Revenue Management with Repeated Customer Interactions

1 Introduction

Many revenue optimization problems pertaining to airlines, hotels, online advertising and e-commerce are modeled as the so-called network revenue management problem (NRM). The most general version of NRM can be abstractly thought of as a platform’s control problem, where the platform matches heterogeneous pools of customers and, respectively, resources (or products), so as to maximize its revenues. While NRM has been intensely studied in the literature, the bulk of results approach the problem as a one shot, stateless interaction between the platform and its customers. In turn, the resulting prescriptions, such as the celebrated bid-price control policy [6], are optimal assuming this one-shot regime. In many practical settings, however, customer relationships with the platform are longer term: interactions happen repeatedly over many distinct epochs and stateful customers may maintain “memory” that changes their goodwill towards the platform. These repeated interactions can be modeled as a sequence of one-shot NRM problems, linked together by the changing state of the customers. In this paper, we explore whether incorporating customer memory into the platform’s decisions can yield meaningful revenue improvements, compared to a myopic approach that treats each decision epoch independently and uses traditional one-shot NRM machinery.

While we think repeated interaction models are widely applicable, we focus our work on a particular problem pertaining to online advertising platforms, where advertisers can monitor the quality of their old campaigns and renegotiate the parameters of new ones on a continuous basis. Our model is the following: we have a population of advertisers spanning multiple epochs, and a supply of impressions which is renewed at the start of every distinct epoch. The advertisers are endowed with valuation vectors for the different impressions.
At the start of a single epoch, each advertiser negotiates the terms of her campaign, which are specified by two parameters: a budget which is a hard constraint on the campaign’s aggregate spend, and a vector of prices for impressions. Subsequently, the platform decides how to allocate impressions to advertisers while respecting their budget constraints. In the next epoch, campaign parameters are re-negotiated and the process repeats with a new supply of impressions. We model advertiser state and its dynamics over multiple epochs via the budget an advertiser commits to their campaign. We believe this is a reasonable proxy for the advertiser’s participation and goodwill towards the platform. Our budget dynamics equation is such that an advertiser increases or decreases their budget from one epoch to the next through an exponential smoothing process that takes into account the quality of the advertiser’s last campaign. The platform’s goal is to maximize its own discounted reward over the epochs, but our results also transfer to a finite time horizon formulation.

2 Literature Review

In the stateless customer case, the NRM problem has a long history within the operations management literature. Of particular note are the fluid models of [5, 6], which yield tractable control policies such as bid prices. Work on customer loyalty programs, such as [4, 3] is also implicitly tied to managing customer goodwill. The literature on repeated customer interactions is more limited: [2] study a stylized model of how a firm sets service levels to customers over time and give a characterization of the steady-state level. In a paper most similar to ours, [1] consider a monopolist who manages the allocation of scarce inventory of a single good type to multiple customers whose demand functions in a given period depend on previous fill rates, and develop ADP based heuristics to solve the corresponding infinite horizon average cost problem.

3 Results

Myopic optimality conditions. Surprisingly, we identify a set of conditions pertaining to the valuation and price vectors of a given advertiser for which the myopic policy remains
optimal in the repeated setting. The condition translates to a constant rate of return on the impressions in an advertiser’s consideration set: this is a realistic condition, as in many display advertising systems, advertisers specify a single price for the entire array of impressions they deem acceptable for their campaign. Moreover, implementing the myopic policy requires only price information which is naturally available to the platform, while not requiring information about valuation which may be private to the advertisers. We emphasize that this result differs from [1] in that (a) we consider heterogeneous goods (impressions) along with advertisers and (b) we state our guarantee with respect to the discounted or finite time horizon formulations: thus our model incorporates the transient performance of the system rather than only steady-state.

A heuristic policy for cases when myopic is not optimal. As suggested above, there exist problem instances when ignoring customer state may be sub-optimal. We show that in general the performance gap could be arbitrarily large and find that computing an optimal policy via typical dynamic programming approaches is prohibitively expensive due to the curse of dimensionality. Thus, we develop a heuristic with universally good performance. The heuristic can be interpreted as a one-step lookahead policy computable via a linear program which optimizes the platform’s policy over only the current and the subsequent epoch.

References


