Agent-Based Supply Chain Management: Bidding for Customer Orders

David Pardoe and Peter Stone
Department of Computer Sciences
University of Texas at Austin
Austin, TX 78712 USA
{dpardoe, pstone}@cs.utexas.edu

Abstract

Supply chains are a current, challenging problem for agent-based electronic commerce. Motivated by the Trading Agent Competition Supply Chain Management (TAC SCM) scenario, we consider an individual supply chain agent as having three major subtasks: acquiring supplies, selling products, and managing its local manufacturing process. In this paper, we focus on the sales subtask. In particular, we consider the problem of finding the set of bids to customers in simultaneous reverse auctions that maximizes the agent’s expected profit. The key technical challenges we address are i) predicting the probability that a customer will accept a particular bid price, and ii) searching for the most profitable set of bids. We first compare several machine learning approaches to estimating the probability of bid acceptance. We then present a heuristic approach to searching for the optimal set of bids. Finally, we perform experiments in which we apply our learning method and bidding method during actual gameplay to measure the impact on agent performance. Full details can be found in the extended version of this paper [1].

1. Introduction

Supply chains are a current, challenging problem for agent-based electronic commerce. One problem commonly faced by agents acting in supply chains is that of negotiating with customers in order to sell goods. Such negotiations are often handled through reverse auctions in which sellers submit sealed bids in response to requests for quotes (RFQs) from customers. This situation becomes particularly difficult when sellers must bid in multiple auctions simultaneously, because an agent cannot await the outcome of one auction before bidding in another. When deciding which auctions to bid in and what bids to place, an agent with limited resources must be able to judge and balance the competing risks of not winning enough auctions and of winning too many. In the former case, it is unable to fully utilize its resources towards profitability; in the latter, it will be unable to meet its obligations to customers.

The Trading Agent Competition Supply Chain Management (TAC SCM) scenario [3] provides a perfect testbed for the study of this problem. In TAC SCM, agents competing as computer manufacturers must handle three basic subtasks: acquiring components, managing a local manufactur-
the current game is unlikely to yield accurate predictions. We therefore turn to machine learning methods using training data from past games.

We follow the approach used by [4] to solve a similar conditional density estimation problem. This approach involves dividing the price range into several bins and estimating the probability of winning the auction at each bin endpoint. A post-processing step converts the learned set of probabilities to a probability density function, in part by interpolating between bin endpoints. In this method, a separate predictor is trained for each endpoint to predict the probability of winning at that point.

In this section we focus on the task of training these individual predictors. We describe the format of the training data, compare the effectiveness of several learning algorithms, and then look at the impact that the choice of training data has on the predictions.

The data for our experiments is taken from the game logs of the semifinal and final rounds of the first TAC-SCM competition held in August 2003. A training instance is created for each RFQ. The 23 attributes included in each instance reflect the details of the RFQ it represents, along with the information available to agents at the time about the level of demand in the game and the recent prices for which the requested type of computer has been sold.

We first performed an experiment comparing the effectiveness of using several different regression learning algorithms to train predictors using data taken from the final round, and found that similarly good prediction accuracy was obtained using M5 regression trees and BoostTexter, a boosting method using decision stumps.

We then considered the case of an agent participating in the final round of the competition. The agent’s best source of training data would be games from the semifinal round; however, this data would reflect the behavior of all agents in that round, of which only half advanced to the finals, raising the question of how well the trained predictors would generalize. An experiment showed that predictors trained on the semifinal round were only slightly less accurate than predictors trained on the final round in predicting bid acceptance during the finals.

4. Bid Selection
We cast the bidding problem as an optimization problem and developed a heuristic approach to finding the optimal set of bids to offer in response to a single day’s customer RFQs. By making several simplifying assumptions, we were able to apply a greedy production scheduler to approximately determine the set of bids that maximizes the agent’s expected profit.

5. Agent Performance
In this section, we evaluate the effectiveness of our learning approach and bidding method when used as part of a complete agent in TAC SCM gameplay. We do this through a series of experiments in which agents using different combinations of bidding methods and prediction methods play against each other repeatedly.

In our experiments we consider two bidding methods (the method described in Section 4, and a previously developed method described in [2]) and three methods of predicting the probability of bid acceptance (two different heuristics and the learning method described in Section 3). Each of the six combinations of bidding methods and prediction methods is used by one agent.

Three rounds of 30 games were played between the six agents. The first round was used to generate training data for the learned predictors. In the second round, the agents using these predictors significantly outperformed the agents using heuristic predictors. In the third round, the learned predictors were replaced with predictors trained on games from the semifinal and final rounds of the 2003 TAC SCM competition, to determine how well these predictors would generalize to a different set of agents. The agents using these learned predictors still outperformed the agents using heuristic predictors, although by a smaller margin than in the previous round. In each round, the agents using the bidding method from Section 4 scored higher than agents using the bidding method from [2]).

6. Conclusion
We presented a learning-based approach to the problem of bidding on customer RFQs in TAC SCM auctions. We compared the effectiveness of using different learning algorithms to learn to predict the probability of bid acceptance, and experimentally verified that using learning resulted in strong agent performance. Our results suggest that the learned predictors generalize well to new situations, both in terms of prediction accuracy and of agent performance. This gives us hope that our learning approach can be used successfully in competition when facing varying sets of agents or agents that change their behavior over time.

References