Mobility of Innovators and Prosperity of Geographical Technology Clusters:
A longitudinal examination of innovator networks in telecommunications industry

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Abstract

Although knowledge spillovers have long been considered a critical element for development of technology clusters by facilitating innovations, the relationship between characteristics of knowledge spillover network and regional cluster's growth is ambiguous. Based on patent co-authorship data, we construct inventor networks for two geographical telecom clusters – New Jersey and Texas – and investigate how the networks evolved longitudinally as the technology clusters were undergoing different stages of their lifecycles. The telecom industry in the former state had encountered a significant unfavorable environmental change, which was largely due to the breakup of the Bell System and evolution of the telecom industry. Meanwhile, the telecom cluster of Texas has been demonstrating a growing trend in terms of innovation output and is gradually replacing New Jersey's leadership in telecom innovation as measured by number of patents per year. We examine differences and similarities in dynamics of the innovator networks for the two geographical clusters over different time periods. The results show that TX's innovator networks became significantly better connected and less centralized than the ones of NJ in the later years of the time series while the two clusters were experiencing different stages of lifecycle. By using network visualization tools, we find the overwhelming power of Bell System's entities in maintaining the NJ innovator network to be lasting a very long time after the breakup of the company. In contrast the central hubs of TX's networks are much less important in maintaining the networks.

Key words: Social network, Technology clusters, Innovation, Telecommunications R&D

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1. Introduction

Today's economic map demonstrates that industries tend to cluster together geographically. Clustering has become one of the key carriers of regional economic growth by promoting local competition and cooperation. The impact of clustering on business competitiveness and regional prosperity has been well documented (Porter, 1998). Although it is known that innovation activities are the fundamental driving force for cluster development, R&D spending does not always guarantee the growth of a cluster. Other facilitating factors include the presence of functioning networks/partnerships and available human resource pools, etc. (Porter, 1998). Among these factors, knowledge spillovers are considered to be a prominent component in explaining the differential stages of cluster evolvement. To what extent technology spillovers are associated with regional economic growth nowadays is an area of active research.

In this study, the authors provide a new approach of monitoring cluster evolution by conducting a longitudinal analysis of the dynamics of inventor networks. The paper focuses on the telecom sectors of New Jersey and Texas. For almost a century, New Jersey has been the leader in telecommunications innovation, due to the presence of Bell Laboratories. With the break-up of AT&T and passage of 1996 Telecommunications Act that drove the de-regulation of US telecommunications market, New Jersey's telecom sector went through a period of rapid change. In mid to late 1990s, many start-ups emerged in NJ, a phenomenon observed in some other regions of US as well. However, since the industry downturn of 2000, the NJ's telecommunications sector has been experiencing a hard time. While NJ is struggling to recover from the downturn, we've observed that some other states, such as Texas, have been able to pull ahead and show greater growth (He and Fallah, 2005) as measured by telecom patent output. It seems that New Jersey's telecommunications cluster is currently stuck in a stagnant state. The analysis of inventor networks within the telecom industry can provide further insight into the evolution of NJ's telecom cluster and the influence of such networks on performance of the cluster.

The rest of this paper is organized as follows: Section 2 provides a theoretical overview of social network analysis. Section 3 investigates the patterns of telecom inventor networks of New Jersey and Texas, and employs a visualization tool to show the evolution of these networks over time. The final section provides a summary of findings and direction for future research.

2. Inventors Networks

In the context of technology innovation and interpersonal networks as the channel for knowledge diffusion, social connections between individuals are often conceptualized to examine the effect of knowledge spillovers on the network actors' innovation performance. Indeed there is a long tradition of exploiting the relationship between network actors' innovation efficiency and their relative positions in social network (Coulon, 2005).

Complex networks are often quantified by three attributes: clustering coefficient, average path length, and degree distribution. The clustering coefficient measures the cliquishness of a network, which is conceptualized by the likelihood that any two nodes that are connected to the same node are connected with each other. The average path length measures the typical separation between any two nodes. Degree distribution maps the probability of finding a node with a given number of edges. Following the discovery of "small world" network phenomenon, which is characterized by short average path length and high degree of clustering properties (Watts and Strogatz, 1998), many empirical studies proved that small-world properties are prevalent in many actual networks such as airline transportation networks and patent citation networks. Studies in social networks suggest that knowledge diffusion would be best supported by networks that exhibit small world properties, based upon the assumption that small world structure allows clustered and dense relationships to coexist with distant and weak relationships. The dense and clustered relationships encourage trust and close collaboration, whereas distant ties act as bridge for fresh and non-redundant information to flow (Fleming et al., 2004). There is evidence that the rate of knowledge diffusion is highest in small-world networks (Bala and Goyal, 1998; Cowan and Jonard, 2003; Morone and Taylor, 2004).

In order to test the relationship between knowledge transfer network and regional innovation output, Fleming et. al (2004) analyzed co-authorship network data from US patents of the period between 1975 and 2002. Their results are inconsistent with the generally believed proposition that "small world" networks are associated with high level of innovation. It appeared that decreased path length and component agglomeration are positively related to future innovation output; however clustering, in that study, has a negative impact on subsequent patenting. In fact, the existing empirical literature is not rich enough to illustrate the role of knowledge spillovers, created by inventors' mobility or/and collaboration, in promoting the development of clusters. In this study, we will investigate the evolution of telecom inventor networks of New Jersey versus Texas, and examine their significant differences which may explain the differences in innovation growth and cluster development of the two states.

3. Data and analysis approach

In this study we map the network of telecom innovators using patent co-authorship data. We believe patent co-authorship data is a good quantitative indicator for knowledge exchange. As majority of patents are delivered by teams instead of independent individuals, it is reasonable to assume that co-authors know each other and technical information exchange occurs in the process of innovation. Secondly, patent data can reflect the mobility of the inventors as long as they create patents in different firms or organizations. Cooper's study (2001) suggests that a higher rate of job mobility corresponds to greater innovation progress because parts of the knowledge generated by a mobile worker can be utilized by both firms involved.

The data for our study was originally collected from the United States Patent and Trademark Office (USPTO) and organized by Jaffe, et. al. (2002). This dataset provided us with categorized patent information covering the period between 1975 and 1999. The objective of our study is to analyze the dynamics of inventor networks for different geographical clusters over time. For this study, we selected the telecom patents granted to inventors in New Jersey and Texas between 1986 and 1999 for analysis. We consider a patent belongs to either New Jersey or Texas, as long as one or more inventors of the patent were located within that state. Those patents belonging to both states were deleted for this initial study (accounts for 0.9% of the total number of patents). Since the USPTO dataset sorts data using patent number as the primary index, certain inventors' names on different patents may not quite match (e.g. full middle name vs. middle initial, etc.). We screened the dataset to minimize the impact of this type of duplication errors. If the first names and last names matched, then we compared the middle names and their hometowns and companies to remove any discrepancies, and appropriately represented inventors with their full names.

For each state, we investigated how the inventor network evolved over time by moving a 3-year window. The patent dataset enables us to develop a bipartite network (upper portion of Fig. 1) which consists of two sets of vertices---patent assignees and patent inventors. This type of affiliation network connects inventors to assignees, not assignees to assignees or inventors to inventors, at least not directly. The bipartite networks are difficult to interpret as network parameters such as degree distribution have different meanings for different sets of vertices. In order to make the bipartite network more meaningful in terms of knowledge spillovers, we transform the bipartite network to two one-mode networks. Figure 1 illustrates an example of this transformation from bipartite to one-mode networks. The network analysis tool –Pajek- was used to explore the patent network and visualize the analysis results. We created two one-mode networks from the bipartite network: a network of assignees and a network of patent inventors. We omitted those patents assigned to individuals.

For the one-mode network of assignees, a link between two nodes means that the two organizations share at least one common inventor. In this network, a link indicates that one or more inventors have created patents for both of the organizations during that time frame. In practice this happens when an inventor who creates a patent for company A joins a team in company B or moves to company B and creates a new patent that is assigned to company B. In either of the scenarios, one can assume there would be a knowledge spillover. When the first type of spillover is dominating, it may suggest the R&D collaborations between firms are relatively popular in that geographical area. In the second case, the number of mobility-induced ties is a good indicator of job mobility of professionals in the area.

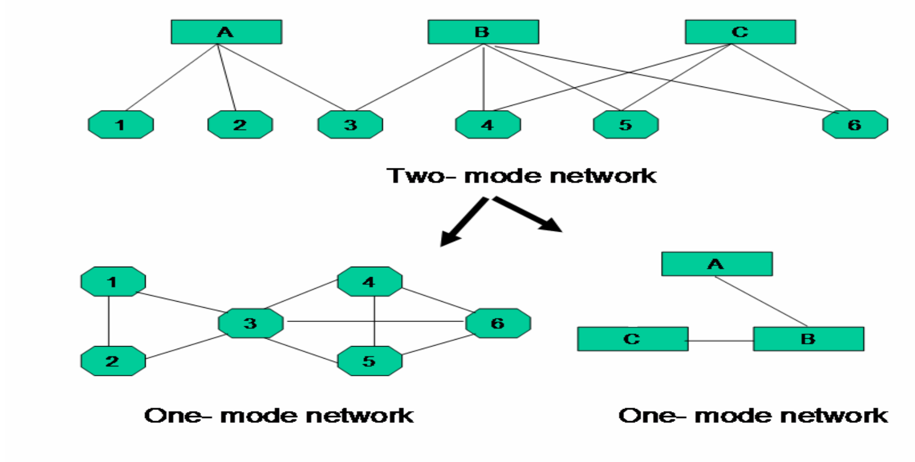

Figure 1: Transformation of a two-mode network to one-mode networks

For the one-mode network of inventors, the visual picture would become too busy to be interpreted, just because the number of individual inventors far exceeds the number of assignees. Obviously, the presence of giant companies such as Lucent Technologies will create some extremely busy cliques in which every inventor is connected to everyone else in such a one-mode network. This kind of busy cliques cannot deliver much meaningful information regarding knowledge spillovers between nodes. Moreover, it makes the network less readable. For this reason, we used a specific network analysis technique, *m*-slices, to reduce the clutter. The m-slices technique is designed to filter out the "unimportant" nodes based upon the multiplicity level of the ties between nodes (De Nooy, 2005). For example, suppose inventor A and inventor B both created patents for multiple companies, x, y, and z, during a same period, then in the one-mode network of inventors, there are three overlapping ties between A and B (can be represented by a line with multiplicity value of 3). In our study, by filtering out the ties whose multiplicity level is less than 2, the m-slices technique is able to remove the dense cliques created by the cloud of large number of inventors belonging to single assignees. Thus, a 2-sliced inventor network contains only those inventors who created patents for multiple companies during a same window period. Similar to our previous discussion, this scenario in practice may indicate joint R&D projects between firms or mobility of inventors among different employers.

4. Findings and interpretation

As described, using Pajek network software, we constructed two sets of one-mode networks for each geographical cluster with a longitudinal approach. The first set is the one-mode networks which consist of organizations, in which a tie between any two nodes indicates at least one patent inventor is shared by both assignees during the window period.

Before proceeding to examine the network structures and level of inventors' mobility, we had noticed from the original patent dataset that some assignees indeed represent entities which are associated with a large organization. The Bell System's multiple entities form linkages between their innovators via patent co-authorship and those linkages could account for a considerable portion of linkages over the whole network (He and Fallah, 2006). Since this kind of linkage is not directly associated with the spontaneous job mobility of innovators, which is the focus of our study, we regarded them as noise for our interpretation and therefore treated multiple entities of an organization as one unit by reassigning a new unique name to them.[2]

[2] Specifically, for the NJ cluster, we assigned a new name, Bell Replace, to replace Lucent Technologies, AT&T Corp., Bell Communications Research, NCR Corporation, Telcordia, AT&T IPM Corp., AT&T Global Information Solutions Company, and AT&T Wireless; also, HITACHI, LTD. and HITACHI America, LTD. were replaced with a common name, HITACHI Replace; NEC USA and NEC research institute, Inc. were replace with NEC; Globespan Technologies, Inc. and Globespan Semiconductor, Inc. were replaced with Globespan Technologies,

Figure 2 shows the average node degree of all vertices for each state over different three-year window periods. A higher degree of vertices implies a denser network, which in this case indicates inventors are more likely to move from one organization to multiple other ones. Figure 3 shows the percentage of non-isolated vertices in the networks over different window periods, non-isolated nodes here indicate the organizations are connected to at least one other organization via inventors' movement or collaboration. Based on the two figures, it appears the NJ network was better connected in the earlier years, but the advantage was lessened gradually as the time window moves ahead and NJ finally fell behind of TX in the last period of observation. The situation of NJ in patent network connectedness during the early years may correspond to the regulatory adjustment of the telecom industry. The *1984 Bell System Divestiture* broke up the monopoly of AT&T and forced AT&T to operate only in long-distance telephone markets. As AT&T expanded its business into the areas of information system that were unregulated, it led to acquisition on NCR and other subsidiaries. In 1996 AT&T restructured again spinning off Lucent Technology and NCR. These restructurings necessitated by business and regulatory forces led to some redistribution of employees including some of the R&D people. The Telecom deregulation created a substantial undeveloped new market which could be exploited with new technologies. As new starts-ups emerge in a cluster, the job mobility among organizations can be expected to grow also. As can be seen in Figure 2 and 3, the connectedness of NJ's patent network had experienced a dynamic change during the period between 1986 and 1993. The network of TX maintained a low level of connectedness in that period because there was very little telecom R&D work in that state. Starting from 1993, the networks in both NJ and TX demonstrated a significant growing trend in connectedness. Indeed, largely due to the further openness of telecom market, that was also a period in which the total patent output for both states was growing rapidly (Figure 4).

As the structure of the one-mode network consisting of organizations is concerned, the major difference between the NJ network and the TX one is the level of degree centralization. Degree centralization is defined as the variation in the degree of vertices divided by the maximum degree variation which is possible in a network of the same size (De Nooy, 2005). Put it differently, a network is more centralized when the vertices vary more with respect to their centrality; a star topology network is an extreme with degree centralization equals one. We observe that the NJ network is more centralized than that of TX, especially for the later period of observation (Figure 6). As shown in Figure 7, compared with the counterpart of TX, the main component of the NJ network always accounts for a larger portion of the total connectivity, and the difference becomes more significant in the later periods. This may correspond to the disappearance of many of the start-ups that emerged between mid and late 1990s. Based on the network measurement in overall connectedness, though the NJ network also shows a growing trend after 1993, we conclude that the growth was largely corresponding to the size growth of the main component rather than a balanced growing network.

Figure 8 and 10 visualize the one-mode network of assignees for NJ and TX, respectively (window period of 1997-1999). Figure 9 and 11 correspondingly demonstrate the main components extracted from the parent networks. Interestingly, we notice that the "Bell Replace" which represents the entities of the old Bell System is the key hub maintaining the main component of the NJ network (Figure 9).

Consistent with above-mentioned findings, the visualization of TX network demonstrates a decentralized pattern, in which most of the network connections would still exist even if the most connected hub is removed (Figure 10, 11).

Inc.; David Sarnoff Research Center, Inc. and Sarnoff Corporation were replaced with David Sarnoff Research Center, Inc.; RCA Thomson Licensing Corp. and Thomson Multimedia were replaced with RAC Thomson Licensing Corp. For the TX cluster, Alcatel Network Systems, Inc., Alcatel USA Sourcing, and L.P. & Alcatel USA were replaced with a common name, Alcatel Replace; Lucent Technologies and AT&T were replace with AT&T (Replace); Nortel Networks Corporation, Nortel Metro Cellular and Northern Telecom Limited were replaced with Nortel Networks Corporation; Nokia Telecommunications OY and Nokia Mobile Phone, Ltd. were replaced with Nokia Telecommunications OY; Siemens Business Communication Systems, Inc., Siemens Aktiengesellschaft, Siemens Information and Communications Networks, Siemens Rolm Communications Inc., and Siemens-Allis, Inc. were replaced with Siemens Business Communication Systems, Inc.

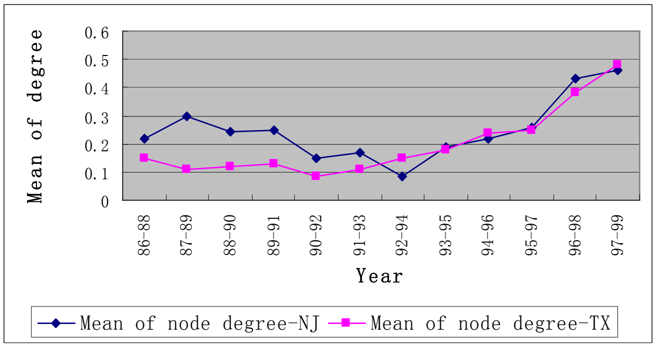

Figure 2: Mean of Degree – NJ vs. TX

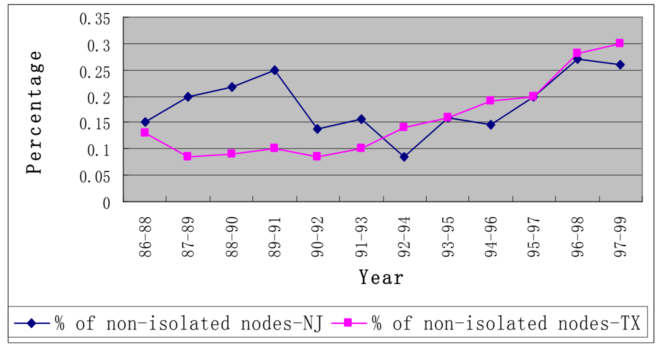

Figure 3: Percentage of connected nodes – NJ vs. TX

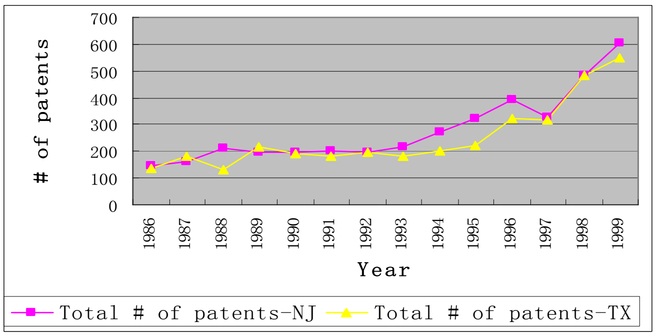

Figure 4: Total number of telecom patents – NJ vs. TX

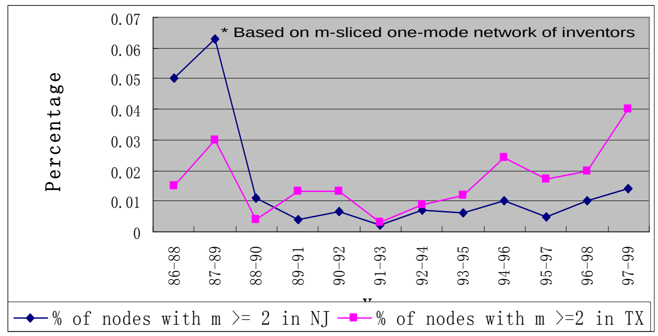

Figure 5: Percentage of nodes with m-value >1 – NJ vs. TX

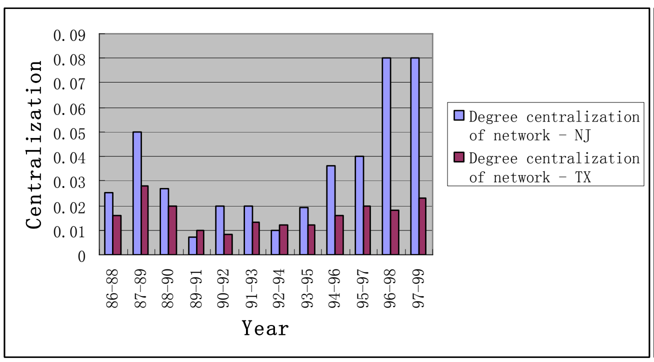

Figure 6: Network centralization – NJ vs. TX

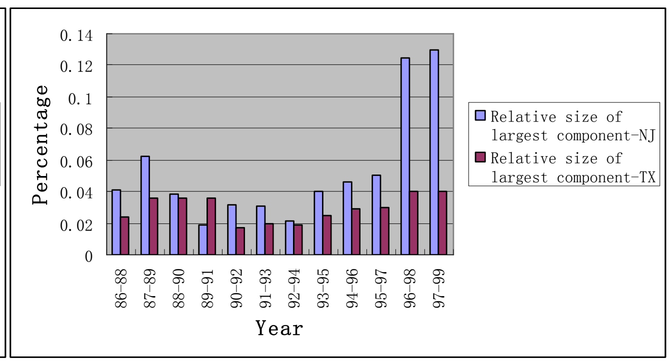

Figure 7: Relative size of the largest component – NJ vs. TX

We interpret the highly centralized network structure as a weakness of NJ's telecom industry which may explain the cluster's performance in innovation output. As a majority of job movements in the cluster originate from a common source, the diversity of the knowledge transferred within such a network is limited if compared to a network in which innovators move around more frequently with a variety of random routes. Also, considering the history and background of AT&T and the change of regulatory environment, there is a good possibility that the AT&T-hubbed patent network may, to a large extent, correspond to a firm-level adjustment resulting from the corporate fragmentation, rather than the macro-dynamics of labor market; while the latter scenario is a more desirable attribute for encouraging cluster development.

When the other set of one-mode networks which consists of patent inventors is analyzed, the trends of network evolvements for the two geographic clusters are very similar to the patterns observed before. As discussed in Section 3, Figure 5 shows the proportion of nodes with m-value greater than 1 in the m-sliced networks for each state. The edges represent inventors who moved among two or more organizations in the certain time window. Using this approach, we highlight the most active mobile inventors. Figure 5 demonstrates that the TX network was growing more mobile than NJ's during the later period of observation, which is consistent with the results from the first set of one-mode networks.

5. Conclusions and future work

This paper uses complex network modeling and shows how the inventor networks in New Jersey and Texas evolved while the corresponding geographic clusters went through different stages of lifecycle. Our results illustrates that patterns of job mobility may be predictive of the trend in cluster development. The study suggests, compared with New Jersey, Texas telecom inventors were more frequently changing their employers, starting their own business or/and joining others teams from different organizations. The latter scenario may often result from formal collaborations between organizations, such as contracted R&D projects. Either way these types of ties increase the possibility of technical information flowing within the industry cluster, though the two classifications of ties may vary in their capability for knowledge transfer. One limitation of the network analysis is that, based on the patent dataset itself, the proportion of connections corresponding to each type of ties cannot be explicitly measured, so future researches may benefit from interviewing those inventors to further investigate their motivations or duties involved with the connected patents.

Besides, by investigating multiple technological clusters, future research can examine whether certain patterns of job mobility tend to emerge when clusters experience significant growth or decline and how significant the predictive relationships are.

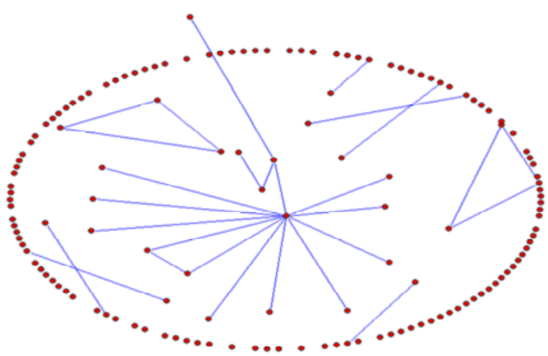

Figure 8: NJ's one-mode network of assignees – 1997-1999

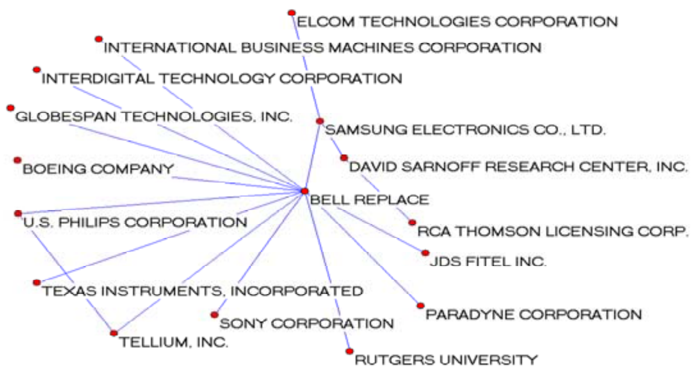

Figure 9: Main component extracted from Fig. 8

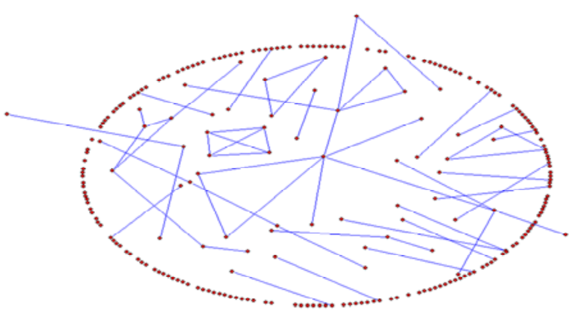

Figure 10: TX's one-mode network of assignees – 1997-1999

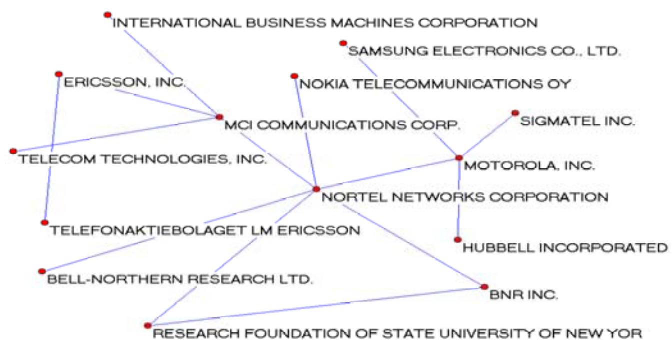

Figure 11: Main component extracted from Fig. 10

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