Emerging behavior in electronic bidding

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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 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 \( n_{\text{agent}} \) and the total number of recorded bids for the item \( n_{\text{bids}} \), where \( n_{\text{bids}} \approx n_{\text{agent}} \), as each agent...
can place multiple bids. In Fig. 1, we show the distribution of $n_{\text{agent}}$ and $n_{\text{bid}}$ over all auctions recorded on eBay, finding that these both follow $P(n) \sim \exp(-n/\bar{n}_0)$, where $\bar{n}_0 \approx 5.6$ for $n_{\text{bid}}$ and $\bar{n}_0 \approx 2.5$ for $n_{\text{agent}}$. We obtained similar results for the Korean market, with $\bar{n}_0 \approx 10.8$ for $n_{\text{bid}}$ and $\bar{n}_0 \approx 7.4$ for $n_{\text{agent}}$. 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. 1. Bid and agent distribution on eBay. (a) Distribution of number of agents $[n_{\text{agent}}]$ and number of bids $[n_{\text{bid}}]$ simultaneously bidding on a certain item and number of bids $[n_{\text{bid}}]$ 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 printed and recorded music. 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).

FIG. 2. Frequency of bids placed by individual agents. (a) Cumulative distribution of total number of bids, $\kappa_{\text{bid}}$, 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, $n_{\text{auct}}$, 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 $P(\kappa_{\text{bid}}) \sim \kappa_{\text{bid}}^{-2.9}$ and $P(n_{\text{auct}}) \sim n_{\text{auct}}^{-3.5}$, 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 $\kappa_{\text{bid}}$ 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 $\kappa_{\text{bid}}$ follows a power law

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

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, $n_{\text{auct}}$, frequented by individual agents, finding that

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

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 $\kappa_{\text{bid}}$ and $n_{\text{auct}}$ would be the same. Players, however, bid normally more than one times for each item, so that the two exponents $\gamma$ and $\beta$ are distinct. The power-law distribution shown in Fig. 2(a) implies that while most
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 $N(N_{\text{item}})$ containing $N_{\text{item}}$ items is also likely to follow a power-law with the exponent close very roughly to $1.2 \pm 0.2$ (Fig. 3), it is not obvious how $N(N_{\text{item}})$ is related to $P(n_{\text{auc}})$.

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 participates 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 $N(N_{\text{item}})$ containing $N_{\text{item}}$ items is also likely to follow a power-law with the exponent close very roughly to $1.2 \pm 0.2$ (Fig. 3), it is not obvious how $N(N_{\text{item}})$ is related to $P(n_{\text{auc}})$.

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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 \( P_{\text{win}} \), the average of the winning prices for items won by agent \( i \). For the same agent, we also calculated \( P_{\text{lost}} \), 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 \( P_{\text{win}} < P_{\text{lost}} \). 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 \( P_{\text{win}} < P_{\text{lost}} \)), 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).

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.

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[16] V. Pareto, Cours d’Economie Politique (Rouge, Lausanne, 1897).