Strategic Sales Management Guided By Economic Regimes

Wolfgang Ketter

Department of Computer Science and Engineering

University of Minnesota

Erasmus University

Rotterdam - June 13th 2006

Overview

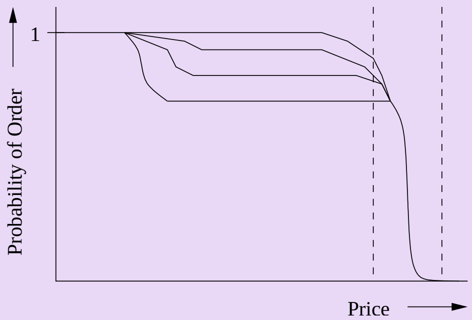
- Motivation
- Trading Agent Competition for Supply Chain Management (TAC SCM)
- Related Work
- Proposed Solution
- Future Work
- Conclusion

Motivation

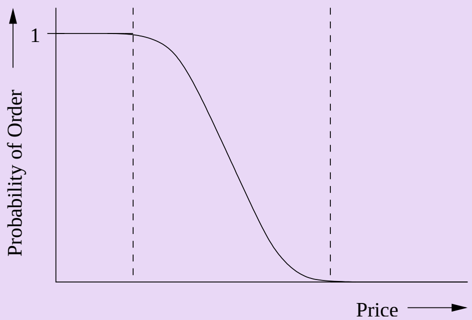
- Economic theory suggests that economic environments exhibit 3 dominant market patterns: scarcity, balanced, and over-supply.
- We call these distinguishable conditions *regimes*.
- The long term objective of our work is to show how knowledge of current and anticipated regimes can enable an agent to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

Relationship between Prices, Order Probability, and Regimes

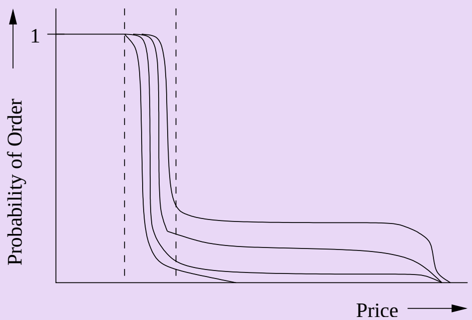
Scarcity:



Balanced:

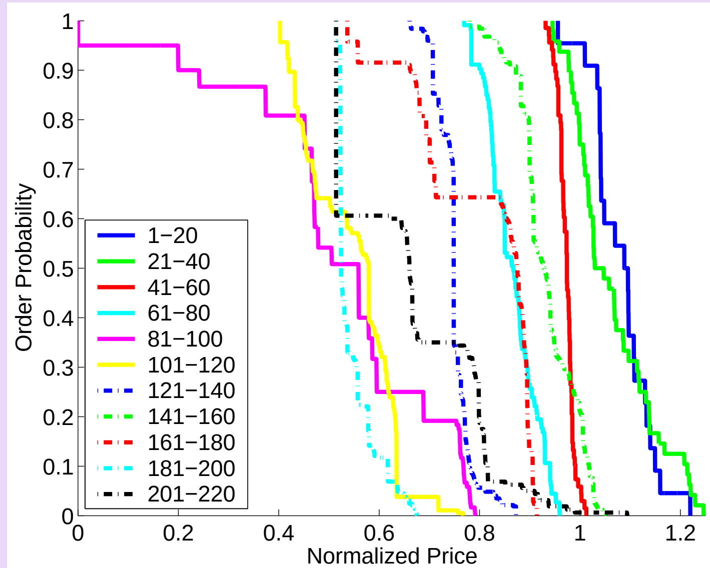


Over-supply:



Reverse cumulative density function represents probability of order.

Experimental:



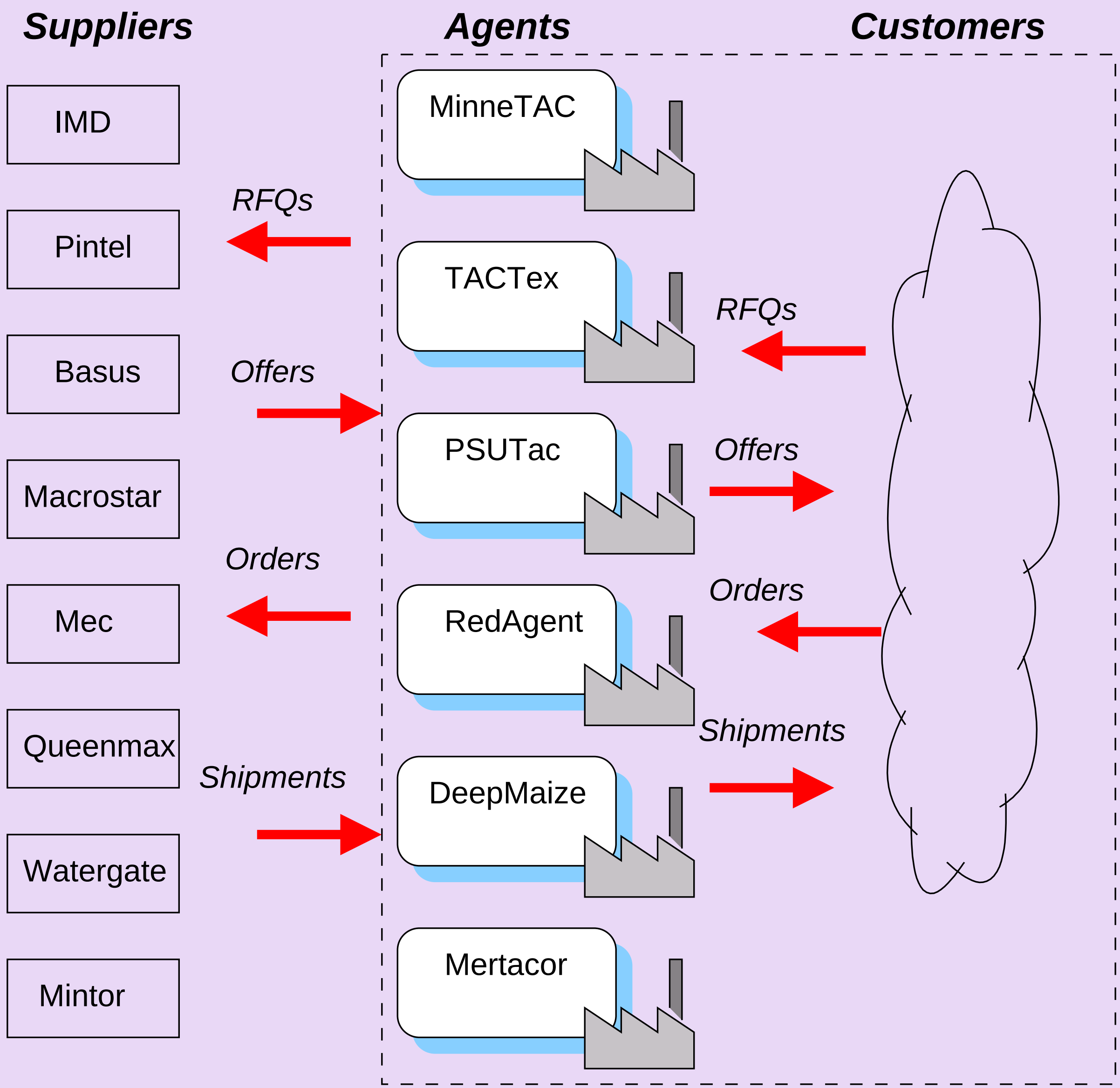
Application Areas (1)

- 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-Chrysler).
- Automated supply-chain management, e.g.,
  - i2
  - SAP

Application Areas (2)

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

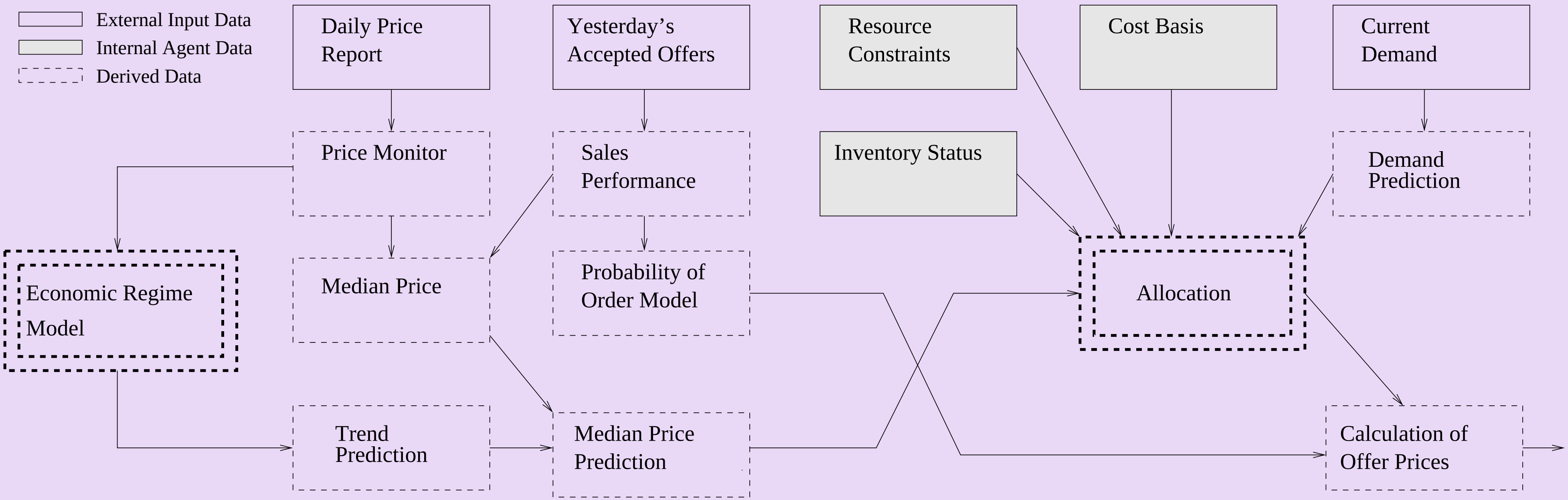
TAC SCM - Scenario



Use Regime Prediction For Sales Strategies

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

Pricing Chain



Related Work

Demand and Price Prediction

- Ghani, 2005 – PDA auctions on eBay
- Ghose et al., 2006 – used books sales on Amazon
- Kephart et al., 2000 – information goods and shopbots
- Massey et al., 2005 – reaction caused by regime shifts
- Osborn et al., 2002 – Macro-Economic regimes
- Pauwels et al., 2002 – windows of change in marketing

Demand and Price Prediction in TAC SCM

Benisch et al., 2004, Ketter et al., 2004, Pardoe et al., 2004, Wellman et al., 2005

Proposed Approach

1. Off-line identification of regimes from past game data.
2. Online identification of regimes from data available in the current game.
3. Prediction of regime transitions.
4. Prediction of price density and trends using regimes.

Estimating Price Density Functions (1)

- Estimate price density functions and use them to define regimes.
- A Gaussian mixture model (GMM) can estimate arbitrary density functions.
- GMM is a semi-parametric approach:
  - fast computing
  - less memory

Estimating Price Density Functions (2)

We use a Gaussian mixture model (GMM):

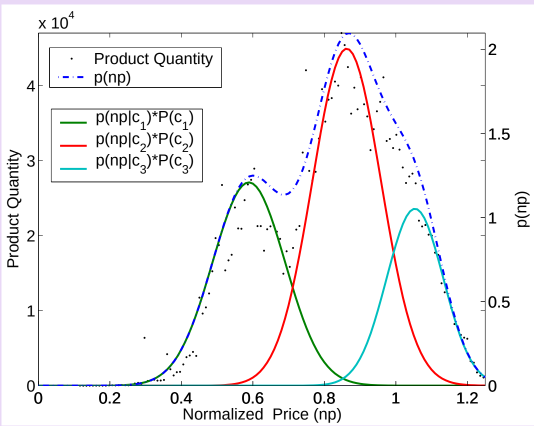
$$p(\mathrm{np}) = \sum_{i=1}^{N} p(\mathrm{np}|c_i)\, P(c_i)$$

where

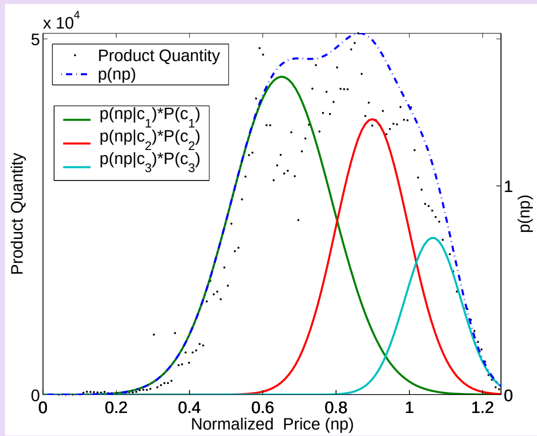
- $p(\mathrm{np})$ is the density of the normalized price (np).
- $p(\mathrm{np}|c_i) = N[\mu_i, \sigma_i](\mathrm{np})$ is the i-th Gaussian of the normalized price density from the GMM.
- $P(c_i)$ is the prior probability of the i-th Gaussian.

Estimating Price Density Functions (3)

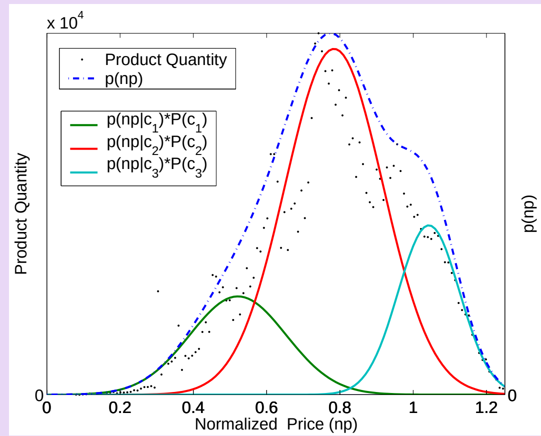
The EM-Algorithm determines the Gaussians (μ_i,σ_i, and $P(c_i)$) of the GMM, where $\forall i = 1, \cdots, N$. Assumption: $N = 3$.



Low Market



Medium Market



High Market

Using Bayes' rule we determine the posterior probability:

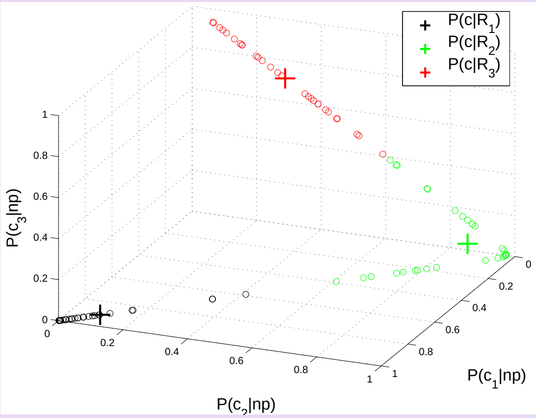
$$P(c_i|\text{np}) = \frac{p(\text{np}|c_i)\, P(c_i)}{\sum_{i=1}^{N} p(\text{np}|c_i)\, P(c_i)} \qquad \forall i = 1, \cdots, N$$

Definition of Regimes

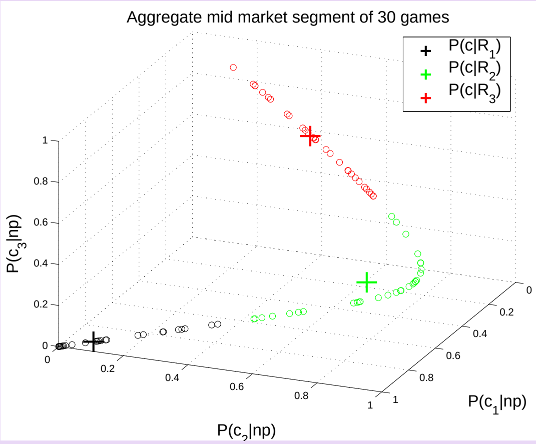
We define the N-dimensional vector

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

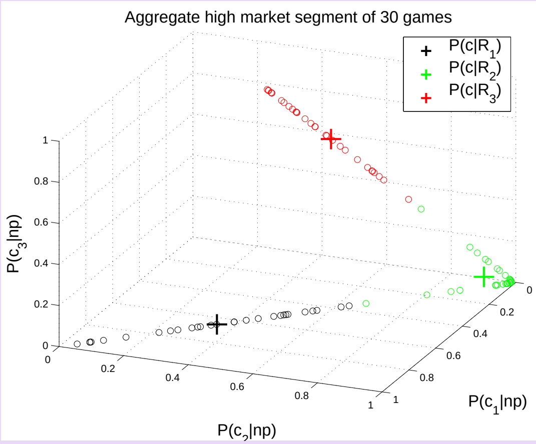
1. Compute $\vec{\eta}(\mathrm{np}_j)$ which is $\vec{\eta}$ evaluated at the np_j price.
2. Cluster these collections of vectors using k-means.
3. The center of each cluster corresponds to a regime R_k.



Low Market



Medium Market



High Market

Off-line Regime Identification

Marginalizing over the components c_i we obtain:

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

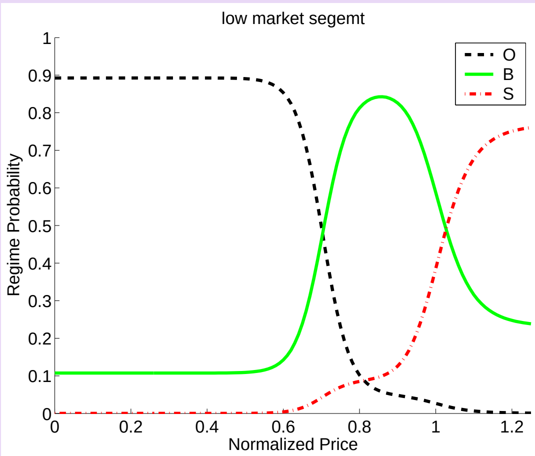
where R_k is a specific regime.

Using Bayes' rule we determine the posterior probability:

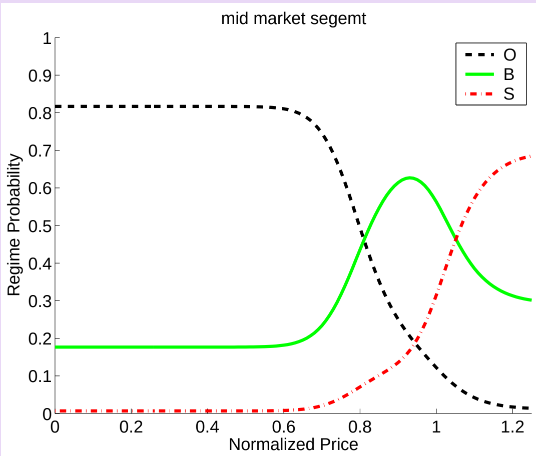
$$P(R_k|\mathrm{np}) = \frac{p(\mathrm{np}|R_k)\, P(R_k)}{\sum_{k=1}^{R} p(\mathrm{np}|R_k)\, P(R_k)} \quad \forall k = 1, \cdots, M$$

The prior probabilities $P(R_k)$ are determined by a counting process over a collection of entire games.

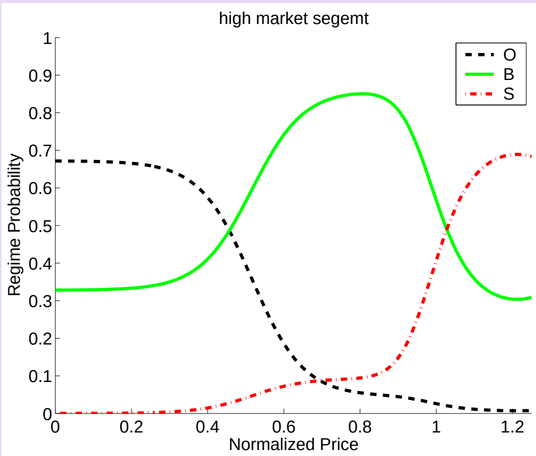
Example Regime Probability – offline



Low Market



Medium Market



High Market

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

Proposed Approach

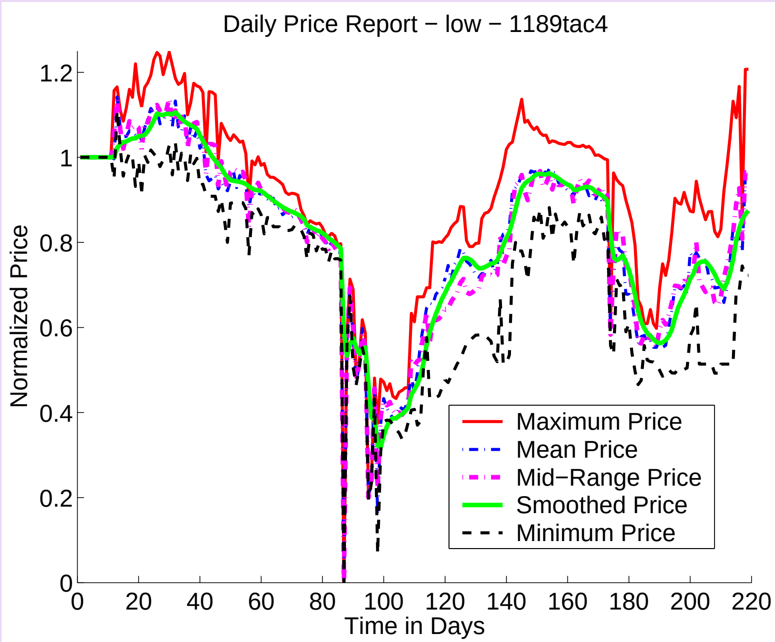
1. Off-line identification of regimes from past game data.
2. Online identification of regimes from data available in the current game.
3. Prediction of regime transitions.
4. Prediction of price density and trends using regimes.

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.

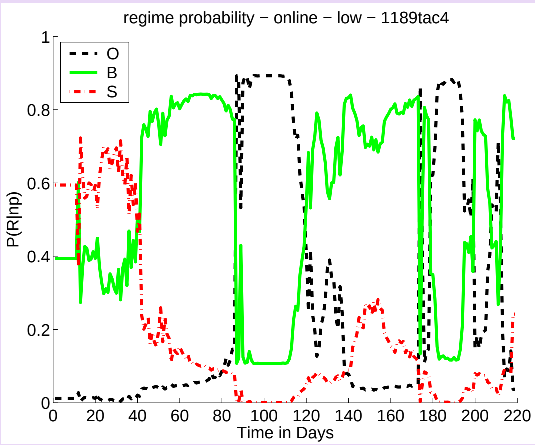
Online Identification of the Current Regime



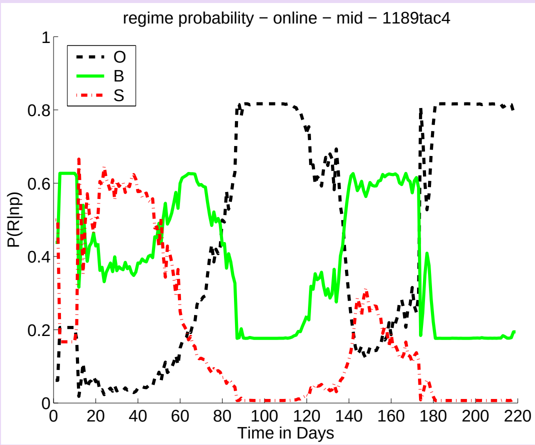
Daily price report: Minimum and maximum order prices.

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

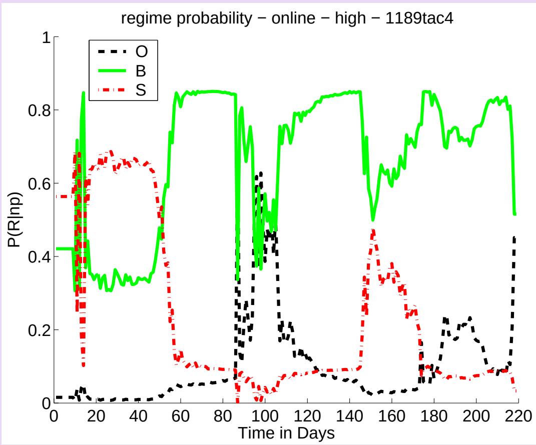
Example Regime Probability – online



Low Market



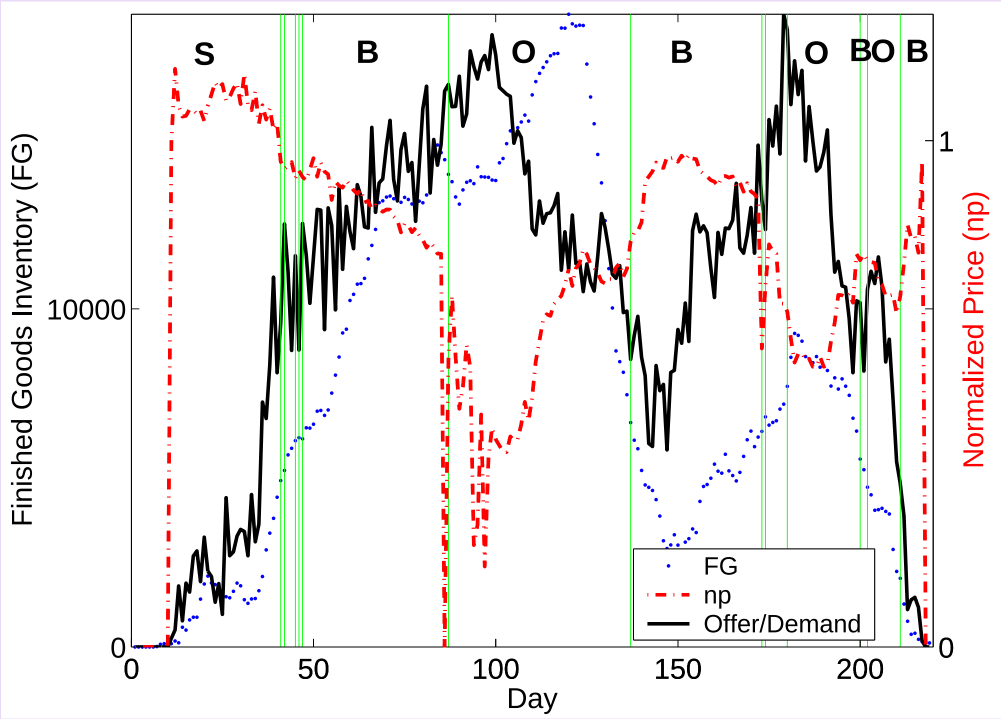
Medium Market



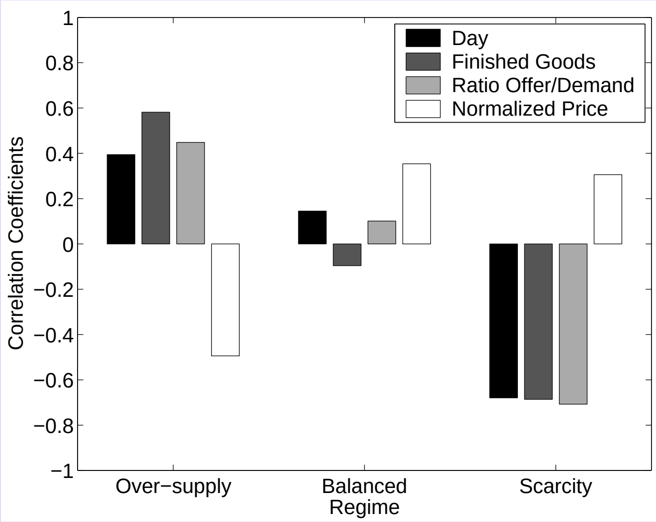
High Market

$\vec{P}(R_k|\overline{\text{np}}_{day})\ \ \forall k = 1, \cdots, M$ calculated online for game 1189@tac4.

Regime Market Parameters for the Low Market Segment



Game 1189@tac4: Ratio offer/demand, finished goods inventory, normalized prices, regime transitions.



Game 1189@tac4: Correlation coefficients of market parameters by regime.

Proposed Approach

1. Off-line identification of regimes from past game data.
2. Online identification of regimes from data available in the current game.
3. Prediction of regime transitions.
4. Prediction of price density and trends using regimes.

Online Prediction of Regimes (1)

We model the prediction of the next regime as a Markov process, using two steps:

Correction: recursive Bayesian update of posterior regime probabilities based on the history of smoothed mid-range normalized prices since the last regime change.

Prediction: posterior regime probabilities are predicted for current and future days based on the history of smoothed mid-range normalized prices since the last regime change.

Online Prediction of Regimes (2)

Prediction of regimes for n days into the future dependent on previous normalized prices since the last regime change.

$$\vec{P}(r_{t+n}|\{\overline{\mathrm{np}}_{t_0},\ldots,\overline{\mathrm{np}}_{t-1}\}) \\ = \sum_{r_{t+n}} \cdots \sum_{r_{t-1}} \left\{ \vec{P}(r_{t-1}|\{\overline{\mathrm{np}}_{t_0},\ldots,\overline{\mathrm{np}}_{t-1}\}) \right. \\ \left. \cdot \prod_{j=0}^{n} \mathbf{T}_{\mathbf{predict}}(r_{t+j}|r_{t+j-1}) \right\}$$

$\mathbf{T}_{\mathbf{predict}}$ is updated in each prediction step.

Results on Prediction of Regimes

Prediction results computed every day for the next 20 days from day 1 to day 199.

	low market	medium market	high market
	avg/stdev	avg/stdev	avg/stdev
# regime changes over an entire game	9.75/9.85	7.88/4.97	3.69/1.72
% correct regime prediction for the next 20 days	73.87%	85.30%	97.83%

Proposed Approach

1. Off-line identification of regimes from past game data.
2. Online identification of regimes from data available in the current game.
3. Prediction of regime transitions.
4. Prediction of price density and trends using regimes.

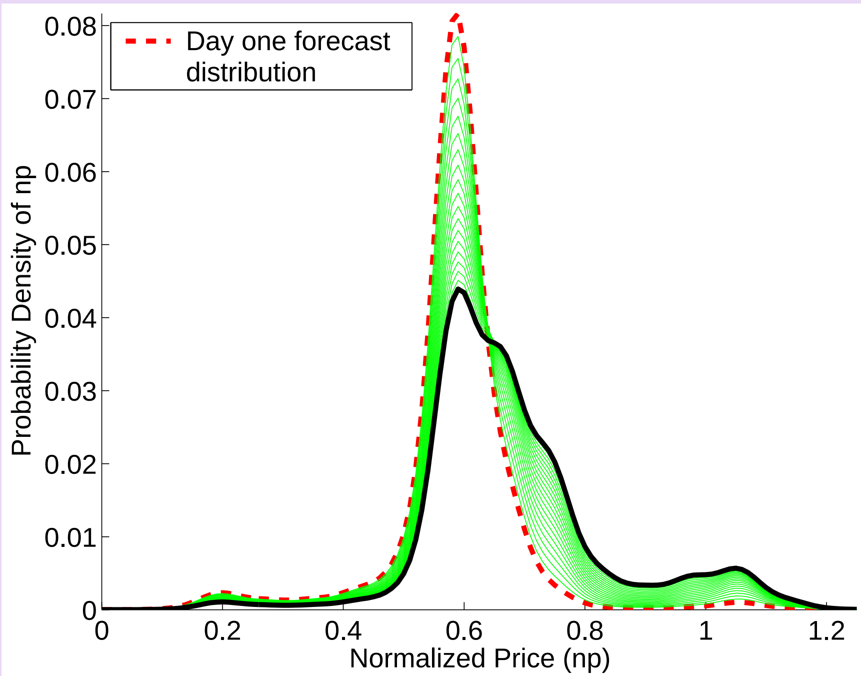
Prediction of Price Density

$$p(\mathrm{np}_{t+n} | \{\overline{\mathrm{np}}_{t_0}, \ldots, \overline{\mathrm{np}}_{t-1}\}) = \sum_{j=1}^{N} P(c_{j,t+n})\, p(\mathrm{np}|c_j)$$

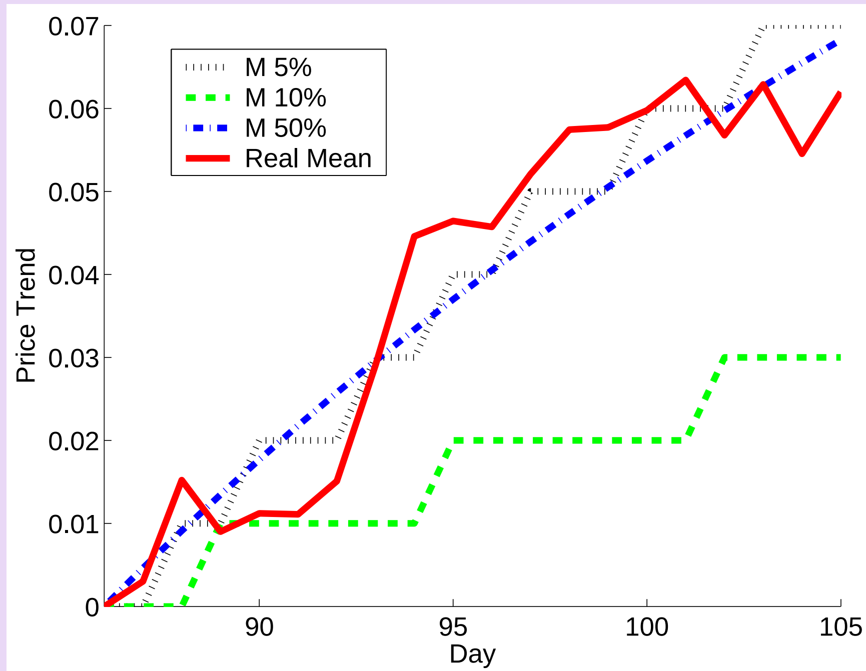
We sample np from 0 to 1.25 with 0.01 price increments.

$\Rrightarrow$

Price Density and Trend Prediction



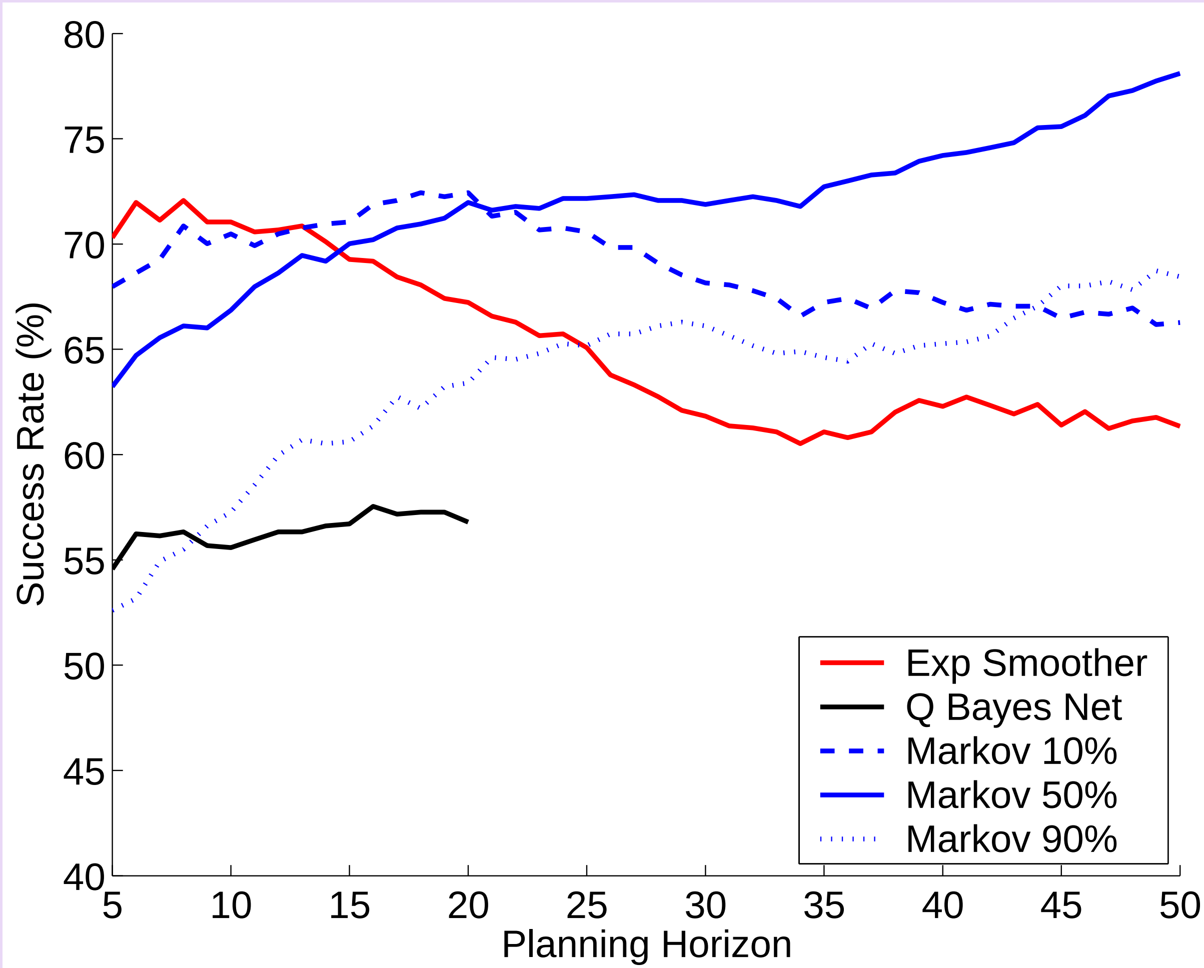
Predicted Price Density



Predicted Price Trend

Example: Game 3717tac3

Evaluating Prediction Quality



Success rate over a varying planning horizon.

Future Work (1)

- Enhance sales strategy to take full advantage of regime forecasting and price density, e.g.,
  - quantify regime prediction
  - measure confidence interval
- Develop procurement strategies that take advantage of regime forecasting.
- 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.

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.,
  - Amazon
  - eBay

Conclusions

- Off-line identification of economic regimes from past game data.
- Online identification of economic regimes from data available in the current game.
- Prediction of economic regime transitions.
- Prediction of price density and trends.

Contact

email: `ketter@cs.umn.edu`

URL: `www.cs.umn.edu/~ketter`

Credits

Many thanks to:

- John Collins
- Maria Gini
- Alok Gupta
- Paul Schrater

Prediction of Price Density

$$p(\mathrm{np}_{t+n}|\{\overline{\mathrm{np}}_{t_0},\ldots,\overline{\mathrm{np}}_{t-1}\})$$

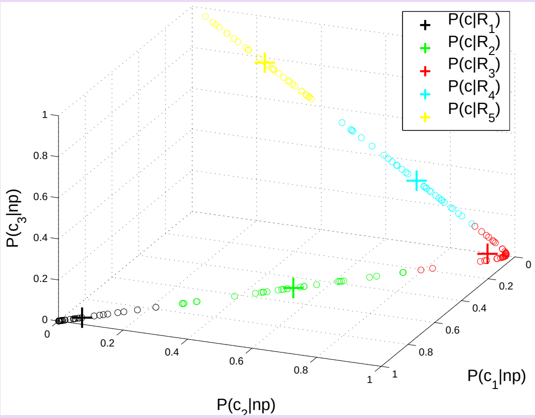
$$=\sum_{i=1}^{M} P(\mathrm{np}|R_i)\, P(R_{i,t+n}|\{\overline{\mathrm{np}}_{t_0},\ldots,\overline{\mathrm{np}}_{t-1}\})$$

$$=\sum_{j=1}^{N} \underbrace{\sum_{i=1}^{M} P(c_j|R_i)\, P(R_{i,t+n}|\{\overline{\mathrm{np}}_{t_0},\ldots,\overline{\mathrm{np}}_{t-1}\})}_{P(c_{j,t+n})}\, p(\mathrm{np}|c_j)$$

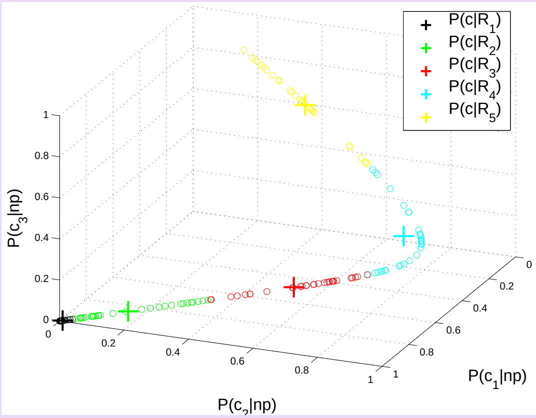
$$=\sum_{j=1}^{N} P(c_{j,t+n})\, p(\mathrm{np}|c_j)$$

$\Lleftarrow$

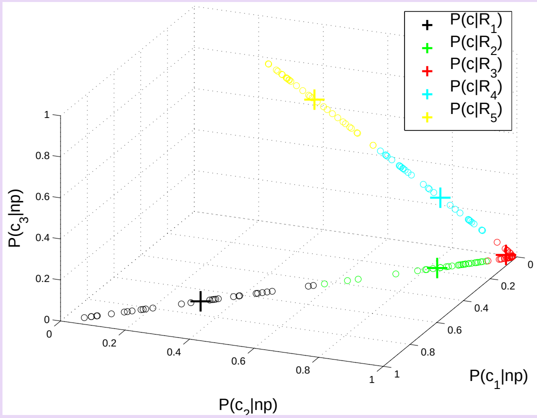
Definition of 5 Regimes with 3 Gaussians



Low Market



Medium Market



High Market