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The Evolution of Online Social Networks

A tutorial survey

The field of social networking studies how people are connected and the dynamics of their relationships within a specific community. Until the emergence of the Internet, most social network research was conducted by social scientists who often focused on understanding the dynamics within a specific physical community. Since the introduction of Web 2.0 technologies, new digital communities have emerged that have further enabled a rich set of novel interdisciplinary research questions. In this article, an overview and evolution of social network research (which now cuts across various disciplines including engineering, computer science, information science, and mathematics and physics as well as social sciences) is first presented. Some of the authors' ongoing research examining user behavior in an online social network of buyers and sellers in an electronic marketplace, known as Sharing-Mart, is then discussed. The ideas discussed in this article encapsulate research questions surrounding the dynamics of social networking and social cognitive theory. Economic behavior in an online social network is investigated and the impact of incentives on user activity is examined for different experimental designs such as single unit and multiunit auctions.

INTRODUCTION

SOCIOTECHNOLOGICAL NETWORKS: HISTORY AND EVOLUTION

Since its commercialization in the 1990s, the Internet, perhaps the most influential invention of the 20th century, has steadily penetrated almost all aspects of modern human life. Together with associated Web technologies, it is reshaping many of our routine daily activities, ranging from how we shop to how we communicate with our friends, in unprecedented ways. Virtually everything, used or unused, tangible or intangible, is now just a mouse click away [1], [2]. Hundreds of millions of people around the globe are now virtually connected to each other by means of various online social networks such as Facebook [3]. Such dramatic changes in our society have also given rise to new research areas to explore and new open research questions to solve in the scientific community. For example, computer scientists and microeconomists are now striving to discover human behavior and equilibrium strategies in online digital auctions [1], and to better predict future

Signal and Information Processing for Social Learning and Networking

Digital Object Identifier 10.1109/MSP.2011.943158
Date of publication: 17 February 2012

actions based on past activities in online virtual platforms [4].

New interdisciplinary themes and analytical techniques are also emerging to help explain many sociologically enigmatic and complex phenomena by processing massive amounts of data generated in online social Web sites, blogs, and instant messaging services. Boundaries between social and technological networks are disappearing. The paradigm of sociotechnological networks research is appearing, in which new interdisciplinary tools such as statistical signal processing, data mining, and machine learning are being used to analyze real human data describing social and economic interactions over technological networks to discover group dynamics in various contexts and to explain complex functional and topological interactions between social overlay and technology underlay networks [5]. Near the beginning of this new research era, the purpose of this article is to provide a survey of recent success stories employing Web technologies as an experimental tool to analyze structure and interactions among individuals, and then to introduce the online Sharing-Mart system recently developed by a group of researchers at Princeton University as a suite of Web-based experimental tools to conduct controlled social experiments cutting across social and technological networks research. In particular, applications of Sharing-Mart experiments in support of the understanding of economic behavior in the context of social learning and online auctions of digital content will be discussed in some detail.

TWO KEY METHODS FOR CONDUCTING QUANTITATIVE AND ANALYTICAL RESEARCH IN SOCIAL NETWORKS AND INTERACTIONS AT LARGE SCALES ARE WEB-BASED EXPERIMENTS AND COMPUTERIZED ONLINE DATA ACQUISITION.

Recent developments in Internet and Web technologies, such as the high penetration and proliferation of online social networks, online gaming platforms, blogs, and instant messaging services in many aspects of human life, have generated a new wave of interest in the field of sociology in general and in the study of social networks in particular. This area has attracted the interest not only of social scientists but also those in other fields such as electrical engineers, computer scientists, physicists, and information scientists, to name a few. From an historical point of view, on the other hand, the study of social structure and interactions is not new. For example, the first analytical introduction and the systematic study of social structure by means of network ideas can be traced back to the works performed by Jacob L. Moreno and his collaborator Helen H. Jennings in the 1930s [6]. The field gained significant traction again in the 1970s, and advanced considerably thanks to the works of Harrison C. White and his students among others. Today, the study of social networks is already a well-established field with its own institution (the International Network for Social Network Analysis), methods, metrics, and standard software programs for social network analysis as well as academic centers for training and research. Broadly speaking, this field constitutes the study of ways in which individuals interact with one another and influence one another. It focuses on the structure in society rather than on individuals in isolation. Many of the important analytical techniques developed up to the mid-1990s are thoroughly summarized by Wasserman and Faust in [7].

This raises the question: What is new in the study of social structure and interactions today? The answer to this question underpins many of the recent exciting developments leading to the sociotechnological networks research paradigm. A fundamentally important but partial answer to this question is the availability of massive amounts of data on social interactions and our ability to conduct controlled Web-based experiments. Indeed, these are only intermediary means enabling us to verify or falsify hypotheses that seek to explain social structure and interactions. They are necessary for doing fundamental research at large scales but they are not motivated by engineering concerns.

From an engineering point of view, a more practical issue is that more than half a billion people are currently using online social Web sites, and more than half of the total Internet traffic is being generated by file sharing systems and online social networks. Furthermore, these figures are growing dramatically. Therefore, the study of social structure and interactions among individuals can no longer be confined to the field of sociology alone. Questions similar to the ones traditionally posed with regard to social structure and interactions by social scientists only have gained the same theoretical and practical significance, if not more, for engineers for the design, control, and management of new network architectures that can best support emerging online social and file sharing networks. These questions are now asked by engineers but in more specific applied contexts with engineering objectives in mind. For example, Sharing-Mart is designed as a virtual money-based online social and file sharing network to discover the value of information and economic behavior in the specific yet practical context of information and file sharing. It is currently open to the general public as a Facebook application.

WEB-BASED EXPERIMENTS VERSUS COMPUTERIZED ONLINE DATA ACQUISITION

Two key methods for conducting quantitative and analytical research in social networks and interactions at large scales are Web-based experiments and computerized online data acquisition, as discussed above briefly. Since the early 2000s, it has become almost commonplace to see either one of these techniques, possibly both, used to prove or disprove proposed analytical models or theories in a research paper. It is, perhaps, this aspect of fundamental quantitative social network research that first attracted physicists and computer scientists to the field, and is now attracting those with more applied mind-sets, too. Therefore, these techniques deserve further discussion as to their research potential. At the end of this section, we also make a case for why we have chosen the Web-based experiment approach [2], [8], [9] over the computerized online data acquisition approach [10], [11] to analyze in the current article.

THE KEY BENEFIT OF COMPUTERIZED DATA ACQUISITION TECHNIQUES IS THE SIZE OF THE DATA SETS THAT CAN BE COLLECTED FROM ONLINE SOCIAL AND FILE SHARING SYSTEMS.

Prior to Web-based online social experiments, most group-based experiments in the social sciences were traditionally confined to the physical limits of laboratories in academic institutions [12]. They could not easily cut across different social circles such as age and ethnicity, and therefore often lacked the required diversity in the backgrounds of the experimental subjects to draw general conclusive statements. Furthermore, most theoretical models require large population sizes and lengthy temporal spans, which are not conducive to being tested by experiments in the physical world. As a result, these factors and others restricted the scope and utility of group-based experiments before the spread of the Internet. From an engineering point of view, these kinds of experiments provide only limited information into the dynamics of economic and social interactions between individuals in online spaces, usually characterized by large group sizes and rapidly changing social network topologies connecting individuals with diverse backgrounds.

Web-based experiments, on the other hand, offer the ability to go beyond the physical limitations of laboratories, scale up the experiments, and tap into the large pools of participants over the Internet. In such experiments, we have the flexibility of controlling several design degrees of freedom, and of understanding their individual or collective effects on the final emerging global network behavior by adjusting them one at a time or in groups. This further enables researchers to analyze rare events, large groups and interacting factors in sociotechnological networks by means of online social experiments. Five works employing Web technologies for experimenting in various social and applied contexts (i.e., two that are set within a social science context and three that are set in a more applied context of social and file sharing networks) will be explained in greater detail in the sections "Sharing-Mart: Online Digital Auctions" and "A Case Study in Web-Based Experiments: Two Success Stories."

Although analytically different, the well-known small-world model of Watts and Strogatz [10] involving short-range and long-range connections does not significantly differ from Granovetter's (structural) strength of weak ties idea [13], which was introduced 15 years earlier than [10], from a conceptual point of view. Roughly speaking, short-range and long-range connections in the small-world model statistically replace strong and weak ties in Granovetter's framework. In this framework, our strong ties tend to be overlapping with a very high probability, and thus are unable to open up channels into more distant social circles, and therefore can be considered as short for the task of searching for resources in networks.

In [11], Barabási and Albert discovered the scale-free feature of many natural and human-made networks including social networks, i.e., most nodes in these networks only have a few numbers of connections but there are a few nodes having large numbers of connections. Further, they showed that two generic mechanisms, growth and preferential attachment, which are common to most systems, give rise to such a scale-free feature. However, well before Barabási and Albert, researchers such as Herbert A. Simon used the same underlying principles to explain the origin of right-skewed distributions in different contexts [14].

These connections to earlier ideas bring up a question: Why, despite their apparent similarity to these two earlier models, have small-world and scale-free networks become much more popular than their earlier counterparts since their inceptions in late 1990s? The answer seems to be the availability and computerized acquisition of large amounts of network data. A wide spectrum of network data describing connections in diverse types of social and technological networks indicates that the same universal principles predicted by small-world and scale-free networks are common to many complex systems. In contrast, such large scale empirical tests were not feasible for the models of Granovetter and Simon due to lack of data and computational constraints at the time these models were proposed. The number of research papers that have been published in the field since 2000 is perhaps more than the corresponding number in the 50 years up to 2000, a phenomenon that instigated the proclamation of a new science of networks. It is this same trend of automated data collection and analysis that still continues with online social networks today to explain social structure, economic and social interactions among individuals as well as many other social phenomena in online virtual platforms [15]–[17].

Returning to our discussion on Web-based and online data acquisition, there are pros and cons associated with each approach. The key benefit of computerized data acquisition techniques is the size of the data sets that can be collected from online social and file sharing systems. However, the biggest bottleneck with this approach is the excessive amount of noise present in this data, which makes the distillation of the data describing and explaining desired interactions from the noisy data a difficult task. For example, a new type of external application can start to spread virally over an online social network, or a new class of users can join the system, which, in turn, can dramatically change the frequency of interactions and the topological properties of the social networking graph [18]. In addition, some system level parameters can also change over time, such as a policy change in the privacy and security system implemented by a site owner, which can further disturb the data collection process. Since social and economic interactions usually describe complex social phenomena, such stochastic variations in multiple parameters simultaneously make it hard to establish clear causal directions.

The key benefit of Web-based experiments is to have several design degrees of freedom over which we have full control. We can change the design parameters of the experiment one at a time or in groups to establish clear casual directions between emerging network behavior and its root causes. Such experiments can also help to mimic long time periods over which subjects interact, thereby enabling many realizations of a social process to determine aggregate behavior. However, the size of the data sets collected by means of an online Web experiment may be much more limited when compared to the automated collection of social data already available and accumulated over a long period of time through ordinary social interactions. Although limited in size, collected data in a carefully designed Web-based experiment is often enough to develop satisfactory evidence explaining and describing root causes for various social processes [8], [9]. Moreover, statistical techniques such as bootstrap sampling can also help us to obtain random samples of the original data set [19], which effectively increases the number of available data points to test proposed analytical models and theories. Therefore, we believe that the advantages of Web-based experiments outweigh their disadvantages, and by considering the above problems characteristic to the collection and processing of online data of social and economic interactions, we focus on the online experimentation approach in sociotechnological networks research for the rest of the article.

SOCIAL LEARNING

We introduce some basic concepts from social learning theory, which will be helpful in interpreting some of our results in the section "Sharing-Mart: Online Digital Auctions." Social learning theory, which is typically credited to Albert Bandura [24], postulates that people learn new behavior through observational learning of the social factors in their environment. Thus it focuses on learning by observation and modeling [24], [26].

Bandura later relabeled social learning theory to social cognitive theory, which claims behavior is determined by expectancies and incentives. For heuristic purposes, expectancies may be divided into the following three types:

1) Expectancies about environmental cues (that is, beliefs about how events are connected—about what leads to what).
2) Expectancies about the consequences of one's own actions (that is, opinions about how individual behavior is likely to influence outcomes). This is termed outcome expectation.
3) Expectancies about one's own competence to perform the behavior needed to influence outcomes. This is termed efficacy expectation (i.e., self-efficacy).

Incentive (or reinforcement) is defined as the value of a particular object or outcome. The outcome may be health status, physical appearance, approval of others, economic gain, or other consequences. Behavior is regulated by its consequences (reinforcements), but only as those consequences are interpreted and understood by the individual [25], [26].

There are several studies that argue that technologies and behaviors spread through social networks [20]–[22]. However a significant point of difference in our experiments [2], [23] from these earlier works is that they are driven by social cognitive and game theoretic principles using the Sharing-Mart application testbed. Our experiments are primarily focused on understanding incentives, economic behavior, and the development of strategic decision making in an online social network of buyers and sellers, in an electronic marketplace. The Sharing-Mart system not only provides the opportunity to examine several different sociological complex problems, but it also offers the ability to investigate different configurations for designing auctions such as single winner and multiwinner package auctions.

A CASE STUDY IN WEB-BASED EXPERIMENTS: TWO SUCCESS STORIES

In this section, we will survey two successful applications of online tools for experimenting to discover social structure, and social and economic behavior in various social and applied contexts. The first two applications are more focused on sociologically inspired problems, yet they perfectly illustrate the fundamental research capabilities of Web-based experiments to discover social structure and interactions. In the section "Sharing-Mart: Online Digital Auctions," we present results from three experiments that were set in a more applied context of social and file sharing networks to learn economic behavior of end users in online digital file auctions.

A GLOBAL-SCALE, SMALL-WORLD EXPERIMENT ON THE WEB

The premise of the small-world phenomenon is the phenomenon that everybody in the world is connected to everyone else by only a few degrees of separation—six degrees in the popular imagination. The first empirical evidence in favor of this idea was provided by a series of experiments conducted by the social psychologist Stanley Milgram in the late 1960s, known as small-world experiments.

A typical realization of a generic small-world experiment is as follows. Two socially separated individuals are selected at random. One of them is assigned as the message originator (i.e., source individual), and the other is assigned as the message recipient (i.e., target individual) to whom the message will be delivered. The source individual is provided with some basic information about the target including name, age, sex, address, place of employment, and occupation. The source is given a message for the target, and is allowed to send the message only to others whom he or she knows on a first-name basis. Therefore, the source is not allowed to send the message to the target directly unless he or she knows the target on a first-name basis. Intermediate message holders repeat the same step until the message reaches the target. Although small-world experiments were originally proposed to expose the structural features of society, they have also been helpful in providing an understanding of targeted search dynamics to locate a piece of useful information in a social network, or digital files in peer-to-peer technological networks or distributed databases.

In one such experiment [27], Travers and Milgram asked 296 randomly selected source individuals located in Nebraska and Boston to generate acquaintance chains connecting them to a target individual in Boston. Messages were in the form of letters over the postal system. Analyzing 64 completed chains out of 217 that actually started, they found, among many other results, that only 5.2 intermediaries on the average were enough to connect source and target. However, as interesting as this result is, it only provides limited evidence in favor of the small-world hypothesis. First of all, the small-world hypothesis claims that the global-scale social graph "on the world" is connected through short chains of acquaintances, not only the one in the United States. Second, only 196 individuals out of 296 were located in Nebraska. Moreover, only 96 individuals out of 196 located in Nebraska were randomly selected. The remaining 100 individuals in Nebraska were blue-chip stockholders, and the target was, surprisingly, a stockbroker in Boston! Therefore, this experiment (and similar ones that followed it) did not cut across diverse social and geographical boundaries simultaneously. A much larger-scale small-world experiment involving source and target individuals with more diverse backgrounds were thus needed to prove or disprove the small-world hypothesis. This became practical with the advent certain Web technologies, and hence had to wait until 2003.

In [8], Dodds et al. report the results of their version of the small-world experiment at the global scale. They used e-mail messages instead of letters, and were able to reach 98,847 participants registered through the experiment's Web site. They had 18 target individuals from 13 countries with backgrounds as diverse as a professor at an Ivy League university in the United States and a potter in New Zealand. As indicated by these numbers, they were able to scale up the size of the original small-world experiment [27] by a factor of 300, and were able to reach a much more diverse population of participants thanks to the Internet. Some further comparative statistics between these two experiments are also summarized in Table 1.

One of the problems encountered in the global small-world experiment was the extremely low chain completion rate: Only about 1% of the chains that were initiated reached the target. The chains appear to be randomly terminated due to reluctance of subjects to participate. To rectify this problem, Goel et al. [19] proposed a method of taking missing data into account based on importance sampling. For a given global-scale social network graph, let Ω be the discrete space of all possible paths between source and target individuals, and X_n be the outcome of the nth-started chain. $X_n \in \Omega \bigcup \{\text{NA}\}$, where NA represents the incomplete chain outcome. We have the following theorem to estimate chain length distribution [19].

THEOREM 1

Let P be a probability measure on Ω, and f be an arbitrary (measurable) function from Ω to the real line. Then, an unbiased estimator for $m = \int_\Omega f dP$ is

$$\hat{m} = \frac{1}{n}\sum_{t=1}^{k}\frac{f(X_{n_t})}{Q(X_{n_t})},$$

where $X_{n_1}, \ldots, X_{n_K}$ are completed chain outcomes in Ω, and $Q(\omega)$ is the probability that $\omega \in \Omega$ is observed to be complete.

Given a data set collected in a small-world experiment, Theorem 1 allows us to compute an unbiased estimate of any function of the collected data. Using Theorem 1, and changing the shape of the function f accordingly, we can obtain an unbiased estimate for the probability distribution of chain lengths. This approach leads to an estimated median chain length of six to seven by using the Dodds et al. data [8], [19] under various assumptions on the chain attrition rate.

INEQUALITY AND UNPREDICTABILITY

Today, it is commonplace to see a piece of digital content, containing, for example, video, audio, text, or a combination of these, start to spread virally over a social and file sharing network, become very popular not only in the original network first seeded but also in many others, and see its download count reach to several millions in a relatively short amount of time. At the same time, it is very likely that a similar piece of content, if not the same one, might have been uploaded to another site at other time, but did not gain the same popularity. It would be extremely helpful for content distribution and traffic engineering purposes if we could predict such potential superstar digital content before it catches the attention of large numbers of end users, a phenomenon also known as a flash crowd, and thereby handle the surge in the network traffic accordingly.

[TABLE 1] COMPARATIVE STATISTICS FOR TWO SMALL-WORLD EXPERIMENTS; ONE WAS CONDUCTED USING POSTAL LETTERS AND THE OTHER ONE WAS CONDUCTED USING E-MAIL MESSAGES.

	NUMBER OF PARTICIPANTS	NUMBER OF STARTED CHAINS	NUMBER OF COMPLETED CHAINS	DEMOGRAPHICS (SOURCE INDIVIDUALS)	DEMOGRAPHICS (TARGET INDIVIDUALS)
ORIGINAL SMALL-WORLD EXPERIMENT (TRAVERS AND MILGRAM, 1969)	296	217	64	96 RANDOM IN NEBRASKA. 100 BLUE-CHIP STOCKHOLDERS IN NEBRASKA. 100 RANDOM IN BOSTON.	ONLY ONE. STOCKBROKER IN BOSTON, MASSACHUSETTS.
GLOBAL-SCALE SMALL-WORLD EXPERIMENT (DODDS ET AL. 2003)	98,847	24,163	384	RANDOMLY RECRUITED WORLDWIDE.	18 OVER 13 COUNTRIES WITH DIVERSE BACKGROUNDS.

In fact, much of the same story is also true for professionally generated songs, books, and movies, yet the experts in these fields often cannot predict their success beforehand, i.e., the *Harry Potter* series was rejected by eight publishers before finally being accepted by Bloomsbury. An explanation for this phenomenon is that individuals make decisions under social influence, and therefore the popularity of a particular piece of content, amateur or professional, depends not only on its inherent characteristics and quality but also on many other micro- and macro-level network dynamics. To investigate the issue of inequality and unpredictability in markets, Salganik et al. [9] conducted two Web experiments in which 48 songs from previously unknown bands were presented to more than 14,000 participants.

SHARING-MART IS A VIRTUAL-MONEY-BASED FILE SHARING SYSTEM IN WHICH DIFFERENT DIGITAL RIGHTS OF VARIOUS CONTENT TYPES CAN BE TRADED BY MEANS OF DIFFERENT TRANSACTION STYLES.

The setup of this experiment is briefly as follows. Participants were assigned to either a social influence condition or an independent condition randomly. Then they decided which songs to listen to, rated them, and downloaded them if they wished. Under the social influence condition, the number of download counts of each song was presented to the participants, whereas this information was hidden from them under the independent condition. The number of downloaded songs was used as a signal for social influence. Experiment 1 involved 7,149 participants and was designed to have a weaker social influence signal in which songs were placed randomly in a16 $\times$ 3 matrix along with their download counts. On the other hand, Experiment 2 involved 7,192 participants and was designed to have a stronger social influence signal in which songs were presented in descending order with respect to their current download counts. Under the independent condition, the songs were placed randomly in a 16 $\times$ 3 matrix without any download count information in both experiments. Each participant was randomly assigned to one of eight different noninteracting worlds running in parallel under the social influence condition. Once assigned to a world, a subject could only see information in his or her world but not the others. Initial conditions for all worlds were the same—zero download count at the beginning. Running the experiment in parallel noninteracting worlds with the same initial conditions helped to understand unpredictability of the emerging collective outcome.

In this experiment, the market share of song i was defined as $m_i = \left(d_i/\left(\sum_{j=1}^{S} d_j\right)\right)$, where d_i is the download count of song i, and S is the total number of songs. Under the independent condition, m_i gives a measure of quality of song i, whereas it gives a measure of success of song i under the social influence condition. The main results were as follows. The inequality of success, as measured by the Gini coefficient $G = \sum_{j=1}^{S} \sum_{i=1}^{S} |m_j - m_i| / 2S \sum_{i=1}^{S} m_i$, increased for all eight worlds when going from Experiment 1 to Experiment 2. Moreover, the inequality in all worlds under the social influence condition was always larger than the inequality under the independent condition. These findings show not only that social influence contributes to inequality of success in this artificial market but also that the collective outcome becomes increasingly more unequal under stronger forms of social influence. Hence, a "rich-gets-richer" type of phenomenon occurs, and popular songs become more popular, and unpopular songs become less popular when social influence is exerted on individuals [9].

The unpredictability of success of song i was defined as $u_i = \left(1/(W(W-1)) \sum_{j=1}^{W} \sum_{k=1, k \neq j}^{W} |m_{i,j} - m_{i,k}|\right.$, where $m_{i,j}$ is the success of song i in world j, and W is the number of noninteracting worlds. Intuitively, u_i describes the average amount of discrepancy between success measures of song i in different worlds. The overall unpredictability is, then, equal to $U = \sum_{i=1}^{S} u_i / S$. For the independent condition, since there was only a single world, participants were randomly divided into two subpopulations to obtain a random measure of unpredictability, and then the random outcomes were averaged over 1,000 realizations to obtain an average measure of unpredictability. The results are again quite interesting. Social influence leads to higher levels of unpredictability when compared with the independent condition. Moreover, the stronger the social influence signal, the higher the unpredictability. These results indicate the inherent difficulty of predicting the next superstar content items under social influence before they become popular. Although, something "best" would never perform very badly, or vice versa, anything in the middle is a possible candidate for success.

Another recent work analyzing the spread of behavior by means of a Web-based experiment involving 1,528 participants is given in [28]. We cannot survey this experiment due to space limitations, and refer interested readers to [28] instead.

We now turn our attention to the Sharing-Mart social Web-based experimental platform to examine experiments conducted in a more applied context.

SHARING-MART: ONLINE DIGITAL AUCTIONS

Our main focus here will be on the experimental platform Sharing-Mart, which was recently developed at Princeton University to conduct controlled experiments designed to provide insight into the economic behavior of individuals and social learning in online auctions of digital content. The Sharing-Mart platform differs from the mechanisms used in the works discussed above in two ways. First, it has been designed to address more engineering oriented research problems cutting across social and technological networks research, in contrast with the sociological issues that inspired the experiments reviewed in the previous sections. Second, it has been designed as a suite of generic Web-based experimental tools to serve a wide spectrum of research goals in the emerging field of sociotechnological networks research. As an example, applications of Sharing-Mart will be first illustrated to test game theoretic predictions and then to understand economic behavior in the context of social learning in this section. Although Sharing-Mart experiments conducted to date are still at a relatively small scale, they can be scaled up to larger populations easily (i.e., it is currently open to Facebook users), and are representative of its capabilities as an experimental platform.

INCENTIVE COMPATIBILITY IS AN IMPORTANT FEATURE OF SHARING-MART AUCTIONS SINCE IT INDUCES ALL BIDDERS TO BID ONLY ONCE WITH THEIR TRUE VALUES TO BUY CONTENT IN THE SHARING-MART ECOSYSTEM.

Sharing-Mart is a virtual-money-based file sharing system, in which different digital rights (e.g., view only, download, and resell rights) of various content types (e.g., video, audio, graphics, and documents) can be traded by means of different transaction styles (e.g., marked price transactions and Sharing-Mart auctions). On the one hand, Sharing-Mart is envisioned as being a content equivalent of physical exchange markets such as eBay and Amazon. On the other hand, Sharing-Mart is more than just a new approach to file sharing. It also serves as a powerful testbed to perform controlled experiments with human subjects to better understand human behavior in exchanging content under the guidance of pricing signals, and other sociologically complex phenomena such as the time evolution of the popularity of a content item or a user. Sharing-Mart's monetary incentives together with user ratings eliminate the free rider problem in file sharing systems. In Sharing-Mart, end users determine prices of their content items in terms of a virtual currency called tokens based on the time and effort needed to produce them. Therefore, initial file prices in Sharing-Mart reflect subjective evaluations of their producers. Open market dynamics, competition from similar content, and supply and demand forces determine final content prices.

EXPERIMENT 1: UNDERSTANDING STRATEGIC BEHAVIOR

In one such Sharing-Mart experiment [2], Inaltekin et al. designed an auction-based competition among graduate students in the Department of Electrical Engineering at Princeton University. The purpose of this auction experiment was to understand strategic behavior (or the lack thereof) of users in online auctions. Students were asked to submit buyer and seller strategies for trading files through Sharing-Mart. Then, the submitted strategies competed against each other to garner the maximum number of points, which consisted of a combination of total seller revenue and the number of auctions won. It was observed that the revenue earned by selling content and the probability of winning an auction increase as seller and buyer strategies approach the socially optimal Nash equilibrium of the designed experiment. Next, we will first explain the details of Sharing-Mart auctions and then provide further details of the experimental setup in [2].

Selling a file is different from selling a tangible good via an auction mechanism because multiple copies of a file can be sold in a single auction like a package auction [29]. In support of this type of sales opportunity, the following uniform price, unit demand, and multiple-winner file auction is implemented in Sharing-Mart. The seller enters the minimum price, the auction start/end date and time, and digital rights and the number of copies of the file, M, to be sold. Then, the file is sold to the highest M bidders at the price of the $(M+1)$st highest bid. If the number of unique bidders is smaller than M, the file sale price becomes equal to the minimum price, and all bidders pay this minimum price. An important property of Sharing-Mart auctions is given below.

DEFINITION 1

An auction mechanism is said to be incentive compatible if it induces each bidder to submit a bid that sincerely reflects his or her true value for the item.

An incentive compatible auction is also an efficient (i.e., items are allocated to those who most value them) and standard (i.e., items are allocated to the highest bidders) auction.

THEOREM 2

Sharing-Mart auctions are incentive compatible, efficient, and standard.

Incentive compatibility is an important feature of Sharing-Mart auctions since it induces all bidders to bid only once with their true values to buy content in the Sharing-Mart ecosystem. In other words, Theorem 2 implies that the strategy of successive bidding with bid values smaller than a bidder's true value of content will only decrease the expected utility of this bidder by decreasing his or her chances of losing the auction. This theoretical finding is also justified in the Sharing-Mart experiment reviewed below where it is observed that the average number of bids from the three most successful bidders is around one. The other two properties are self-explanatory.

The setup of the experiment designed in [2] is as follows. It was designed as a 96-h agent-based competition among seven graduate students at Princeton University. Students were given a lecture on game theory and auction theory before the experiment. Therefore, they were familiar with strategic thinking in a game setting. A closed test group was formed among seven students by using Sharing-Mart's group formation function, and 1,800 tokens were allocated per student for file trading. Each student was requested to propose a seller strategy, and to set three Sharing-Mart auctions according to his or her selling strategy. Each student was also requested to submit an automated bidding agent to bid for 18 other auctions. The purpose of automated bidding was to eliminate random factors (e.g., forgetting to bid for an auction) in bidding. The start time/date of all auctions was the same, but the end time/date varied according to seller strategies with the restriction that all auction durations had to be less than 96 hours.

Student i, $1 \leq i \leq 7$, got 100 points from each auction he or she won, and the total number of points p_i that student i got was equal to the total revenue obtained from three auctions (in terms of tokens) plus 100 times the number of auctions won. Therefore, p_i is equal to

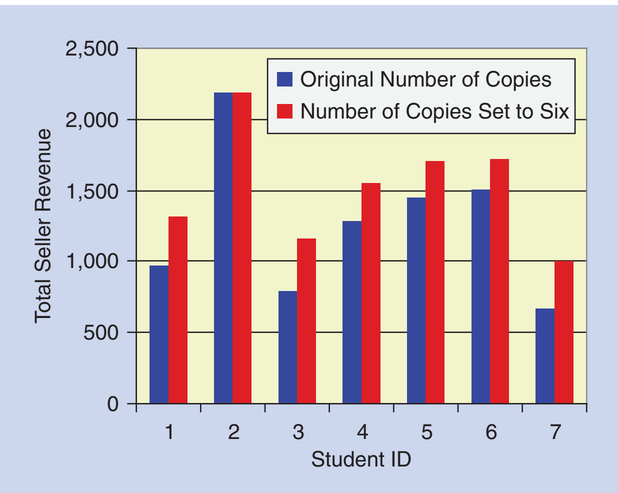
$$p_i = \sum_{k=1}^{3} f_i^k M_i^k + 100 \sum_{j \neq i}^{7} \sum_{k=1}^{7} \delta_{j,i}^k,$$

where f_i^k is the final price of the kth auction from student i, M_i^k is the number of copies in the kth auction from student i, and $\delta_{j,i}^k$ is an indicator function that equals one if student i wins the kth auction from student j, and equals zero otherwise. Here, p_i is a complex function of M_i^k, the minimum sale price R_i^k, the auction duration T_i^k, the bidding strategy $\beta_i(t)$, $t \in [0, 96]$, of student i and the bidding strategies $\beta_j(t)$ of other students. Moreover, bidding strategies also depend on other factors such as the minimum and the current price of the file, which are not shown explicitly for the sake of notational simplicity.

The final score of student i was calculated by normalizing his or her total points with the maximum number of points. Therefore, student i's objective was to solve the following nonlinear (possibly nonconvex) optimization problem:

$$S_i^* = \max_{\substack{\{M_i^k\}_{k=1}^3, \{R_i^k\}_{k=1}^3, \\ \{T_i^k\}_{k=1}^3, \beta_i}} \frac{100 \times p_i}{\max\{p_j : j = 1, 2, \ldots, 7\}}$$

given the bidding and selling strategies of other students. All students knew the utility functions of their opponents. Even though the optimization problem faced by each student was complex, the experiment was set up in such a way that it has a simple, symmetric, and socially optimal Nash equilibrium.



[FIG1] Change in seller revenue when the number of copies to be sold per auction is changed to six.

THEOREM 3

The above experiment has a symmetric and socially optimal Nash equilibrium at which $M_i^k = 6$, $R_i^k = 100$, $T_i^k = 96$, and all students bid 100 tokens for all ongoing 18 auctions.

At this equilibrium point, all students collect 3,600 points, and therefore a score of 100. From a theoretical point of view, a Nash equilibrium point is the point at which all rational and intelligent players in a game setting agree to play. It is also stable since unilateral deviations are not preferable. Based on these theoretical facts and Theorem 3, we expect to see rational and intelligent student behavior in our experiment around the equilibrium point described in the statement of Theorem 3. Note also that the game is set up in such a way that this equilibrium is easy to predict. The results of the experiment support this hypothesis, and we observe that the students collecting the maximum number of points play the game according to the Nash equilibrium described in Theorem 3. Our experiment results are summarized in detail as follows.

When averaged over the best three seller strategies, it was found that the average number of copies maximizing the seller revenue is 5.33, which is close to the six copies suggested by Theorem 3. This finding further motivated the following question: What happens if all students set the minimum number of copies to be sold to six by keeping other parameters constant? Since all the bidding history was saved, it was easy to rewind and then fast forward the experiment from the beginning to obtain the results with this parameter change. The ability to replay experiments under such parameter changes without requiring real participation is also among the advantages of online experiments. In fact, with this parameter change, the file sale price stays the same at the minimum price set at the beginning of an auction, and the total revenue equals the number of unique bidders times the minimum price. The result was quite interesting. Except for one student, revenue of a seller summed over three auctions strictly increased. The average revenue increase is 20%. The student whose revenue stayed the same already set the number of copies per auction to six. These findings are another justification for employing the Nash equilibrium seller strategy to maximize seller revenue. Figure 1 illustrates the revenue increase for each user under this parameter change. By using collected statistics regarding final sale price over minimum sale price ratio and the average percentage of copies sold over 21 auctions, they further showed that the seller revenue peaks when the number of copies is around five to six, which is another empirical justification to employ the Nash equilibrium seller strategy predicted by Theorem 3.

Regarding minimum prices, Inaltekin et al. [2] observed that the average minimum price averaged over all 21 auctions was 96.67 tokens, and the median minimum price over the three best seller strategies was 95 tokens, which are also close to the numbers suggested by the Nash equilibrium in Theorem 3. Regarding the bidding strategies, the three students with the highest success rates snipe within the last 60 s of auctions, which is similar to the sniping behavior commonly observed in eBay [1]. These students won 96.87% of all auctions in which they participated. Furthermore, the average number of bids per auction from the three most successful bidders was 1.316, which is also in compliance with the incentive compatibility property in Theorem 2: just bid once with your true value. Other students employed continuous bidding strategies and withdrew when the current price reached their true value of the file. Their success rates reduced to 61.87%, and they bid 8.625 times per auction. Although small in scale, these results clearly indicate the importance of the role played by the game theoretic equilibrium analysis in predicting economic behavior of end-users in online auctions.

EXPERIMENT 2: SINGLE WINNER PACKAGE AUCTIONS

In two experiments [23] conducted by Leberknight et al. (2011), economic behavior for subjects in a single unit package auction of digital content was examined. The auction experiments consisted of a word game that was designed to simulate the competitive forces associated with a problem solving task in a classroom setting. The objective of the word game used in each experiment was to obtain and correctly organize all the letters for a hidden target word. Each subject was instructed to buy and sell letters in several auctions in Sharing-Mart to collect all the letters. The winner of the game received a monetary prize if she/he was the first player to determine the word, and/or the player who maximized his/her token balance by selling the letters. The game consisted of two rounds. In the first round, subjects were allowed only to purchase letters and in the second round, subjects were free to buy or sell letters. Winners in the first experiment received a monetary reward of up to US$50, and winners of the second experiment received a monetary reward of up to US$25. In addition, all subjects had the same initial token balance. In the first experiment, each subject had an initial token balance of 1,200 and in the second experiment, each subject had an initial token balance of 500 tokens. The budgets of the subjects were kept private.

The set of tunable parameters for the two auction experiments consisted of 1) auction duration, 2) budget, 3) buy or sell rights, 4) number of letters for the target word, 5) monetary reward, and 6) initial price for each letter in the first round. While the relative importance of determining a word with respect to the token balance was not analyzed, one key observation was that subjects with larger initial token balances, in the first experiment, were more active throughout the entire game compared to subjects with smaller initial token balances, in the second experiment. This might suggest that greater perceived purchasing power may encourage greater participation in the system. However, the tokens serve as a proxy for the reward and therefore in future experiments the reward amounts will be reversed keeping all other parameters (token balance, initial price sequence) constant. This will help to clarify whether the reward amount or token balance is the stronger predictor of activity.

While auctions are generally competitive by nature, we further amplified the inherent competition through experiments that investigated the desire of students to cooperate with other students by contributing their knowledge in the form of files containing letters for a target word. This experiment was designed to simulate a student's desire to buy and sell digital course notes as both processes involve the anticipated demand for collaboration in a competitive environment. Students may not wish to sell their course notes to other students if they believe it will compromise their competitive advantage. This belief was operationalized by evaluating subjects' desire to sell files containing letters for the target word to other subjects. Overall, in Experiment 1, 89% of the subjects sold files more than 30% of the time and the average percent of contributions or files sold for these subjects were 47%. In Experiment 2, there were fewer subjects who chose to sell the content they won in auctions, but the average percent of contributions or files sold was approximately the same. Specifically, 60% of the subjects sold files more than 20% of the time and the average percent of contributions or files sold for these subjects was 46%. The higher percentage of files sold in Experiment 1 versus Experiment 2 may have been a result of the reward amount paid to winners. The reward amount in Experiment 1 was twice the amount of the reward in Experiment 2, which may have incentivized the subjects to sell more content to win the game. In addition, while there were fewer winners in Experiment 1 compared to Experiment 2, the winners in Experiment 1 purchased more files on average than the winners in Experiment 2. The inverse relation between the number of winners and files sold initiated further research into perceptions of optimal winning strategies, which will be discussed in the following section. There are other factors that influenced the activity in this experiment. Due to space limitations, interested readers are referred to [23] for further details.

In addition, two research questions and hypotheses (H1 and H2) were presented to understand the economic behaviors and dynamics associated with the package auction for public goods using the Sharing-Mart system. H1, which states that subjects who initially pay more for content are more likely to participate more in the system compared to subjects who pay less, appears to be true. The analysis of the results for the second hypothesis H2, which states that subjects who bid more often have a greater chance of winning compared to subjects who bid less often, was not supported. Therefore, while higher bid amounts may correspond to high activity or participation, the most active bidders and users who paid the most for content do not necessarily win the game. The experimental observations also highlight the challenge of calibrating proper incentives to motivate participation and content contribution in competitive applications, whose success depends on mutual cooperation among the users.

EXPERIMENT 3: MULTIWINNER AUCTIONS

Unlike the experiment described in the previous section, the objective of this experiment was to investigate behavior in multiwinner auctions as opposed to single winner auctions. In addition, using the Sharing-Mart system [2], [23], we designed the experiment to examine only competitive behavior as opposed to competitive and collaborative behavior as described in the experiments in the section "Experiment 2: Single Winner Package Auctions." The content auctioned in this experiment consisted of six questions for a graduate engineering course. Unlike the monetary incentives mentioned in the section "Experiment 2: Single Winner Package Auctions," subjects were incentivized to participate or buy content since these six questions were designed to help students prepare for a midterm exam. Each question was sold in six separate auctions for the same price and the magnitude of the number of winners varied for each auction. This enabled the investigators to specifically focus on a subject's willingness to compete or bid on content based on their perception of winning. Subjects were allowed only to purchase files and were restricted from selling content. One subject who was not enrolled in the course was selected to sell the six questions. The multiwinner configuration and other tunable parameters for the experiment are provided in Table 2.

THE EMERGENCE OF ONLINE SOCIAL NETWORKS PRESENT SEVERAL NEW AND CHALLENGING RESEARCH QUESTIONS THAT ARE OF INTEREST TO A DIVERSE SCIENTIFIC COMMUNITY.

The initial price for each question was preset to ten and the number of winners for each auction was manipulated to closely examine two conjectures pertaining to winner strategies in this online social network. First, we contend that the subjects' bidding activity depends on the number of winners in each auction. Specifically, subjects will exhibit a higher degree of bidding activity when the number of winners in an auction is high compared to when the number of winners in an auction is low (blue cells). This directly relates to expectancies of social cognitive theory as discussed in the "Introduction" section. Second, if the number of winners is duplicated in successive auctions, we contend subjects will bid more in older auctions compared to newer auctions. For example, based on the data in Table 2, we anticipate subjects will be more active in the second auction versus the sixth auction since they both contain the same number of winners (grey cells). We label these two conjectures as C1 and C2 respectively, and present the following summary of the results.

C1) More bidding activity will be observed in auctions that have a greater number of winners (Supported).

C2) More bidding activity will be observed in earlier auctions compared to later ones (Supported).

The results for the first conjecture, C1, are consistent with what was expected. For example, the red bars in Figure 2, which represent the number of unique bidders, illustrate that the greatest number of unique bidders was observed in the auctions that had the greatest number of winners, particularly auctions four and five. Conversely, it can be observed that auction three, which had the least number of unique bidders, corresponded to the case when only one winner was possible. For the second conjecture, C2, when the magnitude of the number of winners is the same in different auctions, we observe that there were more unique bidders in the earlier auction compared to the later one.

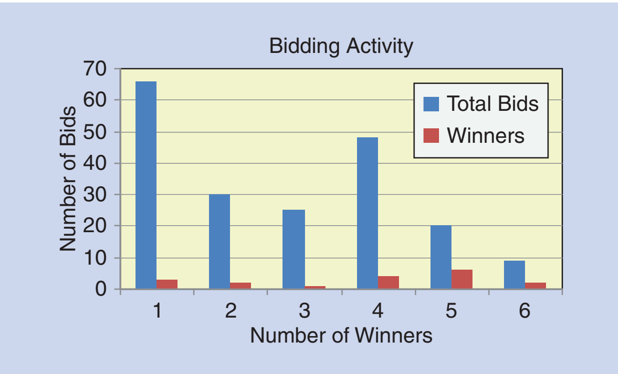
Therefore, both conjectures were supported and a key objective of this research was to demonstrate the use of the Sharing-Mart system as a data collection tool for analyzing economic behavior in online auctions of digital content. The main message from the analysis can help to identify winning strategies by understanding what other players perceive as their best strategy and where to expect more competition. For example, if more competition is anticipated in auctions that allow for many winners, it may be possible to increase the probability of winning and paying less for digital content in less competitive auctions.

We now shift focus to analyzing the number of winners. A time-series analysis of the bidding activity, illustrated in Figure 3, reveals that some subjects bid very high at the beginning of each auction. For example, in the top left graph you see a very high bid in the beginning and a slow increase in bids over time. The slow increase was due to the fact that the bids were private information.

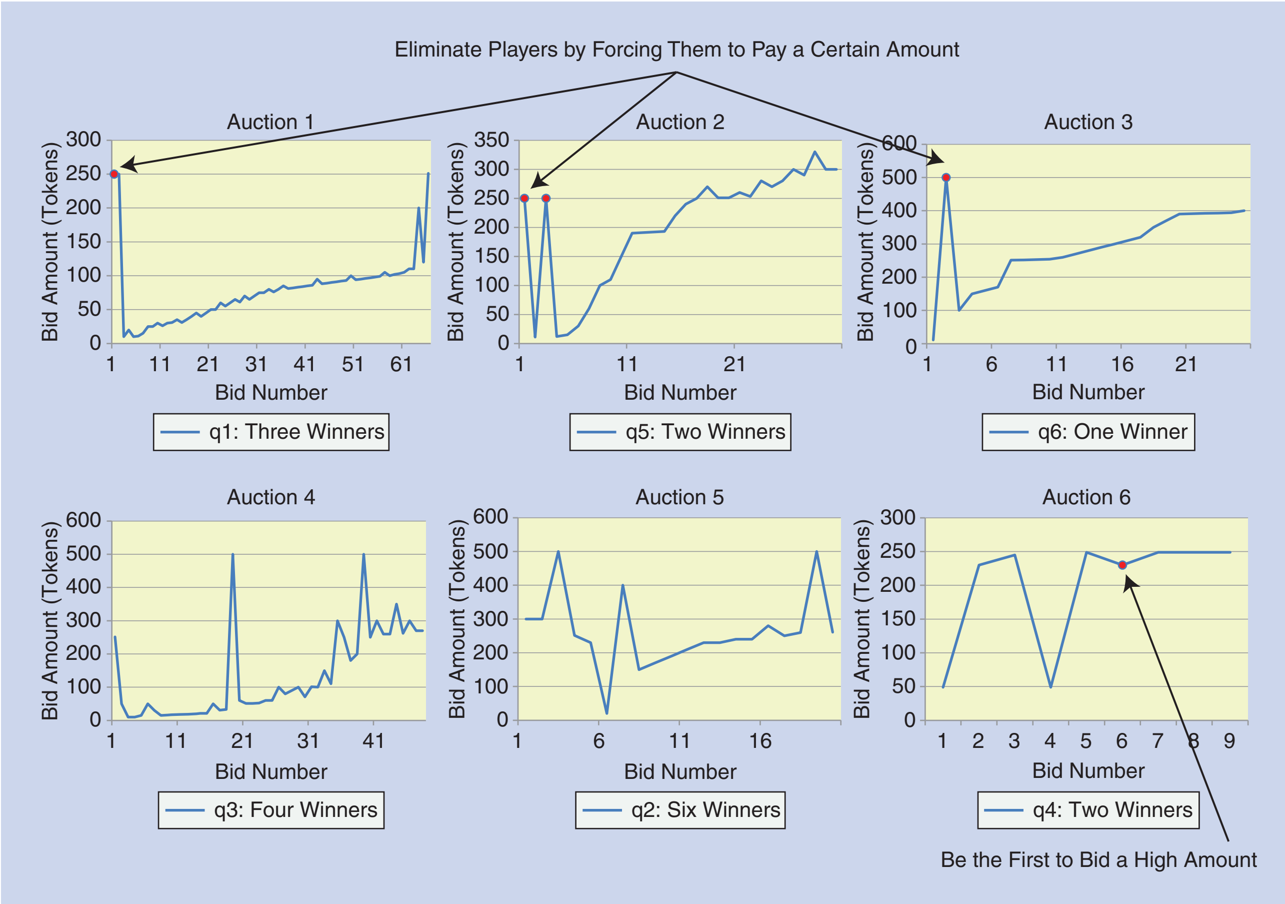
Therefore, no one knew other players' bid amounts. So even though we see a high bid early, other players did not see the value, and rather were only informed that they had been outbid and placed small incremental bids. It can also be observed those placing high bids early were present in almost all auctions. This behavior was determined to be the optimal winning strategy. Subjects who placed high bids early won more times than other subjects. A likely explanation based on the sealed bid, second-highest price auction implemented in Sharing-Mart is as

[TABLE 2] MULTIWINNER CONFIGURATION.

AUCTION	1	2	3	4	5	6
# WINNERS	3	2	1	4	6	2
QUESTIONS	1	5	6	3	2	4
INITIAL PRICE	10	10	10	10	10	10



[FIG2] Bidding activity versus the number of winners in an auction.



[FIG3] **Time series of bid amount based on the number of winners in an auction.**

follows. We assume there are n bidders, x is the highest bidder and y is the second-highest bidder. If no one bids higher than x, then x wins and pays y's bid amount. If y bids higher than x, then y has to pay x's bid amount. The key is to choose the right bid amount that can allow you to compete in successive auctions if you win, but decreases the competitive advantage of other players if you lose. Since everyone had a fixed budget and the budget was public information, it was possible to force subjects to spend too much of their budgets by bidding higher than some threshold value. In this experiment, since all subjects had an initial budget of 500 tokens, if x bids 250 then y will have to bid more than 250 and will therefore not be able to compete in the next auction with x. If no one bids higher than x, then x will pay less than 250 and still be able to compete against y.

An examination of the last graph on the lower right reveals there are three highest bids of 251, but only two winners possible. Therefore, the last person that bid 251 will not win since the system chooses the first k winners that bid the highest amount. In this case $k = 2$ and therefore only the first two highest bids win. The main message from the analysis of the two aforementioned points is that based on our experimental design the strategy that can maximize the chances of winning takes into account a threshold value for placing bids early on, which can results in winning or eliminating competition in successive auctions.

CONCLUSIONS

The field of social networking, which initially focused on the dynamics within physical communities, now extends to digital communities as a result of technological advancements like the Internet. The emergence of online social networks, such as Orkut, LinkedIn, MySpace, and Facebook present several new and challenging research questions that are of interest to a diverse scientific community including engineers, mathematicians, physicists, computer scientists, and information scientists. This article presents a review of several seminal research papers that portray the evolution of the social networking landscape and the opportunities that exist today. In addition, several recent experiments have been described that use the Sharing-Mart system to study and understand social and economic interactions as well as other sociologically complex phenomena of interest among end users in social and file sharing systems. In the future, we plan to run large-scale human experiments to confirm or falsify these findings and explore new theories relating to the behavior we observe in the Sharing-Mart System.

ACKNOWLEDGMENT

We are grateful for discussions with Matthew Salganik and Jacob Shapiro of Princeton University. This work was supported in part by the National Science Foundation (NSF) under grant CNS-0905086.

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