Inf Syst Front (2017) 19:165–185
DOI 10.1007/s10796-015-9591-0

New knowledge in strategic management through visually mining semantic networks

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Published online: 13 October 2015

Abstract Today's highly competitive business world requires that managers be able to make fast and accurate strategic decisions, as well as learn to adapt to new strategic challenges. This necessity calls for a deep experience and a dynamic understanding of strategic management. The trait of dynamic understanding is mainly the skill of generating additional knowledge and innovative solutions under the new environmental conditions. Building on the concepts of information processing, this paper aims to support managers in constructing new strategic management knowledge, through representing and mining existing knowledge through graph visualization. To this end, a three-stage framework is proposed and described. The framework can enable managers to develop a deeper understanding of the strategic management domain, and expand on existing knowledge through visual analysis. The model further supports a case study that involves unstructured knowledge of profit patterns and the related strategies to succeed using these patterns. The applicability of the framework is shown in the case study, where the unstructured knowledge in a strategic management book is first represented as a semantic network, and then visually mined for revealing new knowledge.

Keywords Knowledge representation · Knowledge generation · Strategic management · Information visualization · Semantic networks · Graph visualization

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1 Introduction

In today's highly competitive business world, companies are forced to achieve sustained profitability for survival in the global market and continuously need to dynamically develop the most effective strategies for staying competitive for profitability. To this end, managers should have a comprehensive understanding of the problem domain to make proper decisions, and this makes knowledge one of the most important assets of the company (Grant 1996). Decision making at executive level usually involves a substantial level of vagueness (Elbanna and Child 2007) and complexity rising from organization and environmental settings (Osei-Bryson and Ngwenyama 2008) which should be based on integrated, high quality information (Janjua et al. 2013). Therefore, in positioning the company within the industry, decision makers should consider many aspects, including the environment in which the decision-making speed shapes the performance of the company (Baum and Wally 2003) and the dominant patterns in the environment.

In making strategic decisions, managers retrieve their experience in the field and use their judgments. But when these judgments and the subsequent decisions are incorrect, the resulting strategic mistakes cannot be offset through tactical successes (Barnes 1984). Recovering the destruction and losses caused by misguided strategic decisions is much more difficult and much more costly (if not impossible) than setting up the proper strategy to begin with, because the effects of strategic decisions manifest in the long run (Carroll and Mui 2008). Unfortunately, a deeper understanding of strategic management to develop right strategies is not trivial, and typically takes years to learn and master. Furthermore, managers need to develop a dynamic understanding in strategic management, so they can cope with new situations, or bring novel solutions when faced with recurring situations (Ginsberg 1988; Gary and Wood 2011).

The ability to use existing knowledge and to create knowledge is considered by a number of scholars as the most important source of a firm's sustainable competitive advantage (Zack 2002; Nonaka et al. 2000; Salojarvi et al. 2005). Therefore, managers' skills to derive new knowledge and know-how on strategic management can bring significant long term benefits. "*Organizational knowledge creation*" is the process of making available and amplifying knowledge created by individuals as well as crystalizing and connecting it to an organization's knowledge system (Nonaka et al. 2006). In the meanwhile, a majority of knowledge in an enterprise and in knowledge sources (books, online documents, academic papers) exists in the form of unstructured knowledge, which is knowledge that is not organized in a pre-defined manner and does not follow a data model. The classic example of unstructured knowledge is textual knowledge, such as knowledge available in a book on strategic management. Although extensive literature exists on the strategies that can be applied by managers, the answer to the following question is not clear: "How can new strategic knowledge be methodologically constructed based on existing, and typically unstructured strategic knowledge?" This research question can also be posed as follows: "How can knowledge discovery be incorporated into the knowledge management (KM) supply chain?"[1] This challenging research problem can be resolved by adopting the methods of data mining and information systems, specifically network (graph) visualizations, as illustrated in this paper.

The contributions of the research, in comparison to earlier research, is as follows:

1) A novel framework was developed for generating new knowledge in strategic management. The main advantage of our study over previous proposals is that it enables the generation of new unstructured knowledge from existing unstructured knowledge. Other approaches either do not start with unstructured knowledge, or do not result in unstructured knowledge. This means our proposed framework initially starts with unstructured knowledge and eventually results in novel unstructured knowledge. To the best of our knowledge, our work is the only work in the literature that starts with unstructured knowledge in the strategic management domain and generates new unstructured knowledge for the domain.
2) The proposed framework is based on visually mining semantic networks, which are constructed based on existing knowledge and know-how on strategic management. This approach was not encountered in earlier research in strategic management.
3) To enable the representation of knowledge as a semantic network, a novel knowledge representation scheme was developed and implemented. One novelty of our study is that it encompasses and integrates a multitude of techniques in a coherent framework, rather than applying them in isolation. The most significant challenges in the conduct of our study included the selection of the most appropriate techniques, the integration of techniques as a framework, and the design of the knowledge representation schemes.

The rest of the paper is organized as follows: Section 2 provides a brief review of relevant literature in the field and continues the crucial discussion, the selected information source, the selected methodologies used, and the rationale behind the selections. Section 3 introduces and describes the proposed framework for generating new knowledge in strategic management. Section 4 presents a case study built on the framework using a particular knowledge source and a particular graph visualization algorithm. The various visual patterns observed in the graph visualization are illustrated and the perceptive new knowledge regarding the strategic management domain is explained. Finally, Section 5 summarizes the research and draws conclusive remarks.

2 Literature review

2.1 Strategic management

Properly applied, and in particular types of organizations, strategic knowledge management can make the difference between success and failure.

In the strategic management literature (Cole 1998; Spender 1996, Nonaka and Takeuchi 1995) the knowledge-based perspective refers to the manner of resource combination, an essential function of a company. Moreover, these resources are linked to culture and identity, policies, systems, documents and employees, are considered socially complex and the associated assets have the ability to produce long-term advantages. Knowledge, as the most important strategic resource, can be acquired, integrated, stored, shared, and applied (Spender 1994; Grant 1996).

[1] The reader is referred to Shin et al. (2001) for the illustration of and references to the KM supply chain.

The principal contribution of our study is the proposition and description of an original framework for creating knowledge in strategic management. To this end, our work is an application of information processing methods and network (graph) visualization. To achieve focus and consistency, we decided to select only one of the existing knowledge sources, namely, the profit patterns framework (Slywotzky et al. 1999), as the source of domain knowledge. However, the framework can be applied using other reliable sources of knowledge of strategic management, too: Porter's classic strategy book *Competitive Strategy* is considered by many the reference book on strategy development (Porter 1998). Many other well-accepted strategy works deserve mention, inter alia, Ohmae (1991) & Kotler (2014). Van Assen et al. (2015) present a comprehensive summary of key management models, including those for strategic management.

Seen as a plan of how the organization can achieve its goals (Davies 2000; Mintzberg 2002), or as a "commitment of present resources to future expectations" (Drucker 1999), a *management strategy* is created and applied for one key reason: to ensure long-term sustainability to achieve the principal goals, respectively to offer a solid basis for the decision-making process (Browne 1994; Porter 1988; Robbins et al. 2012). Various forms of knowledge (understanding, insight and experience) have the role to support both decision making and innovation. Hence, company's competitiveness depends on correct and quality knowledge to implement agile and efficient business processes (Kim and Suh 2011).

In recent years, the economy has changed and uncertainty became a medium-term reality; knowledge has a dynamic feature so it needs to be identified, evaluated, acquired, transferred, stored, used, maintained and possibly disposed of (Drucker 1993; Hamel 2002; Nonaka 1991; Pemberton and Stonehouse 2000).

Existing literature highlights a dual relationship between knowledge and strategy. The organization's strategy, performance and results provide input to the firm's knowledge strategy (Callahan 2002; Thorbjørnsson et al. 2004; Zack 2002). Known as an *intellectual capital statement* (Thorbjørnsson et al. 2004), the knowledge strategy defines the actions necessary to ensure the organization's knowledge asset portfolio meets the required outputs. Like competitive strategies, knowledge strategies may be intentional or emergent (Mintzberg 2002).

Functioning together, *knowledge* (for example, Amabile 1998; Sethi et al. 2001) *and strategic orientation* (Grinstein 2008; Im and Workman 2004) are asserted to be two of the most important antecedents to new product creativity. The complexity of the concepts is given by the nature of relationship between them: determination and association. However, the results are organizational development and growth.

2.2 Profit patterns

The *Profit Patterns* book (Slywotzky et al. 1999) is selected as the principal knowledge source of generating new domain knowledge because of several reasons. The book's authors present 30 frequently encountered profit patterns that change the landscape of many industries. Yet, above all, the *Profit Patterns* is selected as the pilot knowledge basis for the case study, because the book is modeled after patterns of profit, and after the business objects, their attributes, and attributes values that signal for the profit patterns. Although the knowledge presented in the book is unstructured, it can be structured easier compared with the content of other sources. The book discusses the strategy rules and outlines the strategy suggestions for each pattern based on the relationships between the mentioned elements. Furthermore, the strategies have been grouped depending on the business functions they belong to. Table 1 illustrates the business functions mentioned in the *Profit Patterns* (Slywotzky et al. 1999) and related departments existing within a typical enterprise (Kotler 2014). The principal step in transforming the book's knowledge into a structured format has been the transition from an unstructured essay style to a structured graph format. This challenge was conveniently resolved through the application of a special mind map, called *Domain Objects Map* (*DOM*).

The book can be considered as a good choice for the study, also because it includes some newly emergent profit patterns (such as "Knowledge to Product" and "Digital Business Design"), as well as classic patterns (such as "De facto Standard" and "Value Chain Squeeze").

While the knowledge contained in the Profit Patterns book was extensive, it did not include the types of insights and the type of knowledge that we have discovered in our research. The knowledge in the book focused mainly on the conditions under which different strategies were the most appropriate. Our research, on the other hand, identifies the strategies that are positioned next to each other on a two-dimensional plane,

Table 1 Business functions in (Slywotzky et al. 1999) and the most relevant departments/business units in a company (Kotler 2014)

Business function	Departments/business units in a company
Product	Purchasing, manufacturing and production, R&D department
Customer	Marketing and sales, customer service, public relations
Knowledge	Information technology, accounting and finance
Value chain	Supply chain and logistics
Organization	Human resources
Mega	Strategic management business development

as well as outlier strategies, which can be easily executed with minimal information. For example, as will be illustrated in Section 4.1, "Reintegration" and "Value Chain Squeeze" strategies are positioned next to each other, and they can be considered together. Hence, our contribution with respect to the generation of new knowledge is not restricted to quantity but also the nature of knowledge.

2.3 Knowledge representation

In our study we apply a graph-based knowledge representation scheme. A graph consists of discrete entities named nodes, and arcs that connect these nodes. Specifically, we represent knowledge as a semantic network (graph), where concepts are shown with nodes and the semantic relationships between the concepts are shown with directed arcs connecting the concept nodes (Sowa 1987; Kamsu-Foguem et al. 2012). Brachman and Levesque (2004) provided a thorough formal treatment of knowledge representation and reasoning. Larkin and Simon (1987) stated that diagrammatic (such as graph-based) representations can be more influential than sensational ones, because diagrammatic representations capture, communicate, and leverage knowledge essential for solving problems. In diagrammatic representations, thinking is varied and enriched through cognitive externalizations (Zhang 1997). Among the knowledge representation schemes, knowledge representation based on graphs has many advantages, especially for modeling the knowledge and facilitating the computations (Chein and Mugnier 2009). On the modeling side, graphs are easily understandable by users because of their descriptive nature; they provide reasoning and they reduce the gap between concepts. On the computational side, graphs construct knowledge of paths and cycles, that do not exist in logical formula representation. Techniques for extracting and analyzing semantic networks can be found in Van Atteveldt (2008) and Goddard (2011), respectively. However, the traditional analyses of semantic networks have not been found to include the use of graph layout/visualization algorithms, so the present paper aims to fill this gap.

2.4 Information visualization and visual data mining

Within the proposed framework, knowledge is represented as a semantic network (graph), and it is analyzed based on the information that has been structured as graph *data*. Data analysis is an indispensable part of applied research and industry problem solving. The goal is to obtain achievable insights into a domain through the multi-faceted study of available data. Fundamental data analysis approaches include *information visualization* (histograms, scatter plots, tree maps, parallel coordinate plots, graph visualization, among others) (Chambers et al. 1983; Hoffman and Grinstein 2002; Keim 2002; Spence 2001), *statistics* (hypothesis test, regression, PCA, etc.) (Wackerly et al. 2008), *data mining* (association mining, etc.) (Han and Kamber 2006; Maimon and Rokach 2005), and *machine learning methods* (clustering, classification, decision trees, among others) (Alpaydin 2009).

The data analysis method applied in our study is information visualization. Information visualization is a rapidly growing interdisciplinary field, which derives from data mining (Han and Kamber 2006), visual arts, communication design, human computer interaction (Schneiderman and Plaisant 2009), and the graphical methods in statistics (Chambers et al. 1983). The aim of information visualization is to make information more accessible and easier to understand by human beings through visualization (Hoffman and Grinstein 2002; Keim 2002; Spence 2001). Information visualization can be perceived as a more general framework compared with data visualization, and has seen remarkable growth in recent years because of advances in computer hardware and software technology, as well as extensive academic and industrial applications.

Many novel information visualization methods are developed continuously, while existing methods are applied in new areas, for innovative applications, or in a wider scope. Lengler and Eppler (2007) presented an integrated view of the various visualization methods, and summarized them as a periodic table. Information visualization and strategy visualization are two of the categories in this periodic table.

Among all the data analyses, information visualization (visual data mining) approach is the one that relies most on the cognitive skills of human analysts, and allows the discovery of unstructured achievable insights through human imagination and creativity. The two principal advantages of information visualization are as follows: First, the analyst does not have to learn any sophisticated methods to interpret the visualizations of the data. Second, information visualization is also a hypothesis generation enabler, which can be, and is typically followed by more analytical or formal analysis, such as statistical hypothesis testing.

The field of information visualization and visual analytics focuses on the integration of human judgment to the analysis of visual representations through interaction. Visual representations of information reduce complex cognitive work needed to perform certain analysis tasks. Yet, in many cases, the human background, knowledge, intuition, and decision-making cannot be automated, and is thus essential. Relying on human judgment is the characteristic of information visualization that distinguishes it from other data mining techniques. The most widely cited and applied method for visual analysis is referred to as the "information visualization mantra", which is "overview first, zoom/filter, details on demand" (Shneiderman 1996).

2.5 Graph visualization

Graph visualization (Delest et al. 2001; Herman et al. 2000), or graph drawing (Battista et al. 1998), refers to the subset of methods (typically graph layout/drawing algorithms) within information visualization specially designed to visualize graphs for knowledge discovery. In the graph visualization literature, particular visualization methods have been and are being developed to enable knowledge discovery based on the structure of graphs.

Graph visualization branches from *graph theory* (Bollobas 1998), originated in the 18th-century work of Euler, and *network research* (Newman 2010), a multi-disciplinary research field dedicated to the analysis of graphs (networks). Network research looks for answers to three families of problems (Christensen and Albert 2007): (1) What are the best metrics that can encapsulate the most salient characteristics of a network? (2) What constraints or processes make a contribution to the way networks grow and change? (3) How does the topology of a complex system affect its dynamics? The present framework is related to the first group of problems. Formal definitions of network metrics and their interpretations can be found in various network research papers (Christensen and Albert 2007; Dorogovtsev et al. 2008; Boas et al. 2008; Strogatz 2001; Newman 2006). In this study, rather than computing the numerical values of the network metrics available in literature, more general, visual patterns are identified at a conceptual level. These patterns, listed in Table 2, are suited for knowledge discovery through human cognition, because they do not require computations, understanding of numerical values, references to benchmark values in other graphs, or even experience with graph visualizations. Thus, having understood these generic visual patterns, any user, including non-technical professionals, can devise new domain knowledge. Still, as shown in Fig. 1, the most appropriate actor in visual analysis is the data analyst that has experience with graph visualizations.

2.6 Applicability of visualization for strategic management

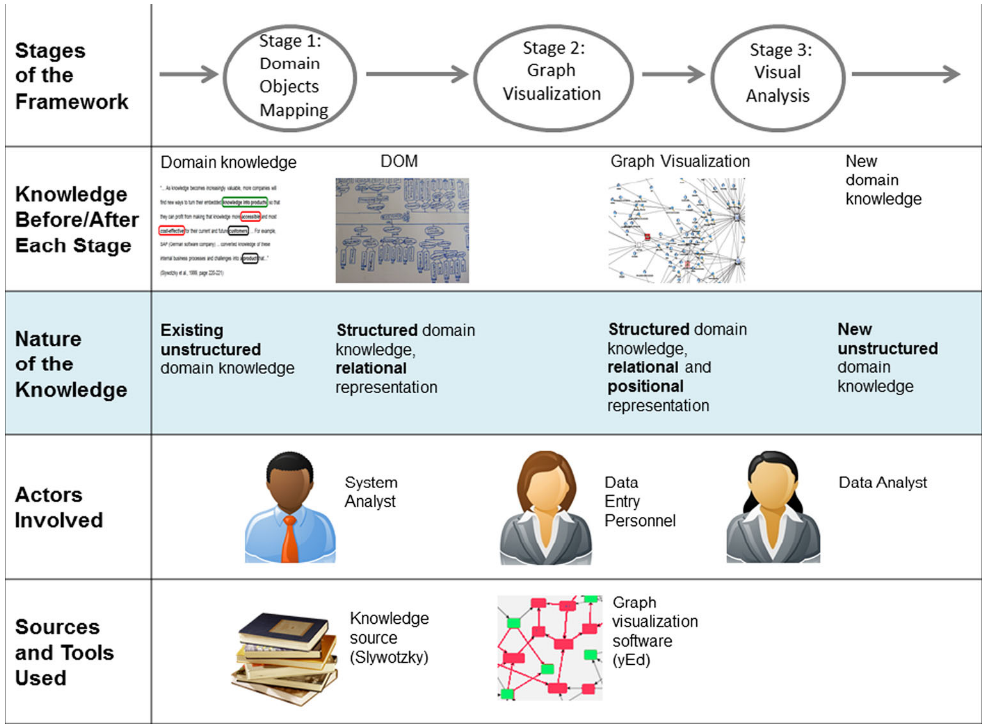
Existing evidence reveals that visualization (Koshman 2006; Ahn and Brusilovsky 2013; Zhang and Zhao 2013) and especially network (graph) visualization (Chen 1999; Lee and Lee 2011) can be applied in knowledge representation and knowledge discovery in information-rich settings. Network (graph) visualizations have even been used to develop a deeper understanding of the sub-fields of information processing (Rorissa and Yuan 2012). Yet, whether semantic networks for knowledge representation and their visualizations are valid for strategic management is an important question. Many academic studies give the answer "Yes". Eppler and Platts (2009) stated that visualization is perceived as a strategy enabler from managers' points of view. The authors discussed the benefits of visualization concerning the strategy challenges. In the framework proposed and illustrated in Fig. 1, visualization is mainly used to help with the challenge of information overload (Leaderer and Sethi 1996; Markides 1999). Visualization also helps solving highly complex problems (Vessey 1991), and discovering data structures and patterns to relieve the information overload (Card et al. 1999).

Many successful industry applications of information visualization have been reported in the literature regarding both strategic management (Eppler and Platts 2009; Pike et al. 2005) and other levels of planning (Cristea et al. 2011; Whyte et al. 2008; Navarro et al. 2008; Jones et al. 2001). Platts and Tan (2004) explained how to use visualization to support strategic decision making. Eppler and Platts (2009) discussed the benefits of representing strategic content visually, and presented a list of cognitive, social, and emotional challenges that visualization alleviates. Our presented

Table 2 The visual patterns investigated in the graph visualization

Pattern id	Pattern name	Gestalt principle	Positional nature	Relational nature
1	Outlier		√	
2	Cluster		√	
3	Gap		√	
4	Proximity	√		
5	Adjacency			√
6	Centrality		√	
7	Confluence		√	
8	Symmetry	√	√	
9	Similarity	√	√	
10	Hierarchy (tree)			√
11	Depth of tree			√
12	Breadth of tree			√

Fig. 1 Proposed framework



framework especially helps with the challenges of struggling with information overload and being stuck in old viewpoints, through facilitating elicitation and synthesis and enabling new perspectives, respectively. Eppler and Platts (2009) reported five case studies from automotive, reinsurance, chemical, finance, and market research industries, illustrating how visual strategizing contributes to strategic management. Two of the case studies reported in Eppler and Platts (2009), namely, TAPS (Two for Action Plan Selection) and Synergy map, are graph-based, similar to our study. Pike et al. (2005) applied information visualization to improve strategic understanding and identify key intangible resources that drive the research and development (R&D) process. The authors investigated three case studies of large R&D organizations, specifically a pharmaceutical company, a human resource training company, and a state-owned research establishment. One of the visualizations employed in their study, namely, the navigator plot, is graph-based as in our study.

In a foresight study, Navarro et al. (2008) used the mind map (a type of semantic network, where concepts are placed hierarchically) (Buzan 1995) to analyze the furniture industry in high-cost countries for maintaining competitiveness against low-cost countries. Jones et al. (2001) adopted mind maps for idea generation about sustainable product design, and their visualization is product ideas tree (PIT) diagram (a graph-based visualization). Cristea et al. (2011) developed a learning technique based on mind maps for representing, learning and teaching the Web development environment within the complex enterprise software SAP. Whyte et al. (2008) explored the different focus in companies using visualization. In two case studies, one about a high-technology equipment manufacturing company, and the other about an architectural design company, they observed that visualization is used for exploitation in the former company, and for exploration in the latter.

Hu et al. (2011) applied graph-based social network analysis to analyze customer-supplier relations in five industries, with the goal of strategy development. Cavdur and Kumara (2014) applied graph visualization to analyze temporal dynamics of companies to identify networks of related companies. Both of these recent studies employ graph visualization and are at a strategic level, alike to our study.

3 A framework proposition

In our study, we propose a three-stage framework for generating new knowledge in a given area, based on existing knowledge. The framework is presented in Fig. 1. The principal idea is to leverage on the existing unstructured or semi-structured knowledge in a given field to capture particular information, then represent it in a structured form as a semantic network, and finally generate new unstructured or semi-structured domain knowledge through the visual mining of the semantic network. Throughout the paper, we apply our framework on strategic management field and demonstrate its benefits for structuring and representing existing domain knowledge. Graph representations have been preferred to text-based rule representations such as the ones in expert systems (Giarratano and Riley 1998). This deliberate choice of graph representation is because of the advantages of visualization discussed earlier. When constructing the DOM, Wertheimer's (1959) Gestalt Principles, Eppler and Burkhard's (2005) knowledge visualization guidelines, and Gavrilova's (2007) ontology design guidelines have been applied. Instead of automatic structuring of the domain knowledge (Clark et al. 2012), the DOM has been constructed manually for maximum accuracy.

Figure 1 shows the activities, knowledge prior and after each stage, its nature, actors involved, sources and tools used at each stage of the framework. These three steps are explained in detail below.

3.1 Stage 1. Object mapping with DOM

The first stage of the proposed framework involves the construction of a domain objects map. DOM is a particular graph specification, introduced by Irdesel (2008) to represent knowledge in strategic management. Irdesel (2008) developed several visual representations, namely, *mind map*, *domain objects map* and *rule map.* Each visual representation is specific to a different stage of the expert systems development lifecycle. The visual representations in Irdesel (2008) are aligned with the goals and tasks of each stage and the technical competencies of the human agents active at that stage.

In our case study, DOM was constructed manually using the unstructured knowledge in the *Profit Patterns* book (Slywotzky et al., 1999) on management strategies for profitability. The scope of DOM building is to represent unstructured domain knowledge as structured knowledge. During this process, the principal concern is to capture field-specific objects with their attributes, sub-attributes and the attribute values and their relationships. As illustrated in Fig. 1, the domain knowledge encapsulated within the knowledge source is in an unstructured format, whereas the same knowledge is represented in a structured format in DOM with the relational representation among the entities within DOM.

First, the relational nature of the unstructured knowledge is reflected as a hierarchical structure in the form of a tree. However, each strategy node can appear several times on the tree as a leaf node, and the business functions that the strategies belong to are not incorporated. Therefore, any visualization at this point would result in a tree with no cycles, still limiting the representation of knowledge to a relational nature. The next stage, Stage 2, enables the display of the positional nature of the nodes, as well.

The following algorithm describes the exact steps of constructing the Domain Objects Map (DOM):

Construction of the DOM Tree

1. Identify the OBJECT described in the strategy selection.
2. Identify the Attribute of the OBJECT, as well as the Sub-attribute, the possible Values of the Sub-Attribute, and the Value of the final Sub-attribute that triggers the suggestion of the Strategy.
3. Draw the arcs for the DOM:

a) From the OBJECT to the BUSINESS FUNCTION
b) From the Attribute to the OBJECT
c) From Sub-Attribute to its Super-Attribute until the final Sub-Attribute.
d) From Values to the final Sub-Attribute.
e) From the triggering Sub-attribute to the Strategy that it triggers.

3.2 Stage 2. Graph visualization

The DOM tree created in Stage 1 is modified by keeping each strategy node unique (to allow cycles). The nodes and the arcs of the graph at this stage are illustrated by Fig. 2, with an example strategy selection rule. At this point, each strategy is represented as a single unique node, and its relationship to the module it belongs is also reflected. The knight icons represent the strategies, the squares represent the objects, the crystal balls represent the business functions, the magnifiers represent attributes and sub-attributes, and the blue balls represent attribute values. The example strategy rule in Fig. 2 states that "IF" in the "**VALUE CHAIN**", the "**Profit**""-**Distribution along the chain**" is "**uneven**" "THEN" the "**Reintegration**" profit pattern can be observed in this environment." ("*If the distribution of profit along the value chain is uneven*, *then the Reintegration strategy can be applied*"). The strategy rule in Fig. 2 also highlights that the "Reintegration" strategy is linked to the "VALUE CHAIN" function (crystal ball) in a company.

The following algorithms describe the exact steps of constructing the Graph for Visualization:

Construction of the Graph for Visualization.

1. While there exists an OBJECT that appears in more than one node
   Eliminate_Redundant_Nodes(OBJECT)
2. For each OBJECT
   While there exists an Attribute of that OBJECT that appears in more than one node
   Eliminate_Redundant_Nodes(Attribute)
3. For each attribute
   While there exists a Sub-attribute of that Attribute that appears in more than one node
   Eliminate_Redundant_Nodes(Sub-attribute)
4. For each sub-attribute
   While there exists a Sub-attribute of that Sub-attribute that appears in more than one node
   Eliminate_Redundant_Nodes(Sub-attribute)

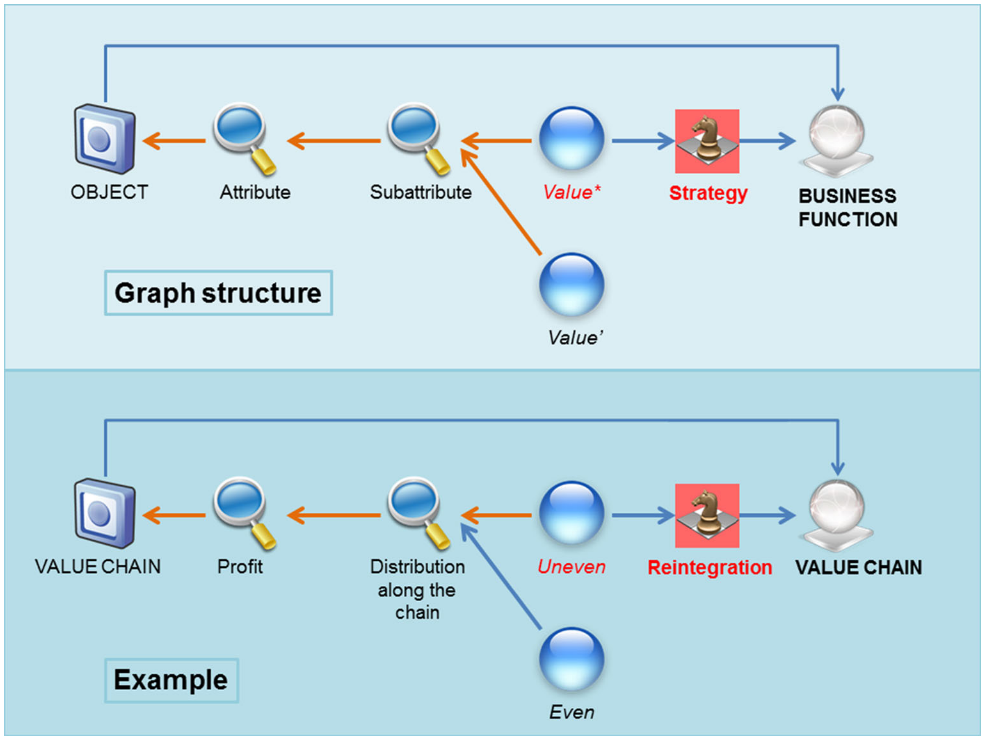


Fig. 2 Graph structure shown with an example

Eliminate_Redundant_Nodes(Node_Name)

a) Select any of the nodes with Node_Name that appear in more than one node.
b) Create a new node with this Node_Name, which will serve as the unique node for that OBJECT.
c) All the arcs to all the different nodes with this Node_Name should now terminate at this new node, rather than the old nodes.
d) Remove all the old nodes with this Node_Name, so that only a unique node remains with that Node_Name.

Once the semantic network is constructed according to the structure in Fig. 2 using a graph visualization software such as yEd (http://yed.yworks.com) or NodeXL (http://nodexl.codeplex.com), the graph is then visualized using appropriate graph visualization/layout drawing algorithm(s). Many layout algorithms with a multitude selection of parameter values have been investigated in the research process. Eventually, the organic layout, constructed using force-directed heuristics (Szirmay-Kalos, 1994), was found the most appropriate visualization/layout algorithm. One major concern in information visualization, and especially in graph visualization, is the scalability of the visualization. This refers to the visualization providing useful insights, even when the visualized information increases significantly. In the case study, the domain knowledge represented as a graph can be visualized in a scalable way, revealing interesting insights. When the knowledge to be visualized is not scalable, it can be decomposed quickly, for example, by identifying clusters in the graph most weakly connected and analyzing each of the clusters.

Some graph visualization methods reveal relational and positional patterns of the nodes of the graph, while others reveal hidden hierarchical patterns. In this study, the former were found the most appropriate in creating domain knowledge. The study uses the yEd software, specifically during the execution of Stage 2 of the framework, and we applied an organic layout. Organic layout applies force-directed algorithms (Szirmay-Kalos, 1994) to determine the positions of nodes on the two-dimensional plane, with the goal of minimizing the number of arc crossings, a fundamental of aesthetics. Detailed discussion and demonstration of force-directed algorithms can be found in Kobourov (2013) and a description of how force-directed algorithms are implemented in yEd can be found within the yEd Manual.

Stage 2 is based on the assumption that rules, which are represented as a graph, will become structured domain knowledge when a force directed (balanced) organic layout is applied. The validity of this assumption will now be discussed. A classic study by Purchase (2000) in the field of human-computer interaction (HCI) investigates the relative worth of graph drawing aesthetics and algorithms. The results of his study show that there is strong evidence to support minimizing crossings. Another study by Dwyer et al. (2009) reports that when humans are interested in extracting insights from a graph, they are primarily focused on minimizing arc crossings. Quigley (2001) suggests that minimizing arc crossings plays crucial role in conveying the information contained in the underlying graph. An experimental study by Vismara et al. (2000) shows that force-directed algorithms are successful in minimizing the arc crossings. Therefore, force-directed layout algorithms, which we applied in our study, are suitable for minimizing arc crossings, improving graph readability, and extracting insights from the underlying graph.

3.3 Stage 3. Visual analysis

The *visual patterns* observable in the graph representations can be classified into two major groups, those with positional nature and those with relational nature. Table 2 lists the visual patterns that were searched for throughout the visual mining in the study. Grouping of the patterns is only for simplification; the positional and relational natures of each of the patterns are crisply distinguished in Table 2. However, because the graph layout algorithm computes the positions of the nodes based on the relationships among them, it is more appropriate to think of each pattern's nature in fuzzy terms.

The definitions and brief explanations of the investigated patterns in the analysis of the graph visualization are presented below. These patterns can be of positional nature, relational nature, or can be a Gestalt principle or combination of those. Gestalt principles are based on visual perception emphasizing that the *whole is greater than the sum of its parts*, which leads to perceptual grouping (Ahokas, 2008).

1. *Outliers* are data points or data clusters, which stand out from the crowd, and are remote from the central clusters and points.
2. *Clusters* are formed when a set/group/cluster of data points are positioned close to each other, but apart and somewhat disconnected from others, on the graph.
3. *Gap* pattern exists when two clusters or set of points are distant from each other, with a large space between, forming a gap.
4. *Proximity* refers to the positional proximity of a group of data points without requiring them to be aside from the remaining points (as is the case in the cluster pattern).
5. *Adjacency* pattern refers to the likeness of two points, because of their relational nature, such as a node being adjacent to another because of a relationship between. Although adjacency enforces some degree of positional proximity, its principal nature is relational, rather than positional.
6. *Centrality* pattern reveals the localized central data points. These locally centered nodes can give us the information how it is connected to the neighboring nodes and how they are related in the influence zone.
7. *Confluence* pattern is the centrality property on a larger, complete graph scale. Confluence refers to the global centrality, the centrality of several centralities.
8. *Symmetry* pattern appears with balanced proportions, through similar arrangements in the opposite sides perceived to be composing a group of their own.
9. *Similarity* pattern emerges when data points that have similar properties in color, shape, attribute or icons are perceived as similar nodes.
10. *Hierarchy* pattern observed in graph visualization indicates the absence of cycles.
11. *Depth of Tree* pattern is directly related to how many levels a tree branches out.
12. *Breadth of Tree* shows how many sibling nodes a tree graph has at the same level.

The pattern library in Table 2 lists the patterns associated with the presented framework and domain, and does not aim at covering the patterns in every type of visualization within the periodic table of Lengler & Eppler (2007). Other Gestalt principles not included in the list of patterns in Table 2 include; *common fate*, not relevant, because there is no direction of movement in the DOM; *continuity* is also irrelevant, because the information visualized consists of discrete entities (objects, attributes, values, strategies, modules) rather than continuous data; *closure* is insignificant, because there are too many cycles (closed contours) in this paper's visualization that cannot be distinguished; *common region* is also unimportant, because nodes are not regulated through any type of boundaries.

Our proposed framework suggests that the above patterns are visually searched on the graphs with the goal of discovering new knowledge.

4 Case study

In this section, we illustrate how various types of new knowledge can be discovered through the visual mining of semantic networks. One can discover one or more visual patterns from a particular section of the visualization, and interpret them to devise new knowledge. This process is shown in the following subsections. The newly generated knowledge is validated logically as a part of the visual data-mining process, and the managerial implications are discussed.

The knowledge representation requires a list of strategy rules to begin with. These strategy rules have to be extracted from the knowledge source and should use a common vocabulary. For example, the VALUE CHAIN object should have the same name in all the rules that contain it, despite the module that the rule belongs to. Figure 3 illustrates the set of rules for the profit patterns/strategies "Reintegration" and "Value Chain Squeeze" and their explanations. Figure 3 displays the abstract form of the rule, based on object-oriented syntax. The objects are shown in parenthesis and in capital letters; attributes and sub-attributes are shown in parenthesis and sentence letters; attribute values are shown in quotes; profit patterns (suggestions fired by the rules) are shown in brackets. Next, the rule is explained using a semi-natural language to illustrate their semantics. Once the rule set is given, the DOM graph is constructed using the scheme in Fig. 2.

4.1 Graph visualization scheme

The analysis and results in the case study are based on the graph visualizations for the profit patterns Slywotzky et al. (1999), constructed using the organic layout algorithm within yEd. Our presentation in this section is a case study that involves a particular knowledge source and a particular graph visualization tool. One can use other knowledge sources (data) or other graph visualization systems (method) or both, and obtain new insights using the same framework. The visualization we discuss here can be requested from authors and new insights, besides the ones presented, can be discovered by anyone. Figure 4 shows a snapshot from the graph visualization.

In the visualization, strategies are colored in tones of red, and the density of the red color denotes the recentness of the particular strategy for visual easement and differentiation. For example, the "Vertical Integration" strategy is known since the 19th Century, when Andrew Carnegie introduced the strategy in the steel industry. However, the "Reintegration" strategy emerged only after the widespread use of information technologies and thus it is represented in dark red. "Reintegration" is a popular pattern in diverse industries, from furniture to oil refining. When manufacturers need to increase their return on investments, it may be necessary to reintegrate their value chain partially. Consequently, when value moves from one value chain to another, reintegration is inevitable to sustain strategic control.

Figure 4 describes how the semantic network was constructed, and how it can be interpreted. Items are identified as regions, and each is explained as follows:

a) Arcs are drawn according to the scheme shown in Fig. 2.
b) For example, the arc of "Reintegration" strategy directly reaches out to the (crystal ball icon) node VALUE CHAIN, which represents the value chain function within a company. In the companion website for the *Profit*

Rules for the "Reintegration" Pattern

```
IF (VALUE CHAIN).(Customer Relevance).(Relation among the chain steps) = "Benefit shift" OR
IF (VALUE CHAIN).(Supply chain).(Channel partners)="Inefficient" OR
IF (VALUE CHAIN).(Supply chain).(Suppliers)="Weak" OR
IF (VALUE CHAIN).(Profit).(Relation among the chain steps)="Benefit shift" OR
IF (VALUE CHAIN).(Profit).(Distribution along the chain)="Uneven" OR
THEN
[Reintegration]
```

Explanation of the Rules for the "Reintegration" Pattern

```
IF in the "VALUE CHAIN", with respect to "Customer Relevance", "Relation among the chain steps" exhibits "Benefit shift" OR
IF in the "VALUE CHAIN", the "Supply chain" formed by the "Channel partners" is "Inefficient" OR
IF in the "VALUE CHAIN", the "Supply chain" has "Suppliers" that are "Weak" OR
IF in the "VALUE CHAIN", with respect to "Profit", "Relation among the chain steps" exhibits "Benefit shift" OR
IF in the "VALUE CHAIN", the "Profit" "Distribution along the chain" is "Uneven" OR
THEN
The "Reintegration" profit pattern can be observed in this environment.
```

Rules for the "Value Chain Squeeze" Pattern

```
IF (VALUE CHAIN).(Effect on offerings)="Increased commoditization" OR
IF (VALUE CHAIN).(Competitive spirit)="Highly competitive" OR
IF (VALUE CHAIN).(Possibility of producing sufficient earnings)="Not possible" OR
IF (VALUE CHAIN).(Possibility of profit growth)="No opportunity" OR
IF (VALUE CHAIN NEIGHBORS).(Differentiability)="More" OR
IF (VALUE CHAIN NEIGHBORS).(Players)="Consolidated in adjacent value chain steps" OR
IF (VALUE CHAIN NEIGHBORS).(Financial condition)="Stronger" OR
IF (VALUE CHAIN NEIGHBORS).(Size)="Larger" OR
THEN
[Value Chain Squeeze]
```

Explanation of the Rules for the "Value Chain Squeeze" Pattern

```
IF in the "VALUE CHAIN", the "Effect on offerings" is "Increased commoditization" OR
IF in the "VALUE CHAIN", the "Competitive spirit" is "Highly competitive" OR
IF in the "VALUE CHAIN", the "Possibility of producing sufficient earnings" is not there, "Not possible" OR
IF in the "VALUE CHAIN", with respect to the "Possibility of profit growth" there exist "No opportunity" OR
IF among the "VALUE CHAIN NEIGHBORS", "Differentiability" is "More" OR
IF among the "VALUE CHAIN NEIGHBORS", "Players" are "Consolidated in adjacent value chain steps" OR
IF some the "VALUE CHAIN NEIGHBORS" have "Financial condition" significantly "Stronger" than others OR
IF some the "VALUE CHAIN NEIGHBORS" have "Size" significantly "Larger" than others OR
THEN
The "Value Chain Squeeze" profit pattern can be observed in this environment.
```

Fig. 3 The rules for the profit patterns/strategies "Reintegration" and "Value Chain Squeeze" and their explanations

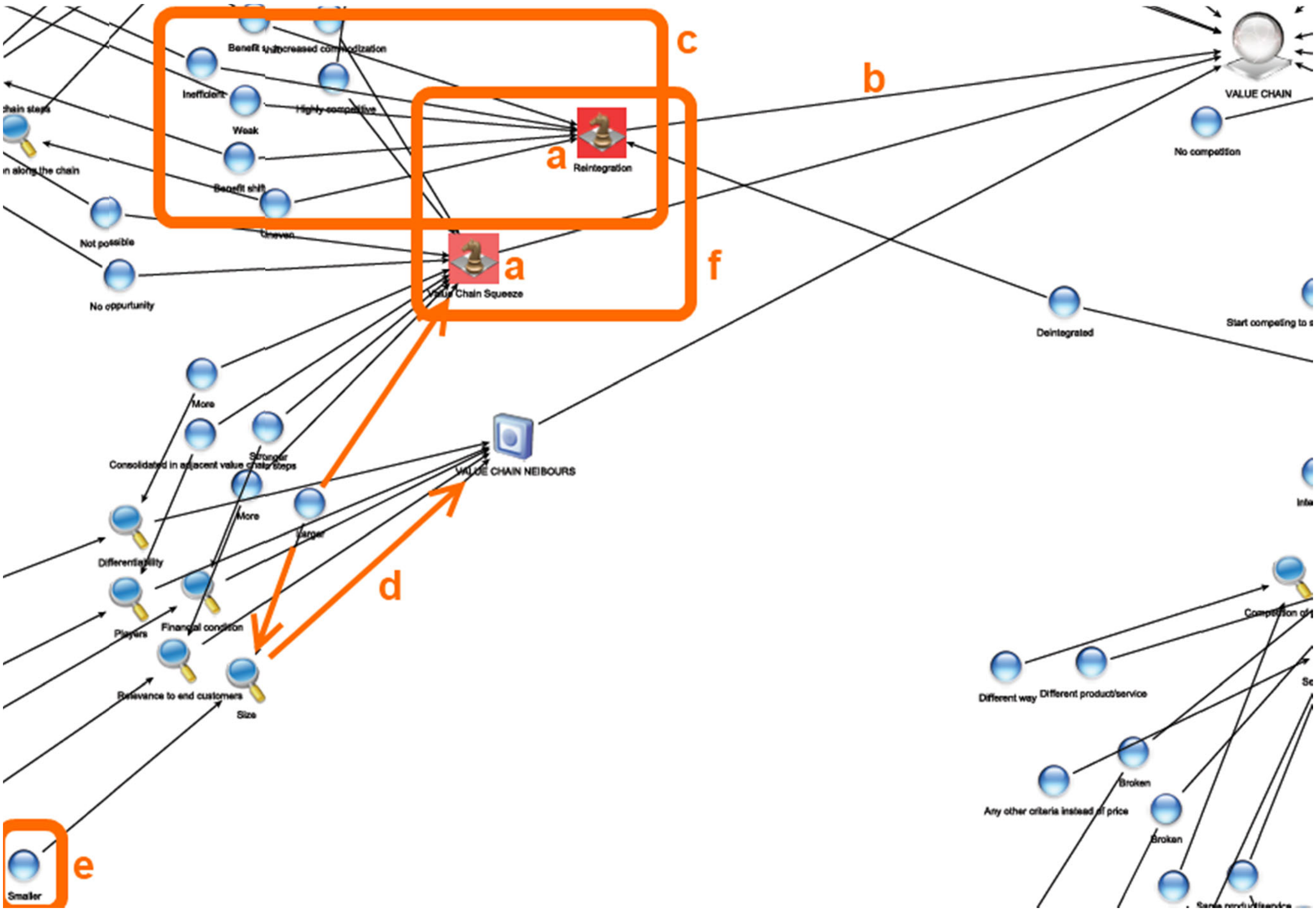


Fig. 4 Graph visualization scheme

Patterns book, the strategies were categorized under the business functions they relate to. This is reflected by directed arcs in our graph with an arc from a strategy into the business function (crystal ball) that it relates to.

c) The arcs that terminate in the strategy nodes (knights) emerge from attribute value nodes.

d) If the Size (magnifier) of VALUE CHAIN NEIGHBOURS (square) is Larger (blue ball), then one should consider "Value Chain Squeeze" strategy (knight). This pattern can occur because of the rising power of the close suppliers and customers. This would result in a squeeze in the business where the company and its competitors operate, and a diminishing of the profit growth prospect. To profit, performance should be improved faster compared with the neighbors and the competitors' performance should be slowed-down by supporting new companies.

e) If the attribute value is Smaller, this does not suggest a strategy.

f) The visualization reveals that the two strategies of "Reintegration" and "Value Chain Squeeze" are relatively close to each other, and form a cluster.

4.2 Outliers and clusters

Figure 5 reveals the information that VALUE CHAIN and VALUE CHAIN NEIGHBORS objects are outlier objects, because of their distant positions compared with the other domain objects. The entities connected to these two objects form a cluster and are interconnected with many arc connections. This means that the strategies involving these two objects (concepts) are much more closely associated than the other business functions.

4.3 Proximity

In Fig. 6, one can find the classic strategy of concentration in proximity to a new strategy, "Reintermediation". This suggests that if a company has been applying "Concentration" strategy in the past, it should explore the possibility of applying the more novel "Reintermediation" strategy. The reason that these two strategies are near each other is because of relational proximity. The layout algorithm translates relational proximity into positional proximity, which enables the discovery of this insight, and forthcoming others.

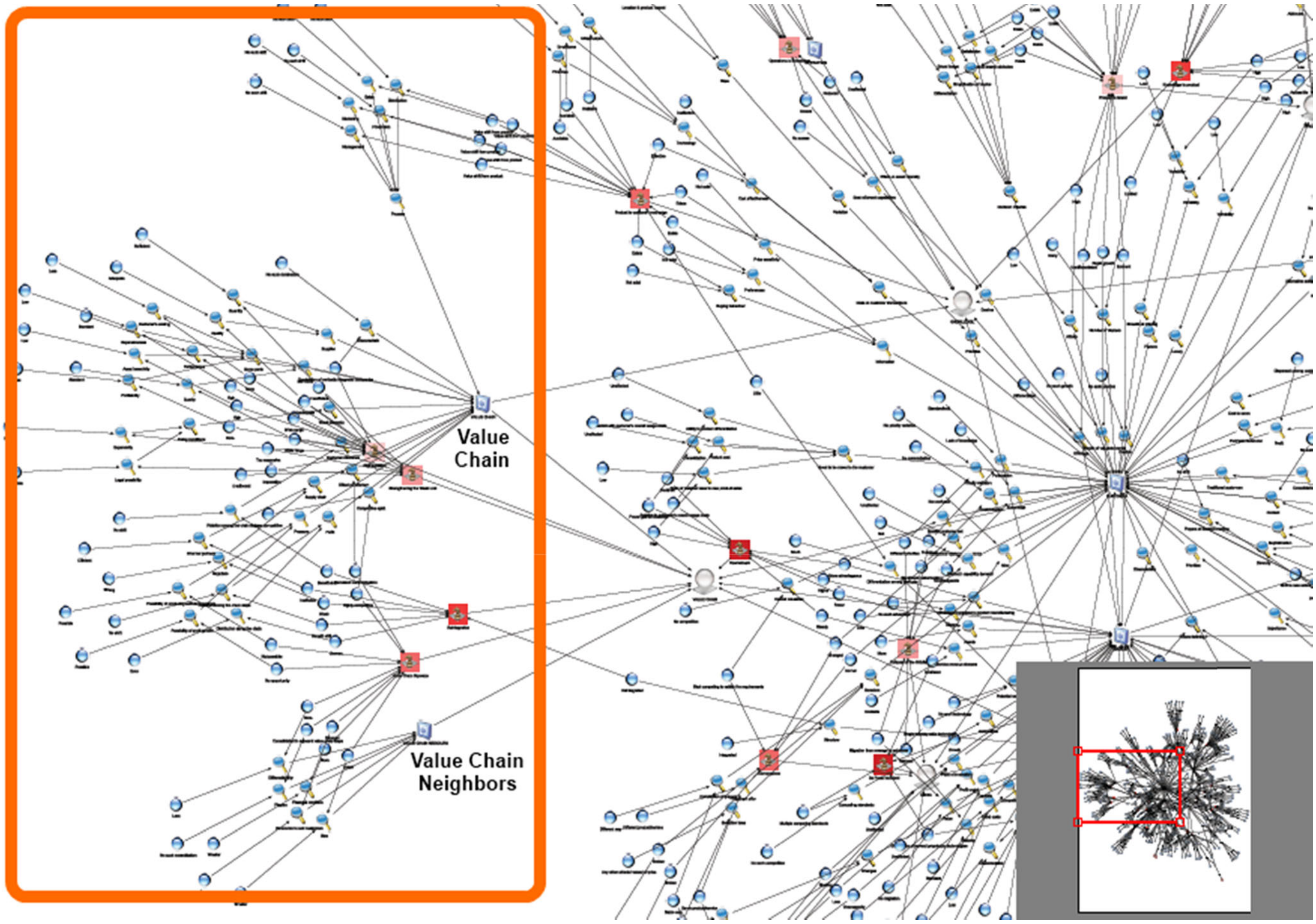


Fig. 5 Outlier objects

"Concentration" strategy can be summarized as "from many to fewer": the small decomposed shops and service offerings are combined into larger ones by innovators. Some companies that have succeeded with "Concentration" strategy are Carrefour France, BlockBuster, and Barnes & Noble. Implementation of this strategy leads to better selection of products, more shopping convenience, improved service and price for customer.

"Reintermediation" strategy, on the other hand, aims at creating a new value-added step in the system. Intermediaries result from the direct relationship between supplier and customer. Transformation of many-to-many relationships into many-to-one for both the suppliers and the consumers exist. This strategy has been applied successfully by Charles Schub Company (Slywotzky et al., 1999). Therefore, in "Reintermediation", there is an elimination of value chain complexity by adding a new intermediary node. This strategy provides the customer with efficient means of transacting with the company.

Figures 7 and 8 provide other insights for which strategies can be considered about each other, though they were not declared to be so in Slywotzky et al. (1999).

In Fig. 7, "Back to Profit" strategy is positional proxy to the "Cornerstoning" strategy, suggesting that a company readily implementing one of these strategies can consider the other. "Cornerstoning" strategy provides to find the best next direction that the organization should take. In "Cornerstoning" strategy, company must be already at a good strategic condition and experiment to find the next-best direction.

The two mentioned strategies in Fig. 8 go hand in hand in various business functions. This is an insight that does not exist in the *Profit Patterns* book. "Compression" strategy eliminates the redundant stages throughout the CHANNEL, such as eliminating the intermediation that can bring proportional performance improvements.

The insufficiency of current business designs to meet the changing concerns in the market, such as consumers' search for lower prices and greater ease, has caused compression or disintermediation of conventional supply channels for the benefit of more efficient, closer, or even direct relationships between customers and suppliers. Consequently, some steps in the distribution system are removed or replaced. For example, customer dissatisfaction and inefficiency are transformed into customer satisfaction and streamlined delivery.

Because of the advances in technology, conventional businesses are transformed into digital ones, which

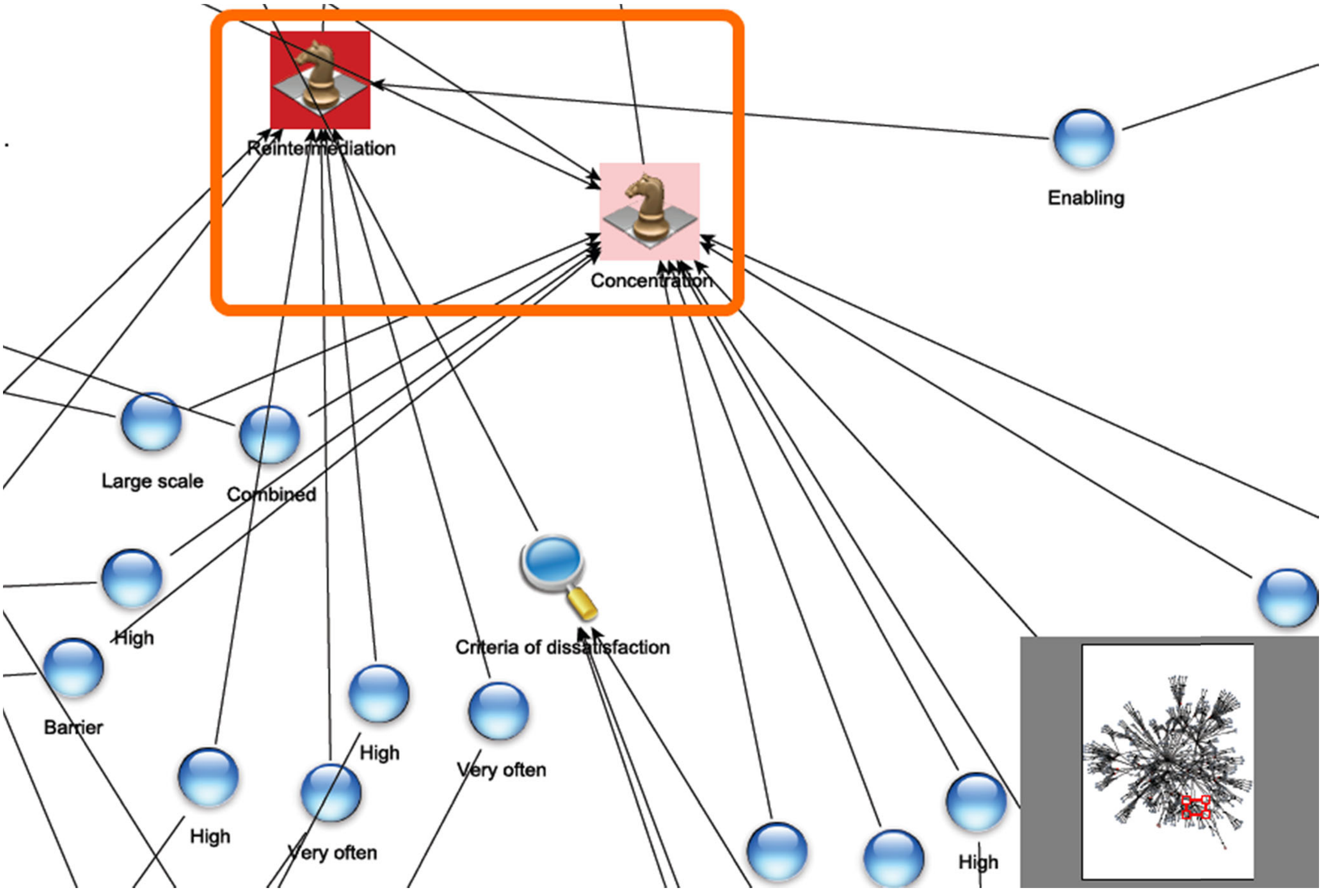


Fig. 6 Proximity of "Reintermediation" and Concentration" strategies

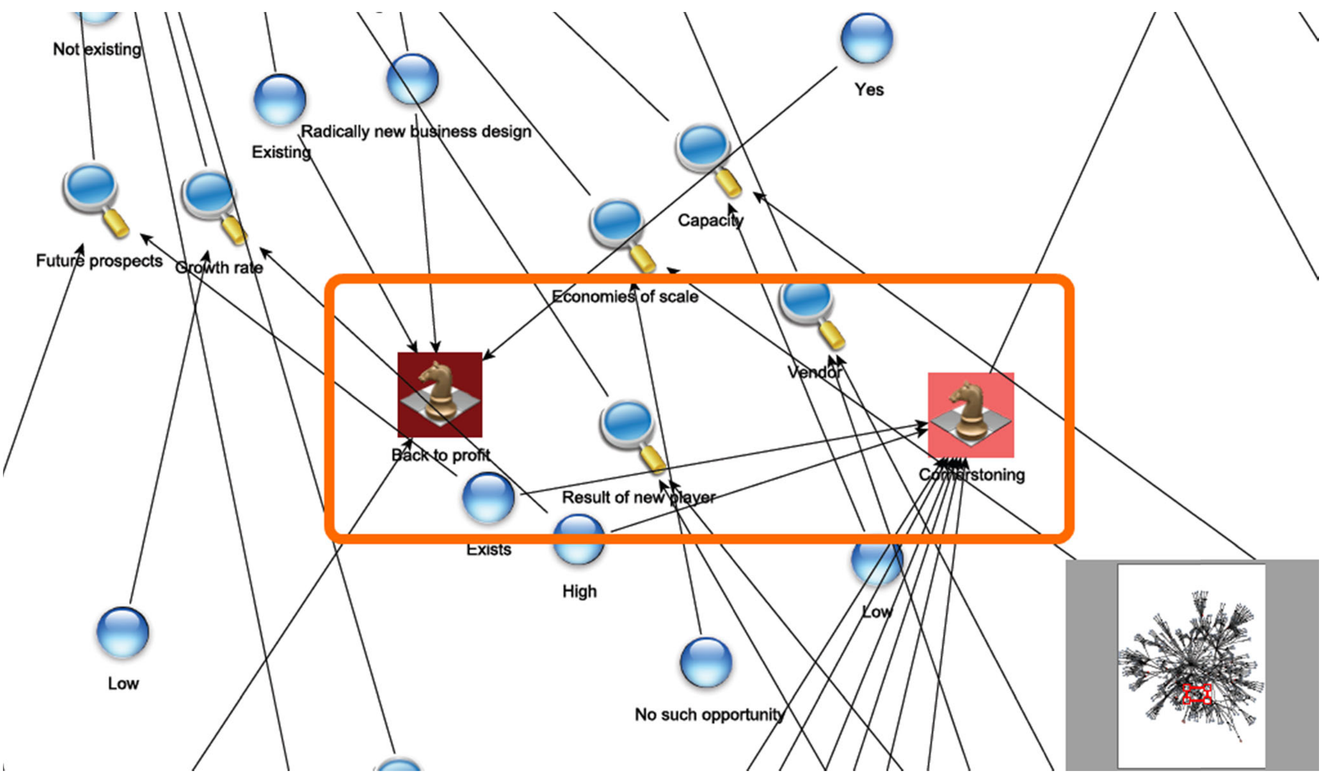


Fig. 7 Positional proximity of "Back to Profit" and "Cornerstoning" strategies

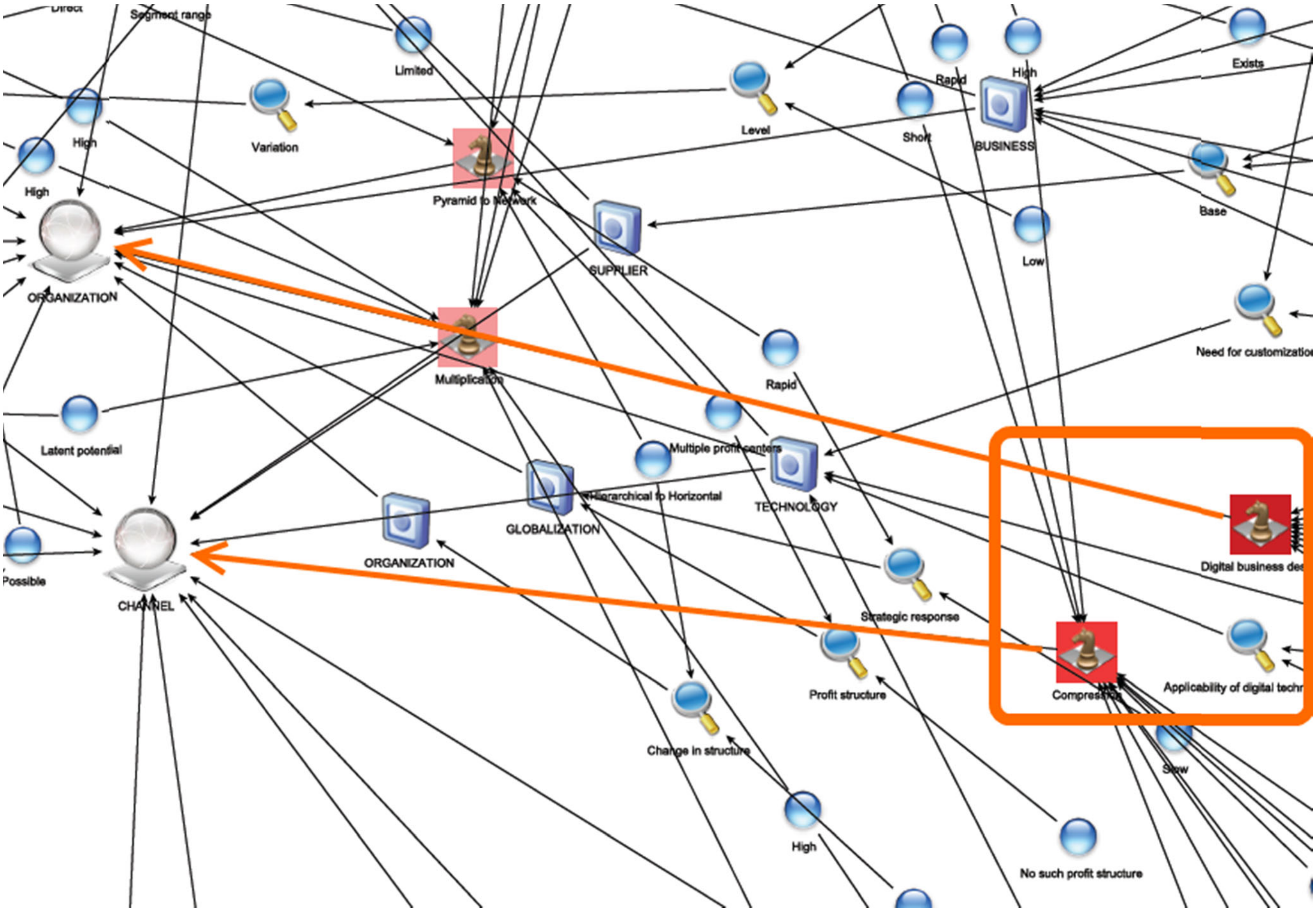


Fig. 8 Positional proximity of “Digital Business Design” and “Compression” strategies, which belongs to various business functions

provide huge advantages for the organizations with new networking structure and digital business setup. This pattern requires organizations to shift their state of mind and actions primarily forcing organizations focus to basic business matters and transform them into electronic platforms. In this pattern, profit is obtained through new interactions with the customers.

Therefore, within the ORGANIZATION, The “Digital Business Design” strategy eliminates redundant processes, and achieves an order of magnitude performance important through a fundamental conversion of physical requirements (ex: human beings, machines, among others) into electronic form. These are especially the data and the software, which have practically infinite multiplicity at next-to-zero cost per new unit generated.

4.4 Outliers and depth of trees

Several new types of insights can be obtained from other regions of the graph visualization. In Fig. 9, one can discover the following two insights:

a) Something peculiar occurs with the “Product to Blockbuster and “Product to Profit Multiplier” strategies. To decide on whether one of these strategies should be applied, we need to consider many attributes of a single object. The object attributes that one has to consider before selecting this strategy are completely independent from the object attributes that need to be considered for other strategies. Now let us focus on the nature of these strategies.

In the settings for the “Product to Blockbuster” strategy, because of weakening economics of development and production with the increased diversity in the outcomes for any product, in many industries imbalance has occurred. Rather than a balance portfolio of products, a few blockbuster products are now making the profit. In this pattern, companies should operate to transform the system into a well-developed and cultivated one that would enable them to create stable sequence of blockbusters and thus make profits.

The companies that successfully analyze and identify the way their customers perceive their superior product, service, brand, among others, and effectively reuse those to create remarkable value have activated the “Product to Profit Multiplier” pattern. With this pattern, instead

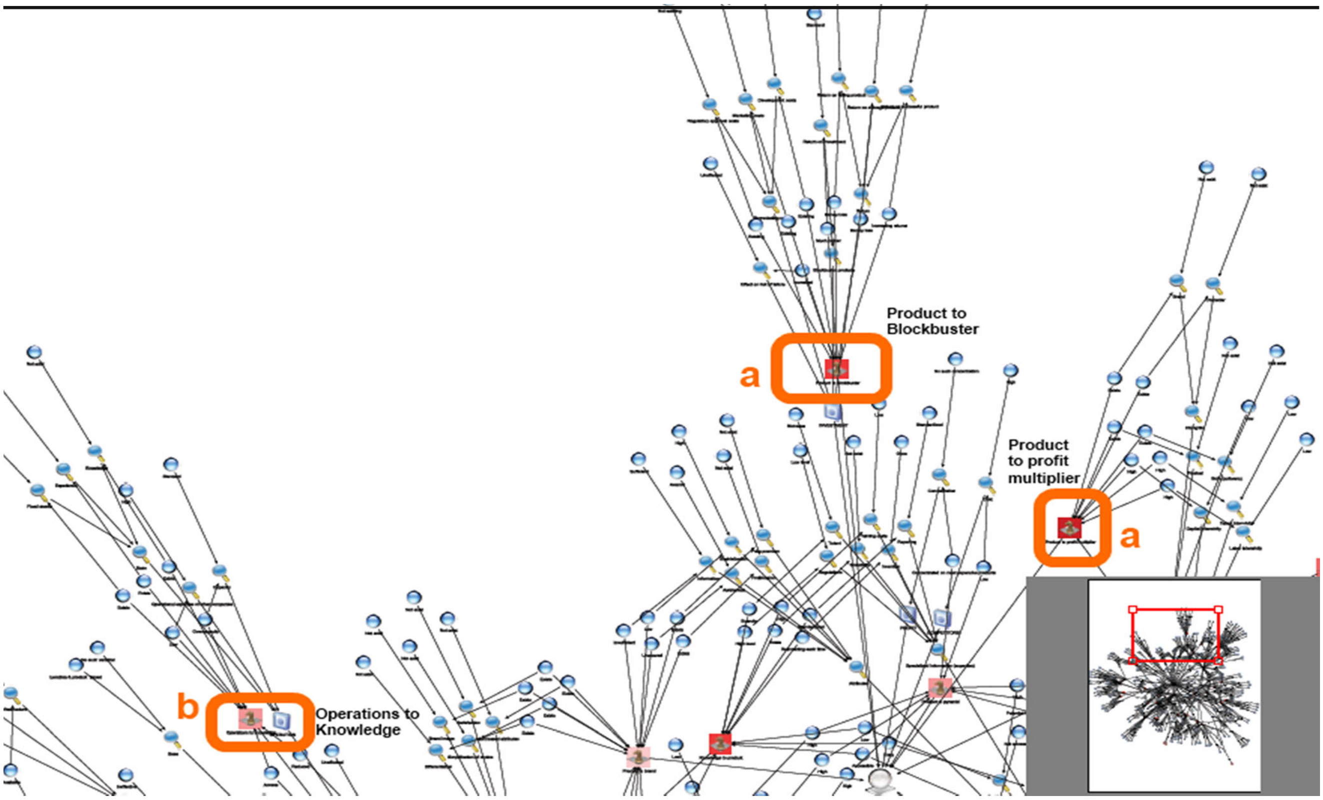


Fig. 9 Outlier patterns, where depth of the sub-tree is observed

of a single product, what makes the maximum profitability is now a system that reuses that product many times. Companies must find all the possible ways their product, brand, or skill can be sold, then select the most suitable ones to build a system; so they can make profits.

b) "Operations to Knowledge" strategy implies the strategy of profiting from the knowledge obtained from operations, shifting the profit. In Operations to Knowledge strategy, profit moves from goods to knowledge-based actions, which can create excellent profits though it is not realized commonly by asset-intensive companies because of a limited mindset. In this strategy, to profit, distinctive knowledge should be created from the existing business actions and a way to market and sell this knowledge should be built. This strategy is affected only by the attributes and attribute values of OPERATIONS object and by the two attribute values, "Reduced and Access", of the object CUSTOMER. The implication is that, to proceed quickly with strategy selection, one can start with these outlier strategies, because the decision of whether to apply them is based on minimal information, with minimal interaction with other strategies.

All the three strategies observed in Fig. 9 are outliers. This visual pattern can be detected through observation of the subtrees that branch out from the principal body of the semantic network. These strategies require only a small amount of information to devise a decision. When deciding the strategy, we need to consider only a few attributes of a single object, or only a few attributes of another object.

4.5 Clusters and proximity

Figure 10 illustrates several other clusters, showing the proximity pattern and forming a larger combined cluster, enabling us to develop a new understanding for strategic management:

a) We can apply the "Redefinition" strategy in the CUSTOMER related business functions, and "Skill Shift" strategy in the ORGANIZATION function.

"Redefinition" strategy suggests re-description of the customer based on various aspects such as segments, value chain participants, influencers, new decision makers and new entrants so the business can be shifted to the most profitable customer group.

In "Skill Shift" strategy, to pursue new profit, a company may move its focus to one of its key functions through processing and evaluating huge amount of data or alter its technical or managerial skills within the functions. This strategy is applied based on the industry's speed of change; in slower industries is it rarely applied while in faster industries it is more common.

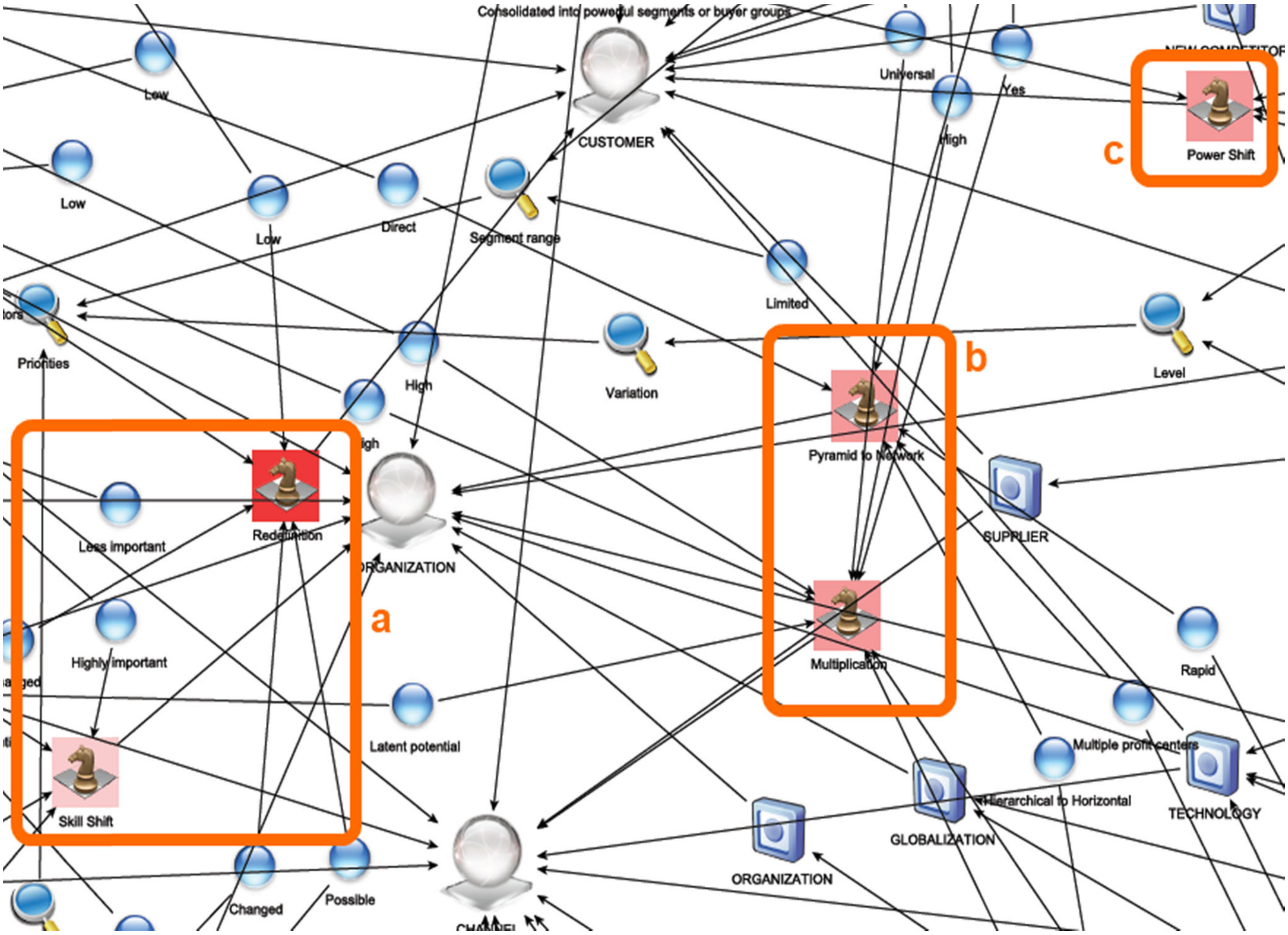


Fig. 10 Several clusters of strategies

b) Similarly, "Pyramid to Network" strategy in the ORGANIZATION function can be coupled with the "Multiplication" strategy in the CHANNEL related business functions.

Just focusing on internal functions of the company is dangerous. In "Pyramid to Network" strategy, companies increase their focus to their external environment more and perform all necessary changes in organization to increase their profit. Based on this strategy, all the deficiencies created by success, growth and size are defeated.

"Multiplication" strategy results from market conditions like customer type. When customers differ with buying behavior, options and preferences, the company should respond by searching for new business channels to profit.

c) "Power Shift" strategy (in the CUSTOMER related business functions) is also close to the four mentioned strategies.

When a supplier cannot answer the changing requirements of the purchasing groups or cannot offer different products or services to the customers, "Power Shift" strategy would be employed. In this pattern, companies should either re-specify the customer or re-stabilize the power equation to profit.

As the three clusters in Fig. 10 are proximate to each other, forming a larger combined cluster, suggests that one can consider not only the most proximate managerial strategies, but also those in the larger cluster. For example, a company successfully applying any of the five strategies in Fig. 10, such as skill shift, can consider any of the other four, such as "Multiplication". Furthermore, the distance on the visualization also suggests a natural ordering in which the proximate strategies within the larger combined cluster can be prioritized. For a company applying skill shift, the next four strategies that can be considered based on proximity are, in order preference, "Redefinition", "Multiplication", "Pyramid to Network", and "Power Shift".

4.6 Proximity and symmetry

Figure 11 reveals another type of insight, which may have been deduced logically, but can be observed easily: Two neighboring strategies of "Product to Brand"

and “Knowledge to Product” are both related to product development, and they can be applied simultaneously in the two business functions of PRODUCT and KNOWLEDGE, respectively. As well as being proximate in the visualization, these two are symmetric strategies because they apply symmetrically in two business functions.

The increased number of products with low differentiation raises buyers' confusion extensively. “Product to Brand” strategy aims to increase customer satisfaction by drifting focus from product to brands, which increases differentiation and customer satisfaction. Therefore, to profit, the focus should be on recognizing customer needs through creating worthy brands.

In “Knowledge to Product” pattern, knowledge, which is subtle and inaccessible is converted into a product so it generates importance to customers and suppliers. Companies increase their profit through transferring their most key knowledge into sellable, improved products.

5 Conclusions

The present study proposed a three stage framework for generating new strategic knowledge from existing knowledge. The goal of the framework is to create unstructured knowledge through the visual mining represented in graph visualizations.

In the first stage of the framework, a visual representation of the domain objects, namely, DOM, is constructed using unstructured knowledge on strategic management. Unstructured knowledge is displayed in a structured format as a semantic network/graph, which depicts domain-specific objects with their attributes, sub-attributes and the attribute values and their relationships. The network has then been modified to include unique strategy nodes and visualized with graph layout software. The relational and positional patterns in the graph enable the discovery of new unstructured knowledge through visual insights. The study of Gavetti (2011) on the psychology of strategic leadership emphasizes the importance of associative thinking as opposed to logical, deductive thinking. Our study enables the discovery of not only associations, but also many patterns for the domain of strategic management.

In the framework-included case study, new unstructured knowledge has been generated for the strategic management domain, using existing unstructured knowledge. In the case study, the proposed framework has been applied for the profit patterns described in Slywotzky et al. (1999).

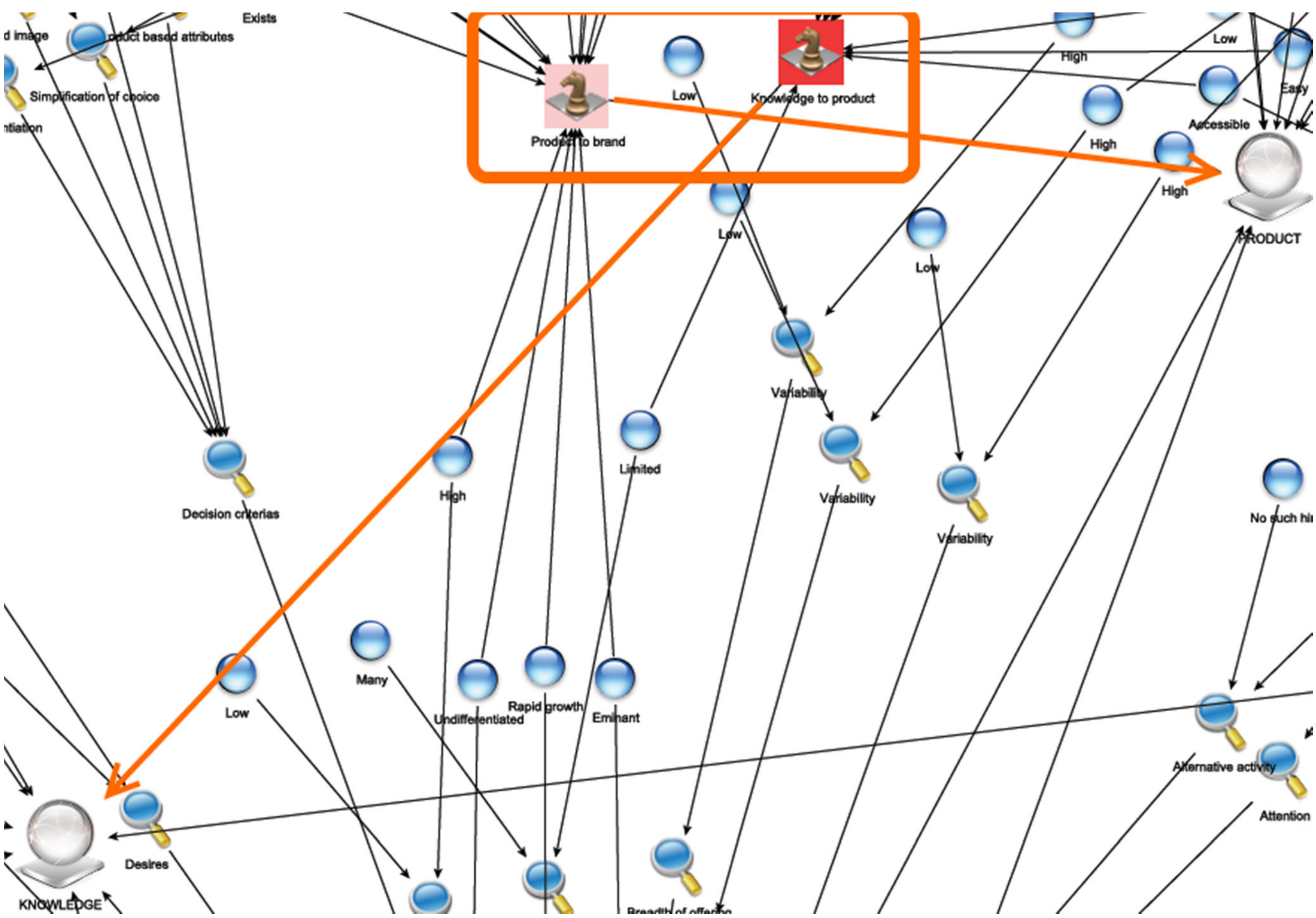


Fig. 11 Discovering proximity product-related strategies

Krogh et al. (2001) described the knowledge management practices at Unilever, one of the largest global corporations in the FMCG industry, and highlighted Unilever's knowledge creation and transfer processes, which authors refer to as "expanding strategy" within knowledge management. Our framework describes how such an expanding strategy can be achieved through the visualization and algorithmic layout of rule bases.

Our study starts with codifying existing expert knowledge in a rule based format, and concludes with newly created knowledge through data mining, specifically information visualization.

Although there have been many related theoretical frameworks and applied studies, none of them contain the solution approach presented in our research.

Rubenstein-Montano et al. (2001) presented a list of 26 knowledge management frameworks in the management academic literature and the business literature. Our framework is closest to the framework formalized by Ernst & Young (Rubenstein-Montano et al. (2001)). The Ernst & Young knowledge management framework consist of the processes of knowledge generation, representation, codification and application. Although the knowledge management frameworks explored by Rubenstein-Montano et al. (2001) provide high level views of knowledge management, they do not describe how information technology, specifically rule-based methodologies and data-mining techniques can be used in knowledge management for creating knowledge.

We suggest and adopt semantic networks and establish the crucial link between rule-based methodologies and data mining. To the best of our knowledge, the use of semantic networks for formalizing knowledge and enabling visual mining of existing knowledge is novel in literature. The study of Noh et al. (2000) also suggests the use of a special type of semantic network, namely, cognitive map, as the principal vehicle of codifying and sharing knowledge, but does not offer a solution for knowledge creation. Although Noh et al. (2000) recommend the visualization of rules as a shareable graph, it does not use graph layout algorithms to derive insights as we do in our study.

López-Cuadrado et al. (2012) provide a collaborative semantic framework for knowledge sharing based on a shared and controlled vocabulary. Our paper also proposes the adoption and implementation of semantic networks for knowledge representation and sharing. However, the presented framework also enables knowledge creation.

One future work to extend the current study could be the incorporation of graph metrics into the visual analysis stage. The nodes in a graph and the graph itself can be characterized through numerical graph metrics. Detailed information about a multitude of graph metrics can be found in Christensen and Albert (2007), as well as Opsahl et al. (2010).

In making strategic decisions, managers should have a comprehensive understanding about the environment and use the available knowledge at their best to direct the company properly for survival. The proposed framework can support managers in making strategic decisions by providing them with a practical process generating new knowledge and novel solutions. Moreover, the developed framework can also provide better understanding and perception of the strategic management domain, and be used in a learning organization for growing the vision and skills of current and future strategists.

Acknowledgments The authors thank Dr. Haluk Demirkan and Dr. Gülçin Büyüközkan for their suggestions on improving the paper. The authors also thank İlter İrdesel for the development of the Domain Objects Map (DOM) specification in his M.Sc. Thesis and the creation of the graphs for the case study, Cem Kanpara for drawing the DOM in yEd software, Kamil Collu and Soner Ulun for their support in editing, and Andreea Avadanei and Richard Wilkinson for their help in proofreading.

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