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.

Categories and Subject Descriptors
I.2.1 [Artificial Intelligence]: Applications and Expert Systems

General Terms
Algorithms, Economics, Experimentation, Performance

Keywords
Autonomous Agents; Simultaneous Sealed-Bid Auctions

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 \cite{6, 7} 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., \cite{5}). Often, such price predictions are represented as histograms (e.g., \cite{3, 9}). Assuming \( m \) goods, each with \( t \) possible discretized prices, it would take space \( O(mt) \) to represent \( m \) marginal histograms. In contrast, it would take space \( O(t^m) \) 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 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 \( \gamma_k \). The vector \( \theta \) specifies all the free parameters of a GMM.

A standard algorithm for estimating the free parameters from data is Expectation Maximization (EM) \cite{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) \cite{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:

\[
AIC(Y, \theta, K) = 2(\kappa - \ln L(Y | \theta)) \quad \text{where} \quad \kappa = K \left( D + \frac{D^2+D}{2} \right).
\]

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 \cite{8}, and further evaluated in the present context \cite{9}. Building on the ideas set forth in these prior works, we propose a simple iterative method to approximate SCPPs.

Let \( Q = (q_1, \ldots, q_m) \) be a random vector with pdf \( f_Q \), representing the clearing prices in an auction for \( m \) goods.

Given an auction environment \( \Gamma \) specifying the number of agents, number of goods, the auction rules (e.g., SimSPSB), and a prior over valuations, at iteration \( t \), the algo-
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 [3], [4], [5], a new method was recently proven very successful in SimSPSB auctions [6]. 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 [7]. Each agent \( i \) requires \( \lambda_i \in \{1, \ldots, m\} \) total time slots (goods) to complete its task. If agent \( i \) procures \( \lambda_i \) at 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 \( \lambda_i \) is fixed at 1. Here, goods are perfect substitutes.

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

Table 1: Average of Expected Utility Estimates

<table>
<thead>
<tr>
<th>Environment</th>
<th>( KL(f_q,f_{q'}) )</th>
<th>LocalBid</th>
<th>JointLocal</th>
<th>%Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>S[5,8]</td>
<td>1.381</td>
<td>4.022</td>
<td>4.014</td>
<td>-0.2</td>
</tr>
<tr>
<td>L[10,5]</td>
<td>0.659k4</td>
<td>6.023</td>
<td>6.01</td>
<td>-0.2</td>
</tr>
<tr>
<td>S[10,5]</td>
<td>5.969</td>
<td>6.557</td>
<td>6.676</td>
<td>8.0</td>
</tr>
</tbody>
</table>

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.

6. REFERENCES