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Johannes van der Pol[a,*]

[a]University of Bordeaux, France;
*johannes.van-der-pol@u-bordeaux.fr

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Stevan Dedijer
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Collaboration network analysis for competitive intelligence

Johannes van der Pol[a,*]

[a]*University of Bordeaux, France;*
**Corresponding author: johannes.van-der-pol@u-bordeaux.fr*

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ABSTRACT The analysis of collaborations is an important aspect of competitive intelligence studies. Collaborations show who players turn to in order to gain access to external knowledge. Networks are often used to analyze collaborations. However, analyzing networks that become increasingly large, especially in a dynamic setting, is a difficult task. Communication on these questions is complex for the same reason. In this paper I propose a method that allows for the identification of collaboration strategies in a static and dynamic setting that also makes it easier to communicate the results. An application of the method is also provided to illustrate how the method can be used for competitive intelligence studies.

KEYWORDS Collaboration analysis, competitive intelligence, dynamic network analysis, network analysis, patents

1. INTRODUCTION

The number of collaborations between innovating firms has been steadily increasing for the last couple of decades (Saviotti, 2007; Tomasello et al. 2013). This observation can be explained on one hand by the complexification of technologies, resulting in firms no longer being able to master all technologies in-house (Powell et al. 1996, Fagerberg et al. 2004). On the other hand, there is value in adapting and combing existing technologies from other domains or searching for solutions in other domains to solve a problem in one's own domain. As a consequence, firms aim to access ressources held by other firms to enter new markets, improve their products or innovate. That being said, collaborations are not without risk. Two main types of risk are involved with collaborations. This first is the intrinsic risk of failure of the collaboration (Masrurul et al. 2012, Porter and Birdi 2018). Failure of the collaboration is mainly due to managerial differences between the contracting parties. It has been shown that for a collaboration to succeed, it is vital to make the aim of the project clear as well as the benefit for all the parties involved (Porter, 2003). This requires firms to be transparent about their strategic objectives, which is often information that firms would rather keep private. Exposition of strategic information is risky as it can be exploited by collaborators. This comes in addition to other opportunistic behaviour the collaborators might have (Gulati, 1995; Williamson 2007; Oxley and Sampson, 2004; Kesteloot and Veugelers, 1995). Nevertheless, overall the effects of collaborations on the performance of the firm have been proven to be positive, especially R&D collaborations. Accessing different knowledge sources is considered beneficial for the firm (McEvily and Marcus ,2005), for innovation (Kogut and Zander, 1992; Tsai, 2001), as well as for industrial performance (Watson, 2007).

Due to its importance, collaboration is an integral part of the innovation strategy. The resources accessed through collaboration are combined with the core abilities of the firm to innovate. This means that from a competitive perspective, collaborators are a rival that is good in some cases and collaborations should be fully included into any technology or competitive intelligence analysis. When creating a technology landscape, it now common practice to use collaboration networks to provide a first impression on where firms search for external resources for innovation (Garcia-Garcia & Rodríguez, 2018). In these networks, firms are nodes and links represent collaborations. Typically, these types of networks lack a dynamic element that allows the analysist to gain insight into the evolution of the collaboration strategy of firms in the network.

The aim of this paper is to provide a method that simplifies dynamic network analysis by first classifying firms into four categories based on their position inside the network. The classification is then computed at different points in time so that we can see if the behavior of the firms changes over time. This will make two aspects of network analysis easier for analysts. First, the complex structure of the network at the firm level is summarized in a category, and the change in position makes it easy to identify firms with atypical behavior. Atypical behavior is understood as a behavior that differs from the other nodes within the same network. This allows for the identification of newcomers, or firms that suddenly have a radical change in collaborative behavior. Once interesting firms are identified, one can zoom in on those firms in order to better understand their behavior.

This paper is organized as follows, first I will present the method that classifies players into four categories based on their position inside the network. I will then apply this method on a case study, lithium-ion accumulators, to illustrate what can be achieved with the method. The final section will conclude.

2. PLAYER CLASSIFICATION

2.1 Theoretical justifications

Given the different risks inherent in collaborating, firms will aim to reduce this risk as much as possible. Part of this can be achieved through managerial aspects such as clarifying the goal or the contribution of each party. Overall, a central force will be trust and reputation. When a firm is required to pick a collaborator, it will have to take into account different dimensions. First of all is of course the expertise of the potential collaborator. This can, however, be off-set by the reputation and/or trust one might have in this collaborator. A firm considered to be an expert in a field but also a notoriously bad collaborator might be put aside for a firm with less expertise but a better track record when it comes to collaborations.

When collaborations finish on good terms, this creates trust between the firms. The more trust, the easier it will become for firms to collaborate again in the future. Trust plays an important role in collaborations and has shown to have a positive impact on performance (Zaheer et al., 1998). After all, a new collaborator is a risky choice compared to a historic one that has already proven its worth. The more firms collaborate, the more they will be able to increase their capacity to absorb each others knowledge (Cohen and Levinthal, 1990) and recombine the knowledge to innovate (Cowan and Jonard, 2007). In addition, repeated collaboration allows for trust to grow and as trust grows, recommandations will also start to flow between firms resulting in strong ties between firms (Granovetter, 1973). Ties between firms are considered strong when there is a significant overlap in the collaborators of both firms. A positive side-effect of these strong ties is that firms know each other well. They are accustomed to one another's work ethic and methods, resulting in more efficient collaborations. Using this type of strategy to collaborate, i.e repeating historic collaborations and relying on strong ties, can result in a very dense network around the firm. This type of strategy, we will refer to as a closed strategy. The reason we call this a closed strategy will become clear when we look at how this looks from a network perspective. When we create nodes representing the firms and link the collaborations, we end up with a network that looks like the network on the left of Figure 1. The node in the center is the one we are interested in and we can clearly see that it has created a network of collaborators around it. Of course this image is a caricature, different levels of closed strategies can exist. Firms embedded in such networks benefit from firms being more willing to share information because of the social cohesion between the individuals in the firms and benefit from the increased productivity (Borgatti and Halgin, 2011; Kilduff and Brass, 2010).

Figure 1 An example of different collaboration strategies. The graph on the left shows a closed strategy while the graph on the right shows an open strategy.

There is, however, a downside to this strategy: there is a redundancy of knowledge inside the network of the firm. When one keeps collaborating with the same firms, the diversity of knowledge runs out, with a negative impact on R&D output (van der Pol, 2018). Creating links to firms that are outside of one's dense community allows the firm to gain access to a larger variety of knowledge. Granovetter referred to this effect as the "strength of weak links." Pushing this idea a bit further, firms can have a more sparsely connected network, like the one on the right in Figure 1. The node in the center of this network has a position that can be qualified as a gatekeeper position (Burt, 2004). This is a desirable position for a firm since it has control over the flow of knowledge between the nodes in the network. It is easy to take advantage of this type of position and it has been shown that firms in such a position can reap the benefits (Hargadon, 2002; Ahuja, 2000). In addition to the particular position of the firm, the fact that firms have more extensive indirect ties to firms in other parts of the network allows the firm to have a larger access to diversified sources of knowledge. These indirect ties are, for this reason, beneficial for the firm (Ahuja, 2000; Reagans and Zuckerman, 2008). This type of strategy we will refer to as an open strategy, in opposition to the closed strategy. An illustration is given in Figure 1. An open strategy is identified by a network position that is less densely connected while interconnecting different parts of a network as shown in the graph on the right.

Experience shows that when one analyses collaboration networks, different communities in a network are often correlated with different technological domains. This supports the theory on the importance of the gatekeeper position and the theory on weak links, since it implies that firms are able to reach different knowledge sources when connecting different parts of the network.

One final word on these strategies should be addressed to newcomers. The barriers to enter a network are not the same in the closed or the open case. In the closed case the barriers to enter are much higher. There will be more control of the different parties involved than in the case of the open strategy. This will be important when we aim at identifying newcomers and their position in the network. A newcomer included in a closed strategy will not have the same impact as a newcomer with a more peripheral role.

Nodes that are on the periphery are more ambiguous. They could either be newcomers or small companies that can only sustain a limited number of collaborations, or large companies that do not wish to collaborate much. In the latter case their position is a strategy while in the first it is merely a result of their status. We will still label this a closed strategy, in any case a player labeled as peripheral should be studied to ensure if the position is strategic or not.

2.2 Relating the strategies to network positions

We now need to find a way to identify the previously described strategies from the network positions of the players. To this end we will use different indicators commonly used in network analysis. The idea is to use two indicators that measure the extent to which a firm has created a dense community around it and the extent to which the firm is connected to other densely connected firms.

2.2.1 Identification of the closed strategy

We require an indicator that identifies the extent to which a firm is located in a densely knitted community. For this purpose, we will use a network indicator called the eigenvector centrality (EC). EC is what is called a prestige indicator that increases in value when a node is connected to highly connected nodes.

As show in Figure 2, low values are in green and the colours tend towards red when the indicator increases. The nodes in the densely connected part of the network have the highest value. The nodes at the extremities have low values when it comes to this indicator. Depending on the relative intensity to which the nodes are interconnected this value will vary between 0 and 1.

2.2.2 The identification of the open strategy

For the purpose of the identification of nodes that interconnect different communities, we use another centrality indicators: betweenness centrality (BC). This indicator computes how central a firm is in a network.

As shown in Figure 3, the firms that are in a more central position have the highest score with this indicator. Firms at the periphery have a lower score. The BC is a score that ranges from 0 to 1 and allows for the comparison between nodes in the same network. A word of caution, when a network is comprised of several connected components, these indicators must be computed per connected component.

Each indicator provides information on the position of the firm, and when combining the two indicators we can identify a higher variety of positions.

The extent to which these positions translate to strategies will be up to the analyst using the method to determine.

2.2.3 Combining both indicators: the position matrix

By combining the previous two indicators we can create a matrix with the BC on the y-axis and the EC on the x-axis. By doing so we create four areas that each reflect a different strategy. Firms with a high score in both indicators (top right section of the matrix) are connected to firms that have themselves many connections, while at the same time having a gatekeeper position. This implies that the firm collaborates with large firms specialised in their domain. This is in opposition to the upper left part of the matrix in which the firms collaborate with other communities through the presence of a supplier or another third party. Firms with a low score in both dimensions have a peripheral position, meaning that they just joined the network, are an exclusive supplier, or a start-up or young firm. The final section of the matrix identifies firms that have a dense community of firms around them.

This matrix can be used to plot the positions of players according to their BC and EC values (which should be centered and normalized). The matrix on the right shows how players can be represented in this matrix. A first dot represents the position of the player in the first period, the arrow indicates how the position of the player changes from one period to the next. In the case of the player at the top of the matrix, its position became more influential while the player at the bottom was pushed towards the periphery. This change in position makes it easier to identify firms that have atypical behavior from a collaboration perspective.

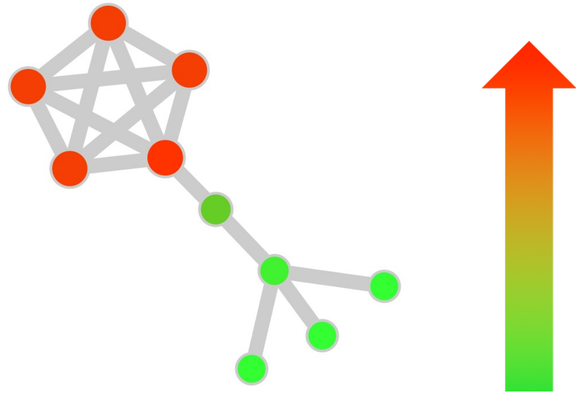

Figure 2 The eigenvector centrality measures the extent to which the firm is connected to firms with an important position in the network. The higher the score the more important the position of the firm.

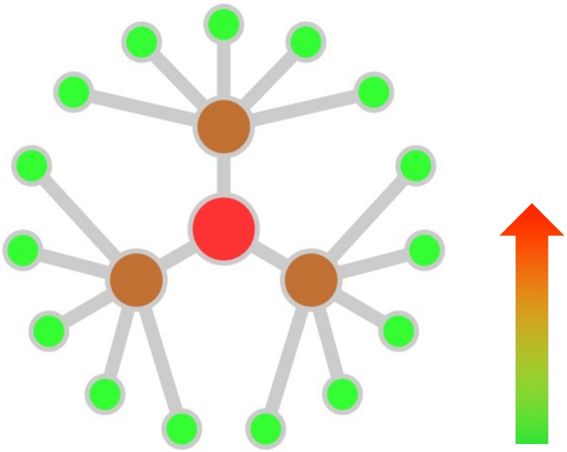

Figure 3 The betweenness centrality measures at the level of gatekeeper of the firm.

3. ILLUSTRATION OF THE METHOD: AN APPLICATION ON LITHIUM-ION ACCUMULATORS

The aim of this section is to show how to exploit the matrix described in the previous section. Even though the method can be used with any form of collaboration data, I will use patent data from the Orbit database from Questel. 28221 patents filed between 1990 and 2016 worldwide from which 3601 patents are co-filings will be used as our data source for collaboration data. Patents are widely used for competitive intelligence purposes (Jürgens & Herrero-Solana, 2017; Shaikh & Singhal, 2018; Flamand 2016).

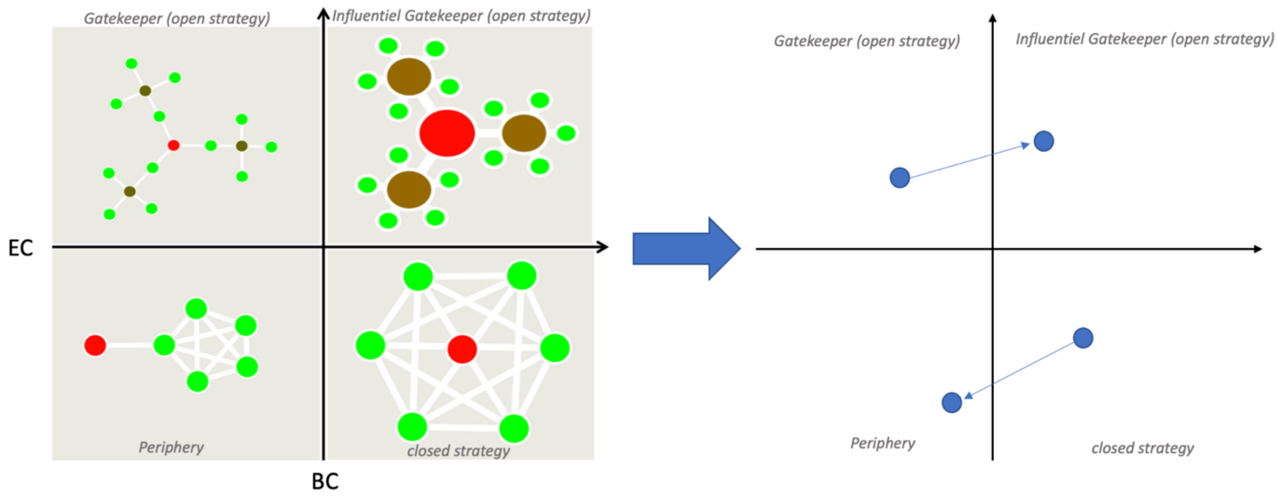

Figure 4 The position matrix in which each quadrant identifies a different collaboration strategy for the firm.

The sharing of intellectual property rights between firms is a strong signal since there is a legal component involved. Collaborations extracted from scientific publications for instance are much less binding and require less legal structure to be co-signed. In addition, patents contain a pool of information about the technology developed by the firms, which we will be able to exploit to further analyse the different collaborations that we have identified. I will show how this is accomplished in this application.

From the patent dataset, we will create a network at two points in time. A first network aggregates all collaborations between 1990 - 2010, a second 1990 - 2016. Figure 5 shows the topology of the network over the period under consideration (1990 - 2016).

Note the absence of secondary components in this network. Network indicators such as BC and EC can only be compared if they are computed within the same component. The secondary components (of which there are still quite a lot) must be analysed separately.

The objective now is to identify from this complex network the strategies of firms, and highlight signals of interest.

3.1 Position classification

For each of the firms I computed both centrality indicators for each of the periods. Then comes the question of the cut-off point where a firm is considered to be in a high or low position regarding each of the indicators.

I normalised the data by subtracting the mean and dividing by the standard deviation. This means that a firm is in the top right corner when its BC and EC are at least above average. A firm is on the bottom left if both indicators are below average.

Using the indicators, it becomes easy to identify firms that have changed their position, have not moved or have entered the network with a specific position. These are the signals we are interested in, the outliers in the data. In Figure 6, some interesting cases are visualised. The red circles indicate the position of the firm in the second period. Firms that do not have a blue dot entered the collaboration network in the second period. Examples are Foxconn and Nanotek Instruments. These firms are more on the supplier side and enter with a closed strategy implying that they are co-patenting with a small number of densely connected firms, which makes sense for a firm in a supplier position. Firms such as Samsung and Toyota work on the development of batteries while also using them in their products.

Figure 5 The giant component of the collaboration network in the technological domain of lithium-ion accumulators. Nodes represent firms and links represent collaborations between firms. The colours of the nodes represent communities of nodes that are densely interconnected as identified by modularity maximization.

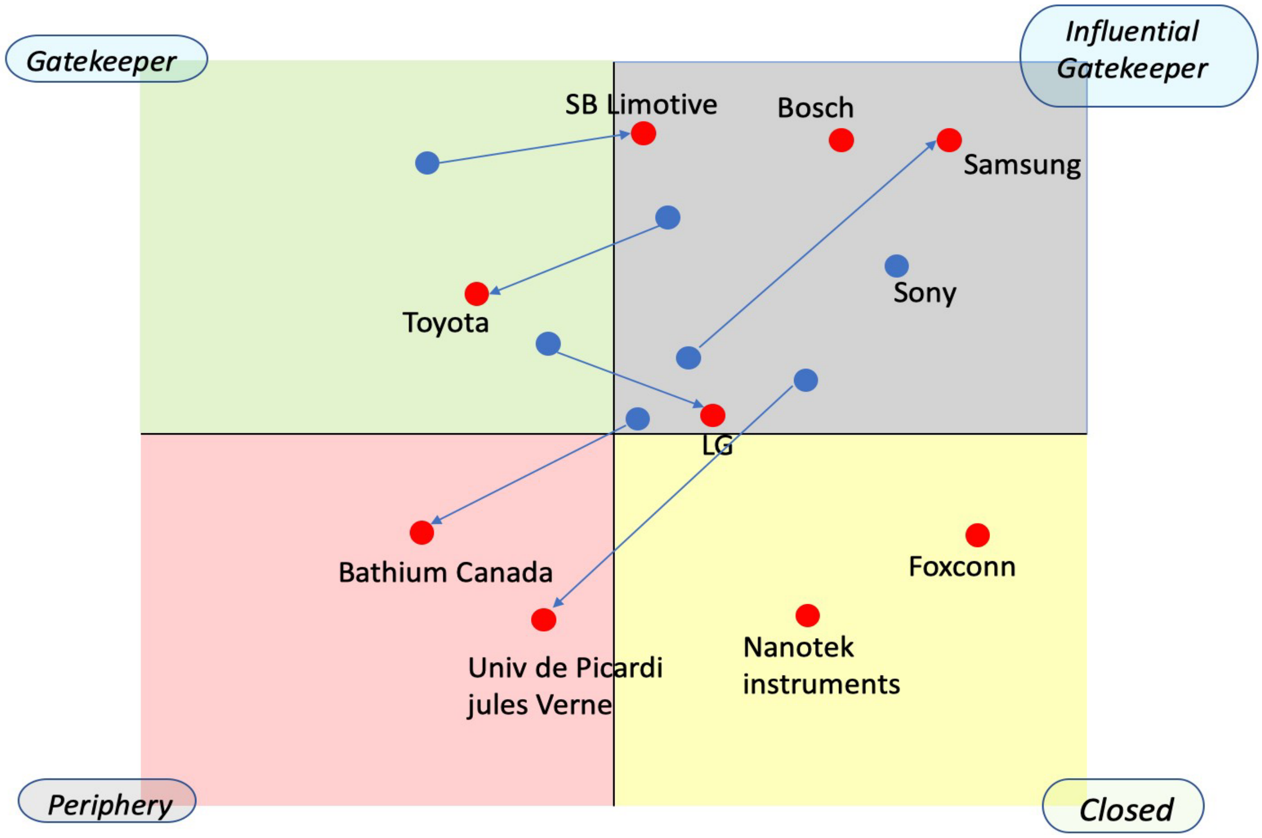

Figure 6 Classification of certain firms in the collaboration network. For clarity not all firms are displayed. The blue dot represents the position of the firm in the first period, the red dot represents the firm in the second period.

We can see that Samsung has strongly reinforced its position in the network and extended its reach since it has an open strategy. This is consistent with the strategy of the firm since it is present on the battery market for anything from smart watches to cars. Samsung announced its cooperation with carmakers for its batteries, but we do not observe any signal for that in the patent data. It could hence be interesting to add other types of collaboration data to the network (for example, publications or project data). Carmakers such as Renault, Toyota, Nissan and Peugeot seem to be mostly collaborating with universities and research institutes.

The position of Bosch, appearing in the second period, is highly linked to the position of Samsung due to a joint venture created by both firms in 2008, SB Limotive, and terminated in 2012. Bosch and Samsung also both reinforced their strategy by starting to co-patent with universities[1].

Not all firms reinforce their position in the network, some are pushed towards the periphery of the network in the second period while they were central in the first period. Bathium Canada and Univ de Picardie both ended on the periphery of the network. This is not so much because their own network changed but rather because the rest of the network evolved at a faster pace. Newcomers in the sector are also easy to detect. They did not simply appear in the network at a peripheral position, they entered the network directly with a highly central position. A simple glance at the table shows that these actors are mostly universities from Asia, with the exceptions of the University of Graz and Bosch.

Finally there is the interesting case of Sony, present in the first period but absent from the network in the second period. We will dig into this case in the next subsection.

3.2 The technological motivation for collaboration: the example of Sony

Once we have identified a company of interest, we can use other data in the patents to analyse in more detail what resources are accessed through collaboration. We can accomplish this

[1] *Note here that since the source of the data is patents it is possible that these collaborations existed before but the universities had no interest in filing patent, which seems to change nowadays.*

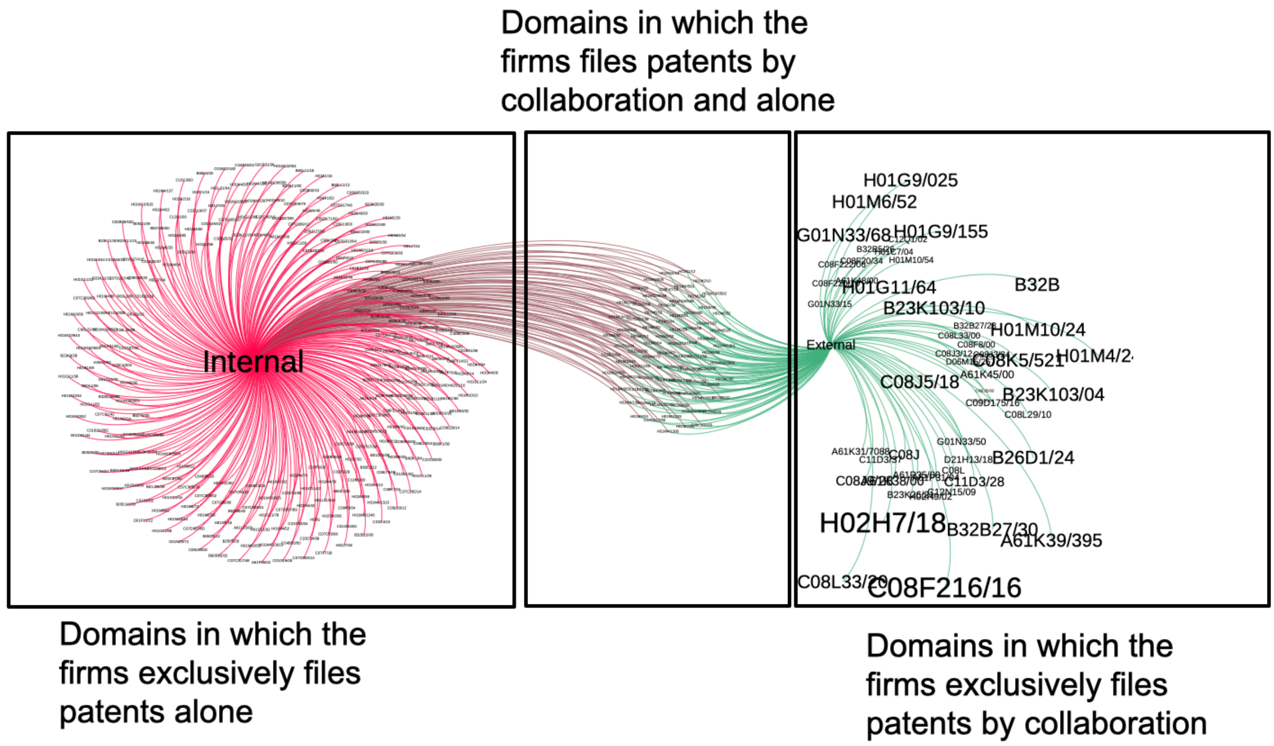

Figure 7 Analysis of the internal and external sources of Sony in the case of lithium-ion accumulators.

by the means of the International Patent Classification codes (IPC codes). IPC codes are added to a patent application by the examiners and provide us with a vision of the technological domain the patent is in. We use this information to analyse what domains the firms collaborate on. For instance, in the case of Sony, we can create a database with all patents filed alone by Sony and a database containing only the co-filed patents. Using these two datasets we can visualise the domains of interest to Sony and how they are mobilised. Figure 7 visualises the different IPC codes. On the left are the different domains in which the firm files patents under only its own name. On the outer right we find the domains with exclusively co-files patents. These are the domains in which the firm relies most on external resources.

As we will recall from the matrix, Sony exited the network in the second period. In order to get a better understanding as to why, we can have a closer look at the patents filed by Sony. In Table 1 I have highlighted some examples of domains that clearly show that in some domains Sony first required collaborations (H01M4/583 and H01M10/56). In 2003 however, the collaborations stopped and the firm started to file patents in its own name. This highlights that somehow the firm was able to internalise the technologies.

In other cases (H01M4/62 and H01M/0566), Sony had been filing patents alone, yet stopped collaborating in 2003, while sole deposits continued.

Table 1 Examples of domains in which Sony filed patents and the corresponding first and last year of first and last filings alone and by collaboration.

IPC code	Technological Domain	First collaboration	Last collaboration	First sole filing	Last sole filing
H01M4/583	Electrodes with graphite-intercalation compounds or CF	1992	2003	2003	2013
H01M10/056	Secondary cells characterised by the materials used as electrolytes	1998	2003	2003	2013
H01M4/62	Secondary cells characterised by the materials used as electrolytes Electrodes with a selection of inactive substances as ingredients for active masses	1996	2003	1995	2016
H01M/0566	Secondary cells with liquid materials	1996	2003	1994	2017

3.3 Comparing one's strategy with another firm

When it comes to competitive intelligence it is always interesting to compare one firm with another. As an example, I compare Sony and Samsung. Figure 8 shows a comparison of different domains of R&D between the two companies. As has been shown before, in the center are domains in common between the two companies. The colour on the links indicate if a code is unique to collaborations or not. In other words, if a code only presents co-filings for a firm, the link to that code is red. In the case of Sony, the code on the outer left indicates the domains Sony works on, but Samsung does not. Amidst those codes, there are five domains that are exclusively accessed through collaboration. These are therefor external resources that Samsung has not positioned itself on in the lithium-ion sector. Samsung has 15 domains in which it used exclusively external resources.

In the center of the graph, we find only one common point when it comes to external resourcing: H02H. Both firms use exclusively external resources in this domain. Even though the firms have some points in common there are still quite some differences between the two companies when it comes to external resourcing. The firms collaborate with different companies and it appears on different domains.

4. CONCLUSION AND DISCUSSION

This paper provides a method to analyze collaboration strategies of players in a dynamic setting. The method uses the structural position of players inside a collaboration network to classify them into a category. When this is done at several points in time, one can see the change in position of the player and trace its change in strategy. This allows the analysist to easily identify firms to analyze in more detail. The matrix in which the positions of the player are represented allows one to communicate the results in an easy and readable manner, since showing dynamic networks is often complex and confusing.

Even though the position of a player in a network is the reflection of its decisions (with whom they collaborate, how many times and when), it is not easy to ensure that these decisions are strategic. The results of the method should not be overinterpreted and results should always be complemented with other types of information to corroborate the findings.

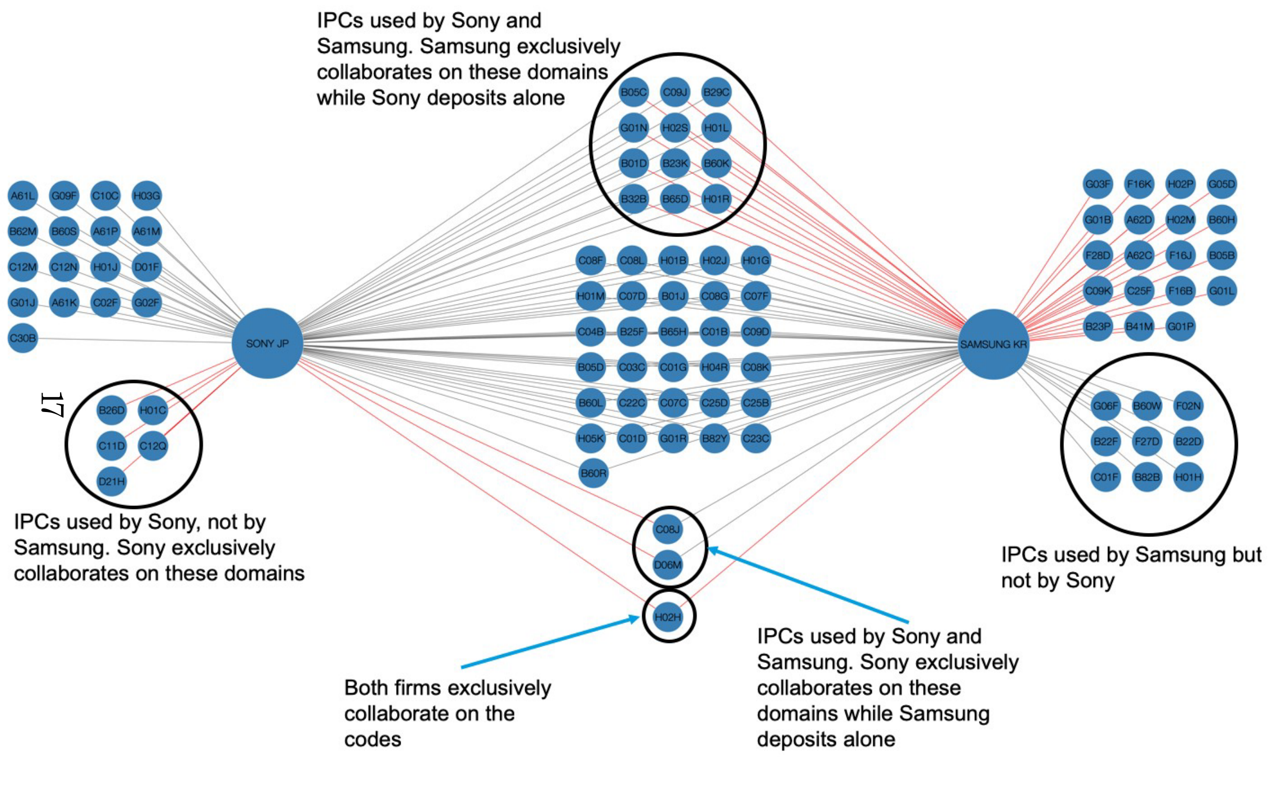

Figure 8 Comparing two firms in the same domain. The aim is to show common interest and specificities between the two companies. On the outer left side: domains specific to Sony, red lines indicate codes uniquely used through collaboration. In the center codes in common between the two companies, red lines indicating external resourcing exclusively.

A particularly tricky part of dynamics resides in the treatment of fusions and acquisitions. A sudden change in position can be the result of a firm acquiring another, and hence combine all the collaboration links. Patent data is often updated so that the latest name of the player will be on the patent document (even though there is no obligation for this in certain countries). For other sources of data (publications, research projects) this updating is not required nor is it usually performed. This can create a lot of noise in the data with new players appearing out of nowhere while they are in fact historic players that have changed their name. For these data-sources a thorough cleaning of the data is required.

The illustration of the method on the domain of lithium-ion accumulators shows how the method can be used in practice for competitive intelligence. We were able to identify players with interesting behavior (Sony, Samsung) as well as players that became less influential (Univ Picardi). The identification of these players allows us to search in more depth how they build their collaboration strategy and how they access external knowledge. In the case of Sony this allows us to see a clear change in their knowledge management since they were able to internalize a technology that they were collaborating on in the previous period.

Even though we have been able to test this method in multiple domains (3D printing, silica in rubber, 5G) and we are convinced of its value, there is an aspect that requires further investigation. The closed strategy is purely identified on the structure, it is possible that the position of the firm remains the same, but the collaborators differ between periods. This should be addresses in further work.

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