Proc. 2nd ACM Workshop on Sponsored Search Auctions
Ann Arbor, Michigan, June 2006

Impact of ROI on Bidding and Revenue in Sponsored Search Advertisement Auctions

Boleslaw K. Szymanski and Juong-Sik Lee[1]
Optimaret Inc., Newtonville, NY, 12128
Rensselaer Polytechnic Institute, Computer Science Department, Troy, NY 12180

ABSTRACT

In this paper, we discuss how advertisers, by considering minimum return on investment (ROI), change their bidding and, consequently the auctioneer's revenue in sponsored search advertisement auctions. We analyze the Vickrey-Clarke-Groves (VCG), Generalized Second Price (GSP) and Generalized First Price (GFP) auction mechanisms in that respect. Analytical results are presented for the dominant strategy bidding prices in the Vickrey-Clarke-Groves auction and the ex-post equilibrium locally-envy free prices in the Generalized Second Price auction. The simulation results are presented for all three mechanisms: VCG, GSP, and GFP auctions. We conclude that the impact of considering ROI during bidding varies among different auction mechanisms, changing the traditional assessment of their merits for sponsored search advertisement.

Keywords

Sponsored search advertisement auction, return on investment, auction mechanism, locally-envy free price, incentive compatible auction.

1. INTRODUCTION

Next to e-Bay, sponsored search advertisement auctions are one of the most common and widespread examples of an electronic auction system in use today with enormous economic impact on advertising and computer industries. The revenues from the sponsored search advertisement auctions have been increasing continuously and have already exceeded billions of dollars annually. They are projected to reach $4.9 billion in the U.S. market alone in 2009 [1]. An important reason for so fast and wide-spread adoption of the sponsored search advertisement is its high return on investment (ROI) for advertisers, compared to other marketing methods [1]. The search engine customers already pre-select themselves by initiating a search for keywords relevant to the advertisement and then show further interest in the advertised products by clicking on the link to the specific advertisement. Hence, as shown in Figure 1, the average cost per leading purchase is lower in sponsored search advertisement than in other marketing channels.

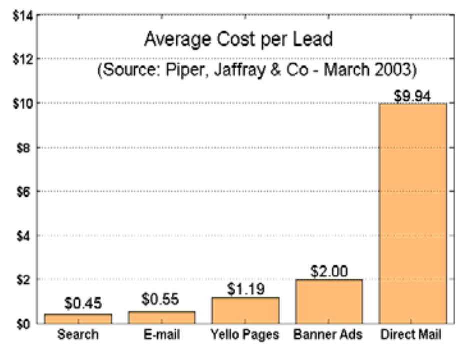


Figure 1: Comparison of average cost per lead to purchase

As in other auction applications, the revenue of the sponsored search advertisement depends heavily on the value that it delivers to advertisers. That value dictates the advertisers' willingness to pay. In addition, the advertisers' bid behavior is influenced by the design of the auction mechanism itself. As a result, understanding the advertiser's bid behavior and ability to model it correctly are of utmost importance in analysis of existing and in design of novel auction mechanisms targeting sponsored search

[1] This work was partially supported by the National Science Foundation through award NGS-0103708. The content of this paper does not necessarily reflect the position or policy of the U.S. Government — no official endorsement should be inferred or implied.

advertisement. In this paper, we analyze the most representative bid strategies in auctions for sponsored search advertisements modeled after the solution used by Yahoo! [1].

The reminder of this paper is organized as follows. In Section 2, we analyze the properties of the sponsored search advertisement auctions and define basic notions of such auctions. In Section 3 we analyze the Vickrey-Clarke-Groves auction and compare it to the Generalized Second Price auction analytically, assuming that bidders achieve ex-post equilibrium of the locally-envy free bid prices. In Section 4, we analyze and create models of the bidder strategies that we then simulate under different auction mechanisms. We discuss the simulation results in Section 5. Finally, in Section 6, we provide conclusions and outline the future work in this area.

2. ANALYSIS OF SPONSORED SEARCH ADVERTISEMENT MARKET

The idea of the sponsored search advertisement is simple. The search engine produces the search result pages with positions for sponsored search advertisements associated with a particular keyword used in the search query entered by a customer. These sponsored positions contain paid for advertisements with embedded links pointing to the advertiser's web pages. Advertisers pay the search engine for their advertising whenever the search engine customer clicks on the link embedded in a sponsored position. Accordingly, this form of advertising is called 'Pay-Per-Click (PPC)' advertisement.

From the auction structure point of view, a search engine company is an auctioneer and advertisers are auction participants who bid for the sponsored positions. Hence this is one-to-many market structure. The resources traded in the sponsored search advertisement auction are ranked advertising positions in a web page produced in response to the user query. It is well known that different positions yield different numbers of user clicks per time period, even when they display the same advertisement [3, 4]. Hence, those positions are heterogeneous resources. They are also perishable, because if they are not used for a time period, they bring no value to the auctioneer ("are wasted") for this time period. Each search keyword or phrase entered by the user of the search engine triggers a new auction round for all the positions available on the response web pages. Hence, sponsored search advertisement uses recurrent auctions for multiple heterogeneous resources [5]. Participants can change their bid prices at any time, and these prices will then apply to the very next auction round. The participants can also specify the maximum daily budget for their clicks, which, when exceeded, would cause a removal of the corresponding bid from the subsequent auction rounds.

The recurring nature of the sponsored search advertisement auction is one of the most important features that differentiate this auction mechanism from traditional ones. In our recent studies, we have discussed problems that arise in recurring auctions for perishable resources if traditional auction mechanisms are applied. We also proposed a novel auction mechanism suitable for such environments [6].

The unique sponsored search advertisement auction properties are reflected also in novel rules designed for those auctions. For example, Google's AdWords system uses ClickThrough Rate (CTR) to rank bids for advertising positions [7]. Another innovation is the pricing rule which evolved from the Generalized First Price auction to the Generalized Second Price auction, both different from the Vickrey-Clarke-Groves auction, itself generalization of the Vickrey auction [8].

In this paper we focus on yet another unique property of the sponsored search advertisement auctions, namely the importance of return of investment (ROI) to the advertisers. The advertising over the search pages is naturally spread over time during which the advertiser needs to maintain a budget for paying for the clicks received to the advertiser's link. Usually, there are many potential search keywords and phrases with which the advertiser may choose to associate its links. Likewise, there are also alternative outlets for advertisement campaigns competing with sponsored search advertisement for advertising money. Hence, the advertisers are not only interested in maximizing their utility from the auction but also in maintaining their minimum return on investment (ROI) for each click received. As a result, the classical auction theory that assumes that bidders maximize their utility from the auction no longer applies. Consequently, we analyze here how considering the minimum return on investment changes the bidding behavior and auctioneer's revenue in different auction mechanisms.

To illustrate the main idea, consider for example a bidder entering an auction in which there are only two positions yielding clicks, p_1, and p_2. Assume that the first position is expected to yield a_1=100 clicks in a time unit while the second position yields only a_2=50 clicks. Two bidders, bidder one and bidder two, bid b_1=\$5.00 and b_2=\$4.00, respectively. The third bidder has private true valuation of each click t_3=$5.06 and sets its minimum required ROI at f=10%.

In VCG auction, according to the classical auction theory, the optimal bidding strategy for the third bidder is to bid its private true valuation, that is to enter the bid b_3=$5.06. As a result, the third bidder will receive the first position and will pay $5.00 for each of the first 50 clicks and $4.00 for each of the remaining 50 clicks of 100 clicks received. This bid indeed will maximize the third bidder utility at 50*$0.06 + 50*$1.06 = $56. But what about ROI? The $250 invested in the highly priced 50 clicks brings only $3 profit, a return of merely 1.2%. The bidder then cannot bid more than the price that when paid would yield at least the required minimum ROI on each click, that is the price equal to bidder's private true valuation divided by the sum of 1 and that minimum required ROI. In our case, this would be b_3=$5.06/1.1=$4.60. With such a bid, the third bidder would win the second position and 50 clicks for which she would pay $200 and reap $53 profit. The saved $250 (that otherwise would be spent on highly priced clicks with the higher bid) can then be used to bid for example for another keyword or for the same keyword in another search engine auction.

The question that we answer in this paper is how does the bid limit imposed by the minimum required ROI impact bidders behavior and auction revenues. We will consider this question in the context of the following three auction mechanisms that implement different pricing rules in a sponsored search advertisement auction.

1. **Generalized First Price (GFP) Auction.** In GFP, a bidder who receives an advertising position pays for each click the price that he bid in the auction.

2. **Generalized Second Price (GSP) Auction.** The GSP auction charges a winner the smaller of his bid price and the bid price of the next highest bidder plus the minimum bid price increment (in case of Yahoo! it is $0.01, but to simplify reasoning, we will ignore this increment in analytical solution and consider it only in simulations). For example, the bidder with the unique highest bid pays the bid price of the second highest bid plus the increment.

3. **Vickrey-Clarke-Groves (VCG) Auction**, also known as Generalized Vickrey Auction. In VCG, each winner of the auction pays for clicks the externalities that the winner imposes on other bidders [9]. Hence, in a sponsored search advertisement auction, VCG will charge the winner the sum of displacement costs computed for each bidder displaced by the winner presence. The displacement cost of a bidder at position j with bidding price b_j is equal to the bid price b_j multiplied the difference between the number of clicks expected to be received at position j-1 and the actual number of clicks received at the current position j.

Additionally, we assume that the bidders have full knowledge of the other bidders (this is true for Yahoo!/Overture sponsored search advertisement auctions because Yahoo! provides a tool for obtaining the bid prices of current bidders and their corresponding ranks for the given keyword auction). Regardless of availability of such a tool, without loss of generality, we can assume that a bidder can learn bid prices of other bidders because the auction is performed recurrently.

3. ANALYTICAL ANALYSIS OF ADVERTISERS' BIDDING BEHAVIOR

In this section, we present an analytical analysis of the impact of ROI consideration on bidders' behavior and auctioneer revenue in sponsored search advertisement auctions under VCG and GSP mechanisms.

Consider a VCG auction with n winning positions and $m>n$ bidders. Let a_i, where $i=1, 2,\ldots, n$ denote the number of clicks expected to be received in a time unit at position i and $c_j=a_{j+1}/a_j$ for $j=1, 2,\ldots, n-1$. We assume that $a_{n+i}=0$ (so $c_{n-1+i}=0$) for all $i= 1, 2,\ldots, m-n$ and $0< c_j<1$ for all $j=1, 2, \ldots, n-1$.

Since the VCG auction is incentive compatible, then for each bidder $j=1, 2,\ldots, m$ we have $b_j=t_j$ where t_j denotes private true valuation of a click by bidder j and b_j denotes bidder j bid. Hence, according to the pricing rules of VCG auction, the auctioneer revenue R_{VCG} is

$$R_{vcg} = \sum_{i=1}^{n}\sum_{p=i}^{n}(a_p - a_{p+1})t_{p+1} = \sum_{i=1}^{n} ia_i(1-c_i)t_{i+1}\,. \quad (1)$$

Consider now VCG auction in which bidders not only seek to maximize their utility but also want to assure that every click received provides them with the minimum return on investment, ROI, denoted as the fraction f of the price paid. Rationale for this strategy is simple. If the purchase of a click does not bring enough profit, the budget for advertisement to buy this click can be redirected to other keywords or even to different advertisement channels in which such a ROI could be guaranteed.

In VCG auction, the price for a click depends on the position of the displaced bidder. The highest priced clicks are those that come from the highest displaced bidder (the bidder ranked immediately behind the bidder whose price is being established). Hence, the bidder must be prepared to pay the price bid for the highest priced clicks, those at his position. Consequently the price bid is limited by ROI as follows: $(t_i - b_i)/b_i \geq f$ so $b_i \leq \frac{t_i}{1+f}$. Denoting $d = \frac{1}{1+f}$, we get $b_i=dt_i$. Indeed, increasing the bidding price (up to the private true valuation) increases the bidder's utility, so the dominant strategy for each bidder is to bid the highest price satisfying the ROI limitation, that is $b_i=dt_i$. Hence, the VCG auction with ROI, denoted here VCG-ROI, will yield the revenue by factor d lower than the original VCG auction:

$$R_{vcg-roi} = dR_{vcg} .$$

Let's consider now GSP auction instead and assume that each of n highest bidding bidders bids its locally-envy free price [9] that for bidder i is the maximum price satisfying an inequality:

$$(t_i - b_i)a_{i-1} \geq (t_i - b_{i+1})a_i \ . \qquad (2)$$

Inequality (2) can be rewritten as $b_i \leq (1-c_{i-1})t_i + c_{i-1}b_{i+1}$. For $i=n$ we know that $c_n=0$, hence $b_{n+1}=t_{n+1}$. By recursion we get that the locally-envy free price b_i^* for bidder i is:

$$b_i^* = t_i - \sum_{j=i}^{n}(t_j - t_{j+1})\prod_{k=i}^{j} c_{k-1} .$$

Hence, $b_i^* < t_i$ for all $0<i<n+1$ and such that $t_i>t_{i+1}$.

It is easy to show that $R_{vcg}=R_{gsp}$. Indeed, rewriting formula (2) as an equation for the locally-envy free price, we get, for all $i>1$ $t_i(a_{i-1} - a_i) = a_{i-1}b_i - a_ib_{i+1}$ from which it follows that

$$it_i(a_{i-1} - a_i) = ia_{i-1}b_i - ia_ib_{i+1} \qquad (3)$$

Adding Equalities (3) together, the left hand side will reduce, according to equation (1), to R_{vcg} whereas the right hand side will reduce to $\sum_{i=2}^{n} a_{i-1}b_i = R_{gsp}$.

It is easy to show that in case of GSP-ROI, the envy free price is $b_i^{'} = \min(dt_i, b_i^*)$, since in addition to being bounded by the maximum utility, it is also bounded by the required minimum ROI. It immediately follows that $b_i^{'} < d * b_i^*$ for all $0<i<n$ and such that $t_i>t_{i+1}$, therefore

$$R_{gsp-roi} > dR_{gsp} = dR_{vgc} = R_{vgc-roi} . \qquad (4)$$

Final conclusion is that the GSP-ROI auction brings higher revenue than the VCG-ROI auction does as long as not all bidders have the same private true valuation of clicks and they bid their locally-envy free prices.

4. MODELING AND SIMULATION OF DYNAMIC BIDDER STRATEGIES

In this section, we expand the analyzed bidding behavior to model and simulate the dynamic bidder strategies under different sponsored search advertisement auction mechanisms. We start with the description of the simulated scenarios.

There are 20 bidders (i.e., advertisers) and one auctioneer (i.e., the search engine company). All bidders bid for the same search keyword. We assume that the bidders are risk neutral and symmetric [5]. There are 10 positions available for sponsored search advertisements that are traded in the simulated auction. Hence, only 10 bidders will receive a position for advertisement in each auction round. The upper bound of each bidder's bid price is restricted by his private true valuation of each click received.

In addition to considering the private true valuation, the bidders also take into account return on investment (ROI) when deciding their bids. In all simulations, the private true valuations of bidders are independently distributed. We simulate three types of the standard distributions of private true valuations:

(i) the exponential distribution with the mean of \$3.00,

(ii) the uniform distribution over the range of [\$0.00, \$6.00], and

(iii) the Gaussian distribution with the mean \$3.00 and standard deviation of 1.

For the sake of simplicity, we assume that private true valuations do not change during the simulated auctions.

Our simulations model an auction mechanism used in Yahoo!/Overture solution. Hence, the ClickThrough Rate (CTR) or factors other than the bid price are not considered in ranking of bidders in the auction[2]. Hence, a rank of a bidder is defined entirely by his bid price. The bidders with the higher bids occupy higher ranked advertising positions. As shown in Table 1, frequency of receiving clicks at any position is dependent on the position rank. To simulate this phenomenon correctly, we use relative frequency of expected number of clicks received for each rank of the advertising positions. The frequencies that we selected for each position were computed on the basis of Yahoo!/Overture sponsored search advertisement results provided in the Atlas reports [4, 10]. We assume that the expected numbers of clicks are only dependent on the rank of the advertising position. Any other factors, such as identity of advertiser or relevance and attractiveness of the presented advertisement are assumed to be the same for each bidder.

Position Rank	Frequency of Number of Click	Position Rank	Frequency of Number of Click
1	100.0 %	**6**	22.2 %
2	73.0 %	**7**	15.9 %
3	59.6 %	**8**	13.2 %
4	40.2 %	**9**	7.3 %
5	28.6 %	**10**	6.0 %

Source: Atlas Institution 2004

Table 1: Expected number of clicks at each position of the sponsored search advertisement

To implement recurring feature of auctions for sponsored search advertisement, the simulated auction consists of a series of auction rounds executed sequentially. In each auction round, bidders select optimal bid prices for the next auction round according to their bid strategy.

Since in this paper we assume that the bidders are risk neutral, deciding the bid price, each bidder i attempts to maximize the utility (i.e., payoff) $U_i(\vec{b})$ of auction round participation:

$$U_i(\vec{b}) = (t_i - p_i(\vec{b})) \cdot a_{r_i(\vec{b})} \; , \qquad (5)$$

where $p_i(\vec{b})$ represents the payment for each click which is decided by the pricing rules of the considered auction mechanisms and $r_i(\vec{b})$ denotes the rank of the advertising position that the bidder i will occupy with bid vector $\vec{b} = (b_1, \ldots b_m)$. Hence, $a_{r_i(\vec{b})}$ represents the expected number of clicks received at the adverting position $r_i(\vec{b})$. To maximize the expected utility $U_i(\vec{b})$, each bidder considers the trade-off between the profit factor $(t_i - p_i(\vec{b}))$ and the expected number of clicks $a_{r_i(\vec{b})}$. If the bidder increases his bid price, the expected number of click may increase by moving the bidder to the higher ranked position in the corresponding search web page. However, the resulting profit factor decreases. Reversely, if the bidder decreases his bid price, the profit factor increases at the expense of the number of expected clicks. Additionally, bidders also consider the minimum required ROI in selecting their bid prices.

Based on utility function expressed by Equation (5), we consider the following three potential bid strategies for deciding optimal bid price of each bidder during recurring auction: Dynamically Adjusting Bid strategy, Locally-Envy Free Bid strategy and Truthful Bid strategy.

Dynamically Adjusting Bid Strategy (DAB): Since each bidder knows the bid prices entered by the other bidders in the previous auction round, the most obvious bidding strategy is to adjust the bid price continuously based on the known bid prices of other bidders in an attempt to maximize the expected utility. Executing this strategy, after each auction round every bidder probes bid prices that can maximize his utility (according to Equation (5)) using as the basis the bid prices of the other bidders in the last auction round. Each bidder selects the series of probing bids, each slightly higher than the existing bid by some other bidder but not higher than his private true valuation adjusted, as discussed above, by the minimum required ROI factor. Then, for each probing bid in the series, the bidder computes expected utility in the next auction round to select the one with the highest utility. If two probing bid prices produce equal utility, then the probing bidder selects the lower of the two as his next round bidding price.

Locally-Envy Free Bid Strategy (LEF): Based on definition of LEF (Locally-Envy Free) equilibrium proposed by Edelman at el [9], the optimal bid price of each bidder that leads to the LEF equilibrium and maximizes each bidder's expected utility is computed according to Inequality (2). Then, the bid is set to smaller of this optimal bid price and the private true valuation adjusted by the minimum required ROI. However, as reported in [7], this

[2] We conjecture that CTR would not change the conclusions of this paper and we are working on a proof of it.

optimal bid price is an ex-post equilibrium price, so the advertisers do not follow this strategy in practice.

Truthful Bid Strategy (TB): Another bidding strategy is for each bidder to bid the private true valuation adjusted by the minimum required ROI consideration. TB strategy is the simplest bid strategy but it is only beneficial to advertiser in incentive compatible auction mechanisms, in which bidding private true valuation is a dominant strategy.

Regardless of the bidding strategy simulated, we assumed that the bidders who were not allocated advertising positions in the current auction round bid their private true valuations (adjusted by the minimum required ROI consideration) attempting to occupy an advertising position. We assume that such bidders never drop out of the sponsored search advertisement and participate in all auction rounds.

For GFP auction, we used only the dynamically adjusting bid strategy, as others were inappropriate for this auction mechanism. Likewise, for VCG auction only truthful bid strategy was used because VCG is incentive compatible. In GSP auction both dynamically adjusting bid strategy and locally-envy free bid strategy were applied. The latter is denoted as GSP-LEF. In all simulated bid strategies, each bidder considers his minimum required ROI (Return On Investment) while selecting the bidding price.

5. ANALYSIS OF SIMULATION RESULTS

For each simulated auction mechanism, our experiments focus on bidding strategies from the bidder (i.e., advertisers) point of view and revenue from the auctioneer (i.e., the search engine company) point of view. In revenue analysis, we focus on the impact of ROI on revenue in different auction mechanisms and under different bidder strategies.

As shown in Figure 2, adjusting bid price continuously based on bid prices of other bidders during recurring auction causes unstable bid pattern in the GFP auction. This is the result of continuously monitoring and adjusting bid prices in an attempt to minimize the payment for maintaining the desired rank of an advertising position, and thereby maximizing expected utility. By analyzing data collected by Yahoo!/Overture [3], Edelman and Ostrovsky verified that such unstable bid patterns indeed appeared in the GFP auction for sponsored search advertisement. They called those patterns "sawtooth" because the bid prices first gradually increase and then suddenly drop in a sequence of auction rounds. In our simulations, we also observe that even if the auction mechanism changes from GFP to GSP (i.e., the pricing rule changes from the first price to the second price), there still exist unstable bid patterns when the dynamically adjusting bid strategy is used. Such unstable bidding creates corresponding unstable revenue patterns in the GFP and GSP auctions with the dynamically adjusting bid strategy

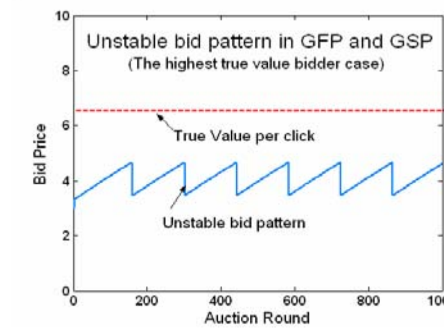


Figure 2: Bid pattern in dynamically adjusting bid strategy

From the revenue point of view, our simulation results demonstrate that, as shown in Figure 3, without considering ROI (i.e., when the minimum required return on investment is 0%), the revenues of GFP and GSP auctions are lower than the revenues of GSP-LEF and VCG auctions. This is caused by the unstable bidding patterns that directly impact the revenue.

The revenues of GFP and GSP auctions are almost the same for all private true valuation distributions. Additionally, our simulation results show that the revenues of GSP-LEF and VCG auction are the same and higher than the revenues of GFP and GSP auction.

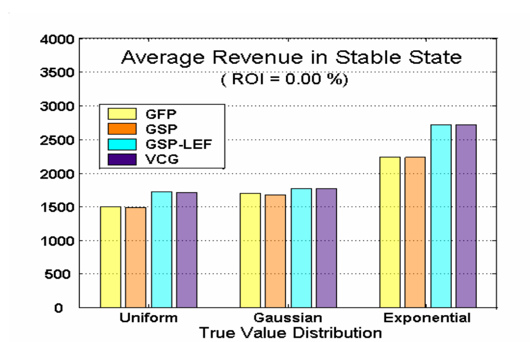


Figure 3: Comparison of revenue of auctions with ROI=0%

However, as shown in Figure 4, once the minimum required ROI is non-zero, the revenues of GSP-LEF and VCG auction mechanisms diverge. As the minimum required ROI increases, the revenue of GSP-LEF auction becomes higher than that of VCG auction for all private true valuation distributions.

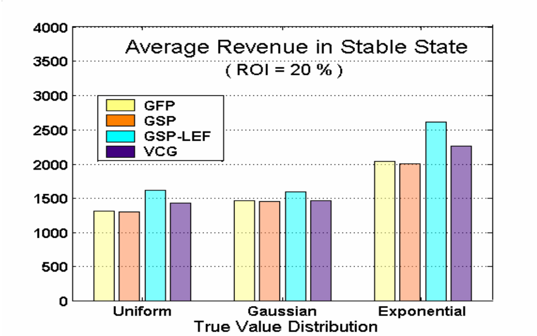
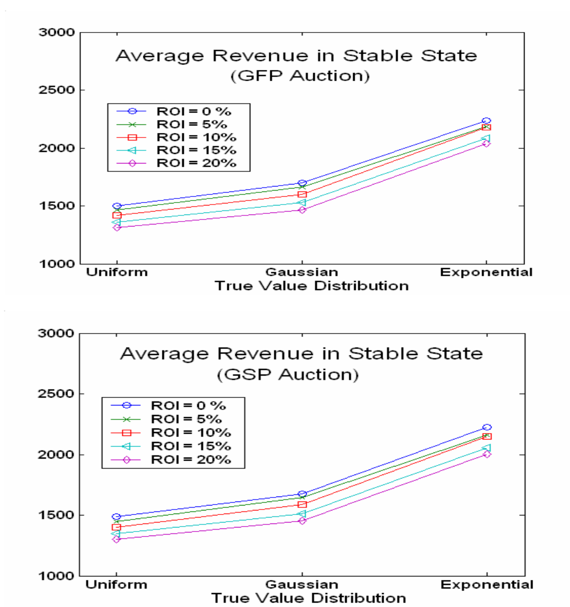


Figure 4: Comparison of revenue of auctions with ROI=20%

Increasing the minimum required ROI for all bidders decreases the resulting revenue in all auction mechanisms with all bidder strategies but in each case to a different degree. This is because increasing the minimum required ROI decreases the upper bound on bid price of every bidder. The tighter limitation on the maximum bid price results in decreased revenue in each auction mechanism. The most affected are of course incentive compatible auction mechanisms in which every bid price decreases in such situation. These conclusions are confirmed by the simulation results presented in Figure 5.



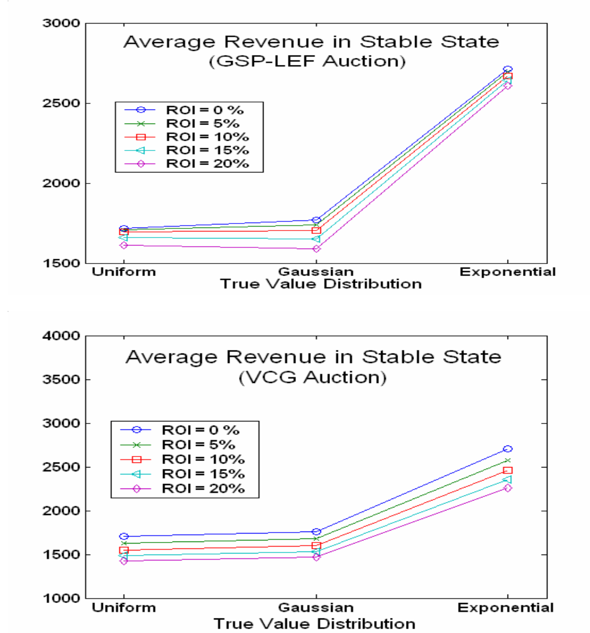


Figure 5: Comparison of revenue with various ROI's for different auction mechanisms

Figure 6 shows the percentage of lost revenues as a function of the change of the minimum required ROI for the uniform distribution of bidders' private true valuations. We also simulated the Gaussian and exponential distributions but since the results were identical, we did not include here the additional plots. Compared to other auction mechanisms, the GSP-LEF mechanism achieves the lowest percentage loss of revenue in response to the changes in the minimum ROI requirement. This means that the GSP auction with the LEF bid strategy provides the most stable solution from the auctioneer point of view. On the other hand, in VCG auction, any increase in the minimum required ROI results in the matching percentage loss of the auctioneer's revenue. Hence, the VCG auction mechanism is the most unstable in terms of its sensitivity to changes to the minimum required ROI.

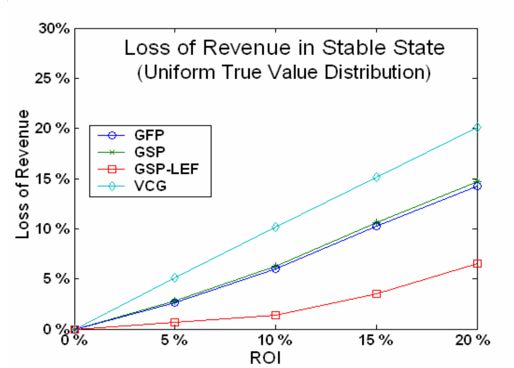


Figure 6: Loss of revenue with different ROI's

In conclusion, our simulations verified the analytical result of comparing the VCG and GSP auctions expressed in Equation (4):

$$R_{gsp-roi} > dR_{gsp} = dR_{vgc} = R_{vgc-roi}$$

6. CONCLUSIONS AND FUTURE WORKS

The following are the conclusions of our study.

Including the minimum return on investment requirement in bidding for sponsored search advertisement auction limits bidder's maximum bidding price from the advertiser point of view and decreases the resulting revenue from the search engine company point of view. The Generalized Second Price auction with the locally-envy free bidding strategy produces the highest revenue among all mechanisms studied in this paper. It is also the most stable mechanisms in terms of revenue sensitivity to changes in the minimum return on investment required by the advertisers.

Even though the classical Vickrey-Clarke-Groves auction mechanism makes the dominant bidding strategy simple, because of its incentive compatibility, it suffers the largest loss of revenue resulting from the changes to the minimum return on investment requirement among all the auction mechanisms considered here. Hence, it is the most unstable mechanism in that respect. As a result the revenue of Vickrey-Clarke-Groves auction is lower than the corresponding revenue of the Generalized Second Price auction with locally-envy free bidding strategy for all non-zero values of the minimum required return on investment. For the larger values of this factor, even the Generalized Second Price and the Generalized First Price auctions with the dynamically adjusting bid strategy can deliver higher revenue than the Vickrey-Clarke-Groves auction.

Our simulations confirm also that even after the change of auction mechanism from the Generalized First Price auction to the Generalized Second Price auction, the unstable bid patterns have not entirely disappeared. This is because the locally-envy free ex-post equilibrium prices cannot be reached by maximizing the bidder's utility in response to the bidding of other bidders. The dynamic bidding behavior in GSP and emergence of unstable bidding patterns have been also analyzed analytically in [12]. Hence, there is room for improvement in the basic auction mechanism for sponsored search advertisement.

In our current and future work, we have been working on developing new auction mechanisms capable of stabilizing bid patterns and increasing the revenue of the search engine auctioneer as well as on extending the simulations of bidding behavior to such novel auction mechanisms.

REFERENCES

[1] M. Moran and B. Hunt, *Advertisement Engine Marketing Inc.: Driving Advertisement Traffic to Your Company's Web Site*, IBM Press, 2006.

[2] M. Bichler, *The Future of e-Markets: Multidimensional Market Mechanism*, Cambridge University Press, 2001.

[3] B. Edelman and M. Ostrovsky, "Strategic Bidder Behavior in Sponsored Advertisement Auctions", *Proc. ACM Electronic Commerce Conference, EC05*, Vancouver, CA, 2005.

[4] N. Brooks, *The Atlas rank report: How advertisement engine rank impacts traffic*, Technical Report, Atlas Institute, July 2004.

[5] V. Krishna, *Auction Theory*, Academic Press, 2002.

[6] J. S. Lee and B. K. Szymanski, "Novel Auction Mechanism for Selling Time Sensitive E-Services", *Proc. 7th International IEEE Conference on E-Commerce Technology (CEC'05)*, Munich, Germany, July 2004, pp. 75-82

[7] H. R. Varian, *Position Auctions*, Technical Report, http://www.sims.berkeley.edu/~hal/Papers/2006/position.pdf

[8] W. Vickrey, "Counterspeculation, Auction, and Competitive Sealed Tenders", *Journal of Finance*, Vol. 16, No. 1, March 1961, pp 8 – 37.

[9] B. Edelman, M. Ostrovsky, and M. Schwarz, *Internet advertising and the generalized second price auction: selling billions of dollars worth of keywords*, http://rwj.berkeley.edu/schwarz/publications/gsp051003.pdf.

[10] N. Brooks, *The Atlas rank report, part 2: How advertisement engine rank impacts conversions*, Technical Report, Atlas Institute, July 2004.

[11] J. Feng, H. K. Bhargava and D. M. Pennock, "Implementing Sponsored Advertisement in Web Advertisement Engines: Computational Evaluation of Alternative Mechanisms", *Journal of Computing*, 2005.

[12] K. Asdemir, *Bidding Patterns in Search Engine Auctions*, http://www.bus.ualberta.ca/kasdemir/biddingWARS.PDF.