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UNDERSTANDING MOBILE ECOSYSTEM DYNAMICS: A DATA-DRIVEN APPROACH

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Abstract

The mobile ecosystem consists of a heterogeneous and continuously evolving set of firms that are interconnected through a complex, global network of relationships. However, there is very little theoretical understanding how these networks emerge and evolve and no well-established methodology to study these phenomena. Traditional approaches have primarily utilized alliance data of relatively established firms; however, these approaches ignore the vast number of relevant ecosystem activities that occur at the personal, entrepreneurial, and university level. We argue and empirically illustrate that a data-driven approach, using both alliance and socially-curated datasets, can provide important complementary explanatory insights into the dynamics of the mobile ecosystem. We present our approach through two recently formed mobile ecosystem relationships – the strategic partnership between Nokia and Microsoft and Google's acquisition of Motorola Mobility. Our analysis is complemented using network visualization techniques. The paper concludes with implications and future research opportunities.

Keywords: mobile ecosystem, transformation, strategic alliances, socially-constructed data, data and knowledge engineering, visualization.

1 Introduction

The mobile ecosystem consists of a heterogeneous and continuously evolving set of firms that are interconnected through a complex, global network of relationships. These firms come from a variety of market segments, each providing unique value propositions (Basole, 2009). It is quite unlikely for a single market segment to deliver all products or services to end-consumers. In fact, value creation and delivery requires a careful orchestration between firms across segments (Basole and Karla, 2012; Dhanaraj and Parkhe, 2006). For instance, the massive rollouts and upgrades of cellular networks by mobile network operators are useless without devices that can fully leverage them. Similarly, smartphones would just be boxes with little or no value without a platform and platform-enabled applications (Basole and Park, 2012). App stores provide third-party developers ways to offer content and reach consumers. Co-creation is hence an essential ecosystem characteristic, because a continual realignment of synergistic relationships of talent, knowledge and resources is required for growth of the system and responsiveness to changing internal and external forces (Rubens et al., 2011).

However, there is very little theoretical understanding how ecosystems emerge and evolve (Ahuja et al., 2011). Methodological approaches to quantitatively study these transformation phenomena have usually focused on event sequences at single levels in the biotechnology sector (Owen-Smith and Powell, 2004), national innovation ecosystem (Huhtamäki et al., 2011), mobile applications (Basole and Karla, 2012), and knowledge-intensive industries (Iansiti and Richards, 2006). Research that would answer how ecosystem emerge and evolve depends on data. The collection of primary data for business network research is time-consuming and costly. There are several potentially complementary data sources – some proprietary, others publicly available and still emerging data, like social media - containing relevant stakeholder activity information. Often these data sources are disconnected and reflect different units and periodicity; they are rarely interoperable. In some instances there is overlap, in others they are complementary, and in others they provide different insights and even conflicting insights. How can researchers leverage the wealth of data available to make new insights into how the ecosystem emerges and evolves? Historically, data acquisition was a resource-intensive step in data-driven research; it was a scarce resource. Open access to online data has made data widely available. A key challenge has now become the qualification and choice of data for analysis.

Our paper contributes in several ways. From a practical perspective, it provides competitive intelligence and insights into the systemic behavior and outcomes of firms. Small companies want to identify opportunities. Large companies want to know what's around the corner - technology and innovation, about which competitors they should worry and with which collaborators they should partner. Together they want to learn who has succeeded, why and how long it took. Theoretically, our paper contributes to the understanding of what elements and processes shape the evolution and transformation of the mobile ecosystem. It also contributes to our understanding how large, disconnected, potentially complementary structured and unstructured datasets can best be handled for insight, exploration, and discovery and how ecosystem evolution can be visually represented.

2 Related Work

Our paper draws on three distinct, but interrelated literature streams: interfirm networks and ecosystems, socially-constructed and curated data, and visualization and visual analytics.

2.1 Interfirm Networks and Ecosystem

An ecosystem consists of interdependent firms that form symbiotic relationships to create and deliver products and services (Basole and Rouse, 2008; Dougherty and Dunne, 2011). The conceptualization of markets as ecosystems is a result of theoretical extensions of work in inventor networks (Powell and Giannella, 2009) and of interfirm networks, alliances, and innovation (Gulati, 1998; Moore, 1993;

Oliver, 1990). With the complexity of product and service development and markets becoming increasingly disintegrated vertically and horizontally, there have been both a need and opportunity for the creation of interfirm relations (Iansiti and Levien, 2004). The formation of networks and alliances has been found particularly beneficial in technology industries as it has allowed firms to share risks in development and have access to synergistic knowledge (Eisenhardt and Schoonhoven, 1996). Studies have shown that interfirm networks are an effective organizational form to improve firm performance, speed of innovation, and organizational learning (Ahuja, 2000; Gulati et al., 2000).

More recently, studies have adopted a complex networked systems perspective to examine why, when, and how interfirm networks and alliances form and change (Gulati et al., 2000). This view combines both the resource-dependency and embeddedness perspective and suggests that interfirm networks are complex systems characterized by co-evolving actors engaged in collaboration, coopetition (Iansiti and Levien, 2004) and collective invention (Powell and Giannella, 2009). The complex networked systems approach has also been used to study value network and ecosystems in a variety of industries (Basole and Rouse, 2008; Rosenkopf and Schilling, 2008).

2.2 Provenance in Socially-Constructed and Curated Data

In the current tsunami of data, the provenance of data is of critical importance. Curated data is perceived to have the advantages of consistent ontologies, predictable data gathering methods and consistently applied data-cleaning rules. With the standardized data practices and policies of curated data, analytical methods can become standardized, and interpretation of analytical results benefits from consistent comparisons and a shared understanding of metrics. These very advantages, however, bring with them some disadvantages. Bias becomes baked into the data policies. Categories and classifications sometimes persist in data practice long after real world semantics have shifted to new classifications or reformulated categories. The time required for the curation processes may introduce significant delays into the timeliness of even the most recently available curated data. Additionally, many curated databases have limited availability and access may be exclusive and/or very expensive.

While some have argued that data in and of itself has little meaning and that the knowledge (Borgman, 2007) and meaning of data (Smagorinsky, 1995) are inherently socially constructed, the social nature of the Internet has added a new data frontier – in socially constructed data. Extensive data about businesses is now openly available through company websites, published announcements and filings, blogposts and microblogging, and community-built information resources. These sources provide unprecedented access to data, updated in real-time. One of the firsts of its kind, Wikipedia established itself as the most reliable source of accurate information (Giles, 2005) because it invited additions and tracked the provenance of changes; a data source that is socially constructed has observable patterns of governance (Leskovec et al., 2010). Advantages include its open access and availability, potentially large coverage, timeliness, and community verification of data quality. Some of the disadvantages are the potential of incompleteness and inconsistencies, lack of established perspective, and the issue (although slightly different from that of curated data) of incompleteness and inconsistencies.

2.3 Visualization and Visual Analytics

While an analytical approach provides valuable insights to the structure and dynamics of ecosystems, important knowledge can also be gained through the visualization of complex ecosystem data. Contrary to the perception that visualizations are merely artistic approaches to depicting structure, they have been used to explore, interpret, and communicate data in order to aid humans in overcoming their cognitive limitations, making structure, patterns, relationships, and themes visible, and providing a means to efficiently comparing multiple representations of the same data in fields such as medicine, dentistry, computer science and engineering. It has been suggested that visualization approaches can be extremely valuable for understanding and analyzing business issues, including strategy, scenario planning, and problem-solving (Tufte, 1983).

One explanation for the relatively slow uptake of visualization technologies in organizational and management sciences may be that visualization of complex systems is not only a very challenging and difficult task and but also, if not developed, implemented or applied correctly, may lead to non-conclusive results. Particularly in visualizing temporal changes of business ecosystems, node-link configurations are not necessarily unique and results may be misleading. The boundary-setting problem, or inclusion of nodes, is often artificial. Conclusions based on these models must thus be carefully scrutinized for the possibility of alternative explanations. Along the same lines, the amount of information that is captured and presented can often be overwhelming to the end-user. In many instances, what and how ecosystem data is visualized depends not only on the nature of the data but also on the question that is being asked and ultimately the cognitive abilities of the user. In order to overcome the aforementioned challenges, researchers must therefore ensure a balance between detail, abstraction, accuracy, efficiency, perceptual tension, and aesthetics in their complex network visualizations (Segel and Heer, 2010). These observations highlight the importance of setting the context and defining the elements in an ecosystem visualization study very carefully.

3 Data

We explore the dynamics of the mobile ecosystem using two complementary types of data sources – SDC Platinum and the IEN Dataset. Because the validity of our results and insights depends heavily on the nature and quality of the datasets, we first describe those datasets and then explain our conceptual approach and present our empirical results.

3.1 SDC Platinum

The SDC database is one of the most prominent, comprehensive, and accurate commercial databases used in the study of global interfirm relationships across multiple sectors (Schilling, 2009). It has been used extensively in strategic management and the management and organization sciences (e.g. Hsu (2006); Sampson (2004); Schilling and Phelps (2007)). Alliances and inter-organizational relationships are thus only one aspect of this broad database. The SDC database contains information on joint ventures, strategic alliances, R&D agreements, sales and marketing agreements, supply and manufacturing agreements, and licensing and distribution data, curated from SEC filings, trade publications, wires and news sources. In addition, it provides access to 200+ additional data elements, including names, SIC codes and nationality of participants, and relationship terms and synopsis.

3.2 IEN Dataset

The Innovation Ecosystems (IEN) Dataset (Rubens et al., 2010) is a quarterly updated collection of socially constructed data about technology-oriented companies in the ICT fields and the service companies (legal, accounting, advertising) that support them. Drawn from press release type information on multiple websites that permit comment and correction, it includes data about more than 68,000 companies (including accounting, legal and marketing services firms, and includes a high proportion of startup companies), their executives and board personnel, investment organizations, and financial transactions. People included in the dataset are key individuals in their respective companies (e.g. founders, executives, lead engineers, etc.), members of boards of advisors, or investors. The dataset further includes background data of individuals (e.g. degrees and institutions).

3.3 The Complementarity of the Two Datasets

The utilization of both datasets promises enormous complementary value for the analysis of ecosystem dynamics. While the SDC Platinum database contains validated alliance information for primarily large, global, and public companies, the IEN dataset contains information about small, private companies and startups. As many innovation activities occur in entrepreneurial settings or at the people level, the IEN dataset thus fills in the “blanks” between major ecosystem events. In contrast to high-quality and validated SDC data, however, the IEN dataset also inherits both the advantages and disadvantages of socially constructed data. Some of the advantages are availability, large coverage, timeliness, and community verification of data quality. Some of the disadvantages are potentially erroneous data and public bias (vs. the editorial bias often extant in traditional data settings). A comparative summary of the two datasets is provided in Table 1.

Table 1. Comparison of Datasets

	SDC Platinum 4.0	IEN Dataset
Source	Proprietary (Thomson Reuters Financial) based on U.S. SEC data	Open-Source based on socially-curated data from news, press releases, and social media
Type of Data	Alliance data (strategic, R&D, marketing, manufacturing, licensing, and supply) and status (active, terminated, pending) of public and private firms (37 SIC Codes, 4-digit)	Relationship Data of Public and Private Firms, Financial Organizations, Educational Institutions, Funding Rounds, Acquisitions, Investments by Individuals and Companies
Years covered	1/1/1990 - 12/31/2011	1/1/1994 - 01/31/2012

4 Approach

We use a three-stage process for analyzing the dynamics of the mobile ecosystem, consisting of boundary specification, metrics identification and computation, and analysis and visualization.

4.1 Step 1: Boundary Specification

Boundary specification involves determining the primitives of the network architecture (Ahuja et al., 2011), including nodes, node types (e.g. firms, people, universities, etc.), and relationship types (e.g. R&D, supply chain, marketing, licensing, etc.) and specification of the desired analysis timeframe (e.g. start/end-date). The choice of these parameters is driven by the nature and intent of the problem.

The specification of nodes, however, is not a trivial task, as firms continuously enter and leave the ecosystem. If the analytical focus is on the evolution of a particular market segment, one may begin by considering all companies that operate in that market sector and the second level companies to which the selected first-level companies connect. This leads to a related decision concerning the number of third, fourth and subsequent levels of companies to include in the selected data. Which other companies should be included in the analysis (only those directly connected companies outside of the first-level market sector or companies connected k-steps from companies in the focal first-level market sector)? The larger k is (upper bound limit defined by the maximum k-steps of the graph), the more companies will be included. However, this expansion carries risks of diluting the analysis with potentially irrelevant companies. The smaller k is, however, the greater the risk of ignoring important companies that may be a few steps removed.

The specification of the appropriate timeframe is an equally challenging task. How far back in time does the data need to go in order to capture the events and activities that led to the alliance? In many instances, researchers either choose the largest timeframe available (e.g. the first activity for any of the companies involved in the alliance) or a particularly important or relevant point in time (e.g. announcement, product launch, policy decision). It is quite foreseeable that a singular event/activity did not necessarily cause the activity the researcher is trying to explain. It may have been a result of multiple events/activities that occurred in a particular order.

4.2 Step 2: Metrics Identification and Computation

There are many social network and graph theoretic metrics that can be useful for understanding the dynamics of an ecosystem. Broadly, these can be categorized at two levels of analysis – the whole network (ecosystem) and the node level (firm/individual). This differentiation is important because network dynamics at each level, although related, are also distinct (Zaheer et al., 2010). A description of representative metrics (e.g. (Ahuja et al., 2011) is provided in Table 2.

Table 2. Node and Network-Level Ecosystem Dynamics Metrics

Level	Metric	Description
Network	• Size	Change in the size of the network is reflective of the overall growth of the relevant ecosystem.
	• Degree Distribution	Change in the degree distribution is reflective of changes in the status hierarchy of the observed system.
	• Diameter	Change in the diameter is reflective of the connectivity or "small worldness" of the network.
	• Clustering	Change in clustering represents the reconfiguration of clusters or constellations of firms that may be competing against each other as alliance networks.
	• Density	Change in density (the proportion of ties that are realized in the network relative to the hypothetical maximum possible) represents how tightly the network is connected.
	• Degree Assortavity	Change in degree assortavity is reflective of the degree to which nodes with similar degrees connect to each other.
Node	• Degree	Change in the degree is reflective of the number of new connections a firm has gained or established.
	• Betweenness Centrality	Change in betweeness centrality measure is reflective of the positional prominence of a firm (node) in a network.
	• Cluster Coefficient	Change in the cluster coefficient is reflective of the level of connectivity between a firm's directly connected partners.

4.3 Step 3: Analysis and Visualization

There are a number of ways analyzing and visualizing temporal data. One approach includes a tabular description of key metrics; another includes a timeline representation of changes in key network metrics. If multiple metrics want to be compared simultaneously and structural patterns matter more than specific metric levels, sparklines or small-multiples are a frequent choice. Ideally, an interactive, animated approach is required. Due to page constraints, we utilize a tabular representation and cumulative network visualization to depict the dynamics of the mobile ecosystem in the paper and provide an interactive representation online.

5 Illustrative Examples

We illustrate our data-driven approach to understanding mobile ecosystem dynamics with two recent examples. The visualizations represent a 2-step network using two layout algorithms: OpenORD to create clusters; ForceAtlas2 to aesthetically space nodes. Node and relationship types are differentiated by color (e.g. red=firms; green=investment firms; blue=people; purple=educational institutions).

5.1 Nokia and Microsoft

The alliance between Nokia and Microsoft in February 2011 was considered by many pundits to be an inevitable move given the recent struggles of both companies in the mobile ecosystem. Once a leader in the global handset market, Nokia has been falling behind other device manufacturers in the lucrative smartphone segment. Microsoft, a perennial leader in the desktop market, never really achieved any traction in the mobile market despite its Windows Mobile platform. Many attributed Microsoft's shortcoming to a lack of an appropriate hardware partner. A collaboration became increasingly realistic when Nokia appointed Stephen Elop, a former Microsoft executive, as its next CEO in 2010.

Figure 1 shows the SDC alliance network of Microsoft and its partners, Nokia and its partners, and alliances between the partners. Microsoft and Nokia have direct relationships with 275 and 123 companies, respectively. Both firms have many second order relationships. The strength of ties between Microsoft and Nokia can be observed in their proximity to each other and in the thickness of the edges connecting the two major nodes.

Figure 2 shows the IEN network, which adds company leadership, investment firms, and educational institutions. The patterns of relationships among these constituents show multiple connections, with key individuals as critical nodes in the network of relationships. The importance of the personal network in creating relationship pathways between Microsoft and Nokia is visible. Stephen Elop, shown as the individual at the top of Figure 2, with direct connections to both Nokia and Microsoft, is not the sole relationship connection. The links to investment firms from Microsoft's second order companies creates a venture-influenced mega cluster. The cluster of companies around Nokia is less influenced by different investment firms. A few investment firms and their key people link Microsoft to Nokia. The multiple relationship pathways through which information, resources and talent can flow between Microsoft and Nokia reflect a multidimensional form of collaboration.

5.2 Google and Motorola Mobility

Google's proposed acquisition of Motorola Mobility in August 2011 received significant attention by players in the mobile ecosystem. Motorola Mobility had been struggling to (re)gain market share in the lucrative smartphone segment. Through various business transformations in recent years it had tried to reposition itself, but still failed to deliver on its past innovative pedigree. Contrary, Google - not a traditional mobile player - was speculated to enter the ecosystem full-force on many occasions. For instance, Google was a key bidder on wireless spectrum a few years back. More recently, Google was a key investor and creator of the Android mobile platform. However, there were no signs that Google would offer its own hardware.

Figure 3 shows the SDC alliance network of Google and its partners, Motorola Mobility and its partners, and alliance between the partners (both firms are both shown in the upper left area). Google and Motorola Mobility are directly connected to 16 and 22 companies, respectively. There is no direct alliance between the two firms. Interestingly, Microsoft dominates this network, due to the first-degree connections between Microsoft and both Motorola and Google and the second degree connections to the other strongly connected firms.

Figure 4 shows the IEN network. This network is characterized by a dense web of companies and investment firms – a venture network. Google shows two connections to investment firms – Sequoia and Google Ventures. Two observations are of particular interest: the lack of a node connecting Google with Motorola and the relative independence from investment firms for both. Motorola Mobility hangs on a connection to Motorola Solutions and links to this ecosystem with a connection to Vivotech, which has a connection to Draper Fisher Jurvetson, and a connection to a123systems, which has investment from Fisker and Sequoia Capital, which is connected to Google.

The relative isolation of Motorola from the Google and venture subnetworks is apparent in this graph. The sole link visible here is one individual who is connected to both Motorola and Motorola Mobility, and is also connected to another company that received investment from Sequoia Capital. Indirect pathways between Google and Motorola are created by the relationships of several individuals, but these appear to be relatively few, especially in contrast to the Microsoft-Nokia network.

The strong presence of Google in the IEN Dataset is highlighted by the fact that Google's absolute degree value is larger for IEN data even though the total network for IEN data is significantly smaller than for the SDC network, see Table 3. As indicated by data drawn from the IEN Dataset one could argue that this is due to Google's strategy of growing through acquiring small startups rather than forming alliances. Seen from a network perspective, the acquisition of Motorola Mobility by Google is more likely to be an event in which Motorola Mobility and its relationships are consumed by Google.

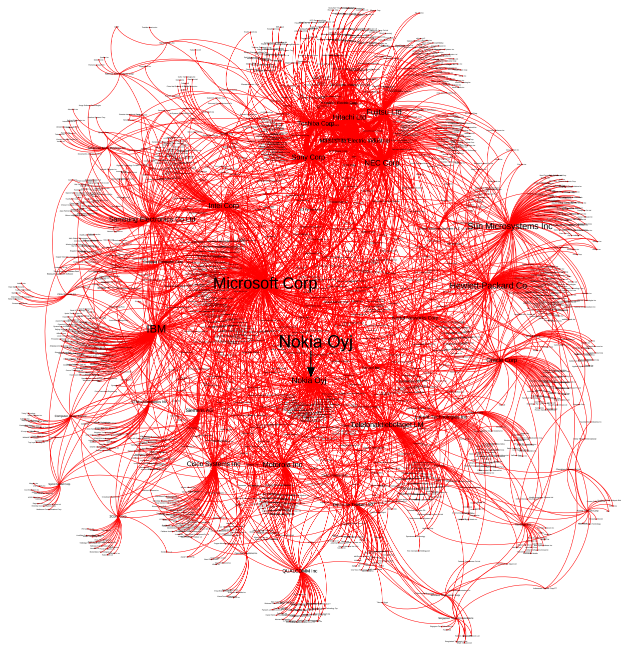

Figure 1. *Nokia & Microsoft -- Cumulative Network using SDC Alliance Data*

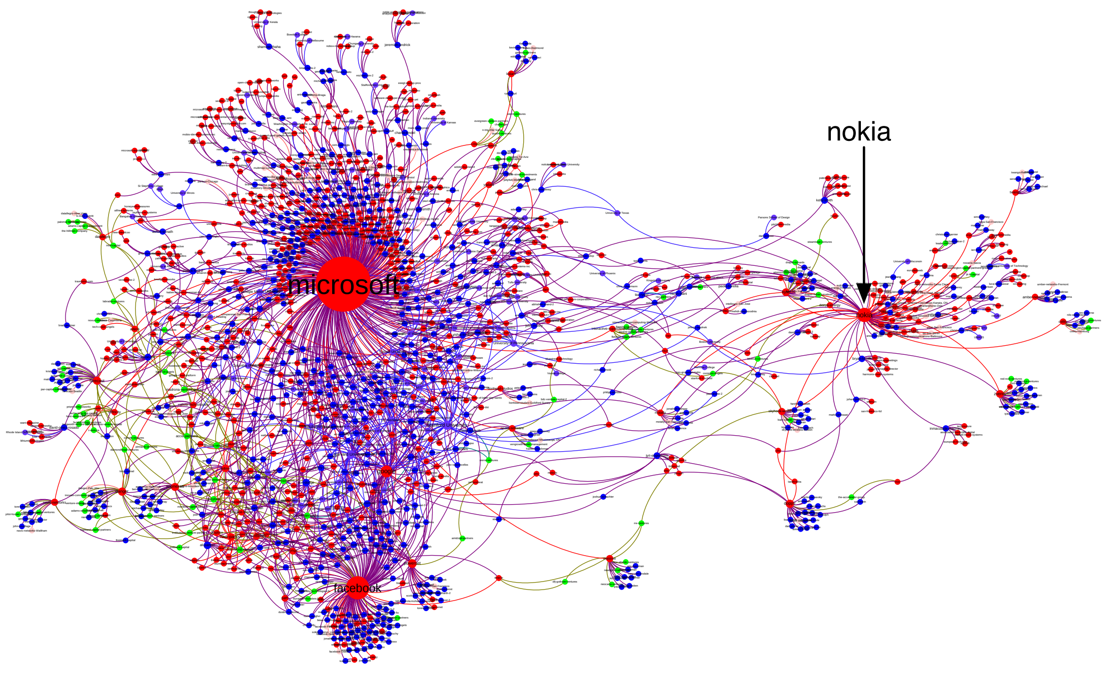

Figure 2. *Nokia & Microsoft -- Cumulative Network using IEN Data*

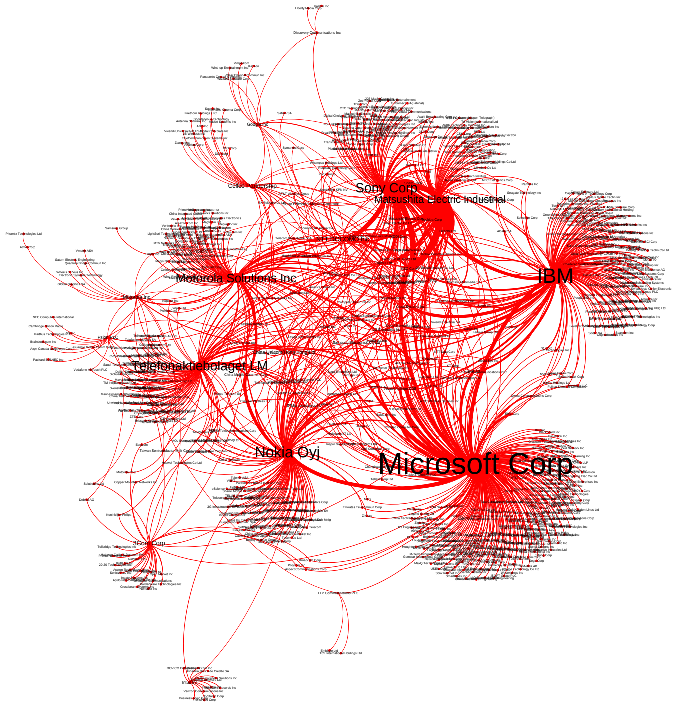

Figure 3. *Google & Motorola Mobility -- Cumulative Network using SDC Alliance Data*

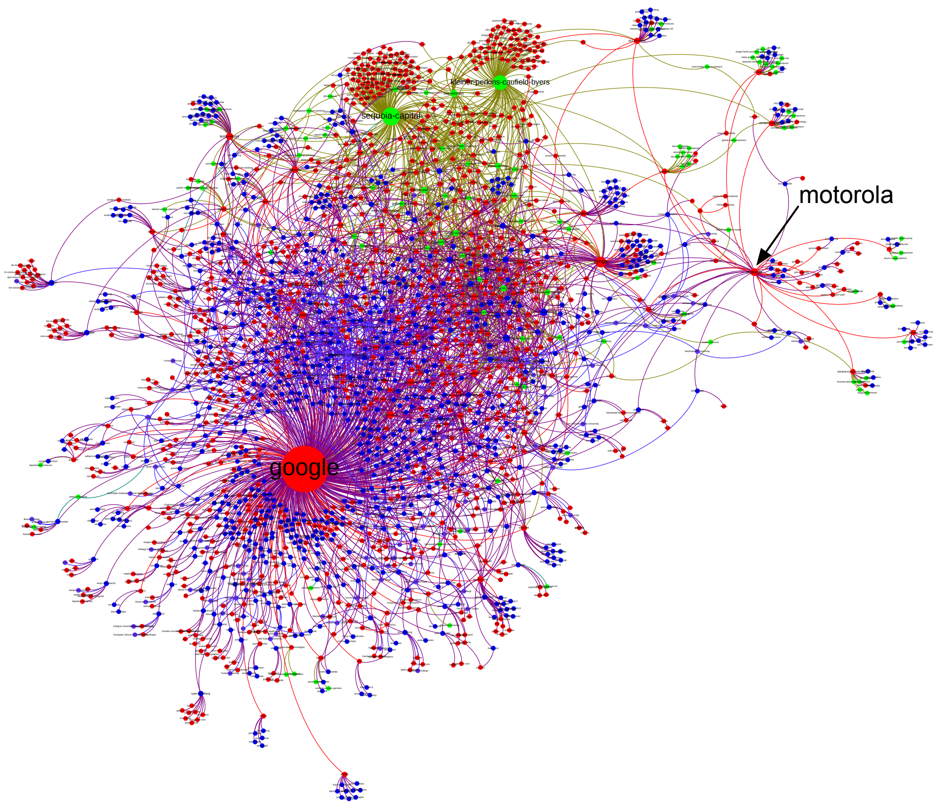

Figure 4. *Google & Motorola Mobility -- Cumulative Network using IEN Data*

Table 3. *Nokia and Microsoft -- Comparison of Representative Ecosystem Dynamics Metrics*

		SDC Data						IEN Data					
		6/2009	**12/2009**	**6/2010**	**12/2010**	**6/2011**	**12/2011**	**6/2009**	**12/2009**	**6/2010**	**12/2010**	**6/2011**	**12/2011**
Network	• Size	1,621	1,643	1,646	1,652	1,659	1,666	125	142	146	155	156	157
	• Diameter	4	4	4	4	4	4	4	4	4	4	4	4
	• Clustering	1	1	1	1	1	1	2	2	2	2	2	2
	• Density	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.016	0.014	0.014	0.13	0.013	0.013
Node	**Nokia Oyj**												
	• Degree	197	120	120	122	122	123	14	17	19	20	20	20
	• Betweeness Centrality	135193	135220	135197	138627	139011	140970	104	205	292	342	342	342
	• Clustering Coefficient	0.035	0.036	0.036	0.035	0.035	0.035	0	0	0	0	0	0
	Microsoft Inc.												
	• Degree	266	272	273	274	274	275	69	72	72	74	75	76
	• Betweeness Centrality	405609	416156	417728	419434	421013	424517	5624	6846	6846	7649	7775	7902
	• Clustering Coefficient	0.014	0.014	0.014	0.014	0.014	0.014	0	0	0	0	0	0

Table 4. *Google and Motorola Mobility -- Comparison of Representative Ecosystem Dynamics Metrics*

		SDC Data						IEN Data					
		6/2009	**12/2009**	**6/2010**	**12/2010**	**6/2011**	**12/2011**	**6/2009**	**12/2009**	**6/2010**	**12/2010**	**6/2011**	**12/2011**
Network	• Size	719	788	789	792	794	797	60	73	91	118	129	137
	• Diameter	6	6	6	6	6	6	4	4	4	4	4	4
	• Clustering	1	1	1	1	1	1	2	2	2	2	2	1
	• Density	0.0038	0.0036	0.0036	0.0036	0.0036	0.0036	0.033	0.028	0.022	0.017	0.016	0.015
Node	**Google Inc.**												
	• Degree	14	16	16	16	16	16	45	51	65	78	87	98
	• Betweeness Centrality	14200	16224	14725	9450	9691	9720	1416	2097	3432	5587	6812	9067
	• Clustering Coefficient	0.077	0.1	0.108	0.117	0.117	0.117	0	0	0	0	0	0
	Motorola Mobility												
	• Degree	22	22	22	22	22	22	3	4	4	6	6	7
	• Betweeness Centrality	8363	8881	8886	8953	8977	9011	5.0	9.0	9.0	33.0	33.0	795
	• Clustering Coefficient	0.087	0.087	0.087	0.087	0.087	0.087	0	0	0	0	0	0

Note: Due to page constraints, we did not include a detailed description of the degree distribution metric.

6 Concluding Remarks

This paper advocates a data-driven approach for understanding the dynamics of the mobile ecosystem. We illustrate our approach with an exploratory analysis of two recently formed relationships – Microsoft/Nokia and Google/Motorola Mobility – using two data sources. Our initial results show that each dataset has its advantages and disadvantages, but used jointly can reveal consistent patterns and create synergistic insights. The SDC dataset emphasizes deal-based relationships and does not include data about key individuals in the companies; the IEN dataset includes individuals and emphasizes the relationships formed among companies through those individuals' leadership activities. We think that the data-driven approach can provide important insights into patterns of event sequences between nodes for a particular type of event (e.g. R&D alliance) and the average duration it takes.

Many challenges and opportunities remain. Arguably the most foundational task is the careful integration of datasets. Datasets use different unique identifiers or naming conventions. Consequently, matching names and labels of firms or individuals across datasets is not a trivial task. Firm names may be inconsistent and use different enterprise labelling. As a result of mergers, acquisitions, or corporate restructuring, firms may also change names over time. Appropriate identification and matching algorithms to ensure consistency across datasets must therefore be developed. Another challenge is the selection and assignment of companies to market segments. Various industry classifications exist, but datasets often use different classification schemes. The identification of primary and secondary market segments is particularly challenging for large firms that operate in multiple and equally important segments. Intelligent market segment identification and assignment methods must therefore be developed. As firms transform or enter and exit the ecosystem it is critical to devise appropriate data persistency protocols by identifying events by time and actors involved.

Our study also provides the foundation to explore many interesting ecosystem issues including what relationship configurations characterize growth, how the position and role of firms in the ecosystem influences their access to talent, information, resources, what event windows and types are relevant for observing ecosystem dynamics and what sequences matter.

There are also many opportunities for creating appropriate representations of mobile ecosystem dynamics. This may include the development of an interactive visualization system using multiple views. The alignment and representation of time units at potentially different scales is an important representational aspect. While established datasets may capture large, less frequent events, socially-curated data may capture activities that occur in closer time intervals. Enabling a user-driven selection of time units will enable greater insight and discovery of the temporal nature of ecosystem activities.

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