Dynamic Regime Selection and Prediction Based on Observed Behavior in Electronic Marketplaces

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Abstract

Introduction

Electronic marketplaces are gaining popularity among producers seeking to streamline their supply chains and consumers looking for good opportunities. Intelligent software agents can significantly facilitate human decision processes either by helping users to select strategies that maximize profit, or by making autonomous choices. In either case, agents need methods for making decisions under uncertain and dynamic market conditions. Competitive scenarios are increasingly being used as testbeds for the development of multi-agent systems. A new game, called TAC SCM, was introduced for the 2003 Trading Agent Competition (Collins *et al.* 2004). This game involves a Supply Chain Management (SCM) scenario in which agents attempt to maximize profits by manufacturing personal computers and selling them to customers.

In TAC SCM six autonomous agents compete to maximize profits in a computer-assembly scenario. Agents earn money by selling computers they assemble out of parts purchased from suppliers. The agent with the highest bank balance at the end of the game wins. To obtain parts, an agent must send a *request for quotes* (RFQ) to an appropriate *supplier*. Suppliers respond either by specifying the price for the supplies, or, if they cannot satisfy the request in full, by giving a partial offer with a revised quantity and price, or the earliest date the request can be satisfied in full. Every day each agent receives a set of RFQs from *customers* requesting to buy computers. Customers accept the lowest bid which is at or below their reserve price. Computers are available in three different markets: a low, a medium and a high price market.

We concentrate in this paper on the control mechanism which we are planning to use in our agent, MinneTAC, for TAC SCM 2005. This control mechanism is twofold, first is has impact on the sales strategies which the agent is using and second it will be used as a feedback mechanism between different components, e.g. procurement, production, and sales, of our agent. The sales strategies estimate, as the game progresses, the probability of receiving a customer order for different prices and compute the expected profit.

Research Issue and existing Approaches

The TAC SCM game environment is highly dynamic, since the underlying distributions for the demand and supply processes are changing constantly. The game has a very high uncertainty as well, because the agents change their behavior and adopt to new situations all the time and they don't have any knowledge about the local state of other agents. The usual assumption made in Economics that a single agent does not have an impact on the other players is not working in this environment, since the number of agents, 6, is very small. Each agent is directly influencing the behavior of other agents. Each agent has to make decisions before all relevant uncertainty is resolved.

In (Ketter *et al.* 2004) we describe two sales strategies with different methods to calculate the probability of order which our agent used in a previous competition. Nearly all agents in previous competitions used some way of modeling the probability of receiving an order. Botticelli (Benisch *et al.* 2004) uses a linear cumulative density function (CDF) to determine the relationship between offer price and order probability. We use a reverse CDF and take other factors into account, such as quantity and due date. TacTex (Pardoe & Stone 2004) uses the lowest and highest offer price, which are provided for each product every day by the game server, and determines the probability of an order by linear interpolation. After analyzing the results we came to the conclusion that our approach to pricing and calculating the probability of order is not flexibly enough to adapt to different market situations, such as high product scarsity, product over supply and low and high customer demand. In the next section we will explain our new approach.

Proposed Approach

We believe even though the market is constantly changing, that there are some underlying statistical patterns which characterize certain situations in a market. We define those specific modes a market can be as a *regime*. A way of solving the decision problem an agent is faced with, is to characterize those regimes and apply specific decision making

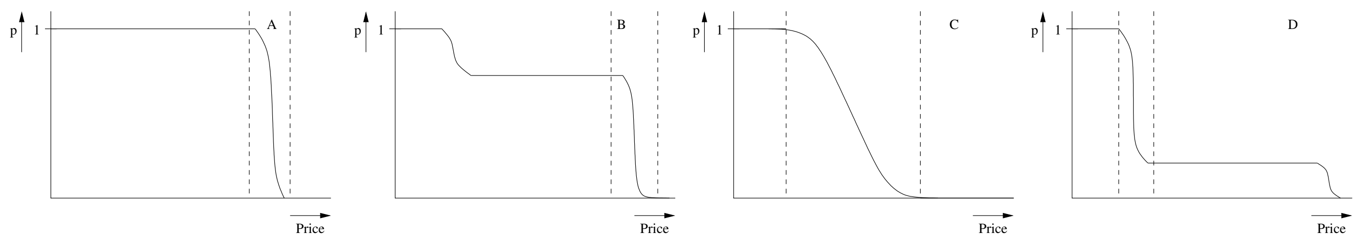

Figure 1: Different regimes in TAC SCM. Figure A shows a region where there is a very high scarcity of products in the market. This situation dominates mostly in the beginning of a game. Figure B depicts a scarcity of products in the market. Then Figure C shows the average case and Figure D illustrates an oversupply situation.

methods to them. An agent participating in a market then has to have methods of figuring out in which regime it is in. This extra layer in the decision making process constitutes a classification problem. Figure 1 depicts the different situations a market can be in. The left most Figure, A, depicts a situation where there is a high scarcity of products in the market. This situation occurs usually in the start phase of each game. If we have products to sell and are in this regime, then we can conclude that we should apply a very aggressive pricing strategy, upper end of the spectrum, since not many of our competitors will have products to sell. The next figure, B, depicts a very similar situation, but this kind of regime can occur at any time of the game. In this case we should apply an aggressive pricing strategy as well, so that we price close to the reserve price. The Figure C depicts a regime where the price elasticity is high. In this regime we can apply a profit maximization procedure, since we have quite a few bids which get accepted and reject with some random factor. The pricing should be done in the medium and upper end of the spectrum. In the right Figure, D, we show an oversupply situation. If the agent detects that it is in this situation than is should primarily control its cost and therefore only do its pricing, if at all, at the lower end of the spectrum.

Mathematically we define a regime with the help of a Gaussian mixture model (Titterington, Smith, & Makov 1985). First we collect all the customer order prices[1] and apply the EM-Algorithm to each market segment to determine the components (μ;σ) of the Gaussian mixture model. In a second step we cluster the posterior probabilities of each market segment to find the regime centers. Through empirical analysis we found out that 4 clusters are good in describing different regimes. To find out for a new game in which regime the market is in, we calculate the mean order price for a particular market segment each day and measure the distance to the four different clusters. With this distance we can determine the posterior probability of the mean order price dependent on each cluster. We take the cluster which has the highest responsibility for this day as the current regime.

We capture all the transitions from one regime to another in a Markov transition matrix. Through this we are able to forecast regimes on each day for manys days out in the future. This enables out to make the kind of strategic decisions that we were not able to do with our old method. Furthermore, we will design different sales strategies and methods of calculating the probability of order dependent on in which regime the market is in.

[1]The statistical analysis is based on the semi-final and final games of TAC SCM 2004.

Evaluation and Verification of the Research Approach

We have done already a lot of work in this new research. The regime definition and detection algorithm are already implemented and tested. We have tested the regime idea and found that our theoretical model and our empirical results are almost identical. This results give us confidence that our approach holds. We are currently working on the regime prediction mechanism.

Open Issues

We need to develop new and different sales strategies and methoda to calculate the probability of order dependent on the regime the market is in. Finally based on the regime information we need to implement a feedback mechanism, so that the different parts of our agent will work more effectively, e.g., the procurement model will not purchase more material if the market is already in an over-supply situation.

Current Status of My Dissertation Studies

All the work to satisfy the Ph.D. course requirements will be completed by the end of this spring semester. The qualifying written examination has been successfully completed. The oral preliminary examination is planned at the end of this spring semester.

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