

The Price of Independence in Simultaneous Auctions

(Extended Abstract)

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ABSTRACT

We present a computationally feasible method for predicting joint probability distributions over auction clearing prices, together with a bidding heuristic that exploits these price predictions. We demonstrate experimentally that our heuristic outperforms the state-of-the-art heuristic for bidding in simultaneous, second-price, sealed-bid (SimSPSB) auctions.

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1. INTRODUCTION

Current autonomous bidding agents in complex auctions typically employ a two phased architecture known as a *price prediction (PP) strategy*: first, the agent predicts a distribution over prices for available goods, and then, the agent attempts to optimize its bids with respect to those predictions. For computational reasons, state-of-the-art methods [6, 7, 9] assume that prices are independent across goods, and bid based on marginal price distributions. However, prices for goods are typically dependent, especially for complementary and substitutable goods.

In this paper, we present techniques for prediction and optimization that operate in the joint price space. To predict, we use a mixture of Gaussians to efficiently represent a joint price distribution, which we learn repeatedly from simulation data generated via a best-reply dynamic. Our approach to optimization extends a known local-search heuristic that bids based on marginal price distributions rather than the joint. We evaluate our techniques in a variety of SimSPSB auction environments and show that our approach outperforms the reigning champion.

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2. LEARNING JOINT PRICE PREDICTIONS

Past work on learning price predictions has been concerned with learning marginal price predictions: i.e., making predictions on a per-good basis (e.g., [5]). Often, such price predictions are represented as histograms (e.g., [3, 9]). Assuming m goods, each with l possible discretized prices, it would take space $O(ml)$ to represent m marginal histograms. In contrast, it would take space $O(l^m)$ to represent the corresponding joint histogram. Consequently, it is not realistic to attempt to accurately model a joint price probability distribution as a histogram when m is large. In this work, we assume the price distribution is a mixture of Gaussians.

2.1 Gaussian Mixture Models

We use a *Gaussian mixture model* (GMM) to represent joint price predictions. A GMM is a model of a probability distribution of dimension D as a weighted sum of K Gaussian components, each of dimension D . The number of components, K , determines the *complexity* of the model. Each component, k , is defined by its mean and covariance parameters. In addition, each component is weighted by γ_k . The vector θ specifies all the free parameters of a GMM.

A standard algorithm for estimating the free parameters from data is *Expectation Maximization* (EM) [2], an iterative approach which guarantees that the likelihood of the data never decreases with successive iterations. However, the number of components K must be specified in advance.

Rather than guess K , we use the Akaike Information Criterion (AIC) [1] to drive model selection. That is, we learn models for various values of K , and then select the model that minimizes AIC score. The AIC score is a standard measure of goodness of fit, defined as the likelihood of the data under the model discounted by the complexity of the model: $AIC(\mathcal{Y}, \theta, K) = 2(\kappa - \ln L(\mathcal{Y} | \theta))$ where $\kappa = K \left(D + \frac{D^2 + D}{2} \right)$.

2.2 Self-Confirming Price Predictions

There are many ways one might build probabilistic price predictions from data. We employ *self-confirming price predictions* (SCPPs), originally introduced and evaluated in the context of simultaneous ascending auctions [8], and further evaluated in the present context [9]. Building on the ideas set forth in these prior works, we propose a simple iterative method to approximate SCPPs.

Let $\mathbf{Q} = \langle q_1, \dots, q_m \rangle$ be a random vector with pdf $f_{\mathbf{Q}}$, representing the clearing prices in an auction for m goods.

Given an auction environment Γ specifying the number of agents, number of goods, the auction rules (e.g., SimSPSB), and a prior over valuations, at iteration t , the algo-

rithm simulates M instances of Γ , with all agents playing price-prediction strategy PP assuming prediction $f_{\mathbf{Q}}^t$. These simulations vary across sample valuation functions drawn for each agent. Given the ensuing data set \mathcal{X} , a new price distribution $f_{\mathbf{Q}}$ is learned.

KL-divergence is a standard measure of similarity between probability distributions: $KL(p, q) = \int_{-\infty}^{\infty} p(x) \ln \left(\frac{p(x)}{q(x)} \right)$. A symmetric form of KL-divergence is $KLS(p, q) = KL(p, q) + KL(q, p)$. The KLS distance between two GMMs can be approximated using Monte Carlo sampling.

If the new learned distribution is sufficiently close to the old as determined by the KLS, then the new distribution is returned and the procedure terminates. Otherwise, a new price distribution is formed by combining the new and the old (in some parametric way), and the process repeats. As this procedure is not guaranteed to converge, it automatically terminates after L iterations.

3. LOCAL SEARCH BIDDING HEURISTICS

Once an agent has derived price predictions, it must decide how to bid given those predictions. Although this problem has been studied for over a decade [7, 6], a new method was recently proven very successful in SimSPSB auctions [9]. The **LocalBid** heuristic iteratively updates its bids for each good j in turn, by computing the bid for good j that maximizes its expected utility, holding all other bids are fixed, and computing the expectation with respect to marginal price distributions. This heuristic is guaranteed to converge to a bid vector that locally maximizes expected utility, assuming prices are truly independent across goods. Under this price-independence assumption, the optimal bid for good j can be efficiently computed as j 's expected marginal value, meaning the difference between the expected valuation of winning j and losing j .

We define **JointLocal** to be a heuristic that, like **LocalBid**, bids expected marginal value, but computes that expectation using the full joint, rather than the marginals. Specifically, the expectation is computed using Monte Carlo sampling, where samples are drawn from a price prediction represented as a GMM. In general, **JointLocal** does not converge to a bid vector that locally maximizes expected utility. Nonetheless, **JointLocal** is an effective bidder when prices are correlated, as our experiments will now demonstrate.

4. EXPERIMENTS

We explore the effects of assuming price independence in a class of SimSBSP auctions where agents' valuations take the form of scheduling valuations [4]. Each agent i requires $\lambda_i \in \{1, \dots, m\}$ total time slots (goods) to complete its task. If agent i procures λ_i time slots by time t , it receives valuation $v_i(t)$. $S[m, n]$ represents the scheduling environment where n agents are bidding for m time slots, and $\lambda_i \sim U[1, m]$ and $v_i(t) \sim U[1, 50]$. In these environments, goods exhibit complementarities. $L[m, n]$ represents a similar environment except λ_i is fixed at 1. Here, goods are perfect substitutes.

We computed a GMM-SCPP $f_{\mathbf{Q}}$ for each scheduling environment listed in Table 1. Let $f_{\mathbf{Q}'}$ be the independent distribution derived from the resulting $f_{\mathbf{Q}}$. The amount of price correlation in each environment was quantified by approximating $KL(f_{\mathbf{Q}}, f_{\mathbf{Q}'})$ via Monte Carlo estimation. For each environment, 1000 random valuations were drawn, along with 1000 initial bids. For each valuation-initial bid pair,

LocalBid and **JointLocal** both used the same set of 10000 samples from the environment's GMM-SCPP to produce bids. The expected utility of each bid was estimated with a second set of 10000 samples drawn from the GMM-SCPP. The average estimated expected utility for each heuristic, and $KL(f_{\mathbf{Q}}, f_{\mathbf{Q}'})$ for each environment, are reported in Table 1.

Table 1 shows that for a fixed m , a low KL value correlates with no discernible difference in the performance of **LocalBid** and **JointLocal**. We see this in $S[5, 8]$ and $L[10, 5]$, where KL is small, and the difference in performance is less than 0.2%. However, when KL is large, as in $S[5, 2]$ and $S[10, 5]$, indicating that $f_{\mathbf{Q}}$ is highly correlated, **JointLocal** outperforms **LocalBid**, increasing expected utility by about 8% and 2%, respectively. These results suggest that the KL value might be predictive of the loss experienced by heuristics that assume price independence.

Environment	$KL(f_{\mathbf{Q}}, f_{\mathbf{Q}'})$	LocalBid	JointLocal	%Diff
$S[5, 2]$	4.477	8.983	9.698	8.0
$S[5, 8]$	1.381	4.022	4.014	-0.2
$L[10, 5]$	0.6593	6.023	6.01	-0.2
$S[10, 5]$	5.969	6.557	6.676	8.0

Table 1: Average of Expected Utility Estimates

5. CONCLUSION

We exhibited a novel two-tiered strategy for bidding in SimSPSB auctions, which includes a method of deriving joint price predictions based on GMMs and SCPPs; and a bidding heuristic, **JointLocal**, that exploits those predictions. We showed that the current state-of-the-art heuristic, **LocalBid**, is outdone by **JointLocal** in environments with strong price correlations. When correlations are small, the performance of **LocalBid** and **JointLocal** is similar. Future work will compare **JointLocal** to generic local-search optimizers, analyze worst-case bounds for bidding with marginal price predictions, and replace the AIC criteria with a nonparametric Bayesian method for learning GMMs.

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