Strategic Sales Management in an Autonomous Trading Agent for TAC SCM

Wolfgang Ketter, Eric Sodomka, Amrudin Agovic, John Collins, and Maria Gini
Department of Computer Science and Engineering, University of Minnesota, Minneapolis, MN 55455, USA
{ketter,sodomka,aagovic,jcollins,gini}@cs.umn.edu

Introduction

To operate successfully in a competitive trading environment such as the Trading Agent Competition for Supply Chain Management (Collins *et al.* 2004) (TAC SCM), an agent has to allocate resources and set prices in a way that maximizes its expected profit. This requires the ability to detect changing market conditions and act accordingly.

In TAC SCM six agents buy parts, assemble personal computers, and sell them in daily auctions to customers. Sales decisions in our agent, MinneTAC, are driven by three different models: an automated characterization and prediction of market conditions, which we call economic *regimes* (Ketter 2005), a linear program that optimizes daily sales quotas, and a model of order acceptance probability. While economic regime models are commonly used at the macro economic level (Osborn & Sensier 2002), such predictions are rarely done for a micro economic environment.

We focus on the sales decisions the agent has to make, where predicting prices and customer demand play an essential role. The strategies we present have been inspired, among others, by the work of Kephart et al. (Kephart, Hanson, & Greenwald 2000).

MinneTAC makes sales decisions in two steps. The first step is a *strategic decision*, where resources are allocated over a planning horizon in a way that maximizes expected profit over the horizon. The second step is a *tactical decision*, which determines the offer prices that are expected to sell the quantities determined by the strategic decision, given the current demand and the pricing model.

Strategic Sales Decision

The strategic decision sets daily sales quotas by solving a linear program that maximizes total profit, computed as expected sales price minus cost basis, over the selected horizon and over the set of product types the agent can produce, subject to constraints on inventory and production capacity. This strategy sets relatively large quotas for the current day if prices are predicted to fall, and small quotas if prices are predicted to rise. Successful use of this approach therefore requires good prediction of price trends, which we describe next.

Regime Identification and Prediction

Off-line Regime Characterization. We characterize market regimes by analyzing off-line data from previous games. The agent then uses these results along with real-time observable information to identify regimes during the game, forecast regime transitions, and adapt its procurement, production, and pricing strategies accordingly. For our experiments, we used training data from a set of 24 games played during the semi-finals and finals of TAC SCM 2005.

Agents can build and sell many different types of computers. Each computer type has a nominal price, which is the sum of the nominal cost of the parts needed to build it. We normalize the prices across the different computer types. We call np the normalized price.

We define regimes with a Gaussian mixture model (GMM). We use a GMM with fixed means, μ_i, and fixed variances, σ_i, since we want the same set of Gaussians to work for all games. We use the Expectation-Maximization (EM) Algorithm to demarginalize the GMM and determine the prior probability, $P(c_i)$, of the Gaussian components. The density of the normalized price can be written as $p(\mathrm{np}) = \sum_{i=1}^{N} p(\mathrm{np}|c_i)\, P(c_i)$, where $p(\mathrm{np}|c_i)$ is the i-th Gaussian from the GMM. For our experiments we chose $N = 16$, because we found experimentally that this works well for price trend predictions.

Using Bayes' rule we determine the posterior probability $P(c|\mathrm{np})$. We then define the N-dimensional vector

$$\vec{\eta}(\mathrm{np}) = [P(c_1|\mathrm{np}), P(c_2|\mathrm{np}), \ldots, P(c_N|\mathrm{np})]$$

whose components are the posterior probabilities from the GMM, and for each normalized price np_j we compute $\vec{\eta}(\mathrm{np}_j)$ which is $\vec{\eta}$ evaluated at the np_j price. We cluster these collections of vectors using the k-means algorithm. The center of each cluster is a probability vector that corresponds to regime $r = R_k$ for $k = 1, \cdots, M$, where M is the number of regimes.

In Figure 1 we distinguish five regimes, which we call extreme over-supply (R_1), over-supply (R_2), balanced (R_3), scarcity (R_4), and extreme scarcity (R_5). Regimes R_1 and R_2 represent a situation where there is an over-supply situation, which depresses prices. Regime R_3 represents a balanced market situation, where most of the demand is satisfied. In regime R_3 the agent has a range of options of price vs sales volume. Regimes R_4 and R_5 represent a situation

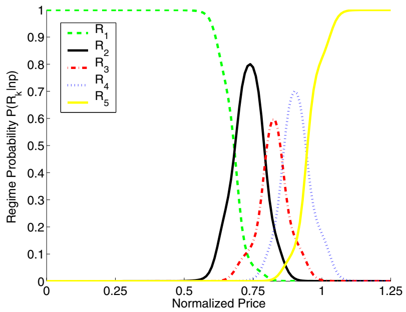

Figure 1: Regime probabilities over normalized price.

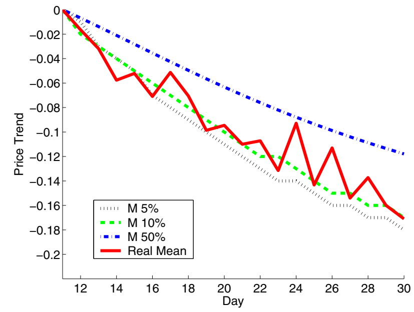

Figure 2: Predicted price trend from day 10 to day 30. The solid curve is the real mean price trend and the dashed and dotted curves are predicted prices trends based on the 5%, 10% and 50% percentiles of the predicted price density.

where there is scarcity of products, which increases prices. In this case the agent should price close to the customer reserve price – the maximum price a customer is willing to pay.

We marginalize the product of $p(\mathrm{np}|c_i)$ and $P(c_i|R_k)$ over all Gaussians c_i to obtain $P(\mathrm{np}|R_k)$. The probability of regime R_k dependent on the normalized price np can be computed using Bayes rule as:

$$P(R_k|\mathrm{np}) = \frac{P(\mathrm{np}|R_k)\,P(R_k)}{\sum_{k=1}^{M} P(\mathrm{np}|R_k)\,P(R_k)} \quad \forall k = 1, \cdots, M.$$

where M is the number of regimes, which in our case is 5. The prior probabilities $P(R_k)$ of the different regimes are determined by a counting process over multiple games. Figure 1 depicts the regime probabilities for a sample market.

Online Regime Identification. During the game, the agent estimates the current regime every day by calculating the mid-range normalized price $\overline{\mathrm{np}}_{day}$ for the day and by selecting the regime with the highest probability, i.e. $\mathrm{argmax}_{1 \le k \le M}\, \vec{P}(R_k|\overline{\mathrm{np}}_{day})$. The mid-range price is computed from the daily report of the minimum and maximum prices of the computers sold the day before.

Online Regime Prediction. Since regimes are correlated with prices, predicting regime changes can help predicting price changes. We model regime prediction as a Markov process and construct a transition matrix off-line by a counting process over past games. This matrix represents the posterior probability of transitioning in day $t+1$ to a regime given the current regime in day t . The prediction is based on two distinct operations: (1) a correction (recursive Bayesian update) of the posterior probabilities $\vec{P}(r_{t-1}|\{\overline{\mathrm{np}}_{t_0}, \ldots, \overline{\mathrm{np}}_{t-1}\})$ for the regimes based on the history of measurements of the mid-range normalized price $\overline{\mathrm{np}}$ from the day of the last regime change, t_0, to the previous day, $t-1$, and (2) a prediction of the regime posterior probabilities for the current day, t, $\vec{P}(r_t|\{\overline{\mathrm{np}}_{t_0}, \ldots, \overline{\mathrm{np}}_{t-1}\})$.

Price Density and Trend Prediction. The agent predicts the price density using the predicted regime distribution and the learned GMM for every day over the planning horizon n using a range of values for np. To predict price trends we track the 5%, 10%, and 50% percentiles of the predicted price density. Figure 2 shows price trends for a sample game from day 10 until day 30. These predicted price trends are then used to compute optimal sales quotas.

Tactical Sales Decision

Given the daily sales quotas, price trend predictions, and the current demand d_g, the final decision is to set the highest possible offer price op_g for each product g at which g's sales are expected to reach its desired quota q_g. We maintain a current pricing model that approximates the probability that customers will accept an offer. This is a simple linear approximation giving the expected median price m_g (derived from $\overline{\mathrm{np}}$) and slope s_g of the acceptance probability function. Using this model, the offer price op_g for each product is

$$op_g = \frac{1}{s_g}\left(\frac{q_g}{d_g} - \frac{1}{2}\right) + m_g.$$

Offer prices are slightly randomized, and actual sales performance is used to update the model.

Conclusions and Future Work

We have described an approach to sales decision-making that uses economic regimes, resource allocation, and prediction of order probabilities. The approach presented is focuses on sales decisions, but price trends can also be used for decision making in procurement and production.

References

Collins, J.; Arunachalam, R.; Sadeh, N.; Ericsson, J.; Finne, N.; and Janson, S. 2004. The Supply Chain Management Game for the 2005 Trading Agent Competition. Technical Report CMU-ISRI-04-139, Carnegie Mellon University, Pittsburgh, PA.

Kephart, J. O.; Hanson, J. E.; and Greenwald, A. R. 2000. Dynamic pricing by software agents. *Computer Networks* 32(6):731–752.

Ketter, W. 2005. Dynamic Regime Identification and Prediction Based on Observed Behavior in Electronic Marketplaces. In *Proc. of the Twentieth National Conference on Artificial Intelligence*, 1646–1647.

Osborn, D. R., and Sensier, M. 2002. The prediction of business cycle phases: financial variables and international linkages. *National Institute Econ. Rev.* 182(1):96–105.