Position Ranking and Auctions for Online Marketplaces

(Authors’ names blinded for peer review)

E-commerce platforms such as Amazon, Ebay, Taobao, and Google Shopping connect sellers and consumers. When a consumer enters a search keyword related to a product of interest, the platform’s search engine returns a list. Typically, the consumer looks for a desired item by searching downward in the list. With a large volume of returned results, the consumer rarely considers all of the items because examining each option is costly. Therefore, the way in which items are ranked and displayed to consumers is a critical decision of these platforms. Most prior work on this topic investigates this problem, often empirically, from the perspective of consumers, and shows that efficient rankings benefit website users and improve their surplus. For example, Ursu (2016) finds that rankings based on a products’ expected utility lead to a twofold increase in consumer welfare.

We note that for a sustainable development, a platform should consider the surplus of all participants. A search should provide high-quality product returns that fit the consumers’ particular interest. In addition, to attract and retain sellers, the platform should create and ensure a sufficient profit for them. Surprisingly, the welfare of sellers has not received much attention in the e-commerce platform literature. In this work, we study the problem of ranking products by formulating a multi-objective optimization that takes consumers’ search costs, sellers’ surplus, and platform revenue into account. One of the challenges in obtaining a satisfactory solution is information asymmetry. That is, the platform may be unaware of sellers’ private benefits of each consumer purchase — for example, profits, brand effects, and so on. We construct a near-optimal solution by selling the platform’s top slots to extract this private information. In contrast, we show that an uninformed decision, one in which sellers’ private valuation is unknown, can lead to an arbitrary loss of average welfare.

Our work also provides a theoretical justification for Amazon’s sponsored search program. Amazon introduced this program in 2012 as a tool for sellers to bid for prominent positions within search results. The sponsored search program developed rapidly with 100% annual growth, and drove more than $1.5 billion in sales revenue globally in 2015. In typical sponsored search programs, the few top returned results are “sponsored,” with clear marks indicating as such, while the other results are “organic.” The sponsored sellers are not charged if the consumer does not click on their products. We demonstrate that this is a robust approach to obtain a high surplus when information asymmetry exists. We next discuss our results and contributions in more detail.

A modeling framework. Our work combines consumer sequential search costs, position ranking,
and auctions for online shopping intermediaries. Although sponsored searches and position auctions, as used by search engines such as Google, Bing, and Yahoo! (e.g., see Edelman et al. (2007)), have been studied in online advertising, most of these studies have commonly assumed that the probability that a user chooses a product (i.e., clicks on an ad) can be estimated by multiplying a position-dependent factor and a product-dependent factor. This assumption, often referred to as separability, does not take into account the externalities imposed by sellers on each other, nor does it explicitly model the consumer search costs. We leverage the optimal sequential search model (see Weitzman (1979)) to describe consumer behavior, in which the consumer balances the trade-off between finding a better fit and the cost of acquiring additional information. Thus, a highly desirable product displayed in a prominent position could negatively impact the purchase probabilities of others. In this way, we derive seller externalities with consumer search costs as the micro-economic foundation. This externality effect has been reported by empirical studies, but has not yet drawn much systematic theoretic research in mechanism design. Also, the introduction of search cost allows us to explicitly account for consumer welfare in the objective of platform operations to consider the maximization of the weighted surplus, which is composed of supply-side surplus, consumer surplus, and aggregate sales revenue.

**A sorting solution to the search result ranking design.** Our work theoretically answers the question regarding the optimal platform ranking design that has been highlighted in empirical research. In the complete information setting where the sellers’ private valuations are observed, we show that the optimal ranking problem can be solved by sorting products according to their net surplus, which can be interpreted as the weighted sum of the private valuation of a seller and his quality score. The resulting optimized surplus in the complete information setting provides the benchmark for later discussions of mechanism design. Moreover, sorting solution in a similar fashion is also optimal in the incomplete information setting. A comparison of the complete and incomplete information shows that, as the number of sellers increases, the worst-case average welfare loss due to information asymmetry goes to infinity. This inefficiency requires effective treatment in light of the typical large volume of results returned for consumer searches.

**The value of sponsored search program and the auction mechanism.** Motivated by the optimal ranking with complete information, we propose a simple ranking rule, the Surplus-Ordered Ranking (SOR) in the sponsored search to select the sellers ranked on the top slots. With SOR, we show numerically and theoretically that the difference between optimal surplus from the complete information benchmark and that of selling only a few slots is marginal. In fact, we show that SOR is a near-optimal
solution. The surplus loss from selling a few top slots exponentially decreases in the number of slots sold regardless of the number of sellers in the market. We also study SOR implementation with mechanism design. Additional practical concerns arise in our context. The set of sellers not ranked on top, albeit a part of the mechanism, is not subject to any payment because they are considered organic results. This imposes additional complexities for the mechanism. In addition to proving that the well-known VCG mechanism fails in our environment, we show how to construct the mechanism with SOR as the ranking function to sell the top slots that satisfies all the desired constraints.

**Extensions with other practical concerns.** In practice, platforms often share with the consumer partial product information, such as pictures, prices and so on, through the list page, which displays many items simultaneously. The consumer could use such information to screen out the undesired items, and only click on the interesting ones to visit their items pages and learn further details. To incorporate such stage-wise information disclosure processes, we extend our base model in two different ways to accommodate different consumer search habits. On one hand, during the sequential search on the list page, whenever the consumer sees a good product, she may choose to immediately learn its further information by visiting its item page to make a purchasing decision and leave. On the other hand, the consumer may conduct sequential search on the list page to form her consideration set. She then can gather information from the item pages of the items within the consideration set and choose a desired one. The first model is a novel extension building upon the optimal sequential search framework from Weitzman (1979) while the second bridges the consideration set concept in assortment optimization literature (Wang (2017)). We theoretically derive near-optimal ranking rules in both choice models by slightly modifying the simple sorting solution optimal in our base model. Furthermore, extensive numerical studies show that the surplus loss with optimal solution in our base model is also negligible in these models, demonstrating the robustness of our results.

**Reference:**


