Final Report: Amazon Buy Box

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Abstract

The project sits at the crossroads of economics and computer science. It is a continuation of research that has been done [1]. The research is focused on designing mechanisms to determine which seller will be placed in Amazon's Buy Box and studying how this decision affects the market.

My contribution expanded upon the experiments already conducted. I incorporated the option to set a production cost for each seller and to set a distribution to draw the buyer's value from for each seller's item. I also experimented with three sellers instead of two.

Introduction

Amazon allows multiple sellers to sell the same product. When a buyer is looking at a particular product on Amazon, one seller is given the "Amazon Buy Box." The buttons that correspond to the Buy Box are the "Add to Cart" and "Buy Now" buttons. The sellers who don't get the Buy Box can be viewed by clicking the "See All Buying Options" button. See Figure 1. The buyer must pay a search cost to screen sellers who aren't in the Buy Box to find out their value for the item that those sellers are selling. This increase in search cost gives a better chance of sale to the seller in the Buy Box since the buyer's value for the item is already visible. The Pandora's box algorithm describes the buyer's optimal search strategy that maximizes their utility, and an instance of this is described in [2].

Figure 1: Example of the Buy Box and Non Buy Box for a particular textbook.

The mechanisms that have been studied in [1] are the Lowest Price First mechanism, Random mechanism, Threshold mechanism, and Exponential mechanism. A mechanism determines which seller gets the Buy Box based on the prices they select. For all mechanisms, best response dynamics was used to determine seller behavior. In best response dynamics the sellers take turns. During a seller's turn, the seller gives their best response price based on the competing sellers price, the mechanism being used, and the knowledge of the buyer's search strategy. Best response dynamics ends when equilibrium is reached or a cycle is reached.

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In the Lowest Price First mechanism the seller with the lowest price is placed in the Buy Box (ties are broken randomly). In the Random mechanism the seller placed in the Buy Box is chosen uniformly at random without considering prices. The Threshold mechanism only considers sellers who have a price less than or equal to the threshold parameter and chooses one of them at random. In the Exponential mechanism the probability that seller i (with price p_i) is placed in the Buy Box is $e^{-\alpha p_i}$.

The results from [1] say that the Random mechanism is the best for sellers. The Threshold and Exponential mechanisms had very similar performances and are the best mechanisms for buyers.

Results

I experimented with different production costs for two sellers. I used 0 and 5, and 0 and 10. I tried these two pairs of production costs for three of the distributions from [1]: integer uniform, geometric, and equal revenue. The results found in [1] did not change for the integer uniform and geometric distributions. The Random mechanism continued to be the best for sellers because highest equilibrium price, the highest seller revenue, and the lowest buyer utility. The Threshold mechanism looks like the best for the buyer when integer uniform and geometric distributions are used. Using different productions costs with the equal revenue distribution changed the results found in [1]. The Random mechanism is not the best one for the sellers anymore, but it isn't clear which of the other three mechanisms is the best. The LF and Threshold mechanisms have the lowest buyer utility and highest equilibrium price for seller 1. The Exponential mechanism has the highest equilibrium price for seller 2. All mechanisms have similar revenue. The Exponential mechanism has the highest utility and lowest equilibrium price for seller 1 when the equal revenue distribution is used, so it may be the best for buyers.

Figure 2 and Figure 3 are examples of the plots that the code produces. This experiment was for all four mechanisms and integer uniform distribution with support of 100 integers from 1 to 100. The production cost for seller 1 is 0 and the production cost for seller 2 is 5.

The demand graph can be used to see how often the non buy box is opened (see Figure 2e). In cases when there is not a buy box (which happens for the Threshold mechanism when both sellers set prices above the threshold) the second box's demand is included in the total non buy box demand. When the buyer utility at a specific interval of search costs for a mechanism remains constant (see Figure 2c, Random mechanism, search costs after 31), the demand being zero for the same search cost interval can explain why this happens. The probability that the non buy box is opened usually decreases as search cost increases (see Figure 2f). This means it is better for the seller to be in the buy box than not to be because it gives them a better chance of selling their item.

I also ran three seller experiments. In my two experiments, every seller had production cost zero. For my first experiment all three sellers had integer uniform distribution with support of 50 integers from 1 to 50. In the second experiment all three sellers had a geometric distribution. In both experiments the results showed that buyer utility eventually decreases as search cost increases for the LF, Threshold, and Exponential mechanisms. In the two seller experiments the results were the opposite.

Conclusion

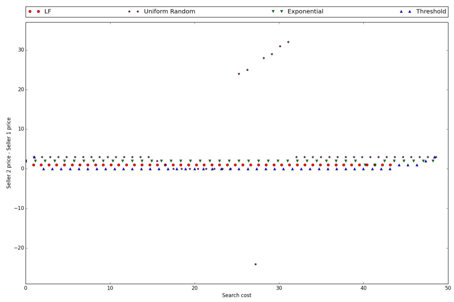
There are still many more experiments that can be run with other production cost and distribution combinations. Work for the future can also include getting a better understanding of the experiments that have already been done. Unexpected results arose during my experiments such as the difference in seller equilibrium prices being less than the difference in seller production costs. There are also more extensions that can be implemented so that new experiments can be run. One extension would be to try other mechanisms that aren't based upon the lowest price first strategy. For example, Amazon may choose to prioritize based on seller rating. Another extension is to try a different way to determine seller behavior. Instead of using best response dynamics, learning dynamics could be experimented with. Sellers would use the price histories of each of its competing sellers to determine what price to set at a given time.

References

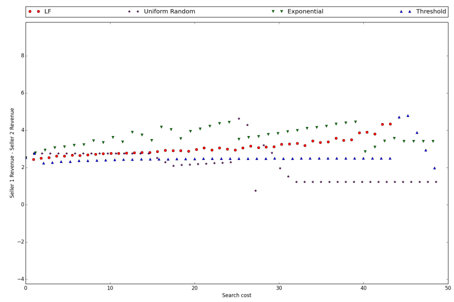
[1] Karlin, Anna, et al. "Mechanism design with search frictions: A case study of the Amazon Buy Box." *Unpublished manuscript.*

[2] Kleinberg, Robert, Bo Waggoner, and E. Glen Weyl. (2016). "Descending Price Optimally Coordinates Search." `https://arxiv.org/pdf/1603.07682.pdf`

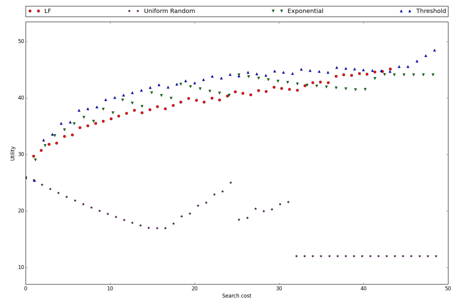
Appendix



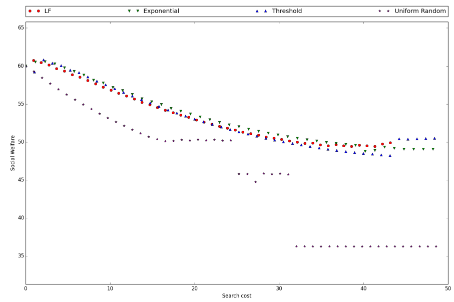
(a) Equilibrium Price



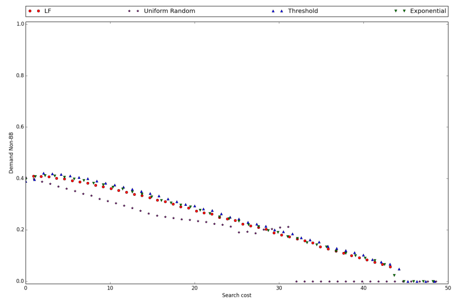
(b) Seller Revenue



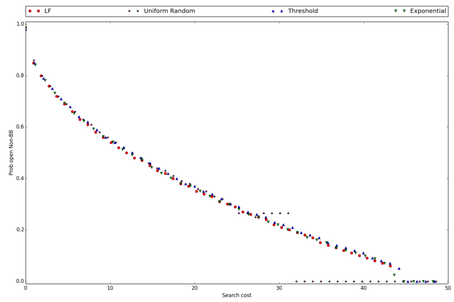
(c) Consumer Utility



(d) Social Welfare

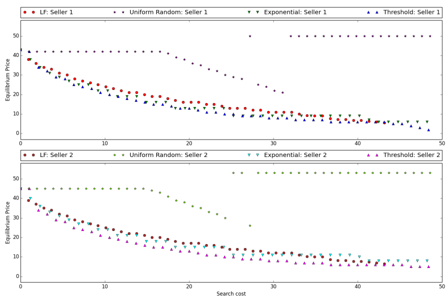


(e) Demand for Non Buy Box

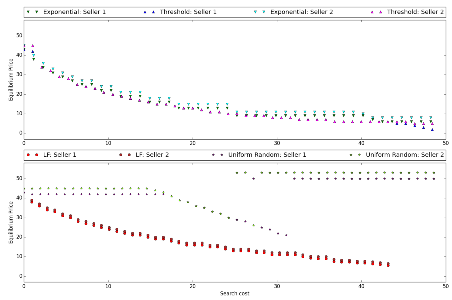


(f) Probability Non Buy Box is Opened

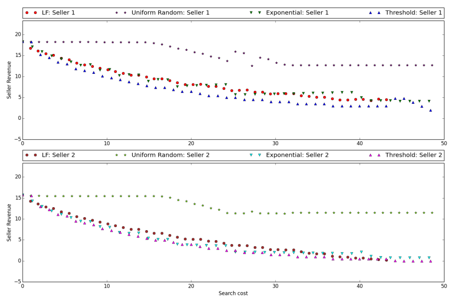
Figure 2: Integer uniform distribution: low=1, high=101. Production cost = [0,5]



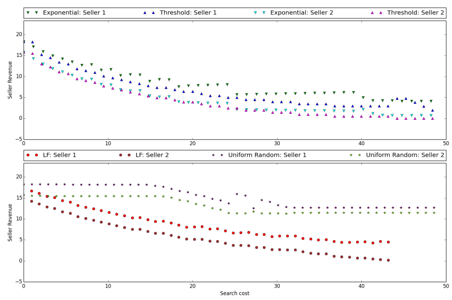
(a) Equilibrium Price: Subplots for Seller 1 and Seller 2



(b) Equilibrium Price: Subplots for LF/Uniform Random and Exponential/Threshold



(c) Seller Revenue: Subplots for Seller 1 and Seller 2



(d) Seller Revenue: Subplots for LF/Uniform Random and Exponential/Threshold

Figure 3: Integer uniform distribution: low=1, high=101. Production cost = [0,5]