EVA: Extraction, Visualization and Analysis of the Telecommunications and Media Ownership Network

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Abstract

We present EVA, a prototype system for *e*xtracting, *v*isualizing, and *a*nalyzing corporate ownership information as a social network. Using probabilistic information retrieval and extraction techniques, we automatically extract ownership relationships from heterogeneous sources of online text, including corporate annual reports (10-Ks) filed with the U.S. Securities and Exchange Commission (SEC). A browser-based visualization interface allows users to query the relationship database and explore large networks of companies. Applying the system and methodology to the telecommunications and media industries, we construct an ownership network with 6,726 relationships among 8,343

companies. Analysis reveals a highly clustered network, with over 50% of all companies connected to one another in a single component. Furthermore, ownership activity is highly skewed: 90% of companies are involved in no more than one relationship, but the top ten companies are parents for over 24% of all relationships. We are also able to identify the most influential companies in the network using social network analysis metrics such as degree, betweenness, cutpoints, and cliques. We believe this methodology and tool can aid government regulators, policy researchers, and the general public to interpret complex corporate ownership structures, thereby bringing greater transparency to the public disclosure of corporate inter-relationships.

1 Introduction

Ownership is a fundamental element of analysis in economics and public policy. An ownership relationship may indicate the flow of capital, information, and influence between two firms. It may also have broader implications for industrial organization, competition, and antitrust. In an era of industry convergence, ownership relationships among companies have become so complex that they resemble directed social networks rather than simple hierarchies. Yet, tracking and analyzing ownership networks are prerequisites to informed public debate on proposed mergers or government regulation. While federal regulations dictate full ownership disclosure for public firms, such information are often decentralized and unstructured, if not unreported, [1] making systematic documentation and analysis of ownership very difficult. Researchers must often sift through large volumes of free-text, a process that is time-consuming, tedious, and non-scalable.

The EVA project has three objectives. The first is to efficiently gather from heterogeneous sources large amounts of ownership information describing the telecommunications and media industries. We format this data as a social network of companies connected by ownership relationships, where ownership is defined as one company's possession of equity in another company. The second objective is to provide access to this information through a simple, intuitive interface.[2] The third is to analyze the ownership network using

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[1] For example, Tyco spent about $8 billion in its past three fiscal years on more than 700 acquisitions that were never announced to the public [17].
[2] The EVA visualization tool is located at <http://denali.berkeley.edu/eva/>.

social network analytic techniques in order to gain insight of the industry at both the firm level and the industry level.

We concentrate on the telecommunications and media industries for two reasons. First, these industries constitute a significant component of the global economy, as companies in these industries control information content and delivery, publishing, broadcasting, and global networking, all essential components of public speech. Second, these industries have been in a state of flux since the Telecommunications Act of 1996 opened up possibilities for new constellations of ownership by lifting regulatory barriers between media and telecommunications companies [8]. The ability to track and analyze these changes would be an important tool for the creation of telecommunications policy.

Using probabilistic information retrieval and extraction techniques, we construct an ownership network of 6,726 ownership relationships among 8,343 companies. Analysis reveals power law distributions for two important network metrics, namely *component size* (number of companies connected together) and *company degree* (number of ownership relationships in which a company is involved). Two results stand out from these metrics. First, one large component connects over half of the companies in the database. Second, ten companies are owners in over 24% of relationships. These findings reveal a sparse but broad network where a few companies claim the majority of ownership.

This paper is structured as follows. Section 2 gives an overview of the EVA system. Section 3 explains the process for extracting and storing ownership relationships. Section 4 describes the visualization interface. Section 5 contains our network analysis and discusses its significance. Section 6 discusses implications of and improvements to the system, and Section 7 concludes.

2 System Overview

The EVA system comprises an extraction engine, a database, and a visualization interface. Figure 1 shows how these components interact. The extraction engine is both a primary and secondary research tool for gathering ownership data. As a primary research tool, the extraction engine identifies ownership information buried within lengthy free-text documents; as a secondary research tool, it gathers ownership data summarized in documents published by organizations that have conducted prior research. The extraction engine can search any number of heterogeneous data sources. If the data from a source are consistently formatted, EVA can gather such data automatically. Otherwise, EVA either probabilistically ranks likely ownership relationships for human review, or else offers an interface for humans to manually enter the data. The database stores the information as a directed network, enabling calculation of overall connectedness and identification of prominent companies. The browser-based visualization interface lets users display subsets of the network and explore different paths among companies. We use the standard network analysis software package UCINET [4] and additional custom scripts for data analysis.

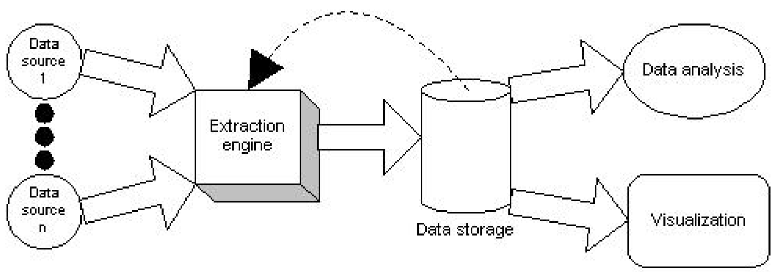

Figure 1. EVA data flow diagram.

Our current sources include three online document collections:

- Public company 10-K annual reports filed with the U.S. Securities and Exchange Commission [26]
- *Columbia Journalism Review's* Who Owns What [18]
- *The Industry Standard's* online Deal Tracker Database [15]

Corporate annual reports (10-Ks) are primary sources because EVA extracts ownership data from paragraphs in these free-text documents. *Columbia Journalism Review* (CJR) and the *Industry Standard* are both secondary sources as the ownership data contained in these documents were gathered, compiled, and verified by other researchers. All relationships were valid at some point between January 1, 1998, and December 31, 2001. Figure 2a shows the number of companies for which each source found at least one relationship, and Figure 2b shows the number of relationships found by each source. Few relationships were found by more than one source. This lack of overlap suggests that the coverage of the data set can be further improved with additional data sources. For example, Mergerstat and Thomson Financial are two leading sources of mergers and acquisitions data, commercially compiled by teams of full-time research staff. Discussions with one vendor reveal a data set for the telecommunications and media industries that contains slightly fewer relationships than our data set.

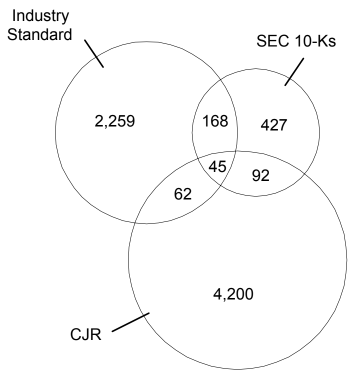

Figure 2a. Number of companies for which each source found at least one relationship (Total = 7,253)

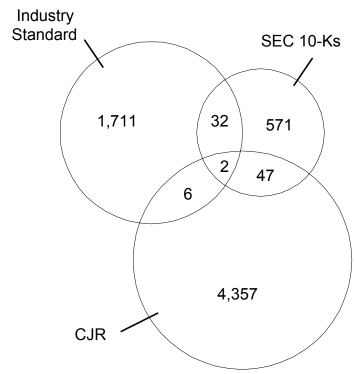

Figure 2b. Number of relationships found by each source (Total = 6,726)

3 Probabilistic Extraction of Relationships from Free-text

EVA uses probabilistic extraction techniques to extract ownership relationships from primary sources such as corporate annual reports submitted to the SEC (10-K documents). The main goal of the extraction heuristic is to minimize the human effort required to conduct primary research. The list below breaks down the time it took to design and run the free-text extraction engine in EVA:

- 160 hours to code and test
- 20 hours to download and process documents (3,374 documents, 1.5GB of text)
- 30 hours to manually train the system and evaluate the top 3,249 relationship paragraphs

Since the extraction code can be reused, EVA would require significantly less time to process additional sources of data.[3]

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[3] We conducted a rough experiment to approximate how much time EVA can save researchers looking for acquisition data in 10-K documents. We timed ourselves reading sampled 10-K documents and manually recorded each acquisition that we found. We calculated that we would have needed about 293 hours to process the entire 1.5GB of text. This is about six times more than the 50 hours needed by the EVA extraction engine to process an additional 1.5GB of data.

3.1 Extraction Heuristic

EVA uses keywords to find relevant parts ("paragraphs") of documents and then probabilistically ranks those paragraphs on the likelihood that they include valid acquisition information. The steps of the heuristic are:[4]

1. Start with a seed list of company names
2. Extend the list of company names using both probabilistic extraction and manual review
3. Use keywords (like "acquisition" and "merger") to identify candidate paragraphs containing at least one company name
4. Use simple noise filter rules to eliminate paragraphs not likely to be useful
5. Rank the remaining paragraphs using a probabilistically trained weighting index and regression-based weighting formula
6. Present the highest ranked paragraphs to humans who:
    a. Eliminate invalid relationships
    b. Identify relationships that are missed by the extraction engine

3.1.1 Probabilistic Weighting

At the core of our heuristic is a probabilistic term weighting formula originally developed by Robertson and Sparck-Jones [21] and advanced by several information retrieval experimental systems at the Text REtrieval Conferences.[5] To probabilistically train the weighting index, we manually rate randomly sampled paragraphs as *valid* or *invalid*, where a valid paragraph describes an acquisition that results in an ownership relationship between two companies. We use SQL to convert rated paragraphs into a weighting table in a database. By summing the word weights for each paragraph, we compute a confidence score that ranks the likelihood that similar paragraphs contain valid relationships.

Using linear regression, we find that paragraph word weights alone explain 45.7% of the variance between paragraphs. We improve this result by adding two more variables to the formula: the probabilistic weight of the words in the sentence containing the keyword and

[4] A detailed account of the extraction heuristic is in our technical report (http://denali.berkeley.edu/eva/tech-report).
[5] http://trec.nist.gov/. We also tested the widely used OKAPI-BM25 weighting formula designed to normalize document lengths. It performed slightly worse than RSJ in terms of precision and recall because all our paragraphs are the same length (600 characters).

the proximity of the keyword to the acquired company's name. Using linear regression a second time, we add together the paragraph weights, sentence weights, and proximity measures after multiplying them by their regression coefficients.[6] The combined weighting formula explains 52.4% of the variance and produces a ranking confidence value for each paragraph.

3.1.2 Probabilistic Weighting Performance: Precision and Recall

Although the EVA extraction engine is primarily designed to save time, we do measure precision and recall.[7] We keep the 35% of paragraphs with the highest probabilistic rankings for possible inclusion in our data set. Examining these paragraphs, we find that the extraction module has a precision of 55.4% and a recall of 50.0%. This performance compares favorably with the performance of DARPA-sponsored Message Understanding Conferences (MUC) systems,[8] where good performance in simpler event extraction domains translated to precision and recall measurements between 50% and 70% [14].

We present two examples of false positives that underscore the difficulty in automatic extraction of acquisition events that result in changes in equity holdings.[9] In many cases, the language in 10-K documents is so ambiguous that even humans are confused. The first example comes from a 10-K filed by Aether Systems and contains an acquisition that does not meet our definition of equity ownership. At one point, text in the document appears to describe Aether's acquisition of the company Motient:

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[6] We use a linear regression method similar to the logistic regression technique by Cooper, Gey and Dabney [9] to estimate weighting formula coefficients.

[7] Precision is the number of records returned from a search satisfying a query, divided by the total number of records returned from a search. Thus, if four of ten records returned by a search engine were valid, then precision would be 40% (4 / 10). Recall is the number of good records returned from a search, divided by the total number of good records in all documents searched. Thus, if there are eight total good records, but the search engine only returned four, then recall would be 50% (4 / 8). For these calculations, we need to know the number of good relationships that EVA finds for a given set of documents, as well as the total number of good relationships in those documents. The first metric simply requires that we track the number of good acquisitions found during our reviews. The second metric is more difficult; without reading all documents thoroughly, we do not know how many acquisitions are contained in all the documents. However, while reviewing paragraphs we search for additional acquisition data to manually enter, so as an approximation we use the total number of acquisitions found during the review phase.

[8] MUC evaluations helped researchers set standards to evaluate the performance of tasks such as named entity recognition (NER), entity attribute recognition, entity relationship fact-finding, and entity event finding. Soderland compares several successful information extraction systems that MUC participants have created [23].

[9] Freitag points out additional difficulties when extracting information within the "acquisition" domain [12].

> … In connection with the acquisitions of Cerulean, Sinope, RTS and Motient, the Company [Aether Systems] has accrued $29,800 as of December 31, 2000 for the remaining portion of the purchase price. Such amount has been allocated to the fair value of the assets purchased and the liabilities assumed… [27]

Subsequent text, however, clarifies that Aether has simply acquired one of Motient's business units, rather than any equity in Motient itself:

> … On November 30, 2000, we [Aether Systems] acquired Motient's retail transportation business unit for $49.2 million in cash… [27]

Companies routinely report acquisitions of assets in their 10-K filings, but by definition these events do not give rise to equity ownerships. Furthermore, these acquisitions are sometimes financed by the equity of the acquirer, so a transfer of equity ownership can actually occur in the reverse direction. In this second example, the excerpt from the 10-K filing of Nextel Communications is tagged as containing an acquisition event that results in Nextel's becoming an equity owner of Motorola:

> … we [Nextel] acquired all of Motorola's 800 MHz SMR licenses in the continental United States in exchange for 41.7 million shares of class A common stock and 17.8 million shares of nonvoting class B common stock … [28]

However, human review reveals that Nextel acquired some licenses from Motorola using its own stock, and therefore Motorola emerges as an equity owner of Nextel as a result of this transaction.

Precision and recall can be improved using category filters. As the examples indicate, we want the extraction engine to exclude acquisition events such as asset acquisitions, proposed, pending and future acquisitions, and acquisitions of warrants. We create category filters that probabilistically identify the type of acquisition contained in each paragraph. Paragraphs with a high likelihood of being in a category other than equity ownership are eliminated and excluded from manual review. Experiments on our data set show that, given a fixed number of paragraphs, category filters can increase precision up to 6% (Figure 3). Although category filters do not eliminate the need for human review, they do allow reviewers to examine fewer paragraphs yet still receive a higher yield.

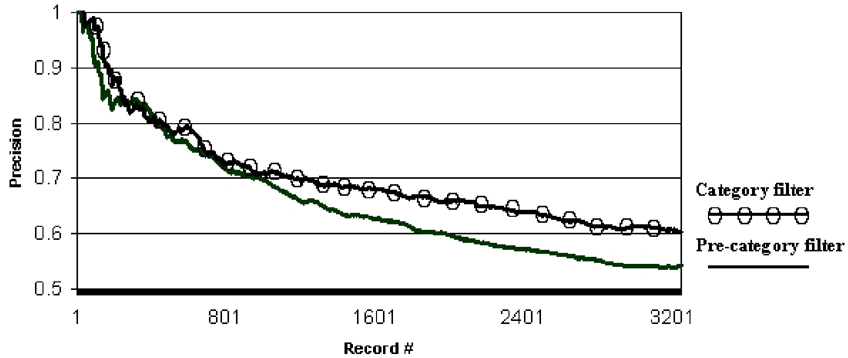

Figure 3. Category filter improves extraction precision.

More fundamentally, the ambiguity of free text can be avoided altogether by forming documents according to a semantic structure such as the XML schema in Appendix 1. How such a schema might be implemented (required or optional inclusion in corporate filings) would be a matter of public policy. If used, XML could encourage a more transparent understanding of major ownership events.

3.1.3 Manual Evaluation

The final step in the free-text extraction process is to manually review the top 35% ranked paragraphs. Ranking the paragraphs allows human reviewers to focus first on paragraphs that are most likely to be useful. A web interface allows reviewers to quickly accept, reject, reverse, and add relationships. Altogether, the manual evaluation process takes approximately 22 seconds per paragraph. Since multiple paragraphs often describe the same acquisition, it takes reviewers an average of 1.6 minutes to confirm or reject each possible acquisition. We add the approved relationships to the EVA data set, which has a precision level of 100%.

4 Information Visualization

Understanding networks can be difficult without a visual explanation. Graphs have long been the primary method of representing social networks [5]. Because EVA treats corporate ownership as a social network, it is logical to expect a graphical component to this work. Graphical representation reveals a macroscopic view of an industry, plus sub-structures that would otherwise remain hidden. Following the principles of information visualization [25], our goal is to present this information without overwhelming the user or cluttering the display.

The browser-based visualization prototype displays the ownership network stored in the EVA database. Users can search for companies, generate ownership graphs, and read source documents. Given the appropriate data, the interface can also visualize changes to ownership networks over time.

4.1 Related Visualization Work

Visualizing ownership networks is an interdisciplinary endeavor drawing from the fields of social network analysis, business intelligence, media criticism, and information design. Specific works related to the EVA visualization tool therefore include graphics and software from several sources. [22] contains an example of a static graphic image explaining media mergers described in a news article. Orgnet[10] and TheyRule[11] are two applets that display information similar to the EVA data set. A few visualizations deal directly with corporate ownership relationships. Strategic Landscapes from Goldridge[12] generates textual reports and graphical maps of companies related by many factors, including ownership. The Centre for Global Corporate Positioning[13] offers a similar service.

4.2 Graphical Interface

Figure 4 shows an overview of the interface prototype. Major elements include the search feature, the graph display panel, and the metadata panel. Users generate graphs by first searching for specific companies and then adding the ownership networks of those companies to the display panel. The display panel is a Java applet implementing a version of the spring embedder graphing algorithm described in [10]. The metadata panel on the left lists details about the selected company, including links to the source documents substantiating that company's ownership relationships. Figure 5 shows the graph's legend with definitions for colors, arrows, node sizes, and borders.

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[10] http://www.orgnet.com/inetindustry.html
[11] http://theyrule.orgo.org/
[12] http://www.goldridge.net/
[13] http://www.cgcpmaps.com/demo.php

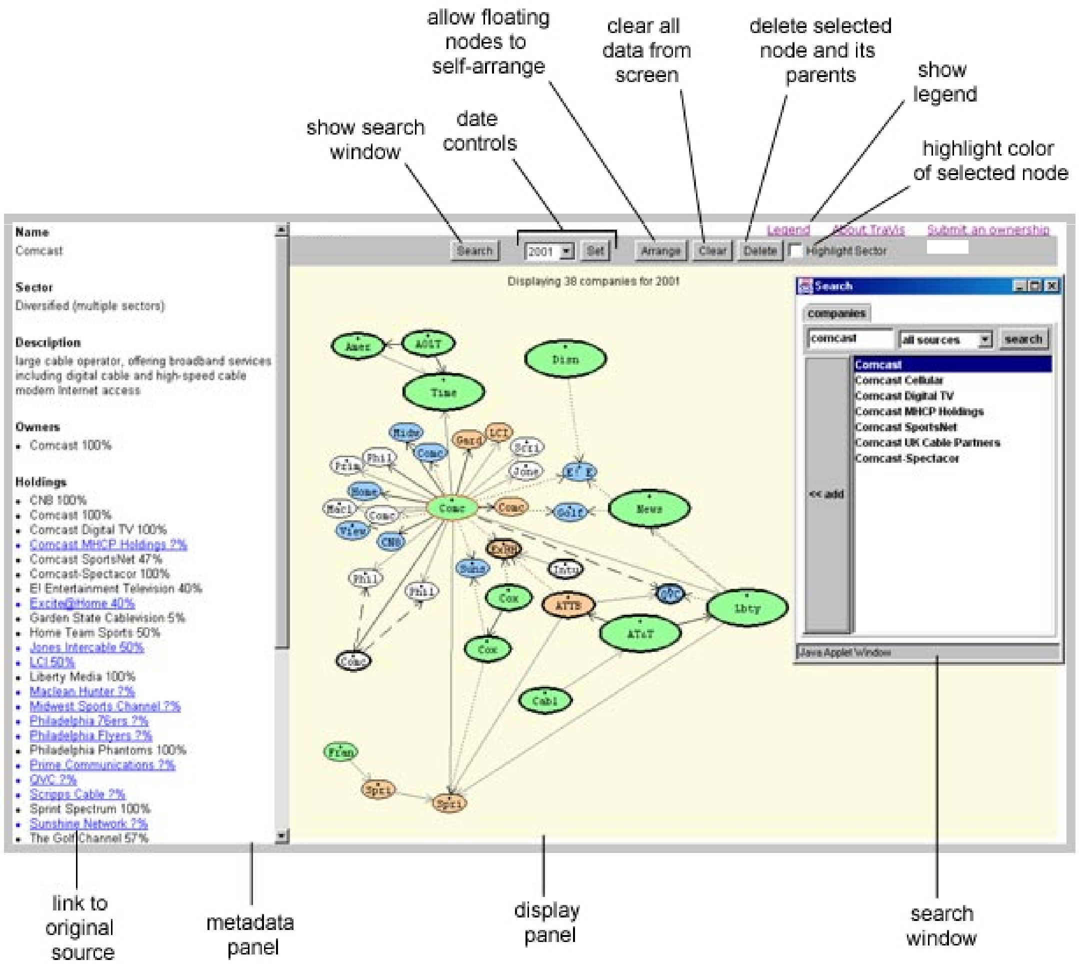


Figure 4. EVA display.

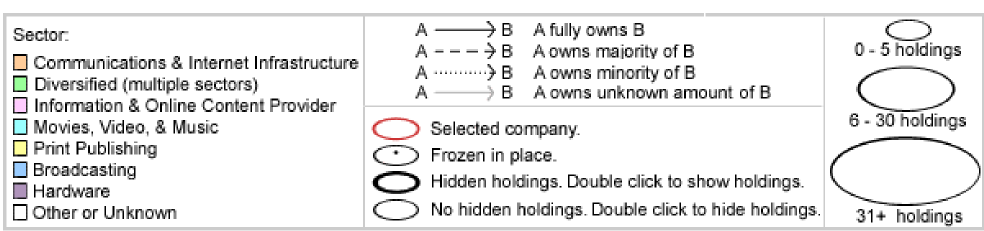


Figure 5. Legend for EVA display.

For every company displayed on the screen, all parents (owners) of that company are also visible. This approach helps users to quickly identify top-level companies, see how local clusters fit into the overall network, and identify previously hidden relationships. As an example, a recent user of the interface selected *Sunset Magazine*, and to his surprise found that AOL-Time Warner was an indirect owner (Figure 6). This discovery provided an explanation for the AOL trial disk enclosed between the pages of his latest issue of *Sunset*

Magazine. Figure 6 shows the indirect relationship between *Sunset Magazine* and AOL-Time Warner.

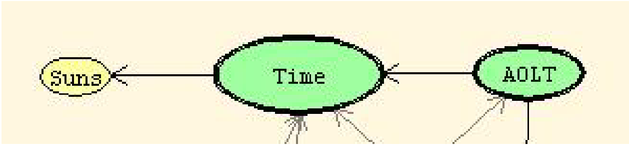
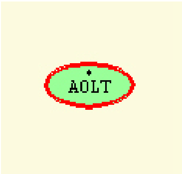


Figure 6. All parents are automatically added to the display along with the selected company. Here, *Sunset Magazine* is shown with its parents, Time Warner and AOL-Time Warner.

Ownership paths are browsable [13] to allow visual exploration of subsidiaries in limited screen space. Users navigate networks by double clicking on nodes with thick borders. This action "opens" the node, displaying all its holdings (children). To "close" a node, users double click on it to hide its holdings. Figure 7 shows how a user can discover a path between Bertelsmann and AT&T simply by displaying the children of AOL-Time Warner.

a) 

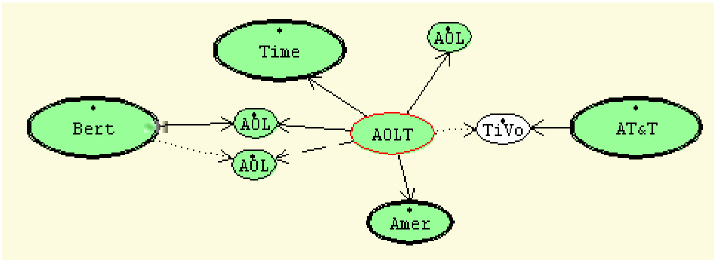
b) 

Figure 7. a) Parent companies appear automatically when a company displays in the EVA interface. Here, AOL-Time Warner has been added to the screen. b) Double clicking the node AOL-Time Warner reveals its direct subsidiaries and their other owners.

5 Network Analysis

In this section, we analyze our data set as a social network. Our results describe the landscape of the network, identify prominent companies in our data set, and illustrate the insights revealed by applying social network analysis to corporate ownership structures.

To summarize our findings:

- Two metrics follow power law distributions: company degree (the number of relationships each company has) and component size (number of companies connected together);
- The largest component contains 53.6% of the companies in the network;
- Ten companies are the parents for over 24% of all relationships;
- 87% of companies are involved in at least one ownership relationship;
- Only 10% of companies are involved in more than one ownership relationship;
- The greatest outdegree (number of holdings) for a company is 552; the greatest indegree (number of owners) for a company is six;
- The removal of small a proportion of companies (8.9%) and relationships (2%) would produce non-trivial changes to the network topology (in terms of increasing component count) if removed.

Table 1 is a summary of the companies with the largest values for various network metrics. We refer to this table throughout this section.

5.1 Related Network Analysis Work

Network analysis has been applied to many different fields, including: 1) engineered systems, such as the Internet [11], the world wide web [6,16], and electric power grids [32]; 2) biological systems, such as the neural network of the *Caenorhabditis elegans* [32]; and 3) social networks, such as movie actor collaboration [1] and terrorist networks [20]. Social network analysis has also been applied to corporate ownership networks [3,7]. For example, [24] and [30] investigate changes to the ownership networks of Hungarian companies during the 1990's and show how these networks dissolved after a period of industrial privatization.

We base our network analysis methods on the principles outlined in [31], particularly on those used to determine network prominence. We use UCINET 5 [4] to calculate the prominence measurements including degree, Freeman Betweenness, cliques, cutpoints, bridges, and network size.

Table 1. Network Analysis: Metric summaries

(a) Cutpoints (total components)		(b) Cutpoints (total non-isolates)		(c) Outdegree		(d) Indegree		(e) Overall degree / Ego network size		(f) Betweenness[14]	
Company	***Components created***	***Company***	***Non-isolates created***	***Company***	***Outdegree***	***Company***	***Indegree***	***Company***	***Overall degree***	***Company***	***Normalized Betweenness***
Clear Channel Communications	550	Time Warner	16	Clear Channel Communications	552	United Video Satellite Group	6	Clear Channel Communications	552	Liberty Media	18.35%
Liberty Group Publishing	288	Viacom	15	Liberty Group Publishing	288	Sprint Spectrum	5	Liberty Group Publishing	288	Time Warner	10.12%
CNHI	209	News Corp	12	CNHI	209	Excite@Home	5	CNHI	209	Clear Channel Communications	8.87%
News Corp	164	Microsoft	9	News Corp	177	Open Market	5	News Corp	178	AT&T	7.18%
CBS Radio	146	Bertelsmann	8	CBS Radio	147	Go2Net	5	CBS Radio	148	News Corp	6.76%
Lee Enterprises	146	Advance Publications	7	Lee Enterprises	146	OmniSky	5	Lee Enterprises	146	Emmis Communications	6.25%
Gannett	134	Cox Enterprises	7	Gannett	134	Thirteen other companies have a6-ŒXdegree of 4	4	Gannett	134	Viacom	5.68%
Disney	125	Hollinger	7	Disney	130			Disney	130	WALC-FM	5.55%
PRIMEDIA	124	Liberty Media	7	PRIMEDIA	125			PRIMEDIA	127	Disney	3.62%
Time Warner	100	PRIMEDIA	7	Time Warner	110			Time Warner	114	Open Market	3.42%

(h) Cliques		(i) Ego networks with the largest number of relationships between alters				(j) Ego networks that can reach the largest number of non-isolate companies within two hops	
Company	***Cliques***	***Company***	***Number of relationships between alters***	***Size of ego network***	***Density of ego network***	***Company***	***Percent of non-isolates within two hops of ego network***
Liberty Media	23	Liberty Media	23	85	0.32%	Liberty Media	10.28%
AT&T	12	Comcast	12	50	0.49%	WALC-FM	8.27%
Comcast	8	AT&T	8	30	0.92%	Clear Channel Communications	7.69%
UnitedGlobalCom	6	Ticketmaster-Online CitySearch	7	10	7.78%	Radio One	7.65%
United Video Satellite Group	5	USA Networks	6	29	0.74%	American Tower	7.64%
Go2net	5	UnitedGlobalCom	6	25	1%	Hispanic Broadcasting	7.64%
Six companies are involved in 4 cliques	4	Ticketmaster	6	19	1.75%	SFX Entertainment	7.63%
		Go2net	5	19	11.90%	547 other companies can reach 7.61% non-isolates within two hops	7.61%
		United Video Satellite Group	**5**	**7**	1.46%		
		USA Information and Services	**5**	**7**	11.90%		

[14] We ignore relationship directionality for calculating Betweenness, a common practice according to [31]. When directionality is preserved, Liberty Media still ranks highest and appears in 0.01% of all geodesics.

5.2 Network Topology

5.2.1 Component Distribution

A component is a group of nodes connected only to each other, also called a *maximal connected sub-graph*. The largest component in our data set contains 4,475 companies, or 53.6% of the entire network, while the next largest component contains only 3.5% of the network. We plot component sizes in descending rank order (Figure 8) and observe that component size follows a power law distribution with a slope $\alpha = -0.56$ ($r^2 = 0.87$). In other words, the i-th largest component has a size of $c * i^{\alpha}$, where c is a constant. The fit improves further if we consider separately the top ten components ($\alpha = -2.23$, $r^2 = 0.96$) and the remaining components ($\alpha = -0.48$, $r^2 = 0.89$).

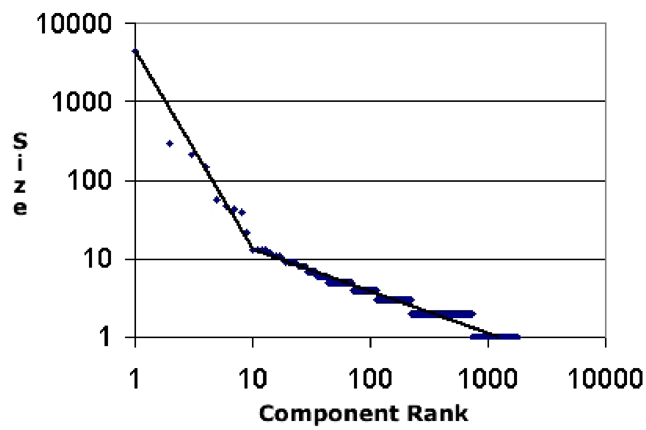


Figure 8. Population distribution of all components, rank-ordered by size.

5.2.2 Density

Density refers to the number of relationships in the network, divided by the maximum possible number of relationships among all nodes in the network. Given a network of size N, the maximum number of relationships is $(N)(N-1)/2$. A dense network would indicate overall strong connectivity while a sparse network would indicate weak connectivity. The maximum possible number of relationships among the 8,343 companies in our database is 34,798,653. However, we have identified only 6,726 relationships, or fewer than 0.02% of the maximum possible. Thus, we conclude that the network is sparsely connected. However, a large network with a low density measurement can still have prominent actors [31]. Indeed, we find several companies whose prominence measurements are significantly higher than those for most other companies in the network (see Section 5.4).

Table 2 groups companies by role (parent, child, both, or neither). Parents that are roots and children that are leaves only participate in one relationship. Isolates participate in no relationships. The population distribution of these node types explains why network density is so low; only 10% of companies participate in more than one relationship.

Table 2. Population distribution by ownership role

Ownership role	Role	Subtype	Number of children	Number of parents	Population distribution
Parent only	Transmitter	Root	1	0	8%
		Star	> 1	0	3%
Child only	Receiver	Leaf	0	1	69%
		Magnet	0	> 1	2%
Parent and child	Carrier	Link	1	1	1%
		Hub	>1	>=1	4%
			>=1	>1	
None	Isolate		0	0	13%

5.2.3 Depth and Diameter

Depth is defined as the longest shortest path (longest geodesic) between two nodes, considering the direction of each relationship. Conversely, diameter is the longest geodesic regardless of relationship directionality. The depth of the EVA network is 12 relationships, and its diameter is 23, both occurring in the largest component. If the largest component were excluded, the depth would only be three and the diameter four. Thus, the largest component is four times “deeper” and over five times “wider” than the next deepest and widest components. Among all companies in the largest component, Comcast has the shortest radius and the greatest depth. That is, ignoring relationship directionality, other companies have longer shortest paths to the edge of the component. Yet, preserving relationship directionality, no other company has a longer shortest path to the edge of the component. Comcast is therefore in the center of the component when directionality is ignored, and at the top when relationship directionality is preserved.

5.3 Sensitivity Analysis: Cutpoints and Bridges

We examine the robustness of the overall network topology by quantifying the number of cutpoints and bridges in the network. Cutpoints and bridges are defined as nodes and links that, if removed, would change the network topology by increasing the number of components. In this context, cutpoints and bridges are important companies and ownership relationships that tie different parts of the industries together.

We find that 742 companies (8.9% of total) are cutpoints, and 273 of these (3.3% of total) would leave behind two or more non-isolate components, i.e., components of size greater than one. Table 1(a) lists the cutpoints whose removal would create the most additional components. With its numerous holdings, radio conglomerate Clear Channel tops the list, creating 550 components when removed from the network. Table 1(b) lists the cutpoints whose removal would create the most additional non-isolate components. Time Warner, if removed from the network, would create 18 non-isolate components.

We find that 89% of the relationships in our data set are bridges. This number is high because so many companies participate in only one relationship (see Table 2). A relationship attached to either a leaf or a root company is always a bridge since its removal isolates the leaf or root from the rest of the network. Only 2% of relationships, however, are bridges that do not join leaves or roots; removing these relationships creates disconnected components that contain two or more companies.

5.4 Prominence

Identifying which nodes are the most important, or prominent, in a network is a common task in social network analysis. A company ownership network presents an interesting twist since certain well-known companies are often assumed to be prominent merely because of their reputation or name recognition. However, the most prominent companies may turn out to be lesser-known but well-positioned companies in the network. We examine two measurements of prominence: degree and Freeman Betweenness.

5.4.1 Degree

Degree measures the number of ownership relationships in which a company is engaged, either as a parent (outdegree), as a child (indegree), or both (overall degree). In social network analysis, outdegree indicates expansiveness, indegree indicates popularity, and overall degree indicates activity [31]. These characterizations are likewise valid for our network; companies with high outdegrees have expanded operations, companies with high indegrees have attracted investment from other companies, and companies with high overall degrees are very involved in corporate ownership. Table 1(c-e) indicates the companies with the highest outdegrees, indegrees, and overall degrees. Clear Channel has the highest out- and total degree, and United Video Satellite Group, with many corporate investors, has the highest indegree.

Figure 9 plots the degree distributions in descending rank order. Like the plot for component size (Figure 8), these plots reveal power law distributions. We use linear regression to compute $\alpha = -0.96$ ($r^2 = 0.94$) for outdegree, $\alpha = -0.13$ ($r^2 = 0.51$) for indegree, and $\alpha = -0.89$ ($r^2 = 0.97$) for overall degree. From these calculations, we conclude that outdegree and overall degree follow power law distributions. A power law distribution for degree means that $D = c * i^{\alpha}$. That is, the i-th largest company degree = $c * i^{\alpha}$, where c is a constant. A power law distribution for company degree not only is consistent with findings showing power law degree distributions in other naturally occurring, social, and engineered networks as reported in [2,11], but also suggests that commonly hypothesized growth models involving incremental growth and preferential attachment may be at work here.

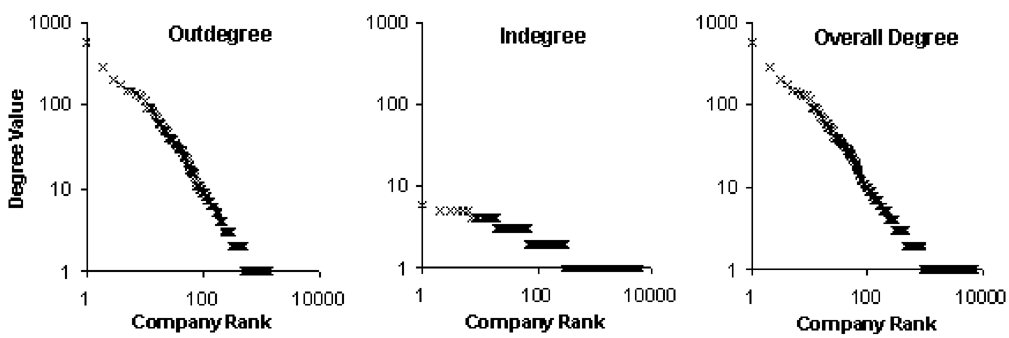


Figure 9. Distribution of node degrees

Only 16% of companies have an outdegree of one or more, while 76% have an indegree of one or more. In other words, most companies are not owners themselves but rather owned by another company. The ten companies with the greatest outdegrees are the parents for 24% of all relationships, and six of them are not owned by any other company. Ownership is therefore concentrated among a few companies, most of which are located at the top of the network. The converse does not hold true for indegree, however; most companies with high indegrees are not at the bottom of the network. Rather, 17 of the top 20 companies are also owners themselves. Finally, overall degree is nearly identical to outdegree because over 90% of companies have an indegree of zero or one. Thus, if a company is active in the network, it is likely doing so as a parent rather than as a child. This finding is consistent not only with the similar values for α as computed above in the linear regressions, but also with the similarity between the first and third graphs in Figure 9. Table 3 provides summary statistics for the degree measurements. We observe that outdegree and overall degree have nearly identical variances, which are much greater than indegree variance. For most companies, overall degree is equal to outdegree plus one.

Table 3. Degree summary statistics

	OUTDEGREE			INDEGREE			OVERALL DEGREE		
	Mean	**Median**	**Std Dev**	**Mean**	**Median**	**Std Dev**	**Mean**	**Median**	**Std Dev**
All companies	0.93	0	9.67	0.93	1	0.46	1.85	1	9.65
Companies with outdegree > 0	4.97	1	21.94	0.43	1	0.79	5.41	2	21.99
Companies with indegree > 0	0.42	0	4.53	1.06	1	0.32	1.48	1	4.58

5.4.2 Freeman Betweenness

Freeman Betweenness measures how often a node appears in the shortest path between all other node pairs, regardless of relationship directionality. Nodes with high Betweenness values are like well-placed hubs in an airport system, linking together more distant outliers. In our network, only 841 companies (10% of the network) have a Betweenness value greater than zero. Of those 841 companies, several are between many pairs of companies. Table 1(f) lists companies with the top Freeman Betweenness measurements. In particular, Liberty Media lies on over 18% of all shortest paths. In other words, when two companies are indirectly connected through one or more intermediate companies, 18% of the time Liberty Media is one of those intermediaries.

5.5 Analysis of Important Subsets of the Network

5.5.1 Bi-Components

A bi-component is a group of nodes that could not become disconnected by the removal of just one node. In a bi-component there is at the very least a circular path that loops through all companies; often, though, there are additional relationships within the bi-component. In our network, bi-components are significant because they indicate strong connections among groups of companies. We found 28 bi-components containing three or more companies. The largest bi-component contains 234 companies and includes AOL-Time Warner, AT&T, Bertelsmann, British Telecom, CBS, Cisco, Comcast, Deutsche Telecom, Disney, Intel, MCI WorldCom, Microsoft, NBC, Sony, and Yahoo!. Its density is 1.4%, which is 72 times greater than the density of the overall network.

5.5.2 Cliques

A clique is a group of nodes that all have a direct relationship to each other. In our case, cliques are significant because they indicate the thickest webs of ownership within a network that is otherwise quite sparse. We found 136 companies participating in 75 ownership cliques. Only one of these cliques has four members; all others have three. The ten companies involved in the most cliques are listed in Table 1(h). Liberty Media outranks all other companies, participating in 23 different cliques.

5.5.3 Ego Networks

Every node has an ego network, consisting of itself (the ego) and all nodes to which it is immediately connected (its alters). Because the number of alters equals the sum of a node's indegree and outdegree, the overall degree values in Table 1(e) equal the sizes of the largest ego networks. An ego network indicates the size and composition of a company's close circle. In the EVA network, most ego networks are small, a result which is not surprising given that most companies are only involved in one relationship. Most ego networks are also sparse; only 130 ego networks contain additional relationships between two alters. Thus, if two companies have relationships with a common third company, there is a low probability that those two companies will have a relationship with each other. This observation supports the finding that ownership is concentrated among a few companies, rather than spread out among many companies.

Table 1(i) lists the companies whose ego networks contain the largest number of relationships between alters. Liberty Media has the largest ego network, with 85 alters and 23 relationships among those alters. Table 1(j) lists the companies whose ego networks can reach within two hops the greatest percentage of non-isolate companies (reachability). Over ten percent of non-isolate companies can be reached within two hops of Liberty Media's ego network.

6 Discussion

Viewing ownership as a social network allows us to analyze the shape and scope of an industry and to identify the companies that play important investment roles. Our analysis of the telecommunications and media industry reveals a sparse but well connected network where ownership is concentrated among a handful of influential companies. However, the network topology we extract and analyze is only a snapshot of a continually changing industry landscape. Each new merger, acquisition, or divestiture can potentially alter the topology and the industry in a fundamental way. Comparative analyses can and should be performed for other industries and across time periods to help shed light on the significance of our findings.

In this analysis, we characterize paths in an ownership network as influence within an industry in a social sense. Here, companies with small investments in many companies surface as prominent while those with a few major holdings may actually hold more market power. We conceive of ownership as a flow of funds, but it may also indicate control over what kinds of content are published over which channels, or how resources such as customer records or technical know-how are shared between companies. Precisely how ownership translates into flows of information or editorial influence is a question for future research.

Ultimately, the validity of the network analysis rests upon the correctness and completeness of the data produced by the information extraction process. State-of-the-art free-text information extraction systems can only achieve 50-70% precision and recall for this problem domain, necessitating manual review to achieve the 100% precision requirement of EVA. We believe the use of extensible markup language (XML) in the authoring of corporate filings will remove the ambiguity of free-text and dramatically improve extraction performance and therefore data quality. The SEC EDGAR (Electronic Data Gathering, Analysis and Retrieval) system is already capable of processing corporate filings with markups for company names, attributes, and simple accounting data. As the SEC proposes rule changes to require more accurate, comprehensive, and timely disclosure by companies [29], we urge the Commission to adopt a standardized XML schema (such as the one described in Section 3 and Appendix 1) for the reporting of ownership and other corporate relationships and transactions.

7 Conclusion

EVA is a prototype research tool for *e*xtracting, *v*isualizing, and *a*nalyzing corporate ownership relationships as a directed social network. Applying EVA to the telecommunications and media industries, we find that over half the companies are connected to one another in a single, large component, and the top ten companies account for 24% of ownership relationships. Liberty Media, Clear Channel Communications, AT&T, Comcast, and Time Warner appear repeatedly in lists of companies with high network analysis measurements, suggesting that these companies are among the most prominent companies in the network. More generally, we show that information retrieval, extraction, storage, and visualization techniques can be used to build a cost-effective system that gathers corporate ownership information from multiple data sources and presents it in a meaningful, analyzable format. As corporate relationships become increasingly complex, tools such as EVA can reveal the shape of ownership networks and enhance the benefits of corporate disclosure by bringing greater transparency to public discourse.

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Appendix 1. Proposed Corporate Ownership DTD

We suggest two XML document types for describing corporate ownership information. The first represents a state, i.e., a relationship with a beginning and end date. The second documents an event, a transaction of a specific type occurring at a specific time. These DTDs could be designated as "open" for use with other namespaces. Mueller suggests a similar approach for adding topical information to news articles [19]. (This solution does not address the problem of parsing and resolving company names to unique ids in the database.)

```
--------------------------------------------------------------------------------
<!--This is an XML schema for corporate ownership relationships.-->
<!ELEMENT ownership-relationship
         (start-date?,end-date?,parent,child,
         stake?,source*,author?)>
<!ELEMENT start-date (#PCDATA)>
<!ELEMENT end-date (#PCDATA)>
<!ELEMENT parent (#PCDATA)>
<!ELEMENT child (#PCDATA)>
<!ELEMENT stake (#PCDATA)>
<!ELEMENT source (#PCDATA)>
<!ELEMENT author (author-name, author-date, author-email*)>
<!ELEMENT author-name (#PCDATA)>
<!ELEMENT author-date (#PCDATA)>
<!ELEMENT author-email (#PCDATA)>
<!ATTLIST source confidence (low | medium | high) #IMPLIED>
--------------------------------------------------------------------------------
<!--This is an XML schema for representing corporate ownership transactions.
(Transactions imply proceeding relationships.) -->
    <!ELEMENT ownership-transaction (date,parent,child,stake?,source*,author?)>
    <!ATTLIST ownership-transaction type (acquisition|sale|spin-
off|combination|rename) #REQUIRED>
    <!ELEMENT date (#PCDATA)>
    <!ELEMENT parent (#PCDATA)>
    <!ELEMENT child (#PCDATA)>
    <!ELEMENT stake (#PCDATA)>
    <!ELEMENT source (#PCDATA)>
    <!ATTLIST source confidence (low|medium|high) #IMPLIED>
    <!ELEMENT author (author-name, author-date, author-email*)>
    <!ELEMENT author-name (#PCDATA)>
    <!ELEMENT author-date (#PCDATA)>
```

```
    <!ELEMENT author-email (#PCDATA)>
--------------------------------------------------------------------------------
<!--This is an example ownership-relationship record. -->
<?xml version="1.0"?>
<!DOCTYPE ownership-relationship
SYSTEM "http://denali.berkeley.edu/eva/ownership_relationship.dtd">
<ownership-relationship>
         <start-date>1999-02-18</start-date>
         <parent>ATT</parent>
         <child>TCI</child>
         <stake>100</stake>
         <source cont]‡°nce =
"high">http://www.fcc.gov/ccb/Mergers/ATT_TCI/</source>
         <author>
                  <author-name> EVA Group (KN) </author-name>
                  <author-date>2001-12--30</author-date>
                  <author-email> knorlen@sims.berkeley.edu </author-email>
         </author>
</ownership-relationship>
--------------------------------------------------------------------------------
<!-- This is an example ownership-transaction record. -->
<?xml version="1.0" ?>
<!DOCTYPE ownership-transaction SYSTEM
"http://denali.berkeley.edu/eva/ownership_transaction.dtd">
<ownership-transaction type = "acquisition">
       <date>1999-02-18</date>
       <parent> ATT </parent>
       <child> TCI </child>
       <stake> 100 </stake>
       <source confidence = "high"> http://www.fcc.gov/ccb/Mergers/ATT_TCI/
</source>
       <author>
              <author-name> EVA Group (KN) </author-name>
              <author-date> 2001-12-30 </author-date>
              <author-email> knorlen@sims.berkeley.edu </author-email>
       </author>
</ownership-transaction>
```