolution*).

Such an approach seems perfectly at easy with the analysis of the structure and evolution of knowledge flows because is based on the intrinsic tacitness nature of knowledge (especially during the initial stages of the invention processes) and whose transmission requires physical and/or cognitive proximity between agents.

The most relevant contributions on the "topological" side of the computational simulation approach (Cowan and Jonard 2003 and Cowan and Jonard 2004) develop formal models that account for the dynamics of knowledge and collective invention, and examine how the architecture of the network of agents influences patterns and rate of innovation. In Cowan and Jonard (2004) they model knowledge diffusion as a barter process in which agents— located on a network and directly connected with few others—trade different types of knowledge when mutually profitable. Here the focus is on the relationship between network structure (along the continuum existing between Ising and Random—RND —networks) and diffusion performance. The results show that the "small world structure" is the most effective

[24] Namely: Forcing, Unilateral initiative and reciprocal confirmation, Tie-based, Pair-wise conjunctive, Pair-wise disjunctive, Pair-wise compensatory (additive).

in diffusing knowledge, while it exhibits the highest variance of knowledge levels among agents, thus signalling the existence of an efficiency-equity trade-off at work. Complementary results are obtained also by Cassi and Zirulia (2008) who explicitly take into account the time horizon of the choice and show that networks characterized by low average distance performed well in the short run, while cliquish networks are more efficient in the long run.

Carayol and Roux (2009) build a bridge between this literature and game theoretical approach to network formation[25] by defining a model, on the basis of Jackson and Wolinsky (1996), in which myopic self-interested agents form costly links to benefit (from positive externality) from agents with whom they are directly, or indirectly, connected in a network. Both costs and externalities depends on the geographic distance between agents. The model determines the structural attributes of efficient and pair wise stable networks according to the knowledge transferability parameter and shows that, for a large region of intermediate values of this parameter, the emergent network structure has a "small world" configuration.

The "evolutionary" side of the computational simulation approach does not take the network structure as given. On the contrary it allows either the structure to be created through the actions of establishing links by each node looking for potential "knowledge partners" within a certain radius of its actual location in the "knowledge space" (see Cowan and Jonard 2008); or to be modified by the use of the existing links which, in turns, modifies the cost of using these links and, consequently, the likeness of a future use of the same link (see Maggioni 2004; Maggioni and Uberti 2008).

The first type of simulation (which has also been used in the context of cluster formation by Maggioni and Roncari 2009) is interesting since it obtains significant results in terms of network structure and topology even if this feature is not part of the objective function of the agents. In Cowan and Jonard (2008) a small world structure emerges as an unintended effect at the macro level of a series of individual decisions taken by agents which are interested only in the knowledge endowment of perspective "partners" with whom they are considering to establish a link. According to such an approach, network structures at the macro level are just consequence of independent individual actions and do not determine the decisions, behaviours and choice of individual actors. The empirical consequences of such a statement would be paramount since in the literature it is commonly assumed that role and position of a node in the networks determine both its behaviour and the behaviour of its (actual a/o perspective) partners.

The second type of simulations (Maggioni 2004; Maggioni and Uberti 2008) aims at showing how network structure may change endogenously and model nodes as mere "crossroads of links". The simulation, firstly depicted in Maggioni (2004), is based on a complete (i.e. with maximum density) network and three simple algorithms: a random generator of couplets; a cost minimization algorithm, which chooses the cheapest between all possible paths connecting the chosen couple, and an evolution algorithm which upgrades the opportunity costs of using certain edges according to the number of times the same edge has been used during previous runs. Aim of this exercise is to show that, even without any attributional difference in the nodes, hierarchy (measured by network centralization) may emerge from the evolution of the opportunity costs involved in the network edges. In particular, when these costs are linear (i.e. transaction opportunity costs decrease steadily with the number of previous interactions), we are modelling a situation in which trust emerges through repeated interactions. Hence we can state that there are constant returns to interactions (CRI) and that the "relational history" (i.e. the number of interactions between a given couplet of node matters (and pays). In such a situation the simulation shows the emergence of an extremely

[25] See Sect. 7.

hierarchical structure of the network (i.e. hub and spokes). When these costs are hyperbolic (i.e. the reduction of the transaction opportunity costs is not constant) we are in a situation of decreasing returns to interaction (DRI). The number of previous interactions (i.e. the relational history of a given couplet) matters (and pays) less and the network evolves toward an intermediated multi-layered structure (with a core—semi-periphery—periphery structure). Finally, when these costs are parabolic, transaction costs are firstly decreasing, then increasing with the number of previous interactions. In this case we are modelling a situation of non-linear (convex) returns to interactions (NRI) which may alternatively describe either a preference for "partner" variation a/o the existence of congestion phenomena of communication channels. The final results of such a simulation is a world of couplets instability and the emergence of temporary leaderships. In other words in any given period there is a structure of hub and spokes, but the node, playing the role of hub, is continuously changing.

In Maggioni and Uberti (2008) the exercise is completed by adding a "simulation prequel" and an "econometric sequel". The "simulation prequel" consists in choosing different initial configurations (i.e. topological structures) of the network before the beginning of the random choice of the couplets; "the econometric sequel" consists in a regression in which the dependent variable is a sort of cumulative version of the betweenness centrality index (i.e. how many times a given node has been "crossed" by the path chosen, because of the costs minimization algorithm, to connect the randomly chosen couplet) and the independent variables are the number of times a given node has been selected as component of the "random couplet" PICK, some NA indexes (such as the degree—DEG—and the closeness centrality indexes—CLOSE –, the clustering coefficient—CLUST) and the value of the parameters shaping the transaction costs evolution (in the linear and the hyperbolic version.[26]) The exercise has been performed on four different initial topologies—Complete Network (CN), Ising (IG), Random (RND) and Small World (SW)—and the resulting estimated parameters have been compared.

In particular, when comparing RND and SW topologies, it is possible to note that while positive in both cases, the PICK coefficient is higher starting from an initial SW topology; CLOSE and CLUST are insignificant starting from a RND topology, while significant in the SW topology; and that the opposite happens when looking at the DEG coefficient. These empirical results therefore show that both the initial conditions and the evolution of transaction costs are extremely relevant in determining the emergence of hierarchy in a network.

7 Rationality within networks

The issue of individual rationality, and especially of the relation existing between individual incentive and overall societal welfare, is almost missing in the NA literature, while it constitutes the object of study of a branch of the game theory literature dealing with "network formation: stability and efficiency"[27] whose aim is to answer questions such as: "How are such network relationships important in determining the outcome of economic interaction? Which networks are likely to form when individuals have the discretion to choose their connections? How efficient are the networks that form and how does that depend on the way that the value of a network is allocated among the individuals?" (Jackson 2004, p. 12)

[26] The non monotonic convex (parabolic) version of the transaction costs evolution has been excluded from this analysis because of the "rotating leadership" outcome.

[27] To quote the title of a well known paper (Jackson 2004).

While this (mostly theoretical) literature, which has developed from the middle of the 1990s, has been recently organized and extensively surveyed in three recent books (Vega-Redondo 2007; Jackson 2009; Goyal 2009), aim of this section is to show what are the possible effects of such a literature on the stream of applied research on the economic geography of knowledge flows.

In particular we are concerned with the endogeneity problem which arises in the econometric analyses of network structures every time that the model assumes that a given performance (i.e. the scientific productivity of a given scientist, or the innovative output of a given region) of a node is a function of some relational variable of the same node (for example its degree centrality index) and it is reasonable to assume that all nodes choose their relational strategy (i.e. to which nodes they want to establish a link) taking into account not only the attributional characteristics of the other $n-1$ nodes, but also some relational features.

In Cainelli et al. (2010) we were confronted with the issue of assessing whether the scientific productivity (as measured by the number per year of articles published by Italian economists in scientific journals indexed in Econlit in the period 1969–2006) is influenced by the co-authorship behaviours of the above-mentioned agents. The endogeneity problems arises if co-authorship influences productivity (as already demonstrated by a vast literature[28]) but also if productivity influences the co-authorship strategies of Italian economists. If this is the case, then it is not possible to use a number of "classical" relational variables (as the numbers of co-authors, or degree centrality index) since they will result in biased and inefficient estimates, due to endogeneity problems. The solution comes from a mixture of econometric "tricks" and NA "subtleties". The econometric side involves the adoption of a IV strategy—i.e. instrumenting the propensity to write co-authored papers with the number of collective volume articles, a proxy of the relational ability of the author, written by each author—the NA sides involves the use of "second order" NA indexes—i.e. indexes that cannot be easily calculated (as the clustering coefficient of the co-authorship network) by the individual author when choosing his/her potential co-authors—as further regressors in the econometric exercise.

A further application of the rationality issue within networks will be dealt in the next section.

8 Conclusion and research agenda

While it is very difficult to summarise such a composite paper in few lines, we would like to use this last section to highlight two interesting lines of research which we haven't so far much explored but we are convinced that are going to produce very interesting results in the analysis of knowledge flows in the near future: the first issue is related to the application of behavioural economics to networks; the second issue is the geographical and relational analysis of words types to link economic concepts and country-based characteristics.

The first line of research concerns a very recent stream of literature—which originated from the seminal papers of Falk and Kosfeld (2003) and Callander and Plott (2005)—designed to assess whether actual people would act as individual rational agents described by the theoretical literature on network formation (Jackson and Watts 2002a,b) when confronted with these kinds of problems.

This stream of literature compares strategies adopted by real agents, when choosing whether to form a link, with "best strategies" identified by game theoretical models and

[28] See, among others: Barnett et al. (1988), McDowell and Melvin (1983), and Hudson (1996).

aims to explain: (i) why agents do not behave as predicted and (ii) what sort of alternative rules a/o heuristics do agents use to guide their actions.

Di Cagno and Sciubba (2008) and Conte et al. (2009) show that agents, when "deviating" from best response, either propose links to those from whom they have received link proposals in the past (reciprocation behaviour) or propose links to those who have a large number of links (hierarchical structuring according to degree centrality).

Even more relevant is the finding that "profits obtained when following these alternative strategies of almost best-response are not very distant from best profits" (Conte et al. 2009, p. 3), thus showing that satisfying behaviours, as those assumed by the evolutionary approach in economics according to the "limited rationality" approach, may well produce empirical evidences at the macro level which have been so far interpreted as confirmations of the "economic orthodoxy" according to the Samuleson (1948) "as if" principle.

As far as the second line of research is concerned, in Maggioni et al. (2009) a meta-analysis on cluster concepts used in economic literature since the beginning of 1970s is conducted to measure the extent of a convergence process of the vocabulary of scientists working on clusters. In particular using correspondence analysis techniques as graphical description of textual elements, the paper investigates the evolution of relationships between specific research topics contained in titles of journal articles (i.e. word types) and specific geographical areas (i.e. countries where authors of papers claim their affiliation)[29] to identify the evolution of cluster concept within this stream of literature. We should stress that the relevance of this analysis is linked to the fact that research interests of a scientist are affected by the social preferences of his/her scientific community.

The balance/trade-off between local and global interactions, between "local buzz and global pipelines" (Maggioni and Bramanti 2002; Bathelt et al. 2004), is one of the crucial issue in science and technology policy and correspondence analysis is useful to detect specialization patterns and the presence of convergence/divergence dynamics of literature on clusters. Results shows that, in general, each national scientific community shows a significant degree of continuity in the choice of research topics and that specialization and differentiation dynamics in the choice of research trajectories by different national scientists' communities coexist. Research communities build their own social preferences (qualitative versus quantitative methods; neoclassical versus institutionalist-evolutionary schools; cognitive versus behavioural approaches, etc.) and their dynamic is strictly connected with these theoretical choices. But at the same time, scientists are often called to confront different (if not opposite) positions in workshops, conferences and journals, and, from these interactions, the robustness of the analyses is increased and theoretical concepts are further refined. This method of comparison of different ideas and knowledge diffusion process produces, in some cases, a strong homogenization of research topics as well as a segregation of original thoughts which cannot be easily integrated in the dominant paradigm. NA of text vocabulary could help to better understand how these global and local interactions are taking place.

In conclusion we are convinced that the interactions of "classical NA" with the "complex system approach" will foster the use and diffusion of relational and structural analysis within the filed of economics with specific reference to the economic geography of knowledge flows.

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[29] An interesting extension of this paper could include the textual analysis of the abstracts.

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