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

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Abstract

We present a method for an autonomous agent to identify dominant market conditions, such as oversupply or scarcity. The characteristics of economic regimes are learned from historic data and used, together with real-time observable information, to identify the current market regime and to forecast market changes. The approach is validated with data from the Trading Agent Competition for Supply Chain Management.

Introduction and Problem Definition

The Supply-Chain Management Trading Agent Competition (Sadeh *et al.* 2003) (TAC SCM) involves a Supply Chain Management scenario in which in each round six autonomous agents attempt to maximize profit by selling personal computers they assemble from parts they buy from suppliers. The agent with the highest bank balance at the end of the game wins. An agent has to make many decisions, such as how many parts to buy, when to get them delivered, what types of computers to build, when to sell them, and at what price. Availability of parts and demand for computers varies randomly through the game and across market segments (low, medium, and high computer price). The market is affected not only by variations in supply and demand, but also by the actions of other agents. The small number of agents and their ability to adapt to and manipulate the market makes the game highly dynamic and uncertain.

Marketing research methods have been developed for improving sales by understanding the relationships between market conditions and actions. For instance, in (Pauwels & Hanssens 2002), an analysis is presented on how in mature economics markets strategic windows of change alternate with long periods of stability. Sales strategies used in previous TAC SCM competitions model the probability of receiving an order for a given offer price, either by estimating the probability by linear interpolation from the minimum and maximum daily price records (Pardoe & Stone 2004), or by estimating the relationship between offer price and order probability with a linear cumulative density function (CDF) (Benisch *et al.* 2004), or by using a reverse CDF and factors such as quantity and due date (Ketter *et al.* 2004). All these methods have the disadvantage that they do not explicitly take market conditions into account.

The approach we present here is motivated by the long-standing realization among economists that market conditions play a critical role in making operational and strategic decisions for raw material acquisition, production, and sales.

Regime Identification

Mathematically, we define a regime with the help of a Gaussian mixture model (GMM). First we collect order prices from past games (in our experiments we use the semi-finals and finals of TAC SCM 2004). Each computer type has a different nominal price, which is simply the sum of the nominal cost of each component part. We use normalized prices (np) and we apply the Expectation Maximization algorithm to determine the components (μ_i,σ_i, and prior probability) of the GMM. The GMM has the following form:

$$p(np) = \sum_{i=1}^{N} \left\{ p(np|c_i) \times P(c_i) \right\}$$

where $p(np|c_i) = N[\mu_i, \sigma_i](np)$ is the i-th component of the normalized price density from the GMM, and $P(c_i)$ is the prior probability of the i-th component. An example is shown in Figure 1 (left). Using Bayes' rule we determine:

$$P(c_i|np) = \frac{p(np|c_i) \times P(c_i)}{\sum_{i=1}^{N} \left\{ p(np|c_i) \times P(c_i) \right\}} \qquad \forall i = 1, \cdots, N$$

In this paper we assume $N = 3$, since this provides a good balance between quality of approximation and simplicity of processing. We define the N-dimensional vector $\vec{\eta}(np) = [P(c_1|np), P(c_2|np), \ldots, P(c_N|np)]$ and we compute $\vec{\eta}(np_j)$ which is $\vec{\eta}$ evaluated at the np_j price. We cluster these collections of vectors using k-means. The center of each cluster corresponds to a regime R_k. We use this clustering technique to distinguish four regimes, namely over-supply (R_1), extreme over-supply (R_2), balanced (R_3), and scarcity (R_4).

Through correlation analysis we validated that regimes have economic characteristics, such as low vs high order prices. Figure 2 plots the normalized price (np), the quantity of finished goods inventory (FG), and the ratio of offer to demand over time, and show the regimes identified by our

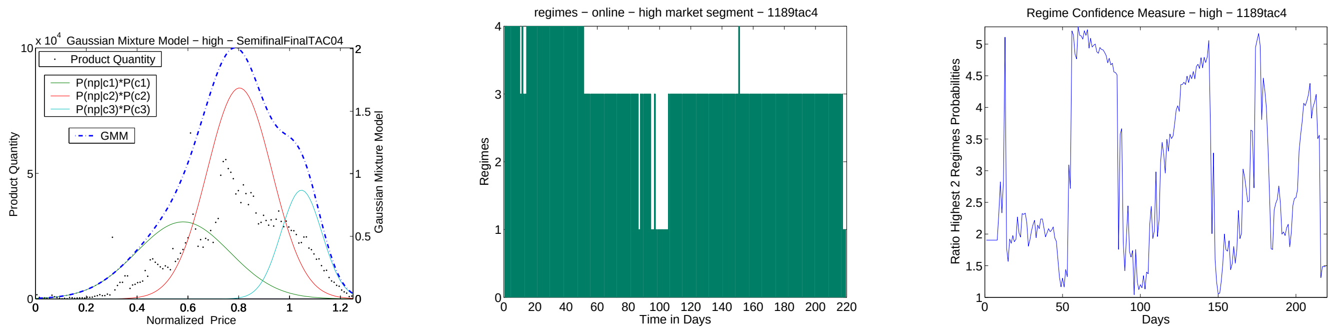

Figure 1: Gaussian mixture model computed from 30 games (left), regimes over time (middle) and ratio of probabilities of best and second best regime (right) computed online every day for the high market segment in game 1189@tac4.

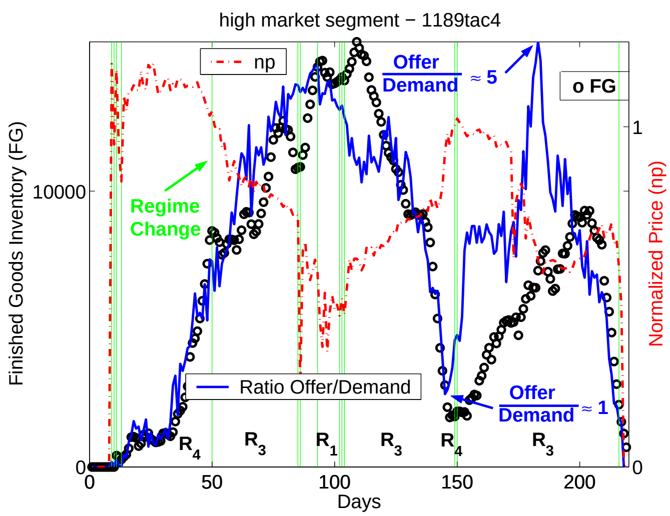

Figure 2: Game 1189@tac4 (Final TAC SCM 04) – Relationships between dominant regimes and ratio of offer to demand, normalized price, and available finished goods inventory in the high market segment over time.

approach. Between day 181 and 184 the ratio $\frac{Offer}{Demand}$ was high (between 4.5 and 4.9), but the balanced regime R_3 remained the active regime in that period. We observe that the ratio $\frac{Offer}{Demand}$ is only one of the parameters in characterizing the multi-dimensional regime parameter space.

We can rewrite $p(np|c_i)$ in a form that shows the dependence of the normalized price np not on the component c_i of the GMM, but on the regime R_k:

$$P(np|R_k) = \sum_{i=1}^{N} p(np|c_i) \times P(c_i|R_k)$$

Using Bayes' rule again we compute

$$P(R_k|np) = \frac{P(np|R_k) \times P(R_k)}{\sum_{k=1}^{R} P(np|R_k) \times P(R_k)} \qquad \forall k = 1, \cdots, R$$

The prior probabilities $P(R_k)$ of the regimes are determined by a counting process over multiple games. During the game the agent estimates every day the current regime by calculating the mean normalized price $\overline{np}_{day}$ for the day and by selecting the regime which has the highest probability, i.e. $\max(\vec{P}(R|\overline{np}_{day}))$. An example is in Figure 1 (middle).

A simple method for predicting regime changes during the game uses the ratio of the probability of the highest vs the second highest regime. A high ratio corresponds to high confidence in regime determination, while a ratio close to one indicates that the current market situation is a mixture of almost equally likely regimes. An example is shown in Figure 1 (right). These ratios are collected over an interval of days in the immediate past and a regime shift is predicted by interpolation. We are currently developing a more sophisticated semi-Markov model for prediction of regime changes.

Conclusions and Future Work

We believe that our proposed formulation will allow the agent to do strategic pricing and market manipulation. Our next steps are to refine the method for predicting regime changes, design sales strategies that take advantage of regime prediction, and integrate them in the decision making process of the agent.

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