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Emerging behavior in electronic bidding

I. Yang,[1] H. Jeong,[2] B. Kahng,[1] and A.-L. Barabási[3]
[1]*School of Physics and Center for Theoretical Physics, Seoul National University, Seoul 151-747, Korea*
[2]*Department of Physics, Korea Advanced Institute of Science and Technology, Taejon 305-701, Korea*
[3]*Department of Physics, University of Notre Dame, Notre Dame, Indiana 46556, USA*
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We characterize the statistical properties of a large number of agents on two major online auction sites. The measurements indicate that the total number of bids placed in a single category and the number of distinct auctions frequented by a given agent follow power-law distributions, implying that a few agents are responsible for a significant fraction of the total bidding activity on the online market. We find that these agents exert an unproportional influence on the final price of the auctioned items. This domination of online auctions by an unusually active minority may be a generic feature of all online mercantile processes.

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I. INTRODUCTION

Electronic commerce (E-commerce) is any type of business or commercial transaction that involves information transfer across the Internet. Over the past five years, E-commerce has expanded rapidly, taking advantage of faster, cheaper, and more convenient transactions over traditional ways. A synergetic combination of the Internet supported instantaneous interactions and traditional auction mechanisms, online auctions represent a rapidly expanding segment of the E-commerce. Indeed, with the advent of the internet, most limitations of traditional auctions, such as geographical and time constraints, have virtually disappeared, making a significant fraction of the population potential auction participants [1,2]. For example, eBay, the largest consumer-to-consumer auction site, boosts over 40 million registered consumers, and has grown in revenue over 100 000% in the past five years. With the rapidly increasing number of agents, the role of individuals diminishes and self-organizing processes increasingly dominate the market's behavior [3,4].

Recently, the self-organizing features of complex systems have attracted the attention of the statistical physics community because these contain diverse cooperations among numerous components of a system, resulting in patterns and behavior which are more than the sum of the individual action of the components. While many systematic studies have been carried out to understand such emerging patterns in various systems, little attention has been paid to electronic auctions. In this paper, we collect auction data and show that the bidding of hundreds of thousands of agents leads to the unexpected emerging behavior, impacting on everything from the bidding patterns of the participating agents to the final price of the auctioned item. We find that the total number of bids placed in a single category by a given agent follows a power-law distribution. The power-law behavior is rooted in the finding that an agent that makes frequent bids up to a certain moment is more likely to bid in the next time interval. Moreover, we find that the number of distinct items frequented by a given agent also follows a power-law distribution. The power-law behavior implies that a few powerful agents bid more frequently and on more distinct items than others. We will show that such powerful agents exert strong influence on the final prices in distinct auctions.

II. ONLINE AUCTIONS

We collected auction data from two different sources. First, we downloaded all auctions closing on a single day, July 5, 2001 on eBay, including 264 073 auctioned items, grouped by the auction site in 194 subcategories. The dataset allowed us to identify 384 058 distinct agents via their unique user ID. To verify the validity of our findings in different markets and time spans, we collected data over a one year period from March 19, 1999 to March 19, 2000 from eBay's Korean partner, auction.co.kr, involving 215 852 agents that bid on 287 018 items in 62 subcategories.

In a typical online auction, a seller places the item's description on the auction site and sets the starting and the closing time for the auction. Agents (bidders) submit bids for the item. Each new bid has to exceed the last available bid by a preset increment. Agents can bid manually, placing a fixed bid, or on some auction sites (such as eBay but not on their Korean partner) these can take advantage of proxy bidding. In proxy bidding, an agent indicates to the auction house the maximum price he (she) is willing to pay for the given item (proxy bid), which is not disclosed to other bidders. Each time a bidder increases the bid price, the auction house makes automatic bids for the agent with an active proxy bid, outbidding the last bid with a fixed increment, until the proxy price is reached. In online consumer-to-consumer auctions, the agent with the highest bid wins and pays the amount of that bid; all other participants pay nothing.

III. EMPIRICAL RESULTS

Most online auction sites keep a detailed, publicly available record of all bids and identify the bidding agents via a unique login name. It is this transparency of the bidding history that allows us to characterize in quantitative terms the auction process. Each completed auction can be characterized by two quantities: the number of distinct agents bidding on the same item (n_{agent}) and the total number of recorded bids for the item (n_{bids}), where $n_{\mathrm{bids}} \geqslant n_{\mathrm{agent}}$, as each agent

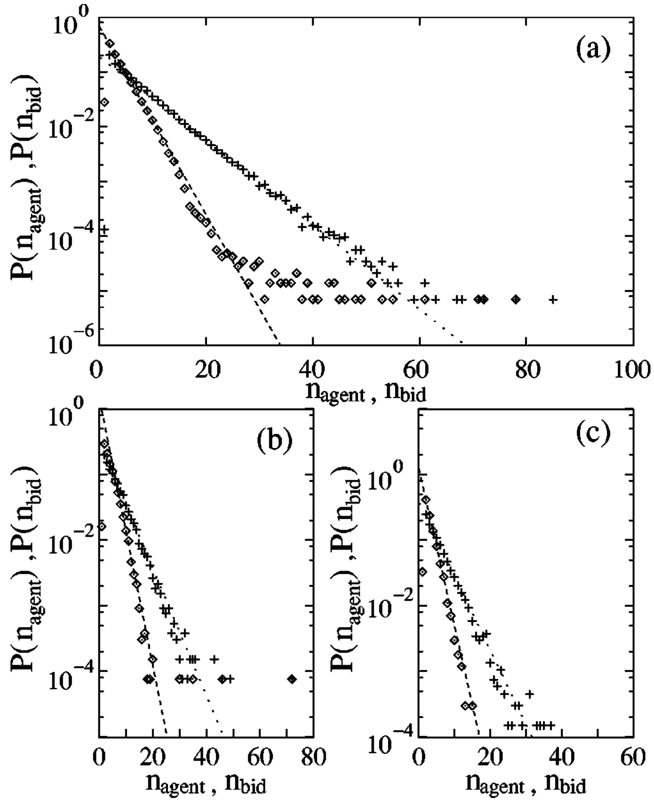

FIG. 1. Bid and agent distribution on eBay. (a) Distribution of number of agents [n_{agent},($\diamond$)] simultaneously bidding on a certain item and number of bids [n_{bids},(+)] received for an item, obtained by considering all items contained in the 194 categories on individual bids that were collected from auctions ending on July 5, 2001 on eBay. (b) and (c) Agent and bid distribution in the largest (b) and the second largest (c) category on eBay. The largest category by the number of auctioned items contains 21 461 items related to sport trading cards, while the second largest category includes 13 610 items related to printed and recorded music. The straight lines correspond to exponential fits and the symbols are the same as in (a).

can place multiple bids. In Fig. 1, we show the distribution of n_{agent} and n_{bids} over all auctions recorded on eBay, finding that these both follow $P(n) \sim \exp(-n/n_0)$, where $n_0 \approx 5.6$ for n_{bids} and $n_0 \approx 2.5$ for n_{agent}. We obtained similar results for the Korean market, with $n_0 \approx 10.8$ for n_{bids} and $n_0 \approx 7.4$ for n_{agent}. This simple exponential form is unexpected, as one expects that the bidding distribution is the result of many independent events, and therefore follows a Gaussian, peaked around the average number of bids and decreasing as $\sim \exp(-an^2)$ with a constant a. The deviation from a Gaussian distribution could come from the fact that Fig. 1(a) collapses data from different categories, displaying different bidding patterns. In Figs. 1(b) and 1(c), we show the distribution in two subcategories (sports trading cards and printed, recorded music), finding that these follow the same functional form as the aggregated data. Therefore, the exponential form for the activity distribution appears to be a general feature of all auctions, indicating that the majority of auctions have only a few bidders and auctions with a large number of bids or participating agents are exponentially rare.

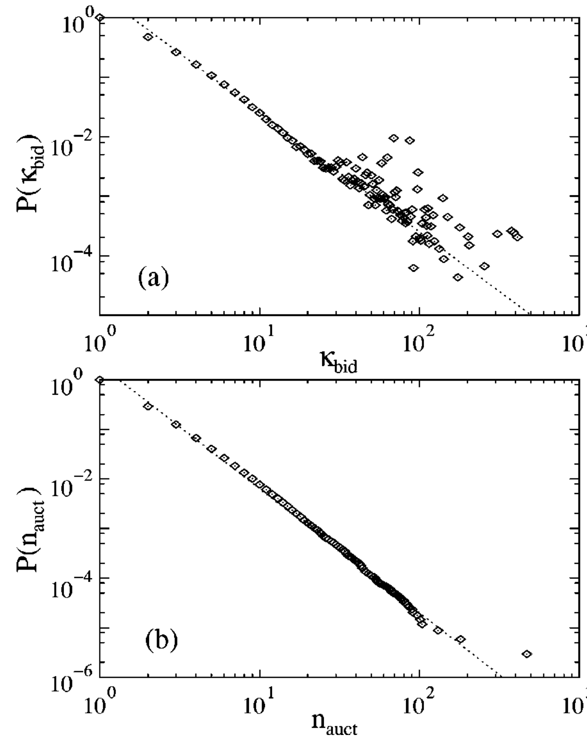

FIG. 2. Frequency of bids placed by individual agents. (a) Cumulative distribution of total number of bids, κ_{bid}, placed by a given agent in auctions in the same subcategory. For each of the 194 categories, we separately determined the cumulative distributions and averaged the obtained curves. (b) Cumulative distribution of the number of distinct auctions, n_{auct}, frequented by a given agent. The dotted line in (a) has slope -1.9, while in (b) it has slope -2.5, indicating that the corresponding probability distribution follows $P(\kappa_{bid}) \sim \kappa_{bid}^{-2.9}$ and $P(n_{auct}) \sim n_{auct}^{-3.5}$, respectively.

To characterize the activity of individual agents, we determined the number of bids placed by each agent on each auction. As agents place simultaneous bids on items, which closely resemble each other, we denote by κ_{bid} the total number of bids placed by the same agent in auctions in the same subcategory. For example, if several similar computers are sold on separate auctions, agents looking for a computer often bid simultaneously for several or all of them. We find that the distribution of κ_{bid} follows a power law

$$P(\kappa_{bid}) \sim \kappa_{bid}^{-\gamma}, \tag{1}$$

where $\gamma = 2.9 \pm 0.3$ [Fig. 2(a)] on both the eBay and the Korean auction. A similar power law characterizes the distribution of the number of different auctions, n_{auct}, frequented by individual agents, finding that

$$P(n_{auct}) \sim n_{auct}^{-\beta}, \tag{2}$$

where $\beta = 3.5 \pm 0.1$ [Fig. 2(b)]. Note that if a bidder is restricted to place a bid just one time for each item, then the two quantities κ_{bid} and n_{auct} would be the same. Players, however, bid normally more than one times for each item, so that the two exponents γ and β are distinct. The power-law distribution shown in Fig. 2(a) implies that while most

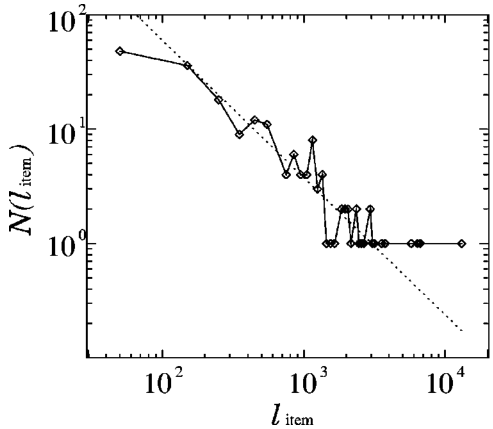

FIG. 3. Histogram of the number of subcategories containing ℓ_{item} items. The dotted line with slope 1.2 is drawn to guide the eye.

agents place only a small number of bids, a few agents bid very frequently, placing several hundred bids on the same day. Similarly, Fig. 2(b) indicates that while most agents participate in a few auctions only, a few agents bid very widely, some placing simultaneous bids on over a hundred distinct items on the same day. Note that while the distribution of the number of subcategories $N(\ell_{\mathrm{item}})$ containing ℓ_{item} items is also likely to follow a power-law with the exponent close very roughly to 1.2 ± 0.2 (Fig. 3), it is not obvious how $N(\ell_{\mathrm{item}})$ is related to $P(n_{\mathrm{auct}})$.

The observed power-law suggests that unknown to most participants, the auction process is dominated by a small number of highly active agents, or *power agents*, that pursue a very aggressive bidding pattern, placing simultaneously a large number of bids on a wide range of items. These power agents are responsible for the power-law tail of the distribution shown in Fig. 2. Our measurements indicate that there is a strong correlation between the number of bids placed by an agent on an item and the number of items the same agent bids for, indicating that power agents simultaneously bid frequently and widely.

One may also wonder if such power agents (buyers) would turn into sellers next days. While our data, focusing only on a single day, cannot provide this information, recent study on eBay auctions by Resnick *et al.* showed that indeed, there is a high correlation between buyer and seller feedback [5]. In particular, they find that 17.9% of all sales involved buyer-seller pairs. However, 89% of them conducted just one transaction and 99% conducted no more than four.

Agents with an aggressive bidding pattern significantly alter the nature of the bidding process, potentially distorting the chance of a typical agent to win an auction. To inspect the effect of the bidding pattern on the success rate of a given agent, we determined the fraction of auctions won by the most, the second, or the kth most frequently bidding agents. We find that in 61% of all auctions, the winner is the agent that makes the most bids, and in 29% of all auctions the second most frequently bidding agent wins the auction [Fig. 4(a)]. Less than 0.3% of the auctions are won by agents whose activity ranks fifth or higher. As most auctions have only a few participating agents [Fig. 1(a)], it is useful to

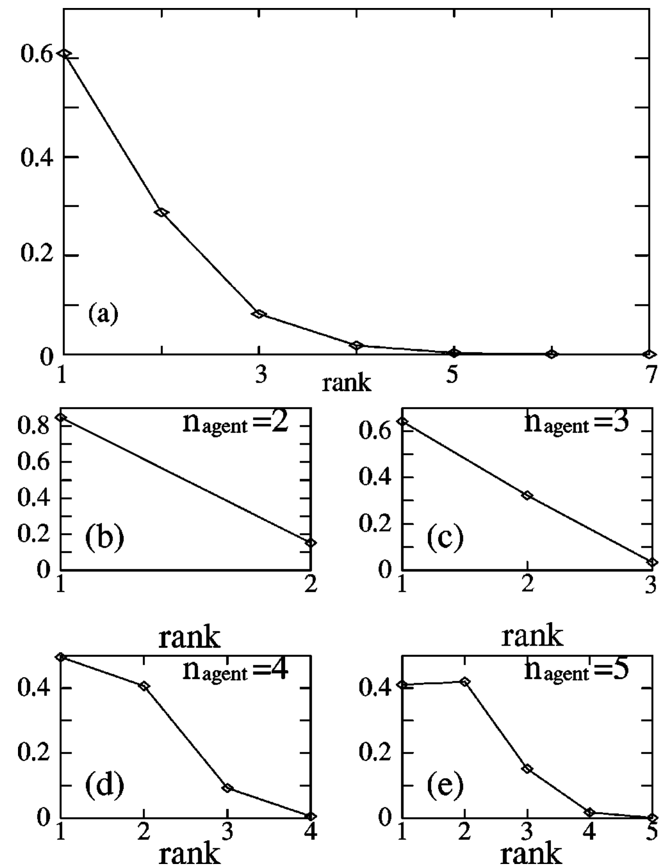

FIG. 4. Frequent bidders more likely to win an auction. (a) The probability that an auction is won by agents with given activity rank. Using all completed auctions, we calculated how many times the most, the second, or the nth frequent bidder wins the auction. (b) The probability that the most frequent bidder wins the auction of two participants. (c)–(e): the probability that an agent wins an auction of n [(c) $n=3$; (d) $n=4$; (e) $n=5$] participants. (a) is based on 143 325 auctions, while (b)–(e) are based on 47 610, 30 205, 20 017, and 13 762 auctions, respectively.

re-examine the winning patterns in auctions with the same number of agents. We find that if only two agents participate in an auction, and each places multiple bids, in 85% of the cases the agent with more bids wins the auction [Fig. 4(b)]. The situation is similar for three agents as well [Fig. 4(c)]: in 64% of the cases the more active agent wins, followed by the second most active, who wins in 32% of the cases. In auctions with larger number of participants [Figs. 4(d) and 4(e)], we observe a similar pattern. These results indicate that frequently bidding agents play a key role in setting the final price of most auctioned items: in the vast majority of the cases, the agents who place the largest number of bids are the winners of the auction process. This finding indicates that despite the widespread practice of sniping among experienced users [6] when bidders place bids only in the last 60 s of the auction hoping to win the auctioned item, on an average, frequent bidders are more successful, because such power agents bid in many distinct items at the same time.

As the power-law distribution [Fig. 2(b)] indicates that some agents bid rather widely, the question is, does such a wide bidding result in an economic advantage for power bid-

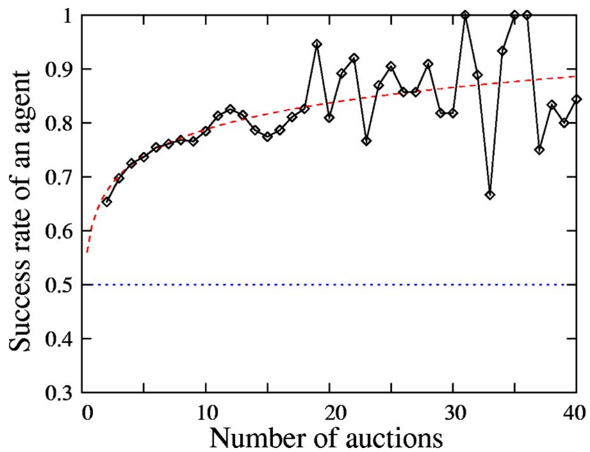

FIG. 5. The dependence of an agent's success rate on the number of auctions in which the agent participates. For each product subcategory (containing highly similar items) we calculated P_i^{win}, the average of the winning prices for items won by agent *i*. For the same agent, we also calculated P_i^{lost}, the average over the winning price over items in which agent *i* participated but lost. A successful agent can get a lower price for the items he won than other agents bidding on similar items on parallel auctions, i.e., for a successful agent $P_i^{\mathrm{win}} < P_i^{\mathrm{lost}}$. We find that the success rate of an agent, measured as the function of auctions won at a lower than average price (i.e., the fraction of agents for which $P_i^{\mathrm{win}} < P_i^{\mathrm{lost}}$), increases with the number of auctions these agents participate in. A horizontal dotted line corresponds to the case when there is no correlation between the frequency of bidding and the chances of getting a better price. A numerical fitting indicates that the success rate increases logarithmically (dashed line).

ders? Our results indicate that power agents not only are the frequent winners of the auctions in which they participate but also pay less than other agents on similar items. Indeed, in Fig. 5, we show the fraction of times the most frequently bidding agent pays less for an item than other agents who win auction of items in the same category. We find that the more auctions an agent participates in, the larger is his chance to pay less for the same item than the less widely bidding agents.

The observed power-law distribution is rooted in the dynamics of the bidding process. Indeed, two processes contribute to the final number of bids placed on a given item: new agents entering the bidding process and agents that already placed a bid increase their bid. We find that this pattern is governed by a process often referred to as preferential attachment, similar to those responsible for the emergence of scaling in complex networks [7]: more bids an agent places on a given item up to a certain moment, more likely is that he (she) will place another bid in the future (Fig. 6). The linearity of the observed relationship is known to lead to power-law distributions, as demonstrated by studies in both economics [8,9] and complex networks [10–12]. Modifying the previous methods used in growing networks [13] and explaining the Zipf law [9], the rate equation approach for the distribution of the number of bids $P(\kappa_{\mathrm{bids}})$ can be used to derive the exponent γ, of which result will be published elsewhere.

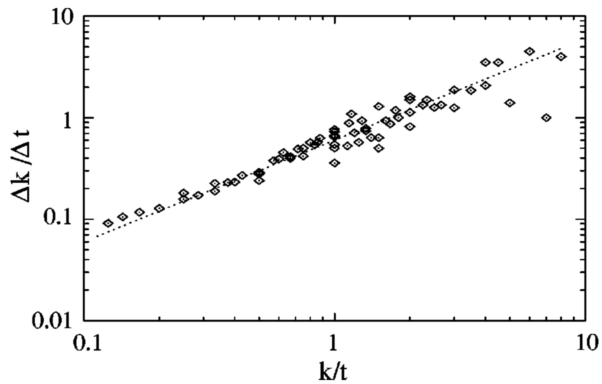

FIG. 6. The origin of the observed power law is in preferential attachment. The figure shows the change in the number of bids placed by an agent *i* that previously placed *k* bids, averaged over all subcategories. The bid frequency *k* is divided by time (bid sequency) *t*. The linear behavior in the log-log plot indicates that the more bids an agent places up to a given moment, the more likely it is that he will place another bid in the next time interval. Such preferential bidding is known to lead to a power-law bidding distribution [7,9]. The dotted line with slope 1 is shown for visual reference.

IV. DISCUSSIONS AND CONCLUSIONS

While power laws have been often observed in economic contexts, ranging from city [9] and company size distribution [14,15] to Pareto's observation of wide income distributions [16] and time series analysis [6], these are rather unexpected during the frequency of bidding of individual users. In order to develop an analytical framework to capture the dynamics of the bidding process, current auction models inevitably make use of equilibrium concept [17,18]. Often this requires the assumption that the number of agents is fixed [17] which, while leads to analytically tractable models, is not realistic in the context of internet auctions. Indeed, the power laws observed here are the result of the auction's fundamental openness and nonequilibrium nature. In the past few years, the observation of such nonequilibrium features in economic phenomena has led to an increased interest among physicists and mathematicians in the self-organizing processes governing economic systems [3,4,14,19,20]. Our finding that similar nonequilibrium processes govern the behavior of online auctions places these mercantile processes in the realm of agent driven self-organization. Meanwhile, in traditional auctions, such as English auctions, Dutch auctions, first-price sealed auction, and second-price sealed auction, the number of bidders is finite and relatively small, so that such emerging patterns are hardly observable [21,22].

In conclusion, we have collected online auction data and analyzed the statistical properties of emerging patterns created by a large number of agents. We found that the total number of bids placed in a single category and the number of distinct auctions frequented by a given agent follow power-law distributions. Such power-law behaviors imply that the online auction system is driven by self-organized processes, involving all agents participated in a given auction activity. We also uncovered the empirical fact that the more bids an agent places up to a given moment, more likely it is that it will place another bid in the next time interval, which plays an important role in generating the power-law behavior in the bidding frequency distribution by a given agent.

ACKNOWLEDGMENT

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