The Role of Social Networks in Online Shopping: Information Passing, Price of Trust, and Consumer Choice

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ABSTRACT

While social interactions are critical to understanding consumer behavior, the relationship between social and commerce networks has not been explored on a large scale. We analyze Taobao, a Chinese consumer marketplace that is the world's largest e-commerce website. What sets Taobao apart from its competitors is its integrated instant messaging tool, which buyers can use to ask sellers about products or ask other buyers for advice. In our study, we focus on how an individual's commercial transactions are embedded in their social graphs. By studying triads and the directed closure process, we quantify the presence of information passing and gain insights into when different types of links form in the network.

Using seller ratings and review information, we then quantify a price of trust. How much will a consumer pay for transaction with a trusted seller? We conclude by modeling this consumer choice problem: if a buyer wishes to purchase a particular product, how does (s)he decide which store to purchase it from? By analyzing the performance of various feature sets in an information retrieval setting, we demonstrate how the social graph factors into understanding consumer behavior.

Categories and Subject Descriptors: H.2.8 Database Management: Database Applications – Data mining

General Terms: Measurement; Experimentation.

Keywords: E-Commerce, Viral Marketing, Recommender Systems, Triadic Closure, Price of Trust.

1. INTRODUCTION

Use of personal social networks to gather information is fundamental to purchasing behavior [6]. It is something so common in our daily routine that we usually do not even make a note of it. When we make a purchase from a retail store, we often speak beforehand to the shopkeeper about suitable products. When we need to purchase something we are unfamiliar with, we consult our friends and family for advice. When we purchase a popular new product, we have an urge to tell everyone we know about it.

Although personal social networks are implicit in the offline shopping experience, their introduction to the online world is a relatively new phenomenon. E-commerce websites, such as Amazon, eBay and Epinions, have successfully integrated product reviews, recommendations, search and product comparison, but they have been much slower at adopting social networking features as a part of customer experience. Recommendation engines and product comparison sites help consumers discover new products and receive more accurate evaluations, however they cannot completely substitute for the personalized recommendations and information that one receives from a friend or relative. Basic behavioral psychology drives consumers to value and trust their friends' purchasing decisions more than anonymous opinions. For example, a Lucid Marketing survey found that 68% of individuals consulted friends and relatives before purchasing home electronics [3].

Understanding how social networks are used and how they shape purchasing decisions is one of the fundamental interests of e-commerce. Only recently have social networks been used in e-commerce applications to some success. For example, group purchasing companies such as Groupon and LivingSocial allow consumers to come together to buy products in bulk and save money, while social shopping sites such as Kaboodle provide consumers the ability to share shopping lists with each other. The use of social networks in online shopping provides marketers and businesses with new revenue opportunities, while providing consumers with product information and both economic and social rewards for sharing [11].

Present work. When discussing the relationship between electronic commerce and social networks, various questions come to mind. How do friends influence consumer purchasing decisions and product adoption? What factors influence the success of word-of-mouth product recommendations? How does social influence and reputation affect commercial activity? In this paper, we will address these questions through a detailed study of the world's largest e-commerce website Taobao.

The fundamental process we focus upon throughout this study is what we term *information passing*: an individual purchases a product, then messages a friend, what is the likelihood that the friend will then purchase the product? Where will he purchase it from? Understanding the flow of social influence in commerce networks is an important question. For example, information passing provides insight into how companies can structure online viral marketing campaigns to target consumers. It can also be used to optimize algorithms within product recommendation engines. However important information passing is to electronic commerce, it still has not been well studied on a large scale due to the inaccessibility of suitable data.

To facilitate our research, we obtained a dataset describing the behavior of one million users in the world's largest e-commerce network Taobao. Taobao connects buyers and sellers, and provides an integrated instant messaging platform for communication

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among all its users. By modeling Taobao as a network of three types of edges (trades, messages, contacts), we are able to directly study how social communication and commercial transactions are interrelated in an online setting. Our study provides insights into three main aspects of the social-commercial relationship: information passing, the price of trust, and consumer choice prediction.

We begin our study of social commerce by quantifying the presence of information passing through analysis of triadic closure processes. We show that the influence of information passing is directly proportional to message strength, and is inversely proportional to product price, as well as the time between the purchase and the recommendation. Additionally, we explain how information passing varies greatly between different product categories. We then investigate the general edge formation process in the context of directed triadic closure, and demonstrate that the formation of triad-closing message and trade edges is highly dependent upon user roles (buyer or seller). Our results indicate that information passing via buyer-buyer communication is one of the primary drivers of purchasing.

A subtle point regarding information passing is that the spread of product recommendations, through word-of-mouth, inherently relies upon a notion of buyer-buyer *trust*. Trust, from the perspective of social psychology, can be defined as perceived credibility or benevolence to the target [7]. In the context of electronic marketplaces, buyer-seller trust, most directly encapsulated by seller reputations and ratings, are the natural concept to study. A fundamental idea behind the nature of trust is its price. How much extra will a buyer pay for transaction security with a highly-rated seller? Although an intuitive idea, initial studies did not find evidence for a price of trust [25], and only recently has a price of trust been established in small, controlled, and single product settings [26, 13, 23]. In our study, we analyze transaction information across over 10,000 products. Using the overall customer satisfaction (i.e., average rating) of the seller, we observe a small but super-linear effect of the seller rating upon the price premium they can charge and still engage in transactions.

To further study the relationship between social networks and consumer behavior, we then consider the question, "How does an online consumer decide upon a seller to purchase from when there are many sellers offering the same product?" We model this question of *consumer choice* through a machine learning task and predict which particular seller a buyer will purchase from, given that the sellers all offer the same relevant product. Utilizing primarily social networking features, we construct a model that can predict, for the case of a buyer choosing from among 10 possible sellers, the correct seller 42% of the time, approximately 4 times better than baseline. We also contrast a variety of feature sets (both graph-based and product/seller metadata), and demonstrate that the social graph is the most important feature in predicting consumer choice. In particular, the social graph is a far better determinant of consumer behavior than metadata features such as seller reputation or product price. Our results nicely connect to Granovetter's work, which argues that economic transactions are embedded in dynamic social networks, and that an individual's social graph dictates how they choose sellers to transact with [10].

Further Related Work. For all of the importance of social networks in consumer shopping, though, their use in electronic commerce still is not well understood. Previous research examined the use of social networks in e-commerce, but has mostly focused upon one aspect of the use of social networks, such as product recommendations [12, 17, 2], product recommendation engines [29, 28], or have been based upon a limited set of data [4, 15].

Network	Nodes	Edges	Avg Deg	Avg CCF
Contact	663,346	3,208,043	9.67	0.0135
Message	750,158	3,908,339	5.21	0.0194
Trade	1,000,000	1,337,497	1.34	0.0086

Table 1: Dataset statistics.

The electronic marketplace eBay is perhaps the most well studied e-commerce website. Various aspects of eBay including auction efficiency [14], product recommendations [31], seller strategies [8], and summarization [22], have been studied. Closely related to our work on consumer choice prediction, Wu and Bolivar created a model to predict item purchase probability [30]. The primary difference here is that we utilize the social networks of the buyers and sellers, along with product and user metadata, to perform consumer choice prediction, whereas they consider only seller and product information.

Our study of information passing and triadic closure builds upon classical works by Rapoport [24] and Granovetter [9]. Triadic closure has been explored in various settings: community growth [1], link prediction [21], signed networks [19], and social [18] and information [27] network evolution. In contrast, we demonstrate the existence of implicit recommendation behavior in a network not specifically designed for information passing.

The paper proceeds as follows. In section 2, we describe the Taobao dataset. In section 3, we analyze dyadic relationships in the network. In section 4, we provide a detailed analysis of information passing and directed triadic closure processes. In section 5, we quantify a price for trust. And last, in section 6, we model the consumer choice prediction problem.

2. TAOBAO NETWORK

The data we use in this study comes from the Chinese website Taobao, one of the world's largest electronic marketplaces, with over 370 million registered users at the end of 2010. Although transactions on Taobao can be either business-to-consumer, business-to-business, or consumer-to-consumer, the bulk of the products are sold by online storefronts operated by small businesses or individuals. Perhaps the most unique aspect of Taobao is its integrated in-browser instant messaging platform, which allows us to correlate users' communication patterns and purchasing behavior. Any user can purchase goods from other users, add other users onto their contact list, and message other users. Note that non-contacts can message each other as well.

Our data is composed of all activities of the set of the first one million users that engaged in at least one commercial transaction during September 1 through October 28, 2009. For each of these users, we have all information regarding their transactions with other users in the set, where a transaction is specified by a product identifier, price, quantity, and timestamp. We also obtained the contact lists and timestamps of messages exchanged between these users during the two month observation period. Note that we do not have the contents of the messages exchanged.

We model the Taobao network as a multigraph composed of directed trade edges, directed message edges, and undirected contact/friendship edges.[1] Table 1 shows the basic statistics of the Taobao network when each edge type is viewed as a separate network. The 3,908,339 directed message edges are equivalent to

[1]The multigraph is modeled such that if there are multiple trades or messages from one user to another, we aggregate it all into a single directed edge, with supplementary message and trade information being associated with that edge. There can be up to 5 edges between a pair of users (2 directed trades, 2 directed messages, 1 undirected contact).

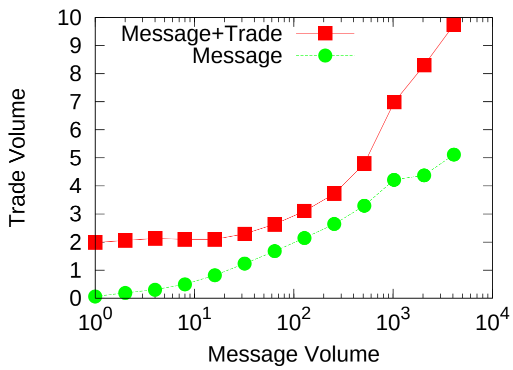


Figure 1: Trade Volume versus Message Volume. *Message* is computed over all pairs of users that exchange at least one message. *Message+Trade* is computed over all pairs of users that exchange at least one message and one trade.

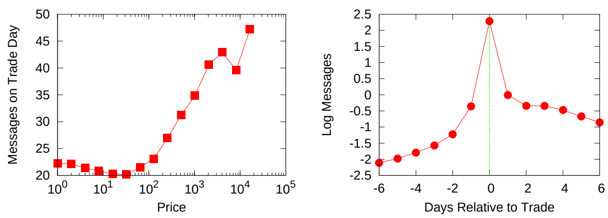


Figure 2: Buyer-Seller Messages vs. Transaction Price (left), relative to Trade Date (right).

2,241,729 undirected message edges, as messages are often reciprocated during discourse between a pair of users. In contrast, the 1,337,497 directed trade edges are equivalent to 1,336,502 undirected trade edges, as purchases are almost never reciprocated.

Throughout the rest of this paper, when we refer to a node as a "buyer" or "seller," we are speaking about its role in a particular transaction. Thus, we do not a priori label the nodes as buyers or sellers, but we use these terms to aid explanation. As a point of reference, 968,149 users make at least one purchase, 69,494 users make at least one sale, and 37,643 users make both a purchase and sale during the observation period. The products purchased and sold by these users are classified by Taobao into 82 categories.

3. DYADIC RELATIONSHIPS

To facilitate our goal of understanding how commercial transactions are embedded in the social networks of buyers and sellers, we first examine dyadic relationships in Taobao. In particular, we are interested in determining if messaging activity is correlated with trading activity. We graph trade volume versus message volume across pairs of users in Figure 1, and find that there is a positive increasing relationship between message volume and trade volume. Ignoring all pairs of users that only message and do not trade, we see an even more pronounced increasing relationship, displayed in the *Message+Trade* curve. The positive correlation between messaging and trading activity across dyads is supportive of our hypothesis that commercial activity is embedded in social networks. We will investigate the relationship between communication and commerce in much greater detail in our study of triadic structures.

Focusing upon the subset of dyads between pairs of users who have historically transacted, our question of interest is, "Do buyers talk to sellers more about expensive products?" We expect that expensive products are talked about more, but how much more are they talked about? To answer this question, we count the number of messages sent from buyer to seller on transaction date, assuming

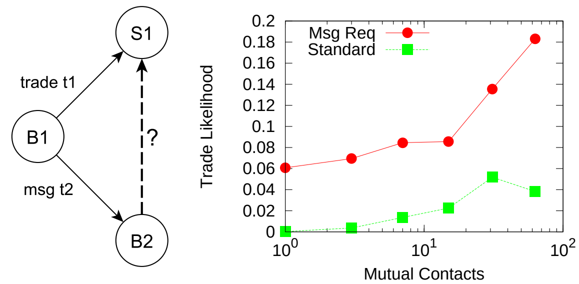


Figure 3: Given that B1 first purchased from S1 and then talked to B2, will B2 purchase from S1? (left) and Mutual Contacts (right).

that at least one message is exchanged, and plot it versus product price (in Chinese Yuan, CNY), displayed in Figure 2(left). We find that the number of messages sent is relatively constant for products of price below 100 CNY, then increases logarithmically for products of higher price. This relationship can be explained by messaging being one of the primary tools in Taobao through which a buyer can minimize transaction risk.

In order to minimize transaction risk, one would expect that buyers speak to sellers often before transaction to inquire about product details. How often do buyers speak to sellers before and after trades? We graph the number of buyer-seller messages versus trade date in Figure 2(right). As expected, most messages occur on the day of transaction, likely being product negotiation. What we find particularly interesting is that post-trade messages are significantly more common than pre-trade messages. In the Taobao system, buyers have an option of using an escrow service, where the seller first ships the product, and payment is exchanged after the buyer examines the product. The observed post-trade messages are likely discussion regarding product satisfaction and payment confirmation.

4. INFORMATION PASSING

From our study of dyadic buyer-seller relationships, we learn that messaging activity is correlated with trading activity across pairs of users. However, dyadic relationships are only the tip of the iceberg when thinking about the interplay between communication and purchasing decisions in a social commerce network. Imagine the following situation: a buyer notices a deal offered at an electronic store, makes a purchase, then messages his friend about the deal. Will the friend also make a purchase from the same store? How large is the influence of the buyer?

We quantify and investigate this economic diffusion behavior which we term *information passing*, illustrated in Figure 3(left). More formally, if buyer B_1 purchases from seller S_1 and then talks to user B_2, will user B_2 then purchase from seller S_1 as well?[2] In the subsequent sections, we analyze information passing through the study of (1) local mutual neighborhoods in static networks, (2) information passing in dynamic networks, (3) influences upon information passing, and (4) directed triadic closure.

Information Passing and Triadic Closure. We begin our study of information passing by examining local neighborhoods in each edge type network (trade, message, contact) of a static endtime snapshot of Taobao. We are interested in understanding how the mutual relationships in one static network are correlated with the edge likelihood in another static network. Of particular interest is

[2]Again, we assign buyer and seller roles with respect to particular transactions. So user B_2 can be a seller and user S_1 can be a buyer in some other transactions.

the question of how *social proximity* is correlated with trade likelihood between a pair of users, where social proximity is measured by the number of mutual contacts between the pair. If we demonstrate that there is correlation between social proximity and trade likelihood, then information passing processes, as shown in Figure 3(left), are likely present in Taobao.

We find that the more mutual contacts a pair of users has, the greater the likelihood that they engaged in a commercial transaction, labeled as *Standard* in Figure 3(right). If we restrict our attention to only users who have exchanged at least one message (*Msg Req*), then for a given number of mutual contacts, the transaction probability is noticeably greater than before.[3] From these results, we can infer that trades are more likely to be embedded in the dense subgraphs of communication networks. This implies that social proximity and trade likelihood are correlated, and are a signal that information passing and product recommendation may be present in the Taobao network. In general, a direct relationship in one network is not only embedded in the local neighborhood of that relationship, but is also positioned in the context of networks with other edge types. This suggests that edges in one network can be used to help understand the link formation process in another. Building on this idea, we next perform a similar experiment in a dynamic triadic closure setting.

Information Passing. Following our examination of the static network, we study network relationships in the dynamic network. In particular, we look at how the message and contact networks influence the trade network by checking for the presence of information passing, as displayed in Figure 3(left).

To quantify information passing in the Taobao network, we measure the *information passing success rate* of the network, which we define as Prob(B_2 buys from S_1 at $t_2 + \Delta \mid B_1$ buys from S_1 at t_1 and B_1 messages B_2 at t_2, $t_2 > t_1$).[4]

Before computing the information passing success rate for the Taobao network, we require a random baseline for comparison. For our baseline, we compute the information passing success rate of an edge-rewired version of the Taobao network, where the edge-rewired network is constructed by randomly rewiring all 3 types of edges in the original network, while leaving node degrees and edge creation times unchanged.

We compute the information passing success rate over 3,906,354 node pair instances in the original network and observe a probability of 0.00203. In contrast, the information passing success rate of the rewired network is computed to be 0.00006. The observed probability of recommendation success is two orders of magnitude more likely than the random baseline, implying that information passing in Taobao is statistically significant and non-random.

Having verified the presence of information passing by checking for edge formation in the forward direction, we confirm the presence of information passing in the reverse direction. Suppose that B_1 buys from S_1 at time t_1 and B_2 buys from the same S_1 at time $t_1+\delta$, we measure the number of messages exchanged between B_1 and B_2 in the time intervals *Before* $[t_1-\delta, t_1]$, *Between* $[t_1, t_1+\delta]$, and *After* $[t_1+\delta,\ t_1+2\delta]$ the purchases of B_1 and B_2. One expects that if information passing is present, then most messages exchanged betweeen the two buyers occur after B_1 purchases, but before B_2 purchases. Table 2 shows the messages for the 3 time periods versus δ, averaged over all instances. We see that the largest proportion of messages exchanged between the buyers occur between their corresponding trade dates. For example, when the buyers transact two days apart, twice as many messages are exchanged *Between* the purchase dates, as compared to *Before* or *After*. Since messages exchanged *Between* are more likely to be recommendations, this is additional evidence that information passing is present in the Taobao network.

Days between purchases	Before	Between	After
1	4.16	5.29	4.76
2	7.78	14.29	7.76
3	8.60	10.52	7.44
4	7.34	15.90	10.79
5	21.87	30.70	21.18

Table 2: Messages between two buyers relative to their trade dates with the same seller.

Through examination of both forward and backward processes, we demonstrate that information passing is present in the Taobao network. In particular, we show that the observed information passing success rate is two orders of magnitude more likely than a random baseline. Prior studies providing evidence of information passing have been primarily conducted in product recommendation networks [17]. Our work shows that information passing, involving both buyer-buyer and buyer-seller relationships, occurs implicitly in Taobao, where the communication tool is primarily intended for buyer-seller communication. This result is significant because it illustrates how offline consumer behavior, asking or informing a personal social network about products, is also manifested implicitly in online social commerce networks.

Influences upon Information Passing. Having demonstrated the existence of information passing in the Taobao network, the next question is, "What factors influence the success rate of information passing?" In the following experiments, we examine how information passing success varies with respect to 4 variables: communication strength, time difference, product price, and product category.

Perhaps the primary influence upon the success of information passing is the amount of communication between the initial buyer, B_1, and his messaging partner, B_2. One can hypothesize that the stronger the communication between the two users, the more likely that B_2 will also purchase the product from the seller that sold to B_1. Counting the number of messages exchanged within time window $[t_1-\delta, t_1+\delta]$, the *Standard* curve of Figure 4(left) shows the probability of closure with δ = 3 days. As expected, the stronger the communication between the two users, the more likely that B_2 will be influenced by B_1. Adding a requirement to consider only users B_2 who have never purchased from S_1 historically (*FirstBuy Req*), we get a slightly lower, but still similar likelihood curve.

Note that an alternative possible explanation for these findings is that both B_1 and B_2 are active users in Taobao who communicate with other users frequently, make more purchases, and are thus more likely to purchase from the same sellers. However, we demonstrate this hypothesis is incorrect by performing an experiment where we keep the communication network and the number of purchases of a buyer unchanged, but randomize the sellers (*i.e.*, buyers buy from random sellers). We find that the increased communication between the two users does not correlate with the information passing success rate (*Random* curve of Figure 4(left)), meaning that the stronger the communication, the stronger the effect of information passing.

The results from this experiment lead to several observations. First, messaging generally increases purchasing behavior in the Taobao network. Second, information passing is present in the net-

[3]To compare, the likelihood that a pair of direct contacts have transacted historically is 0.089.

[4]We only consider the time t_2 corresponding to the first message from B_1 to B_2 after t_1. We also add a requirement of $\Delta \leq 2$ days, i.e., B_2 makes a purchase soon after talking to B_1, to dampen the effects of regular purchases that occur irrelevant to messaging behavior.

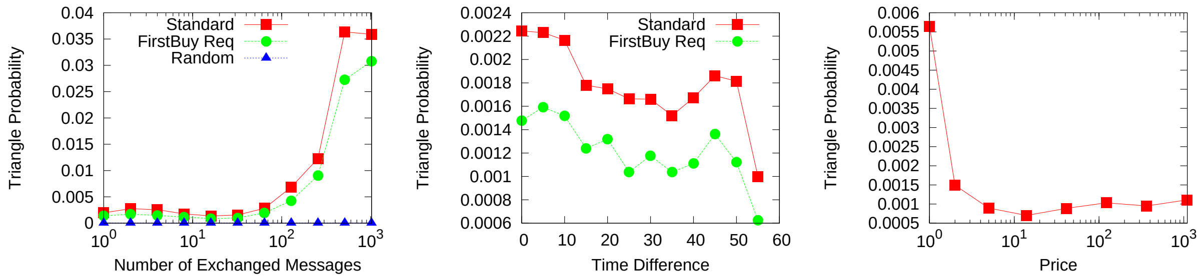


Figure 4: Triadic Closure Probability given Message Strength (left), Time Difference in Days (middle), and Price in CNY (right).

work. Additionally, communication leads to purchases, and social network structure provides a surprisingly strong signal indicating which seller a buyer will purchase from. This latter result will be quite useful later when we study consumer choice prediction.

In addition to counting the number of messages exchanged between buyers, one should also consider the time difference, $t_2 - t_1$, between the initial trade and message from B_1 to B_2. We expect that the larger the time difference between the initial purchase and message, the lower the influence of the message upon the purchasing behavior of B_2. As shown in Figure 4(middle), the probability of information passing success steadily decreases with time. We observe the same effect regardless of whether we require the trade (B_2, S_1) to be a first time trade (*FirstBuy Req*) or any trade (*Standard*). This implies that social product recommendation and influence spreading is most effective when utilized immediately after initial product adoption or purchase.

Although communication between B_1 and B_2 is a significant influence upon information passing, the characteristics of the product itself also affect the success of information passing. We can imagine that the most important product attribute to consider is the price (in Chinese Yuan, CNY) of the initial purchase. As displayed in Figure 4(right), we find that the information passing success rate decreases with product price for the price range from 1 CNY to 15 CNY, then increases slightly for products priced above 15 CNY. The large closure probability at a price of 1 CNY is due to the popularity and virality of virtual goods, such as game credits.

In addition to product price, we also consider the category of the product itself when measuring the information passing success rate. We find that a few categories exhibit recommendation success rates much higher than other categories, while many categories exhibit nearly no information passing at all. For example, the category *women's clothing* exhibits a success rate of over 20%, while the category *home decorations* exhibits a success rate of 1.47%. A major possible influence for the variability of these numbers are the regular group-purchasing deals offered by large stores on Taobao, which provide financial incentives for consumers to convince their friends to join them in purchases.

In summary, our experiments demonstrate that the success of information passing is directly proportional to the communication strength between the initial buyer and their message partner, inversely proportional to the time difference between the purchase and initial recommendation, inversely proportional to product price, and highly category specific. It is clear that influencing an individual to purchase a product is a complex affair. We believe these results are informative and can provide guidance to viral marketing campaigns when trying to promote product recommendation and adoption among online users.

Directed Triadic Closure. Our previous study of local information passing processes can be seen as a special case of the more general directed triadic closure problem. We next investigate the process of directed triadic closure on a global scale. In the following study, we answer various questions regarding triadic closure including: What types of triads are more likely to be formed? What types of edges are more likely to close triads?

For our task, we focus upon the link formation process in the context of triadic closure for the message and trade networks. In particular, consider a triple of nodes U, X, V, where first pairs U, X and V, X interact via messaging or trading, and then a triangle closing edge $U \rightarrow V$ or $V \rightarrow U$ forms. We are interested in how the type of interaction (message vs. trade) and the direction of interaction (i.e., $U \rightarrow X$ vs. $X \rightarrow U$) affects the formation of the triad-closing edge between U and V.

Let us define a Directed Configuration Set (*U*; *X*; *V*) as a situation where an edge forms between *U* and *X* at time t_1, then an edge forms between *V* and *X* at time t_2 (t_2>t_1). We are interested in the probability that a triad-closing edge forms between nodes *U* and *V* at a time t_3 (t_3>t_2). There are 16 possible Directed Configuration Sets, displayed in the first column of Table 3: the left node represents U, middle node X and right node V. For the triad-closing edge, we use the following shorthand notation: m_i is the message edge (*V*,*U*), while m_o is the message edge in the opposite direction (*U*,*V*). Similarly, t_i is the trade edge (*V*,*U*), while t_o denotes the trade edge in the opposite direction (*U*,*V*). We use the term *instance* to refer to a particular example of a configuration set.

Now in Table 3, we examine various properties of configuration sets. In particular, we are interested in knowing, "How many times does a particular configuration set get closed with a third edge? And what is the type of that edge?" For easier reasoning about various configuration sets, we denote hypothetical buyer/seller designations for the middle node *X* in the last column of Table 3. For example, if the configuration contains a purchase by *X* and no sale, then we say that *X* has a "buyer" role. Similarly, if the configuration contains a sale by *X* and no purchase, then we say that *X* has a "seller" role. In all other cases, the role of *X* is ambiguous.

To begin our study of directed triadic closure, first observe that there is little brokerage or reselling in the network, as the two configurations where *X* both "buys" and "sells" have the lowest unique node *X* as well as instance counts (Columns *# Uniq. X*, *# Instances*). This is indicative of the general bipartite structure of Taobao, where users primarily take on either buyer or seller roles.

Another important observation is that configurations where *X* has a "seller" role are represented approximately 100 times more often than configurations where *X* has a "buyer" role. The number of unique buyers exceeds the number of unique sellers in these configurations, as shown in Column *# Uniq. X*, implying that activity levels for sellers are much higher than those for buyers. The large difference in activity levels is likely due to how individuals actually use Taobao. Buyers browse Taobao casually and interact with others primarily when interested, whereas sellers spend their day speaking with potential clients. Given the bipartiteness of Taobao and the general activity level of sellers, we can imagine that seller nodes are local "star" structures in the Taobao graph.

Dir. Config Set	# Instances	# Uniq. X	P(close)	P(t|close)	P(m|close)	s(t_o)	s(t_i)	X "role"
$\circ \xleftarrow{t} \circ \xrightarrow{t} \circ$	590,635	235,088	0.4146	0.4027	0.5973	69.19	63.39	B
$\circ \xleftarrow{t} \circ \xleftarrow{t} \circ$	469,755	28,046	0.3925	0.3295	0.6705	3.09	16.87	
$\circ \xrightarrow{t} \circ \xrightarrow{t} \circ$	410,951	27,302	0.3319	0.3636	0.6364	18.75	6.13	
$\circ \xrightarrow{t} \circ \xleftarrow{t} \circ$	516,941,038	45,741	0.0018	0.1242	0.8758	-18.11	-18.30	S
$\circ \xleftarrow{t} \circ \xrightarrow{m} \circ$	2,661,874	382,690	0.5034	0.3191	0.6809	41.26	101.61	B
$\circ \xleftarrow{t} \circ \xleftarrow{m} \circ$	2,738,167	428,334	0.5470	0.3220	0.6780	41.94	118.83	B
$\circ \xrightarrow{t} \circ \xrightarrow{m} \circ$	253,840,924	45,318	0.0048	0.1308	0.8692	-9.28	-5.40	S
$\circ \xrightarrow{t} \circ \xleftarrow{m} \circ$	252,983,480	45,931	0.0050	0.1299	0.8701	-9.26	-5.03	S
$\circ \xleftarrow{m} \circ \xrightarrow{t} \circ$	3,106,078	421,888	0.5103	0.3309	0.6691	126.17	61.89	B
$\circ \xleftarrow{m} \circ \xleftarrow{t} \circ$	276,047,807	46,475	0.0070	0.1595	0.8405	-0.59	2.09	S
$\circ \xrightarrow{m} \circ \xrightarrow{t} \circ$	3,174,237	475,074	0.5019	0.3324	0.6676	141.02	65.23	B
$\circ \xrightarrow{m} \circ \xleftarrow{t} \circ$	272,424,037	47,524	0.0070	0.1598	0.8402	-0.04	2.63	S
$\circ \xleftarrow{m} \circ \xrightarrow{m} \circ$	420,018,116	403,220	0.0289	0.1386	0.8614	52.92	63.96	
$\circ \xleftarrow{m} \circ \xleftarrow{m} \circ$	280,943,201	436,865	0.0458	0.1369	0.8631	56.03	75.16	
$\circ \xrightarrow{m} \circ \xrightarrow{m} \circ$	276,848,803	442,548	0.0438	0.1409	0.8591	67.61	70.19	
$\circ \xrightarrow{m} \circ \xleftarrow{m} \circ$	272,535,699	469,549	0.0467	0.1398	0.8602	68.69	80.00	

Table 3: Directed Configuration Set (*U*; *X*; *V*), where *X* is the middle node, *U* is the left node, *V* is the right node. # Instances = number of instances. # Uniq. X = number of unique *X* nodes over all instances. P(close) = 100 * probability of a triad-closing third edge. P(t|close) = proportion of triads closed by a trade. P(m|close) = proportion of triads closed by a message. s(t_o) = surprise for directed trade edge (*U*, *V*). s(t_i) = surprise for directed trade edge (*V*, *U*). X "role" = hypothesized role of *X*.

Following our comparison of configuration instance counts, we consider the question, "When will an instance of a Directed Configuration Set be closed by a third edge?" We compute the probability of the configuration (*U*; *X*; *V*) being closed by an edge (*U*,*V*). Observe that configurations where *X* is a buyer have much higher closure probabilities (average 0.0051) than configurations where *X* is a seller (average 0.000046). The large difference in closure probabilities is due to the fact that triads with middle buyers primarily consist of two buyers and one seller, with the required third edge being a buyer-seller edge. In contrast, triads with middle sellers likely contain one seller and two buyers, with the required third edge being a buyer-buyer edge. Since the Taobao network is essentially a bipartite network of buyers and sellers, buyer-seller edges occur much more often than buyer-buyer edges, leading to triadic closure for buyers being over 100 times more likely than for sellers.

Triad-Closing Edge Type Distribution. After computing the instance counts and triad-closing probabilities of each Directed Configuration Set, we next examine the distribution of edge types closing each type of configuration. For each of the 16 configurations c_i, we count the number of instances that are closed by messages and trades in each direction. Column *P(m|close)* of Table 3 shows that messages close most of the triads in the network. However, messages are also approximately 3 times as common as trade edges in the data. Therefore, we need to compute expectations for each of the 4 possible triad-closing edge types (m_i, m_o, t_i, and t_o).

We define a node's *generative baseline* as the proportion of its out-edges that are trades. We assume that when a node A creates an edge, it generates a trade edge with a probability equal to its generative baseline, denoted by $p_t(A)$. For the configuration c_i, the expected number of triads that are closed by a trade from U to V is equal to $\sum_{U \in c_i} p_t(U)$, where the summation is over all instances of the configuration c_i. Similarly, the expected number of triads that are closed by a trade from V to U is $\sum_{V \in c_i} p_t(V)$. Viewing each instance of edge generation as a separate Bernoulli trial, we derive an expression for *surprise* [20] to indicate the number of signed standard deviations by which an observed edge type count differs from expected. For the configuration c_i, the surprise of the triad-closing edge (*U*,*V*) being a trade is $s_{t_o} = \frac{\#observed - \sum_{U \in c_i} p_t(U)}{\sqrt{\sum_{U \in c_i} [p_t(U) * (1 - p_t(U))]}}$, where #observed is the number of instances of c_i that are closed by a trade edge (*U*,*V*). Similarly, we compute the surprise s_{t_i} of the triad-closing edge (*V*,*U*) being a trade. These trade surprise values are listed in Columns *s(t_o)*, *s(t_i)* of Table 3.[5]

After computing these edge type surprises, we can compare observed triad-closing edge counts with expected edge counts from our generative baseline. Our first observation regarding directed edge surprises is that for configurations where X is a buyer, the triad-closing edge being a trade edge is observed significantly more than expected, as shown in Table 3. An explanation for this is that configurations with middle buyers primarily consist of two buyers and one seller, with the required third edge being a buyer-seller edge. Since Taobao is essentially a bipartite network, trade surprises for such configurations vary from 40 to 140 standard deviations more than expected.

For configurations where X is a buyer and only one of U and V is a seller, s(t_o) and s(t_i) differ by a factor of 2. In particular, the trade surprise of the edge directed toward the seller is twice as large as the other direction. This is an example of how the role of each of the nodes in a configuration influence both the edge type and edge direction probabilities of the triad-closing third edge.

In contrast, for configurations where X is a seller, both trade surprises, s(t_o) and s(t_i), are negative. As previously mentioned, when X is a seller, U and V are likely to be both buyers. Since buyers rarely purchase from each other on Taobao, this leads to messages being observed more than expected between U and V.

Our analysis of edge type surprises indicates the significance of user roles in dictating edge formation in the Taobao network. Message edges close the majority of the triads in Taobao due to their relative proportion among all network edges. However, the relative proportion of triad-closing edges being a message edge is primarily dictated by the user role of the middle node X.

[5] We do not explicitly compute the surprises for directed message edges since $p_m(X) = 1 - p_t(X)$, implying that s(m_o) = -s(t_o) and s(m_i) = -s(t_i).

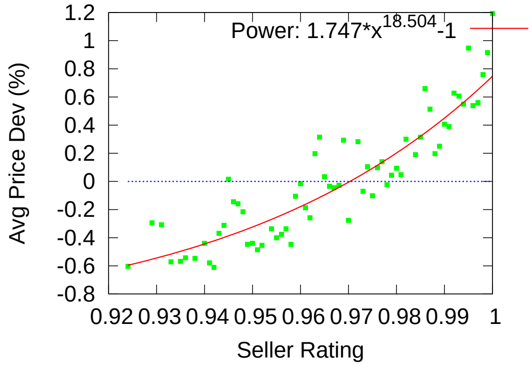


Figure 5: Per Item: Average price deviation from median (%) vs seller rating(%).

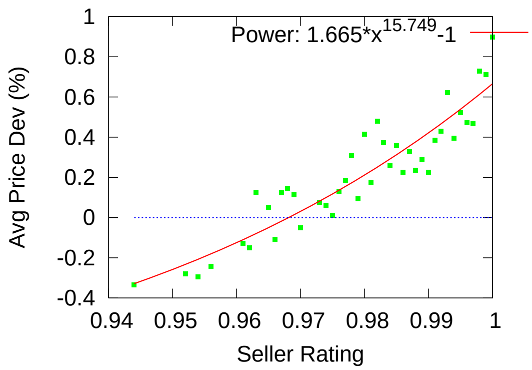


Figure 6: Aggregated Per Seller: Average price deviation from median (%) vs seller rating(%).

5. PRICE OF TRUST

The prior study of information passing relies upon the spread of influence through buyer-buyer communication, which can be seen as an implicit form of buyer-buyer trust. We next examine a more explicit form of buyer-seller trust encapsulated by seller ratings. In the context of electronic marketplaces, buyers are unsure about seller trustworthiness, so buyers put their trust into seller ratings and reviews, and are willing to pay a premium to sellers with good reputations [26]. How much extra will a buyer pay for transaction with a highly rated seller?

Data Preparation. To answer this question, we use the large Taobao transaction dataset to study how good seller reputations are rewarded on Taobao and quantify a price for trust. To facilitate our experiments, we perform a web crawl of the Taobao website to obtain product and seller metadata associated with the transactions in our original dataset. Each transaction in Taobao is rated by the buyer, so we use the percentage of positive reviews that each seller has received in the past as a proxy for seller reputation and trustworthiness. Henceforth, we shall refer to that ratio as seller *rating*.

With this rating information, we compare sellers of the same product and determine how their sale prices differ. The difficult step of the experimental setup is identification of all product listings in our dataset which correspond to the same products. We develop a high precision method targeted toward specific types of products and use our method to identify and group together product listings referring to the same product into *product clusters*. The resulting dataset for our study of trust consists of 382,980 items, 11,293 product clusters (corresponding to unique product types), and 6,199 unique sellers. Each of these product clusters contains a set of items which correspond to the same exact product.

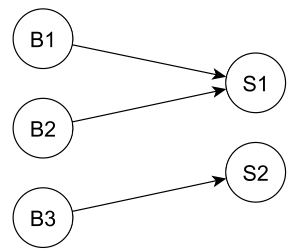


Figure 7: Buyer-Seller Cluster. Given that S1 and S2 both sell exactly the same product that the buyers buy, predict the correct seller for each buyer B1, B2, B3.

Quantifying Trust. With our product cluster dataset, we study the relationship between seller rating and the price at which a seller can transact. For each product cluster, for each listing within a cluster, we compute % deviation from median cluster price. We plot the average price deviation from the median per listing versus seller rating in Figure 5, and fit the data with a power function (R^2 of 0.80). From the super-linear fit, we see that a higher rating is associated with a seller selling his products at a premium compared to most of his peers. Another interesting observation is that a seller rating of 97.1% corresponds to transaction at the median cluster price. The lack of negative reviews in such data has been observed in other e-commerce data such as eBay [25], and has been hypothesized to be the result of a "high-courtesy" social norm.

Next, we aggregate the average price difference of all items sold by a seller and plot that against seller rating, shown in Figure 6. The primary difference between this plot and the previous one is that we now aggregate all the different instances of a seller's transactions within the same cluster, and compare the sellers in a cluster against each other.[6] We find that a power function fits our data particularly well (R^2 of 0.87). Looking across all sellers, the elasticity of product price with respect to seller rating is a small, positive quantity, indicating that there is a direct relationship between seller rating and increased sales price.

One possible explanation for our findings is that highly rated sellers incur higher costs associated with their products, hence they can sell their products at a price premium. For example, highly rated sellers may provide better services, such as replying to messages from customers in a timely fashion, or shipping products more frequently. An alternative explanation is that buyers are willing to pay more to highly rated sellers to minimize transaction risk, thus sellers who maintain good reputations are financially rewarded. Although higher seller ratings are correlated with higher sales prices, the small magnitude of the elasticity indicates that buyer purchasing decisions are likely influenced by other variables, such as the social network in which the purchases are embedded. This leads us to consider the scenario of consumer choice prediction.

6. CONSUMER CHOICE PREDICTION

In order to demonstrate the power of network structure, we now consider the problem of *consumer choice prediction*. Imagine the following situation: a user comes to Taobao and issues an exact query for the product (s)he aims to buy. There is a list of k sellers selling the exact product the buyer is going to buy. Which seller will the buyer purchase the item from? The seller with the lowest price? The most trusted seller? The seller who interacted with the buyer's friends in the past?

[6]There is large variation between activity levels among different sellers, so we only display those who have sold at least 15 items.

Given that our prior experiments have demonstrated the importance of the social network and the strong presence of information passing, we aim to investigate the role that social and communication networks play in consumer decision making [5]. If the social network has no influence upon buyer behavior, then we expect that buyers will purchase from sellers that offer the lowest price. However, as we will see, it is exactly the social network information that gives the strongest signal in predicting which seller a buyer will make a purchase from.

For this consumer choice prediction task, we use the product cluster data described previously in our study of trust. Each product cluster consists of a set of transactions between different pairs of people, but corresponding to the exact same product. We convert each product cluster into a bipartite subgraph composed of buyer and seller nodes, as shown in Figure 7, where the buyers and sellers have all either bought or sold the same particular product. We will term these bipartite subgraphs *buyer-seller clusters*, and henceforth shall perform prediction with these clusters.

Typically a seller will transact with multiple buyers in the same cluster, while a buyer purchases the product from a single seller in the cluster. Both buyers and sellers can be included in more than one buyer-seller cluster if they buy or sell multiple types of products. We restrict our focus to buyer-seller clusters with at least 2 and no more than 10 sellers. Overall, our prediction data is composed of 9,950 clusters, with a per-cluster average of 5.91 buyers and 3.l3 sellers. It is important to understand that, by construction, all sellers offer a product for sale that is exactly relevant to the buyer's interests. The task now is, within a cluster, given a particular buyer, rank the sellers such that the seller the buyer is going to buy from is ranked as high as possible.

Problem Statement: For each buyer-seller cluster C_i, there is an associated set B_i of buyers and set S_i of sellers. For each cluster C_i, for each buyer B_{ij} in B_i, predict which seller(s) from S_i the buyer B_{ij} will purchase their product(s) from.

We model this prediction problem as a ranking problem, where for each buyer B_{ij} in cluster C_i, we wish to generate a ranking of the sellers S_{ik}, such that the true seller from whom B_{ij} actually purchased the product has the highest rank (i.e., score). Since the positive and negative examples for our problem come in sets, it is natural to use a ranking based machine learning approach. In particular, we use the Support Vector Machine SVM-rank [16].

For consumer choice prediction, we use a base set of 23 features that describe product, buyer and seller metadata. We also use features that describe the buyer-seller interactions and network structure. Table 4 lists the features we use in our experiments, along with the networks they are computed on.[7]

Experimental Setup and Evaluation. Our data consists of 58,812 sets of training examples (i..e, buyer-seller pairs where a buyer can buy the same product from multiple sellers). We split the data into 75% train and 25% test sets. The SVMs were trained with linear kernels and loss functions were chosen to minimize the number of incorrect constraints. Since we typically have one positive example per buyer decision, this is equivalent to optimizing Precision@1.

As a point of comparison for our models, we construct three simple rule-based baselines:

- **Random** baseline - rank the sellers randomly
- **MinPrice** baseline - rank the sellers by increasing price.
- **MostMsg** baseline - rank the sellers by decreasing buyer-seller message volume. Defaults to Random if no message edge is present.

[7]For each buyer decision, network features are computed from the snapshot of the network which existed the day prior to the true purchase date. This is necessary to properly model buyer decisions.

Feature Set	P@1	MRR	MR
All Features	0.56	0.72	2.00
Only Network	0.55	0.72	2.02
Only Meta	0.33	0.57	2.62
Meta + Msgs	0.50	0.69	2.13
Meta + Trades	0.43	0.64	2.34
Meta + Contacts	0.42	0.63	2.40
Meta + Direct	0.56	0.72	2.00
Meta + Indirect	0.34	0.58	2.58
MostMsg	0.50	0.69	2.11
Random	0.31	0.53	2.90
MinPrice	0.29	0.54	2.77

Table 5: Customer choice prediction results.

We evaluate the models and baselines using the following three metrics:[8]

- **Precision at Top 1** (P@1) - Fraction of times that the top ranked seller is actually the true seller. (Higher is better)
- **Mean Rank** (MR)- Average *Rank* of the true seller. (Lower is better)
- **Mean Reciprocal Rank** (MRR) - Average *Reciprocal Rank* ($\frac{1}{Rank}$) of the true seller. (Higher is better)

Experimental Results. Table 5 gives an overview of our experimental results where we compare the models using various feature sets and the baselines. First, we note that the model trained on all 23 features gives a 79% improvement over the P@1 of the Random baseline and a 38% improvement over Random's MRR. The model also gives a 13% improvement over the MostMsg baseline and a 93% improvement over the MinPrice baseline. For all our evaluation metrics, the model displays significantly better performance than the 3 baselines. It is interesting to note the poor performance of MinPrice compared to MostMsg. This suggests that communication links and the social graph are essential to understanding how consumers make purchasing decisions in social commerce networks. Note that a natural explanation for the importance of the social graph can be that a buyer first messages a seller, then immediately trades with him. However, we control for this by discarding all communication on and after the trade date.

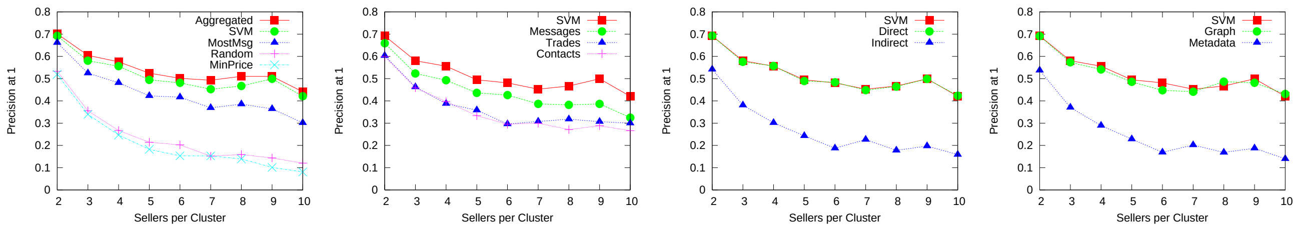
To evaluate prediction performance in more detail, we graph the P@1 and MRR of the Full model (labeled as *SVM*) and the 3 baselines versus the number of sellers in the buyer-seller cluster (i.e., how many different sellers a buyer can choose from) in Figures 8(a),(e). As expected, the performance of all models and baselines decreases as the number of sellers in the cluster increases. Observe that the performance gap between the Full model and MostMsg, the strongest baseline, widens as the number of sellers to choose from increases and prediction becomes more difficult. If we look at the proportional P@1 improvement of the Full model over MostMsg, we see only a 4.5% improvement when there are 2 sellers, but a 39.5% improvement when there are 10 sellers. In particular, we would like to highlight the Full model's strong P@1 of 42.1% for the challenging prediction task with 10 sellers. In general, the full power of the model is not realized until the prediction problem becomes difficult for simple rule-based heuristics.

Different Feature Sets. Having constructed a successful predictive model, we now ask, "What features are most valuable when modeling consumer choice?" In the following set of experiments, we contrast the performance of SVM models trained on different sets of graph and metadata features in order to better understand how consumers make purchasing decisions.

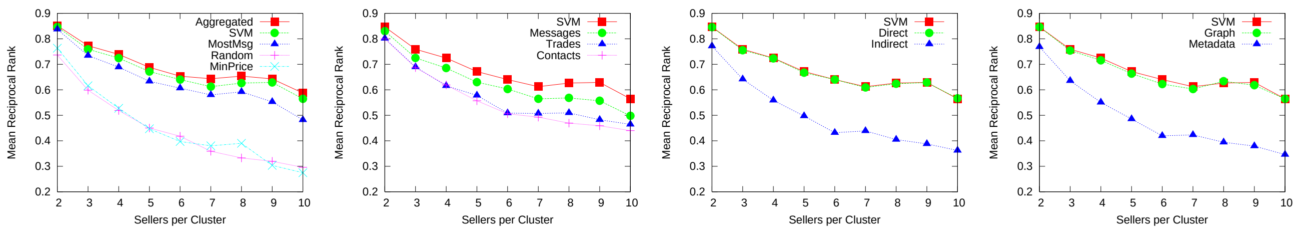
[8]Performance was also evaluated with several other standard ranking metrics. Results are similar, so hence not displayed.

Feature Type	Feature Name	Feature Description	T	M	C
Product Metadata Features	Fractional Price Rank	Seller ranking using their median product price			
	Fractional Rating Rank	Seller ranking using their rating percentage			
	Historical Sold	Num. of all products sold by seller. 1) fractional rank 2) log of value			
	Inventory Sold	Quantity already sold in the particular product listing.			
	Insurance	If the product is insured by the seller			
Direct Network Features	Buyer-Seller Interactions	1) Trade volume 2) Message volume 3) Are they contacts?	X	X	X
	Time Since Last Transaction	Computed for both message and trade networks	X	X	
	Fractional Message Rank	Seller ranking using number of buyer-seller messages		X	
	Nodal Trade Volumes	Number of trades for buyer and seller in the 2 month observation period	X		
Indirect Network Features	Number of mutual partners	Number of nodes who have messaged or transacted with both buyer and seller		X	X
	Seller Clustering Coefficients	Computed for both message and contact networks		X	X
	Mutual Densities	Frac. of edges between the set of nodes mutual with both buyer and seller		X	X
	Seller PageRanks	Computed for static endtime networks	X	X	X

Table 4: Feature Set. T, M, C denote if the feature is computed on the trade, message, and contact networks, respectively.



(a) P@1: SVMs vs Baselines (b) P@1: Edge Types (c) P@1: Direct vs Indirect (d) P@1: Graph vs Metadata



(e) MRR: SVMs vs Baselines (f) MRR: Edge Types (g) MRR: Direct vs Indirect (h) MRR: Graph vs Metadata

Figure 8: Consumer choice prediction performance. The social graph is the most important feature in predicting which seller a buyer will purchase from.

When doing prediction, are network features as valuable as metadata features such as product price and seller rating? We first compare the performance of a SVM trained on network (graph) features versus a SVM trained on metadata (seller profile and product description) features. We find that the P@1 of the graph features SVM is only slightly worse than the Full model, whereas the metadata features SVM is not much better than Random, as displayed in Table 5. Most notably, there is a large performance gap between the graph features SVM compared to the metadata features SVM, as illustrated in Figures 8(d),(h). This implies that prediction using only seller and product information is inadequate, the social and trade networks in the neighborhood of the buyer and seller must be taken into account. Buyers likely do not just use seller profile and product information when making purchasing decisions.

Given that network features are essential when predicting consumer choice, what type of network features are more valuable for prediction: direct features or indirect features (i.e., clustering coefficients, PageRanks)? For this experiment, we train SVM models on direct and indirect network features, the different graph feature classes we use are listed in Table 4. Note that when comparing direct and indirect network features, we include all metadata features in both sets. Figures 8(c),(g) illustrate the large performance gap between the *Meta* + *Direct* SVM vs the *Meta* + *Indirect* SVM, labeled as *Direct* and *Indirect* respectively in the figures. We observe that direct graph information provided by buyer-seller edges is significantly more valuable than the collective information provided by other edges in the local neighborhoods. This is not surprising because powerful information content is present in direct edges. Historical buyer-seller message volume can be indicative of an existing social relationship or historical product queries, while historical buyer-seller trade volume can be indicative of customer loyalty and trust with the seller.

Which network (contact, message, trade) is most useful for predicting consumer choice? In this section, we contrast SVM models trained on each of the separate Taobao networks. We include all metadata features with each set of network features in this experiment as well, prediction results are displayed in Table 5. The performance of the 3 network feature sets versus the number of sellers in the cluster are displayed in Figures 8(b),(f). Our experiment demonstrates that the message network is the most valuable network to utilize when predicting consumer choice. One possible explanation for this finding is that historical message volume is an indicator of familiarity between buyer and seller, i.e., an existing trust relationship between buyer and seller. Historical message volume can also indicate previous potential purchase interest.

We also observe that prediction with the trade network is slightly better than that with the contact network. This suggests that customer loyalty, the primary trade network feature we use, is a more important indicator of consumer choice than the network of contacts. Our explanation for this is that, inherently, contact links are less valuable than trade or message links in such social networks. It takes little effort to add someone to a friends list, as it is a one-time operation. In contrast, maintaining a conversation requires an investment of time and mutual interest on the part of both parties.

Forming a trade link is arguably the most costly as it requires currency and an actual transaction to make the connection.

Per-Category Performance. After performing prediction with a single SVM ranking model, the next question to ask is, "Can we perform better prediction through the use of multiple models?" To answer this question, we segment all historical transactions in our dataset into their respective product categories, and train separate SVM ranking models for each category. The results of our model testing are displayed as *Aggregated* in Figure 8(a),(e). As expected, the aggregated performance of the category SVMs is slightly better than the single Full SVM, with a P@1 of 0.58 compared to 0.56.

Our study of consumer choice prediction demonstrates that in social commerce sites such as Taobao, user communication and social activity is the primary influence upon consumer choice. Utilizing primarily social networking features, we are able to construct an SVM model that can predict, for the case of a buyer choosing from among 10 possible sellers, the correct seller 42% of the time, approximately 4 times better than random. When faced with a selection of substitute goods offered by different sellers, buyers will not just choose their preferred seller through simple heuristics regarding price or rating. We can imagine that buyers utilize many sources of information (seller history, advice of friends, seller's messages), and each buyer processes the information in their own way in order to make a personal purchasing decision. Although we cannot say with certainty what buyers are thinking, we can definitively state that the social graph in which the buyer and seller are embedded is the best feature to look at when predicting consumer choice.

7. CONCLUSION

Our work analyzes the activities of one million users of the Chinese social commerce site Taobao. Through the study of directed closure rules, we empirically verify that implicit information passing is present in the Taobao network, and show that communication between buyers is a fundamental driver of purchasing activity. We then investigate the directed triadic closure process and explain how link formation is highly dependent upon the distribution of buyer/seller roles for the nodes of a social commerce network. Third, we use Taobao review data to demonstrate how high seller ratings are associated with product price premiums, and thus quantify a price for trust. Finally, we develop a machine learning model to accurately predict consumer choice, and demonstrate that the social network is the most important feature in predicting how consumers choose their transaction partners.

We hope that our study will motivate future research into social shopping, as well as give impetus to established e-commerce companies to add more social networking features. Future areas of related study include: analysis of user browsing data to develop refined consumer choice models for social commerce, study of information passing while factoring in both buyer-buyer and buyer-seller trust relationships, and viral marketing to influence consumer choice in social commerce.

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