Learning to Price with Persuasion

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Extended Abstract [1]

Consider the recently proposed model motivated by digital economy from Bergemann et al. (2026), where in addition to the menu design Mussa and Rosen (1978); Maskin and Riley (1984) the seller controls the information buyers' receive about their willingness to pay. The setting is motivated by the modern marketplaces, where the platform or the seller routinely gathers detailed user profiles giving the seller *informational superiority* (see Fig. 1a). The seller can thus control the information buyers' receive about their willingness-to-pay commonly done using recommender systems (see Fig. 1b). A notable constraint on the seller is that in spite of having informational advantage it can not engage in perfect price discrimination (driving the consumer surplus to zero), because existing regulations exclude explicit price discrimination in most markets (Mansoor, 2026). Thus, in addition to designing a *public* menu of quality-price pairs, the seller commits to releasing partial information about the value of buyer-quality matches via a signaling scheme of their choice. Bergemann et al. (2026) show that in contrast to Mussa and Rosen (1978), thanks to the information control, the seller optimally designs a finite menu and the signaling scheme takes a form of monotone partitional in the quantile space i.e. buyer knows the interval his quantile lies in.

We extend Bergemann et al. (2026)'s work towards real world implementability. We design the first scheme, which obtains an approximate-optimal revenue and runs in time polynomial in the inverse of the precision and returns a monotone partitional signaling scheme along with a menu. In addition, we relax the assumption that the seller accurately knows the exact taste distribution of a buyer for the product in question. This is natural as, despite enormous data, the data for liking of a specific product is not available at large. Thus, we consider explicit learning algorithms that dictate how such knowledge may be acquired via data involving past interactions and taste realization, with explicit bounds on data and compute requirements.

More concretely, we make the following contributions:

1. We give a learning algorithm that when given $\widetilde{\mathcal{O}}(1/\varepsilon^3)$ i.i.d. samples from the buyers' taste (or as we will call it going forward, *value*) distribution, produces a signaling scheme and menu that achieves a revenue within ε of the maximum.

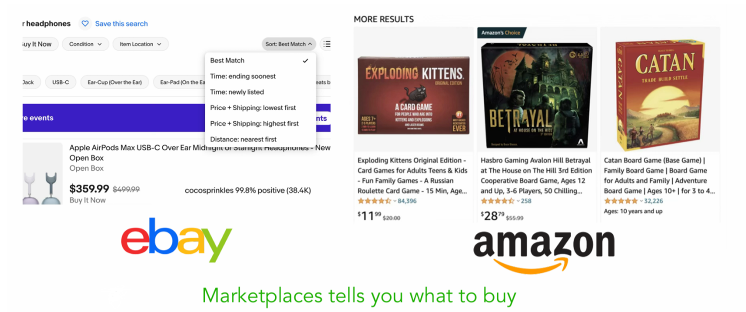
2. The problem of jointly designing a menu and a signaling scheme is non-convex, as noted in Bergemann et al. (2022). Despite this, we give the first FPTAS that computes a solution in polynomial time with revenue within an arbitrarily small additive loss of the optimum.

3. We also study a *demand query* model, where the seller can observe how the buyers behave in presence of the menus and signaling schemes she designs. In this interactive setting, we obtain a constant sample complexity for discrete value distributions and improve to $\widetilde{\mathcal{O}}(1/\varepsilon^2)$ samples for continuous distributions with bounded pdfs. Further smoothness assumptions result in smaller sample requirements; for example, polylogarithmic for analytic pdfs.

4. Finally, we give regret upper bounds for a model in which both the seller and the buyer population jointly learn in an online setting based on the past realizations of values. In this setting, the seller has to design schemes that are somewhat robust to the buyers' beliefs, which are incompletely specified.

[1] Please find the complete version at `https://bit.ly/4wwKzD1`

(a) Informational Advantage of a modern marketplace. Kroger recently had a 62-page document on a user, see Kravitz (2025).



(b) "Best Match" of eBay and "Amazon's Choice" of Amazon acts as a recommendation/signaling device

Figure 1: Properties of Digital Economy

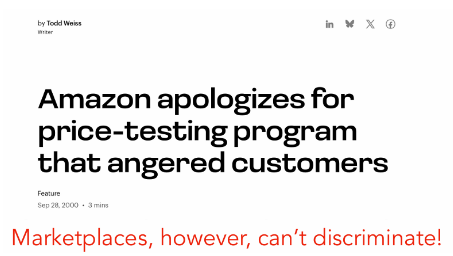


Figure 2: Constrains of Digital Economy Weiss (2000), see also Mansoor (2026) and Bergemann et al. (2026) for more references

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