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SOCIAL NETWORK ANALYSIS OF B2B NETWORKS

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ABSTRACT. The volume of information readily available in the E-Marketplace is massive. Business-to-business (B2B) users, for instance, have an extensive chain of business relationships that have immensely generated a large volume of information. Although this raises problems of information overload, the data is embedded with rich and valuable information, such as internal structure and social networks. While other research focuses on discovering properties of B2C, C2C and P2P networks, there only exists limited work on B2B, attributable to the high complexity of the B2B structure. This paper presents a statistical analysis of B2B networks that amasses dispersed users' social relationships using a social network analysis technique. The investigation performed found that B2B networks are small-world, and thus follow a power-law distribution. The analysis also proved that B2B networks hold stable community structures.

Keywords: Social Network Analysis (SNA), Business-to-Business (B2B), E-Marketplace, Social Networks, Network Science

INTRODUCTION

Interactions amongst multiple components in a set of numerous systems have been investigated in the past few decades. Several studies in the literature, for instance, have shown that many networks already exist in the natural world (Barabasi & Albert, 1999; Watts, Watts, Strogatz, & Strogatz, 1998), including biological, social and technological systems (Bornholdt & Schuster 2003; Pastor-Satorras & Veserlpignani 2007; Newman 2003). Complex real network systems are composed of interconnected actors, which can be represented by nodes, and edges among these nodes, which represent the relations among them. The dimensions of real networks can reach up to millions, or even billions, of nodes (Fortunato, 2010). Social networks, as a common example of complex networks, are concerned with social interactions made among nodes, which generally are persons or corporations.

Electronic Commerce (EC), also known as E-Marketplace, represents a transaction-oriented enterprise model across the Internet (Jailani, Yatim, Yahya, Patel, & Othman, 2008). EC handles business processes, including buying and selling physical items (e.g., car parts and packaging items) or non-physical items (e.g., digital information and services). In the E-Marketplace, we have encountered numerous success stories, especially using the (Business-to-Customer) B2C approach such as Amazon and EBay, where the sellers directly interact with end customers. B2B, nevertheless, is another paradigm of E-Commerce, in which the members of the E-Commerce community perform businesses amongst eachother (i.e., business users).

Social Network Analysis (SNA) is a quantitative technique that has been widely employed in psychology, social sciences, economics and many other fields. It examines the relationships among nodes, the influences of nodes, information flow and modularity in social networks (Currie, Burgess, White, Lockett, & Gladman, 2014; de Souza, de Almeida, Moll, Silva, & Ventura, 2016; Saha, Mandal, Tripathy, & Mukherjee, 2015; Surana, Kumara, Greaves, & Nandini, 2007; Variano, McCoy, & Lipson, 2004). There exist a few recent studies that focus on the statistical properties of E-Commerce social networks. These studies, however, do not adequately address the complex interaction of users, explicitly in discussing the communities of users, and the interaction patterns amongst them. Furthermore, there remains a lack of scientific studies that focus on the B2B E-Marketplace from the perspective of network science.

Business-to-Customer (B2C) E-Commerce networks of EBay were examined by Kumar & Zhang (2007). Their study, however, only shows its preliminary effort of outlining users behaviour patterns of centrality using a tree structure. Furthermore, in another study of B2C E-Commerce networks, market evolution was investigated in by Tian, Zhang, & Guan (2013b), where a scale-free property was found. It suggests that there exists a high number of nodes with only a few links, and only a few nodes with a large number of links. Centrality in this study shows that there exist a few hubs that dominate the entire B2C social network. From an economical perspective, it implies the high centrality of B2C market shares. Nonetheless, this study only focuses on the B2C market evolution, as opposed to the interaction of users in regards to their degree, and the communication of users within its community. Degree centrality and betweenness centrality are discussed, and a multi-agent model of E-Commerce transaction network is established by Piao, Han, & Wu (2010). The position of the users can be visually demonstrated by using their models. Although the study simulates the e-commerce transaction networks, it does not address the structure of the E-Commerce network.

Undirected links among B2B users and three kinds of relationships have been found by Tian, Zhang, & Guan (2013a), namely, vertical, horizontal, and oblique ties. This study uses data drawn from textile industries on AliBaba.com, and demonstrates that the enterprises connection distribution follows the power-law. Furthermore, this baseline study simulates market growth by an enhanced Barabási–Albert (BA) model. Interestingly, a smaller clustering coefficient and shorter average paths were presented when the model is applied and the network structure is even more stable. Meanwhile, the study overlooks the community as a critical element of the evolution of the network structure. As network evolution may evolve to a mammoth scale, it is essential to uncover hidden modules in social networks. This paper addresses properties of complex networks, focusing on the B2B transaction networks in particular. Real data from EBay was employed in conducting the social network analysis in order to investigate the social structure of B2B users through their transaction networks. A scientific study of complex network properties for B2B were analysed extensively to focus on the following research questions:

1. Do the B2B networks hold a small-world property and follow power-law distributions?
2. What is the quality of the community structure held by the communities of B2B networks?

METHODOLOGY

The statistical analysis of B2B networks offers insights and a deeper understanding of the inherent associations of B2B users and the B2B E-Marketplace. In this study, real EBay transactions were used where raw data is captured and processed according to the types of analyses. Five networks from SNA1 to SNA5 were created to represent time-based B2B transactions in one, two, three, five and ten years respectively. The analysis initiates with the discussion of connectivity properties of transactions. Next, the social network analysis results are discussed, namely, degree distribution, average shortest path length, clustering coefficient, and degree-degree correlation. The modularity of the B2B transaction networks were also investigated.

Connectivity properties explain the connections of buyers and sellers. All users were represented as nodes in these networks, and a link or edge from node *i* to *j* indicates a transaction with buyer *i* and seller *j* respectively. Then, a degree distribution describes the probability distribution nodes's degrees over the entire network. The average shortest path length is a concept that is defined as the number of connections required to traverse within the network and the iterations it takes for the two random users in the network to reach each other. In turn, a clustering coefficient is a metric that measures how well the neighbours of any node in a network are locally connected. Degree correlations quantify how nodes are linked with each other based on their degree. An unfavourable correlation implies that high-degree nodes tend to connect to low-degree nodes, and when the correlation is positive, high-degree nodes are inclined to become attached to other high-degree nodes, while low-degree nodes are likely to become attached to other low-degree nodes. Another common characteristic of complex systems is the community structure. A network is said to have a community structure if the nodes of the network can be grouped into sets of nodes that are closer to each other.

RESULTS AND ANALYSIS

Connectivity Properties

Table 1: Network properties of business users' social networks

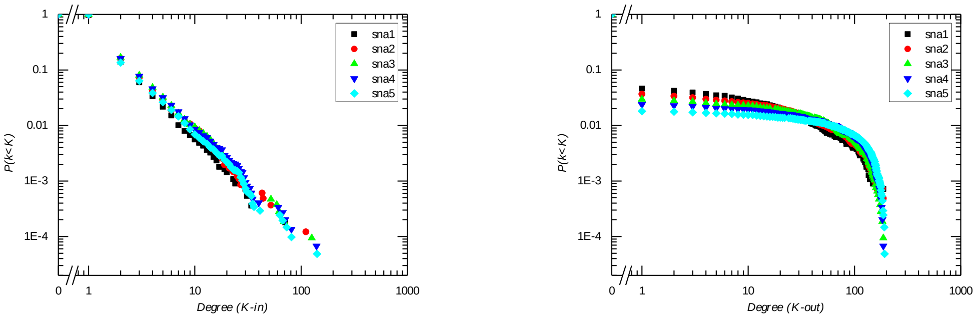
	SNA1	SNA2	SNA3	SNA4	SNA5
N	5563	8220	10650	14832	20520
E	7300	11637	15653	21764	28492
$<K>$	2.62	2.83	2.94	2.93	2.78
K_{out}	0-187	0-187	0-187	0-187	0-192
K_{in}	0-71	0-111	0-126	0-140	0-141
$<Kw>$	3.87	4.25	4.39	4.28	3.92
kw_{out}	0-200	0-200	0-224	0-187	0-249
kw_{in}	0-296	0-564	0-727	0-831	0-832
$\langle l \rangle$	2.405	7.46	5.537	4.803	4.981
l_{max}	8	18	14	12	13
$<c>$	0.003	0.003	0.003	0.003	0.002
$<c_{rand}>$	0.00047	0.00034	0.00028	0.00020	0.00014
Q	0.763	0.719	0.698	0.700	0.731
n_c	59	57	61	65	77
r	-0.0163	0.0167	0.042	0	0.0002
$r_{out\text{-}in}$	-0.1214	-0.1123	-0.1023	-0.1027	-0.0929
$r_{in\text{-}out}$	-0.0002	0.0112	0.0041	-0.0033	-0.0122
$r_{out\text{-}out}$	-0.063	-0.0586	-0.0769	-0.1052	-0.1195
$r_{in\text{-}in}$	0.0294	0.0247	0.0261	0.0213	0.0153

The network properties of SNA1 to SNA5 networks are summarized in Table 1. In general, the increase in the number of transactions (E) and users (N) demonstrates the evolution of the B2B networks over time. The transactions evolve faster compared to users. This implies that more frequent commercial activities are performed amongst B2B users over the years. The growth rates of B2B nodes (users) and edges (transactions) in these networks are around 144%±0.14%. The average unweighted edge degree $<K>$ of each node in SNA1-SNA5 is around 2.6-3, which means that each B2B user on EBay is on average connected to nearly 3 others acquaintances for business activities (either buying or selling). Moreover, every user is connected with more sellers (k_{out} = 0-192) than buyers (k_{in} = 0-141). In the case the number of transactions is considered, the weighted edge degree <kw> of each node in SNA1-SNA5 is around 4, but there are far more selling transactions (kw_{in} = 0-832) than buying transactions (kw_{out} = 0-249). Therefore, in general, a business user performs approximately 4 transactions with other users, although in reality users may perform as many transactions as they desire.

Table 2: Percentage of business users with 0, 1, 2 and more than 2 in-degrees and out-degrees

	k_{in} (%)				k_{out} (%)			
	0	1	2	>2	0	1	2	>2
SNA1	3.2	82.8	8.0	6.0	95.4	0.4	0.3	3.9
SNA2	2.1	81.8	8.9	7.3	96.4	0.3	0.2	3.2
SNA3	1.3	82.0	8.7	8.0	97.1	0.2	0.1	2.7
SNA4	0.5	83.5	8.3	7.7	97.6	0.1	0.1	2.2
SNA5	0.1	86.4	7.2	6.4	98.2	0.0	0.0	1.7

Table 2 lists the portion of business users with zero, one, two, and over two in and out connections. Over 95% of the B2B users have no outward connections (k_{out} = 0) to any neighbour, which means they are pure sellers, and have never purchased anything from the E-Marketplace. Meanwhile, a small percentage of B2B users (i.e. up to 3.5%) are purely buyers, and have never sold anything (k_{in} = 0). Up to 97% of B2B users sold one, but only one product to other business people (k_{in} = 0), and up to 8.1% of B2B users sold more than two products (k_{in} = 2).



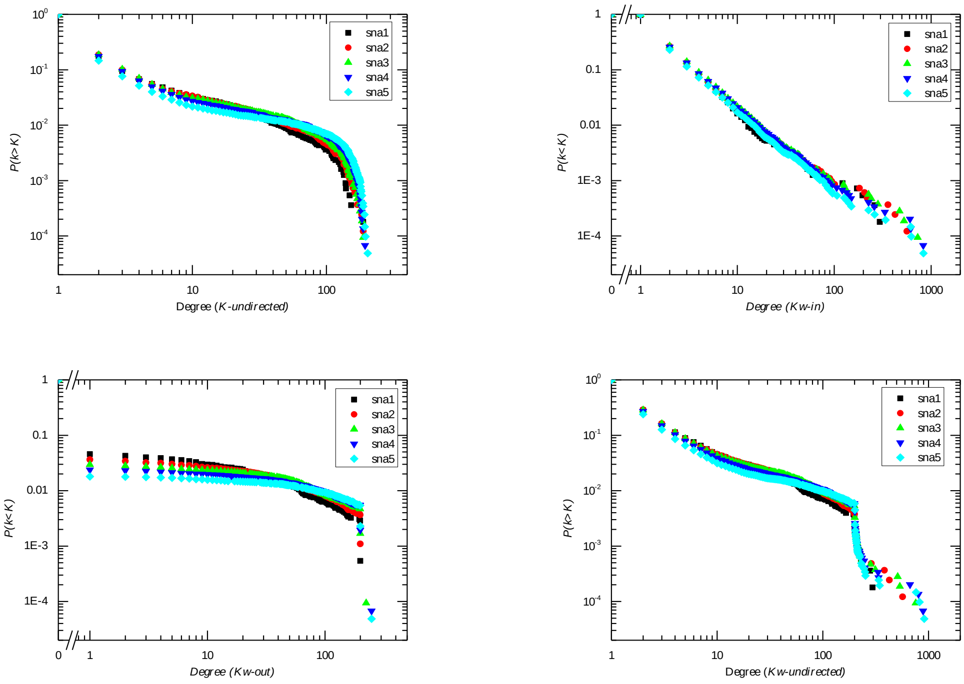


Figure 1: Cumulative in, out, and undirected degree distribution for both weighted and unweighted networks

Cumulative in, out, and undirected degree distributions for both weighted and unweighted networks of SNA1-SNA5 are exhibited in Figure 1. The distributions confirm that B2B transaction networks follow power-law distributions, in which a small number of large sellers are connected with a large number of small buyers. The real E-Commerce market explains that small business firms are more attractive to conduct business transactions with experienced firms. Experienced firms are most likely to be engaged due to their number of sales transactions, which in reality, firms who conduct more business may have extensive skills in managing business activities thoroughly, and stay competitive in the marketplace (A. Kumar & Dash, 2016; D. Kumar, 2015).

Table 3: Exponents γ for weighted and unweighted B2B transaction networks

Networks	Unweighted			Weighted		
	In	Out	Undirected	In	Out	Undirected
SNA1	3.44	8.69	2.21	2.10	1.95	2.21
SNA2	3.25	8.79	8.49	2.22	2.06	1.78
SNA3	2.88	9.73	10.51	2.06	2.18	1.77
SNA4	2.99	37.47	35.98	2.27	1.94	1.74
SNA5	3.26	10.48	25.44	2.34	1.91	1.71

The exponents of these degree distributions are summarized in Table 3. It is worthy to note that a universal exponent has been obtained for most degree distributions (e.g., γ=3 for unweighted in networks and γ=2 for weighted networks), regardless of their specific characteristics (e.g., size, number of edges) (Wang, Moreno, & Sun, 2006). This evidence suggests the existence of a few dominant hubs within the topology of weighted B2B networks. Similarly, when business firms become hubs in the marketplace, this strategy of enhancing firm performance puts other rivals at a disadvantage (Knight & Liesch, 2015; Liu, Kauffman, & Ma, 2015).

Average Shortest Path Lengths

The average shortest path lengths $\langle l \rangle$ in all networks, as listed in Table 1, clarify each user in the B2B networks, and can be reached by another user within 4.58 steps. Remarkably, despite the dynamic environment of the B2B E-Marketplace, this result suggests that B2B networks are small-world because each user can be reached within a maximum of six steps, following the theory of six degrees of separation (Travers & Milgram, 1969). Another significant evidence of the small-world concept in B2B networks is the existence long tail singularity, as shown in Figure 2.a (Adamic, 2001). On the other hand, users in these networks can be reached by a maximum chain of 12 nodes, represented by the network diameter (l_{max}).

Clustering Coefficient

Clustering coefficients enumerated in Table 1 indicate that B2B networks impose low values of clustering coefficients, where neighbours of business users are loosely associated with each other, probably attributable to the large-scale and distributed nature of EBay users. However, the closeness of these B2B social networks is better compared to Erdos Renyi (ER) random graphs (Wang et al., 2006) with the same size and average connectivity, whose clustering coefficients are $<c_{rand}>=<k>/N\approx10^{-4}$-$10^{-5}$, one to two orders of magnitude smaller than those of the B2B social networks. These results suggest that B2B social networks are more closely connected compared to random graphs, where the vertices, edges, and connections among them are generated randomly. The curve clustering coefficient distributions shown in Figure 2.b imply that the dependency of C on k is nontrivial, and thus points to some degree of hierarchy in the network. As a hierarchy is found among animals in their dominant-subordinate interaction, leader-follower network of pigeon flocks, and social and technological networks (Mones, Vicsek, & Vicsek, 2012), this explains that B2B networks are also present in a hierarchical network structure, which is an essential attribute of natural, artificial and social networks.

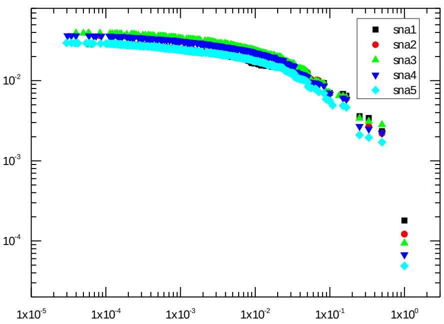


Figure 2.a: Path length in B2B networks

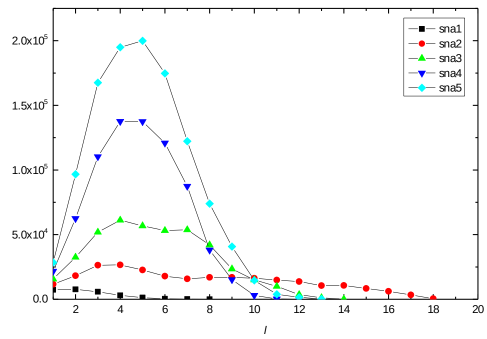


Figure 2.b: Cumulative clustering coefficients of B2B transaction networks

Degree-to-degree Correlations

Table 1 tabulates the correlation coefficients of all types of degree correlations for the B2B networks. The B2B networks of EBay present a consistent assortative (positive) pattern for $r_{in\text{-}in}$, but a consistent disassortative (negative) mixing pattern for $r_{out\text{-}in}$ and $r_{out\text{-}out}$. This means that, in these B2B transaction networks, active or large sellers are typically connected with other active sellers, but active sellers are infrequently associated with frequent buyers, and frequent buyers are less associated with other frequent buyers. The former indicates a few attacks on the sellers will not easily destroy the B2B networks due to the existence of other providers in the system. The latter implies that the B2B networks may be improved by recommending active sellers to active buyers, who may provide better products for these buyers.

Modularity of Community Detection

Many networks, including social networks, computer networks, and metabolic and regulatory networks, are found to divide naturally into communities or modules, as suggested by the study on community structure (Mej Newman, 2006). The quality of community structure (Q) is measured using the Louvain community detection algorithm in Eq. (1), which was chosen due to its accuracy and speed (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Similar to business professional networks of Wealink (Hu & Wang, 2009), B2B E-Marketplace networks of EBay present significantly stable community structures by referring to the modularity values (Q) and number of communities (n_c) presented in Table 1.

$$\Delta Q = \left[\frac{\sum_{in} + \sum_{i,in}}{2m} - \left(\frac{\sum_{total} + k_i}{2m}\right)^2\right] - \left[\frac{\sum_{in}}{2m} - \left(\frac{\sum_{total}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right] \tag{1}$$

The average modularity value of 0.722 from all networks suggests that B2B users work closely with other business people within their circles. It seems that these users perform business activities more with the enterprises they are familiar with, and work loosely with other enterprises outside their norms of business. Furthermore, business firms within the community do not compete in regards to the price of the product, but rather compete to provide better services to other firms.

CONCLUSION

This paper presented an investigation of user relationships and social ties of B2B users in the E-Marketplace. Real data on B2B transaction networks collected from EBay was assessed to reveal the underlying social structure of these networks through statistical analysis. Common complex network attributes were analysed such as degree distribution, average shortest path lengths and clustering coefficients. Other important metrics were also studied, such as degree-degree correlations and modularity. The social network analysis presented in this paper answers the research questions about the properties of complex networks. Despite the dynamic environment in the B2B E-Marketplace, the analysis shows that B2B networks are small-world because each user can be reached within a maximum of six steps, following the theory of six degrees of separation. The communication platform provided by the technological means has made the world among users shrink, despite the great physical distance. The analysis also confirms that B2B transaction networks follow power-law distributions, in which a small number of huge sellers are interconnected to a large number of small buyers. Furthermore, the B2B E-Marketplace networks of EBay present a significantly stable community structures in all networks, suggesting that B2B users work closely with other business people within their circles. It seems that these users perform business activities more with the enterprises they are familiar with, and work loosely with other enterprises outside their norms of business. The findings from the analysis of the real B2B transaction networks provide important information and insights on the fundamental structures of B2B networks and the relationships among B2B users, which may help to provide a better design of future B2B systems, including the E-Marketplace, networks, and other systems such as recommender systems.

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