Identification and Prediction of Economic Regimes to Guide Decision Making in Multiagent Marketplaces

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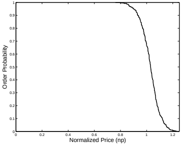
Outline

Motivation

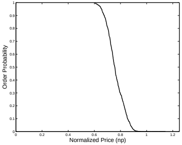
- Economic theory suggests that economic environments exhibit 3 dominant market patterns: scarcity, balanced, and over-supply.
- We call these distinguishable conditions *economic regimes*.
- The long term objective of our work is to show how knowledge of current and anticipated regimes can enable an agent to make better operational and strategic decisions.

Relationship: Prices, Order Probability, and Regimes

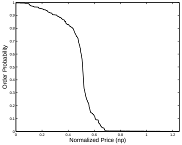
Scarcity:



Balanced:

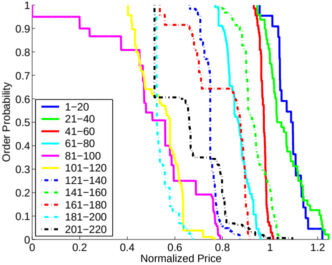


Over-supply:



Reverse cumulative density function represents probability of order.

Experimental:



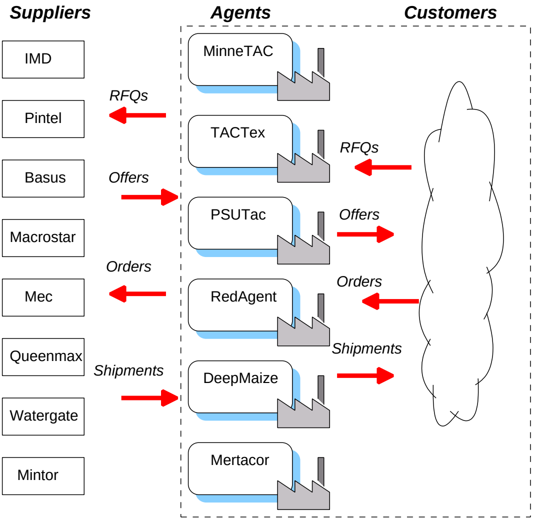
Application Areas (1)

- Identification of economic regimes:
    - Strategical decision making
    - Tactical decision making
- Price and price trend forecasting.
- Forecasting of economic regimes shifts:
    - Whole seller (e.g. book store).
    - Production plant (e.g. Daimler).
- Automated supply-chain management, e.g.,
    - i2
    - SAP

Application Areas (2)

- The approach we propose works in any market:
  - Computational process is completely data driven.
  - No classification of the market structure (monopoly vs competitive, etc) is needed.

TAC SCM - Scenario



Use Regime Prediction For Sales Strategies

1. Allocation (Strategic Decision):
   - Allocating parts and production capacity to most profitable computers.
   - Allocating computers to current vs future sales.
2. Pricing (Tactical Decision):
   - Find the best prices to move the desired inventory.

Proposed Approach

1. Off-line Regime Training
2. Real-time
    1. Regime Identification and Prediction
    2. Sales Pricing

Estimating Price Density Functions

We estimate price density functions using a Gaussian mixture model (GMM)

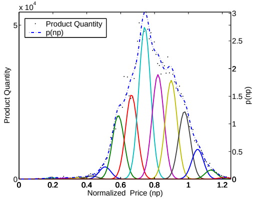
$$p(\mathrm{np}) = \sum_{i=1}^{N} p(\mathrm{np}|\zeta_i)\, P(\zeta_i)$$

where

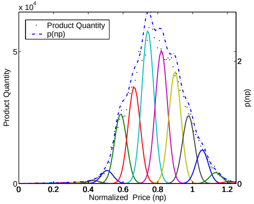
- $p(\mathrm{np})$ is the density of the normalized price (np).
- $p(\mathrm{np}|\zeta_i) = N[\mu_i, \sigma_i](\mathrm{np})$ is the i-th Gaussian of the normalized price density from the GMM.
- $P(\zeta_i)$ is the prior probability of the i-th Gaussian. We determine it using the EM-algorithm.
- N is the number of Gaussians. We use $N = 16$.
- Fixed means μ_i and fixed variances σ_i^2.

Estimating Price Density Functions (3)

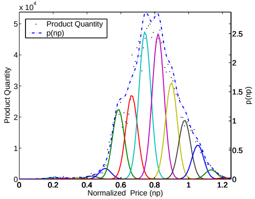
The EM-Algorithm determines the prior probability, $P(\zeta_i)$, of each Gaussian, where $\forall i = 1, \cdots, N$. Assumption: $N = 16$.



Low Market



Medium Market



High Market

Using Bayes' rule we determine the posterior probability:

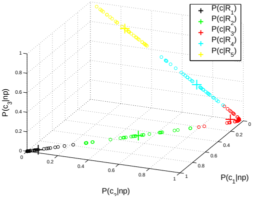
$$P(\zeta_i|\mathrm{np}) = \frac{p(\mathrm{np}|\zeta_i)\,P(\zeta_i)}{\sum_{i=1}^{N} p(\mathrm{np}|\zeta_i)\,P(\zeta_i)} \qquad \forall i = 1, \cdots, N$$

Definition of Regimes

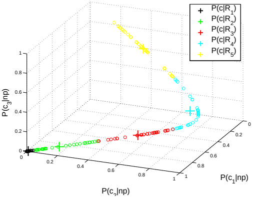
1. We compute at each price np_j the N-dimensional vector

$$\vec{\eta}(\mathrm{np}) = [P(\zeta_1|\mathrm{np}), P(\zeta_2|\mathrm{np}), \ldots, P(\zeta_N|\mathrm{np})]$$

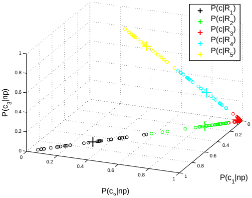
2. We cluster these vectors using k-means.
3. The center of each cluster corresponds to a regime R_k.
4. We compute the posterior probability $P(R_k|\mathrm{np})$



Low Market

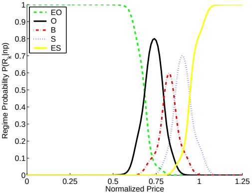


Medium Market

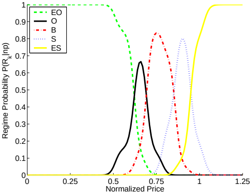


High Market

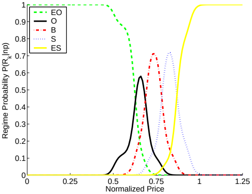
Learned Regime Probabilities – offline



Low Market



Medium Market



High Market

$\vec{P}(R_k|\mathrm{np}) \quad \forall k = 1, \cdots, M$ calculated off-line from 26 games.

Proposed Approach

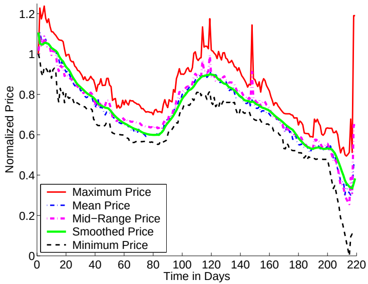
1. Off-line Regime Training
2. Real-time
    1. Regime Identification and Prediction
    2. Sales Pricing

Information Available in the Customer Market

Every day each agent receives:

1. Requests for Quotes (RFQs): computer type, number of computers, due date, reserve price.
2. A price report which includes the lowest and highest price paid per computer type from the previous day.

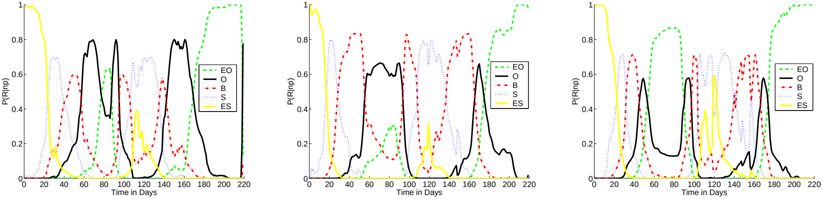
Real-time Identification of the Dominant Regime



Daily price report 3721@tac3 – medium market: Minimum and maximum order prices.

1. Every day we estimate the current regime by calculating the double smoothed mid-range normalized price $\widetilde{\mathrm{np}}_{day}$ based on the daily price report.
2. We select the regime which has the highest probability, i.e. $\mathrm{argmax}_{1 \leq k \leq M} \vec{P}(R_k | \widetilde{\mathrm{np}}_{day})$.

Real-time Computation of Regime Probability



Low Market Medium Market High Market

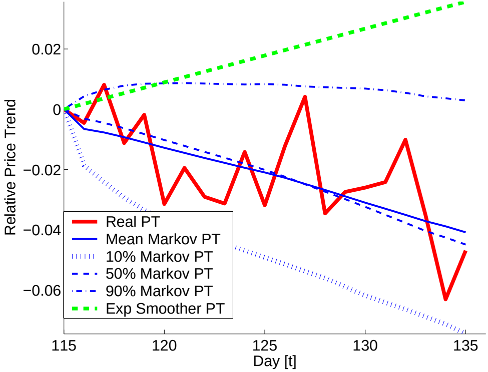
$\vec{P}(R_k|\widetilde{\mathrm{np}}_{day}) \quad \forall k = 1, \cdots, M$ calculated online for game 3721@tac3.

Regime Prediction

We model the prediction of the next regime as a Markov prediction process: The posterior regime probabilities are predicted for current and future days based on yesterday's smoothed mid-range normalized price $\widetilde{\mathrm{np}}$.

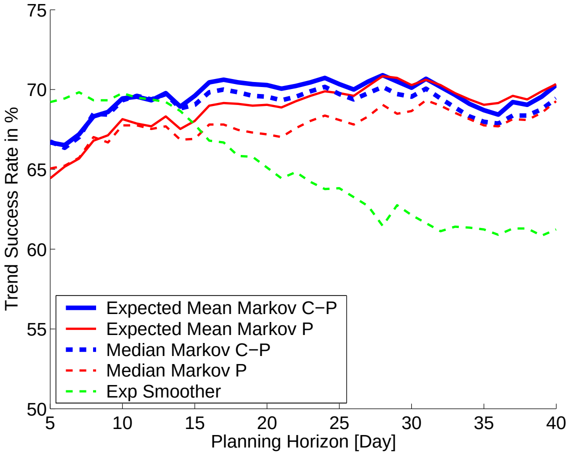
Price Trend Prediction

$$\widehat{Tr}_n = sgn(\widehat{\mathrm{np}}_{d+n} - \widehat{\mathrm{np}}_d), \qquad \forall n = 1, \cdots, h$$



Example: Game 3717tac3

Evaluation of Trend Prediction

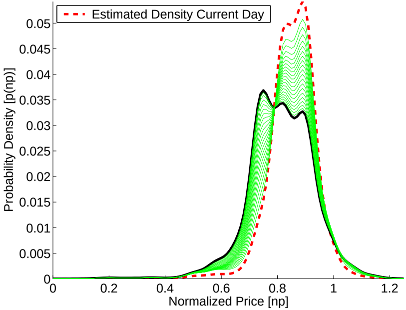


Success rate over a varying planning horizon.

Prediction of Price Density

$$p(\widehat{\mathrm{np}}_{t+n}|\widetilde{\mathrm{np}}_{t-1}) = \sum_{j=1}^{N} P(\zeta_{j,t+n})\, p(\mathrm{np}|\zeta_j)$$

Sample np from 0 to 1.25 in increments of 0.01



Example: Game 3717tac3

Prediction of Order Probability

$$P(order|\mathrm{np}) = 1 - CDF(\mathrm{np})$$

where

$$CDF(\mathrm{np}) = \int_0^{\mathrm{np}} p(\mathrm{np}')\,\mathrm{d}\mathrm{np}'$$

In TAC SCM $\mathrm{np}_{max} = 1.25$,
so that $CDF(\mathrm{np}_{max}) = 1$.

Proposed Approach

1. Off-line Regime Training
2. Real-time
    1. Regime Identification and Prediction
    2. Sales Pricing

Optimizing sales quotas (1)

To optimize profits over time, an agent needs to know:

- Current and future prices
- Its own costs
- Available inventory and production capacity

If per-unit profit for good g sold on day d at price $price_{d,g}$ is $\Phi_{d,g}$, then total profit over a horizon h is

$$\Phi = \sum_{d=0}^{h} \sum_{g \in \mathcal{G}} \Phi_{d,g} A_{d,g}$$

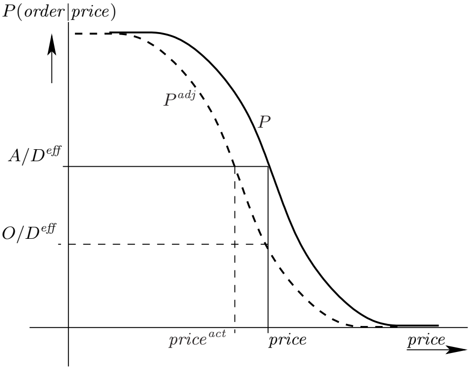
Optimizing sales quotas (2)

LP solver can optimize total profit, subject to:

- Sales quotas cannot exceed expected demand
- Uncommitted finished-goods and raw-materials inventories
- Inventories are augmented by expected deliveries and components available from suppliers over the planning horizon h
- Quotas not satisfied from finished goods are constrained by factory capacity

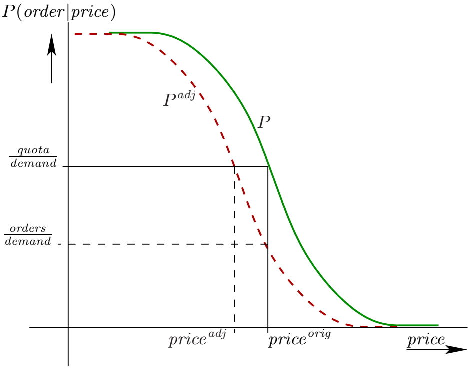
Setting sales prices

To sell our quota, we set prices using our order probability model.



Tuning sales prices

The pricing model is approximate. We tune it using feedback from actual orders.



Mean Profit Results using Different Versions of MinneTAC

Experiment **Strategic:** **Tactical:**	1 Follower Linear	2 Regime-M Linear	3 Regime-M Regime-E
Agent	Mean Profit/Std. Dev. (in $M)		
MinneTAC	1.35/3.70	1.81/4.02	2.12/3.76
TacTex	8.75/5.68	8.87/5.60	9.21/5.39
DeepMaize	8.84/4.63	8.71/4.85	8.32/4.18
PhantAgent	8.05/5.42	7.99/5.38	8.17/5.44
Maxon	4.24/4.52	3.77/4.29	4.02/4.18
Rational	0.74/4.91	0.67/4.69	1.31/4.53

Controlled market conditions. Each column is average of 23 games.

Future Work (1)

- Ensemble price predictions
- Train regime transition matrices:
  - On different time periods (start, mid, and end of the game).
  - Include the effect of substitutability among market segments and products.
- Market segments vs product learning.
- Develop procurement strategies that take advantage of regime forecasting.

Future Work (2)

- Integrate regime forecasting in decision making process. Apply reinforcement learning to map
  - economic regimes to operational regimes.
  - operational regimes to actions.
- Implement and evaluate approach in other application domains, e.g.,
  - Stock market
  - Amazon
  - Dutch flower auction
  - Energy markets

Conclusions

- Off-line identification of economic regimes.
- Real-time identification of economic regimes.
- Real-time prediction of economic regime distributions and transitions.
- Real-time prediction of price density, prices and price trends.
- Real-time prediction of order probability.

Contact

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Prediction of Price Density

$$
\begin{aligned}
& p(\widehat{\mathrm{np}}_{t+n} | \widetilde{\mathrm{np}}_{t-1}) \\
& = \sum_{i=1}^{M} P(\mathrm{np}|R_i)\, P(R_{i,t+n}|\widetilde{\mathrm{np}}_{t-1}) \\
& = \sum_{j=1}^{N} \underbrace{\sum_{i=1}^{M} P(\zeta_j|R_i)\, P(R_{i,t+n}|\widetilde{\mathrm{np}}_{t-1})}_{P(\zeta_{j,t+n})}\, p(\mathrm{np}|\zeta_j) \\
& = \sum_{j=1}^{N} P(\zeta_{j,t+n})\, p(\mathrm{np}|\zeta_j)
\end{aligned}
$$