The Value of Personalized Pricing

Over the last decade, increased availability of high-quality customer information has fueled interest in personalized pricing strategies. At a high-level, these strategies combine customer data with machine learning and optimization tools to predict an individual customer’s willingness to pay and then customize a price for that customer. This customized price can then be delivered as a discount via a mobile application or another channel. The appeal of personalized pricing is clear: if a seller could accurately predict individual customer valuations, then it could, in principle, successfully charge each customer exactly their valuation, increasing profits and market penetration. Unfortunately implementing any form of price discrimination, including personalized pricing, may be costly and/or difficult. A firm would need to engage in market research, invest in information systems to store customer data, and develop analytics expertise to transform these data into a personalized pricing strategy. Moreover, price discrimination tactics involve serious branding risks and potential customer ill-will, and, in some markets, may be of questionable legality.

Considering these trade-offs, in this work we complement the existing operations literature on how to implement personalized pricing by quantifying when personalized pricing offers significant value. Specifically, for a single-product monopolist, we bound the profit ratio between personalized pricing (PP), i.e., charging each customer exactly their willingness to pay, and various simpler pricing strategies. These bounds provide guidance on the potential upside of personalized pricing strategies in a market, depending on the characteristics of the market.

In this work, we model the market as a distribution over customers’ valuations for a product. With full-information about the customer valuation distribution, computing the exact
ratio between personalized pricing over simpler pricing strategies is straightforward. However, a firm not currently engaging in personalized pricing is unlikely to know the full valuation distribution and, moreover, it is not necessary to learn this distribution to price effectively. Consequently, we focus instead on parametric bounds that depend on a small number statistics of the valuation distribution; namely the mean, support, and mean absolute deviation (MAD). These statistics are more easily estimated by a seller not currently engaging in personalized pricing than estimating the full valuation distribution. Further, parametric bounds based on these statistics provide structural insights into the types of markets where the value of personalized pricing is potentially large. Specifically, in the first part of the paper, we bound the profit ratio between personalized pricing and posting a single price for all customers (SP). We prove bounds that are tight, closed-form and depend on various unit-less statistics of the valuation distribution. Perhaps surprisingly, we show this ratio is non-convex and peaks for intermediate values of MAD.

Although it is an interesting theoretical benchmark, our notion of personalized pricing is not directly implementable in practice because it hinges on two idealized assumptions: First, that the monopolist can perfectly predict each customer's valuation, and, second, that the monopolist can charge any price it wishes on a continuum. In the second part of this paper, we quantify how much each of these assumptions contributes to the benchmark by computing the value of personalized pricing over two other price-discrimination strategies: k-market segmentation and feature-based pricing, each of which relaxes one of these two assumptions.

In the k-market segmentation strategy, we assume the monopolist is still omniscient, but can charge at most k distinct prices, relaxing the assumption of a continuum of prices. Under a mild assumption, we show that the value of personalized pricing over k-market segmentation
converges to $1 + C/k$ where $k$ is the number of segments and $C$ is an explicit constant depending on distributional parameters. We prove that this worst-case dependence on $k$ is tight and provide numerical evidence that it is in fact typical of many distributions. This analysis yields a natural rule of thumb; to guarantee halving the gap to the ideal personalized pricing profits, one needs to double the number of prices offered.

In the feature-based pricing strategy, we assume the monopolist can still offer a continuum of prices, but is no longer omniscient. Rather, she observes features (sometimes called a context) for each customer which she can use to (imperfectly) predict the customer’s valuation. Leveraging our earlier results, we prove that the value of personalized pricing over feature-based pricing is bounded by an explicit factor that depends on the coefficient of deviation of the error in the valuation prediction model. Again, we provide numerical evidence suggesting our worst-case analysis is qualitatively typical of many distributions. This yields another natural rule of thumb; to guarantee halving the gap to the ideal personalized pricing profits, one needs to quadruple the prediction accuracy.

Each of our previous bounds depend parametrically on a measure of heterogeneity in the market, namely the normalized mean absolute deviation of the valuation distribution. In the final part of our paper, we provide an algorithmic procedure to compute an essentially tight bound on the value of personalized pricing over single-pricing given any generalized moment of the valuation distribution, for example, its variance or geometric mean. The key ideas leverage continuous linear optimization duality and a careful discretization to construct a near-optimal dual feasible solution. The algorithm is provably computationally tractable under mild assumptions on the function defining the generalized moment. These assumptions are satisfied by the usual typical moments encountered in practice.