Price Distribution and Trend Prediction in TAC SCM Using Economic Regimes

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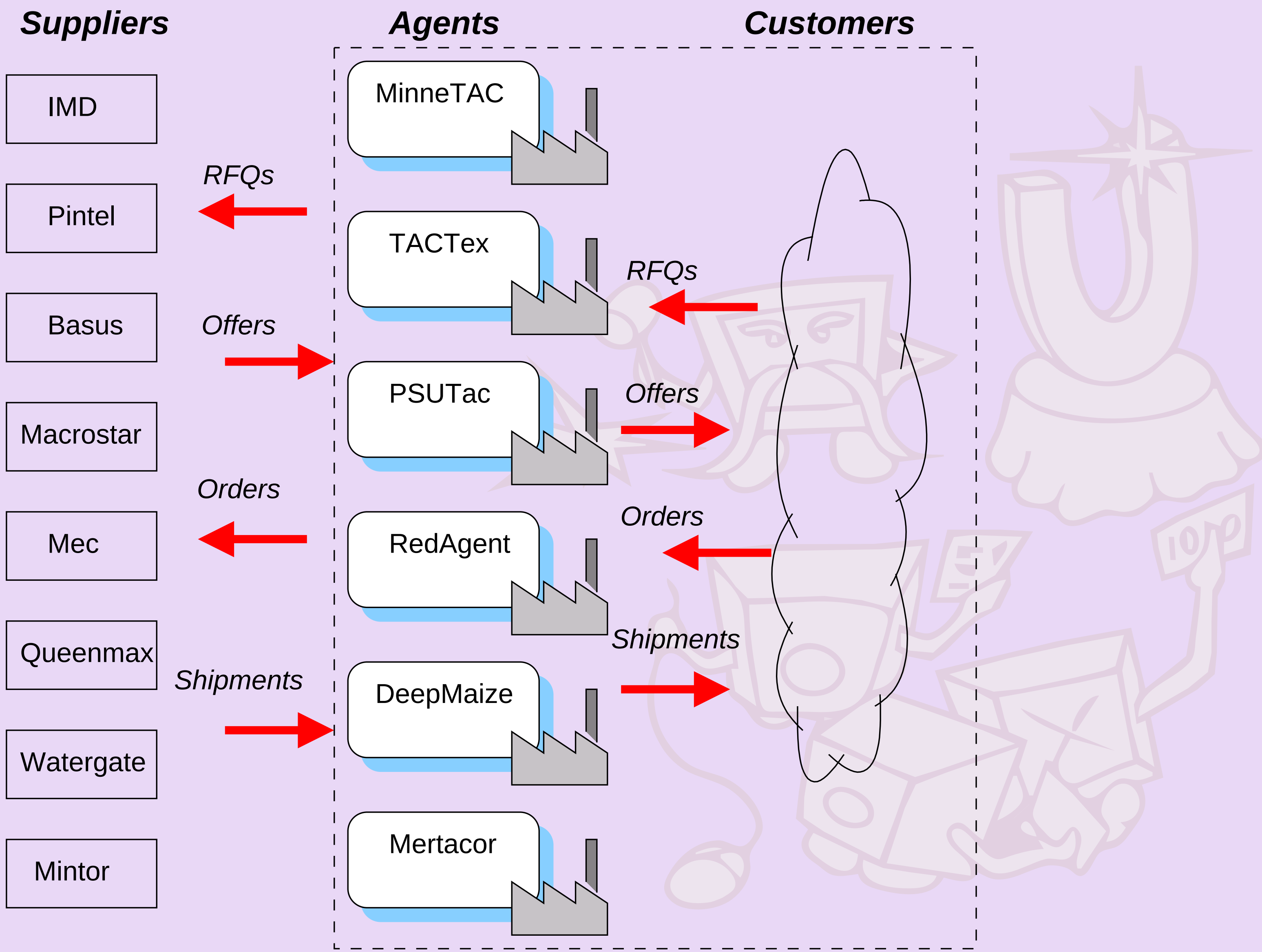
Overview

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

TAC SCM - Game Overview

- Six autonomous agents compete to maximize profits in a computer-assembly scenario.
- Agents compete for customer orders and for procurement of various components.
- The simulation takes place over 220 virtual days, each lasting fifteen seconds of real time.
- At the end (game/tournament), the agent with the most money in its bank account is the winner.

TAC SCM - Scenario



TAC SCM - Components

- PCs are built from 4 component types: CPUs, motherboards, memory, and hard drives.
- CPUs and motherboards have two product families: Pintel and IMD.
- Given at the start of each game:
  - Component catalog: Information about the components (id, base price, supplier, name)
  - Bill of materials: Description of PC types (SKU, components, # assembly cycles)

TAC SCM - Suppliers

- There are 8 suppliers in total, 2 for each component type.
- Each day an agent can send a maximum of 10 Request for Quotes (RFQs) to each supplier.
- This allows an agent to probe the supplier without swamping it with too many messages.

TAC SCM - Customers

- Request PCs of different types to be delivered on a certain due date.
- The quantity of each order is chosen uniformly between [1,20].
- Agents must bid to satisfy the entire order (both in quantity and due date) for a bid to be acknowledged.

TAC SCM - Assembly Agents (1)

These are the competitors in the game!
What do agents do each day?

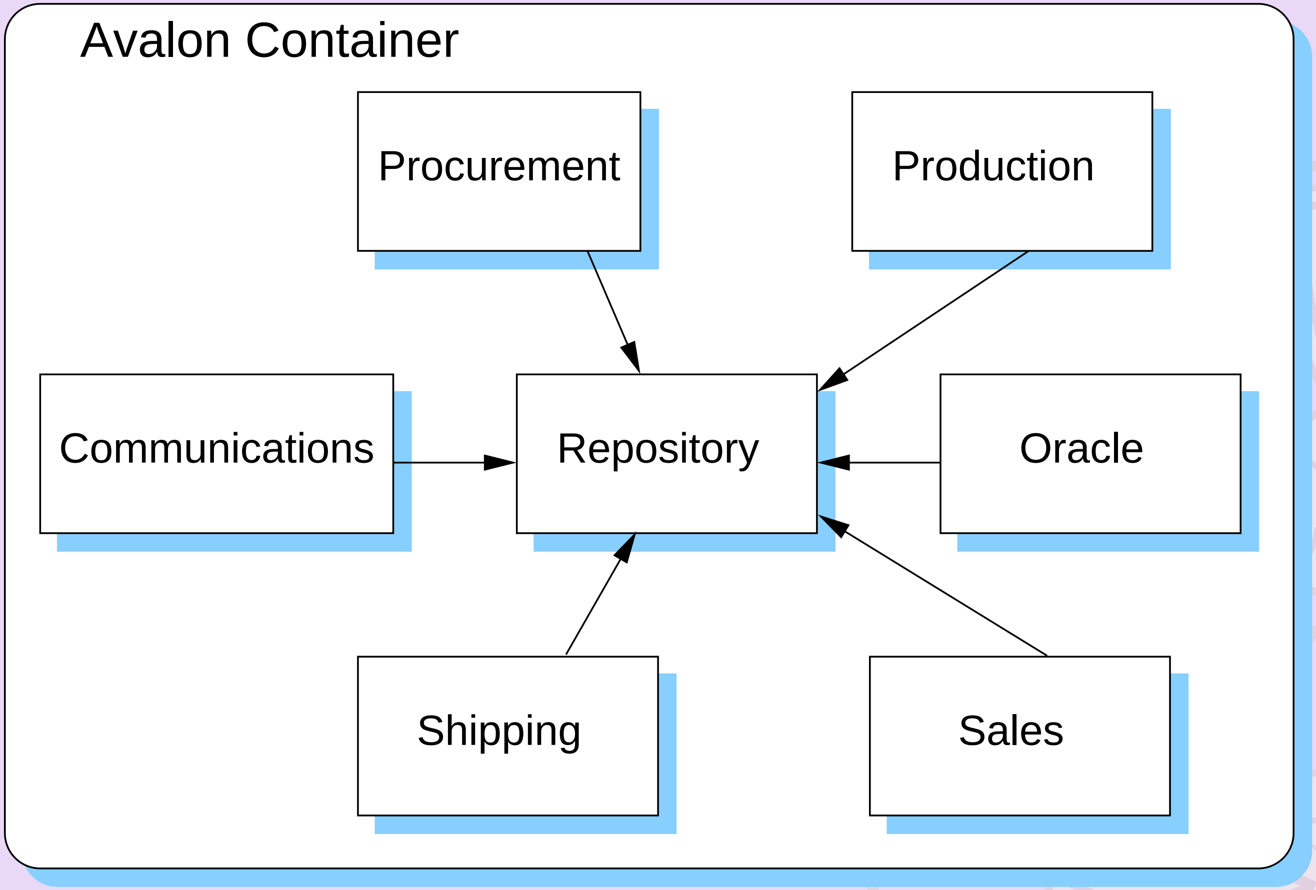
- Negotiate supply contracts.
- Bid for customer orders.
- Manage daily assembly lines.

TAC SCM - Assembly Agents (2)

Each day the agents receive:

- RFQs and orders won from customers.
- Quotes and delivery of parts from component suppliers.
- Bank account statement.
- PC and component inventory report from the factory.

MinneTAC - Architecture



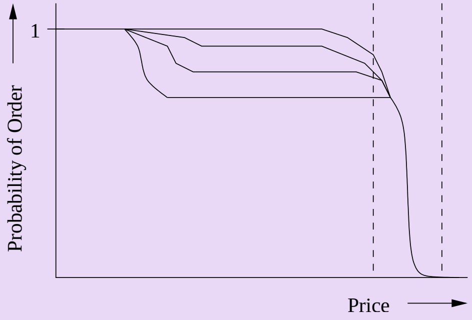
Arrows indicate API dependencies.

Motivation

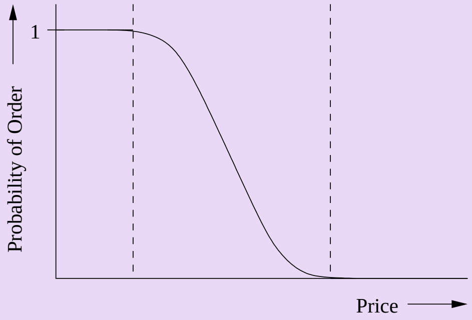
- Economic theory suggests that markets exhibit 3 dominant statistical conditions: over-supply, balanced, and scarcity.
- We call these distinguishable conditions *regimes*.
- The long term objective of our work is to show how knowledge of current and anticipated regimes can enable an agent to make better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

Relationship between Prices, Order Probability, and Regimes

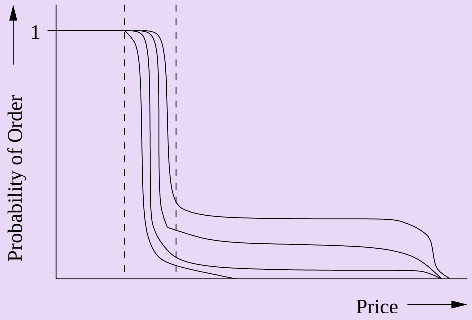
Scarcity:



Balanced:

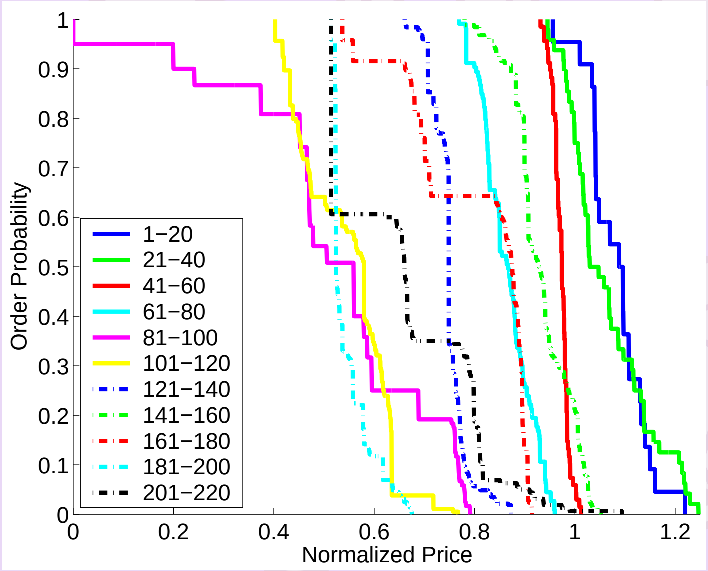


Over-supply:



Reverse cumulative density function represents probability of order.

Experimental:



Related Work (1)

Regime/Demand Prediction:

Pauwels et al., 2002/2004 An analysis on how in economic markets strategic windows of change alternate with long periods of stability.

Wellman et al., 2005 A method for predicting future demand in TAC SCM. Their approach depends on knowing the demand formula.

Kiekintveld et al., 2004 A method for an agent in TAC SCM that uses feedback control actions to suppress deviations from a desired region.

Related Work (2)

Price Prediction

- Kephart et al., 2000
- Brooks et al., 2002
- Schapire et al., 2002
- Wellman et al., 2003
- . . .

Opponent Modelling

- Carmel et al., 1993
- Littman, 1994
- Chajewska et al., 2001

Probability of Order

- Papaioannou et al., 2000
- Benisch et al., 2004
- Ketter et al., 2004
- Pardoe et al., 2004
- . . .

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 distributions and trends using regimes.

Off-line Regime Identification (1)

We use a Gaussian mixture model (GMM):

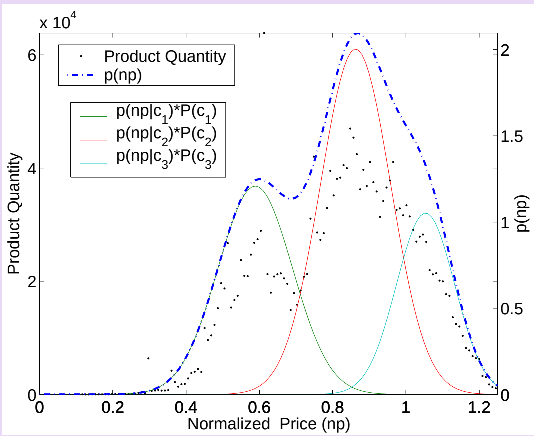
$$p(\mathrm{np}) = \sum_{i=1}^{N} p(\mathrm{np}|c_i)\, P(c_i)$$

where

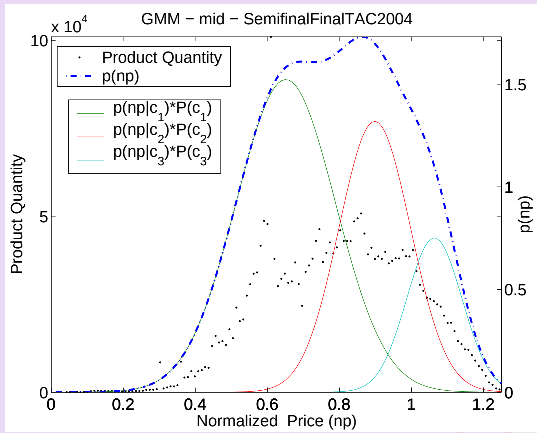
- $p(\mathrm{np})$ is the density of the normalized price (np).
- $p(\mathrm{np}|c_i) = N[\mu_i, \sigma_i](\mathrm{np})$ is the i-th Gaussian of the normalized price density from the GMM.
- $P(c_i)$ is the prior probability of the i-th Gaussian.

Off-line Regime Identification (2)

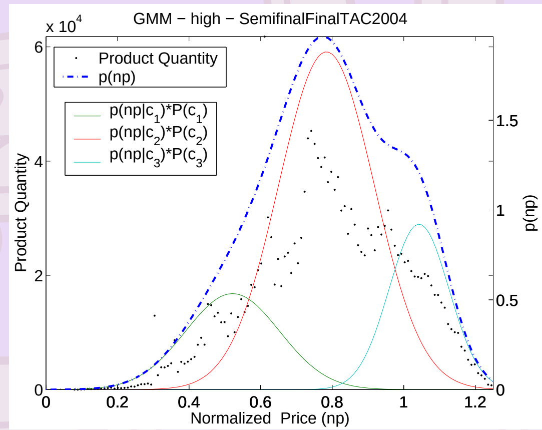
The EM-Algorithm determines the Gaussians (μ_i,σ_i, and $P(c_i)$) of the GMM, where $\forall i = 1, \cdots, N$. Assumption: $N = 3$.



Low Market



Medium Market



High Market

Using Bayes' rule we determine the posterior probability:

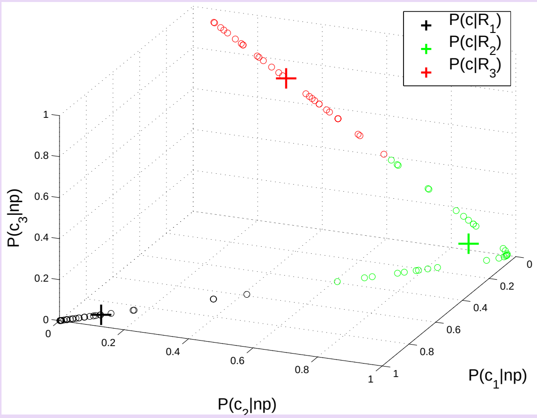
$$P(c_i|\mathrm{np}) = \frac{p(\mathrm{np}|c_i)\,P(c_i)}{\sum_{i=1}^{N} p(\mathrm{np}|c_i)\,P(c_i)} \qquad \forall i = 1, \cdots, N$$

Off-line Regime Identification (3)

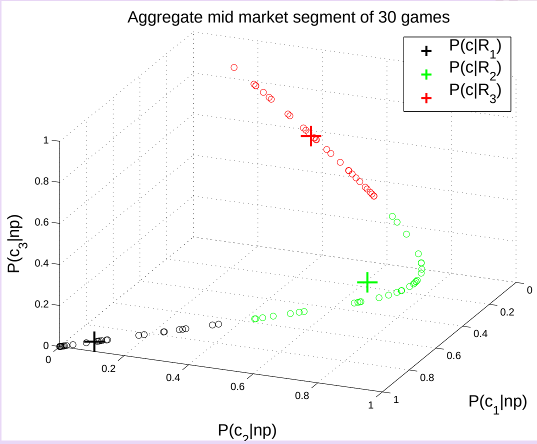
We define the N-dimensional vector

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

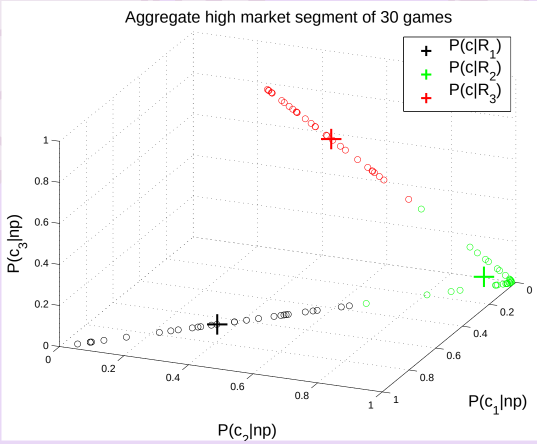
1. Compute $\vec{\eta}(\mathrm{np}_j)$ which is $\vec{\eta}$ evaluated at the np_j price.
2. Cluster these collections of vectors using k-means.
3. The center of each cluster corresponds to a regime R_k.



Low Market



Medium Market



High Market

Off-line Regime Identification (4)

Marginalizing over the components c_i we obtain:

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

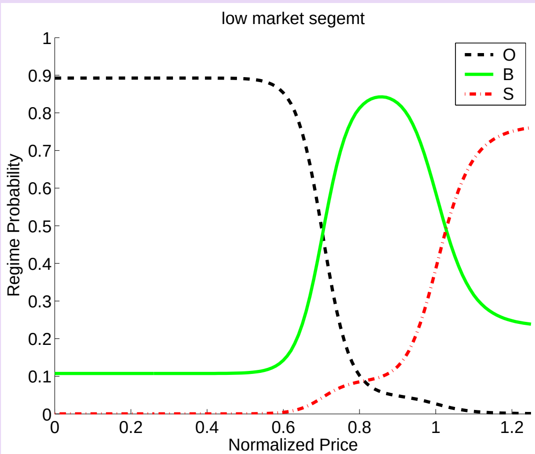
where R_k is a specific regime.

Using Bayes' rule we determine the posterior probability:

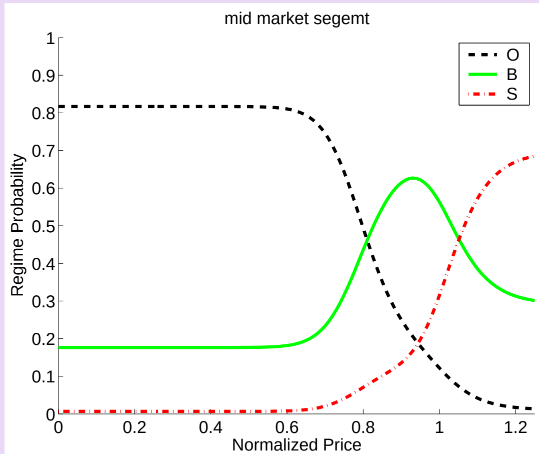
$$P(R_k|\mathrm{np}) = \frac{P(\mathrm{np}|R_k)\, P(R_k)}{\sum_{k=1}^{R} P(\mathrm{np}|R_k)\, P(R_k)} \quad \forall k = 1, \cdots, M$$

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

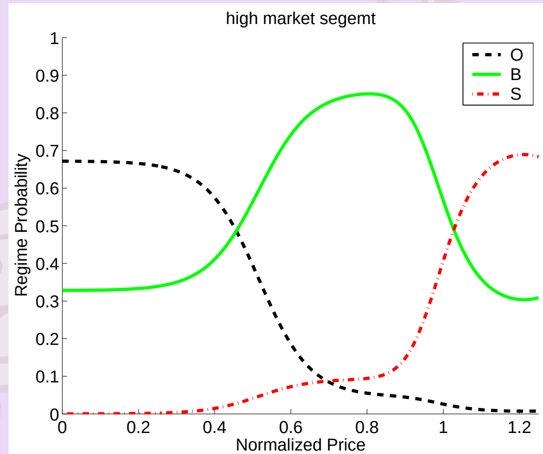
Regime Probability over Price for the 3 Market Segments



Low Market



Medium Market



High Market

$P(R_k|\mathrm{np})$ calculated off-line from 26 games.

Proposed Approach

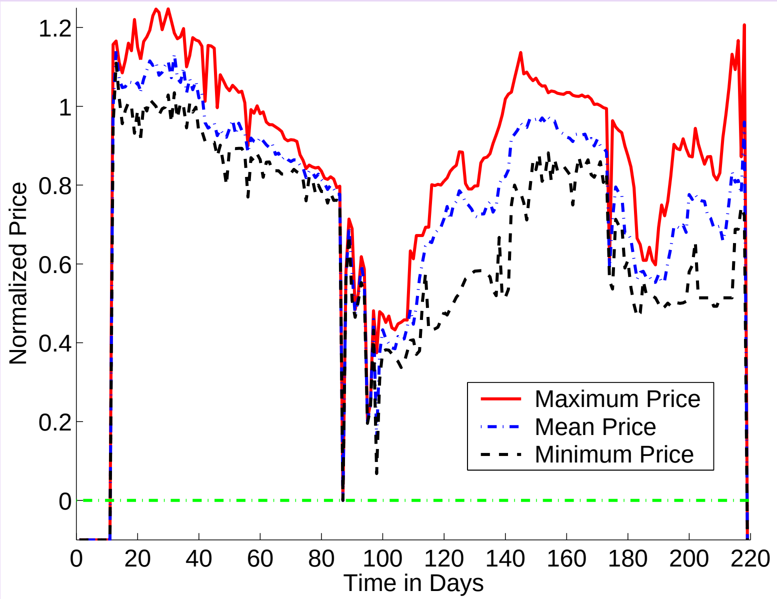
1. Off-line identification of regimes from past game data.
2. Online identification of regimes from data available in the current game.
3. Prediction of regime transitions.
4. Prediction of price distributions and trends using regimes.

Available Information 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.

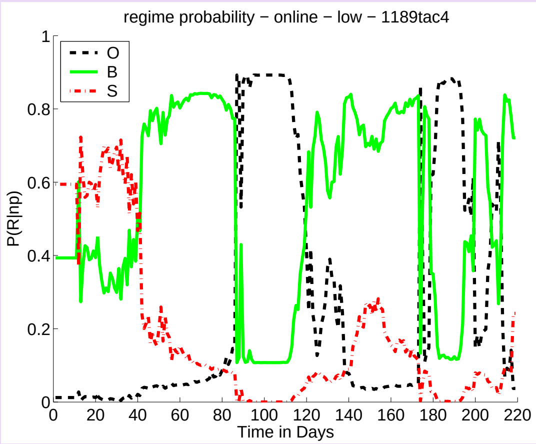
Online Identification of the Current Regime



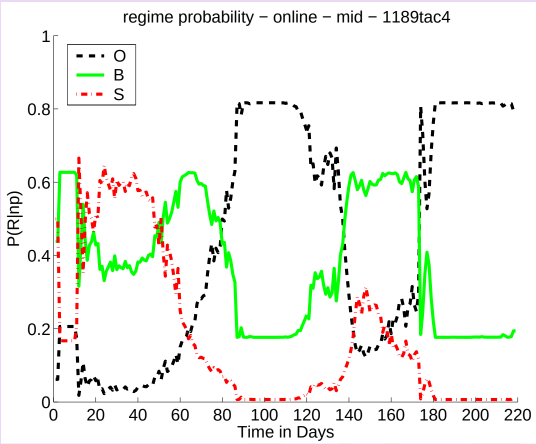
Daily price report: Minimum and maximum order prices.

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

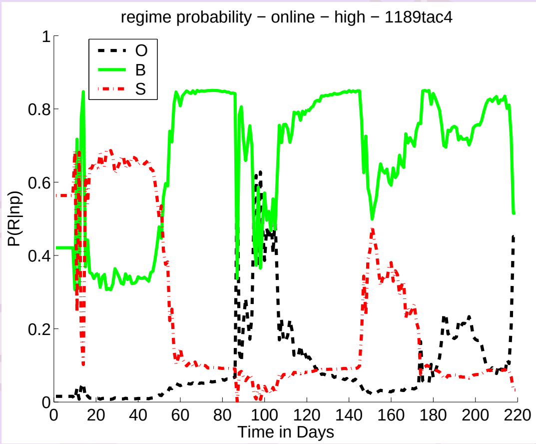
Regime Probability – online for the 3 Market Segments



Low Market



Medium Market

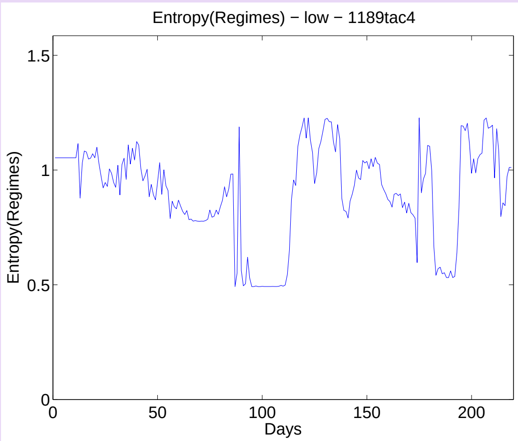


High Market

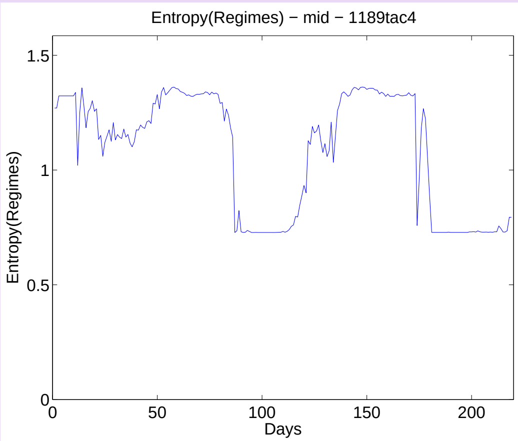
$\vec{P}(R_k|\overline{\mathrm{np}}_{day})\ \forall k = 1, \cdots, M$ calculated online for game 1189@tac4.

Regime Confidence Measure

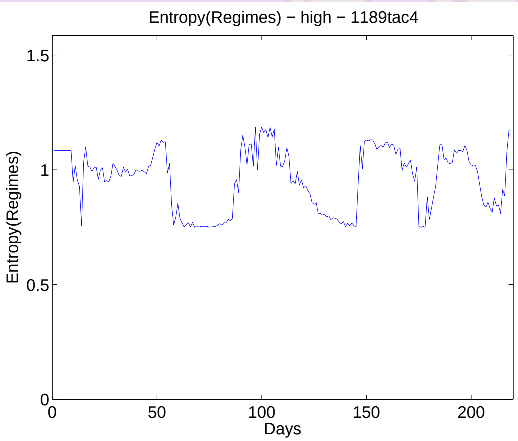
$$Entropy = \sum_{k=1}^{M} -P(R_k|\overline{\text{np}}_{day}) \log_2 P(R_k|\overline{\text{np}}_{day}) \qquad \forall k = 1, \cdots, M$$



Low Market



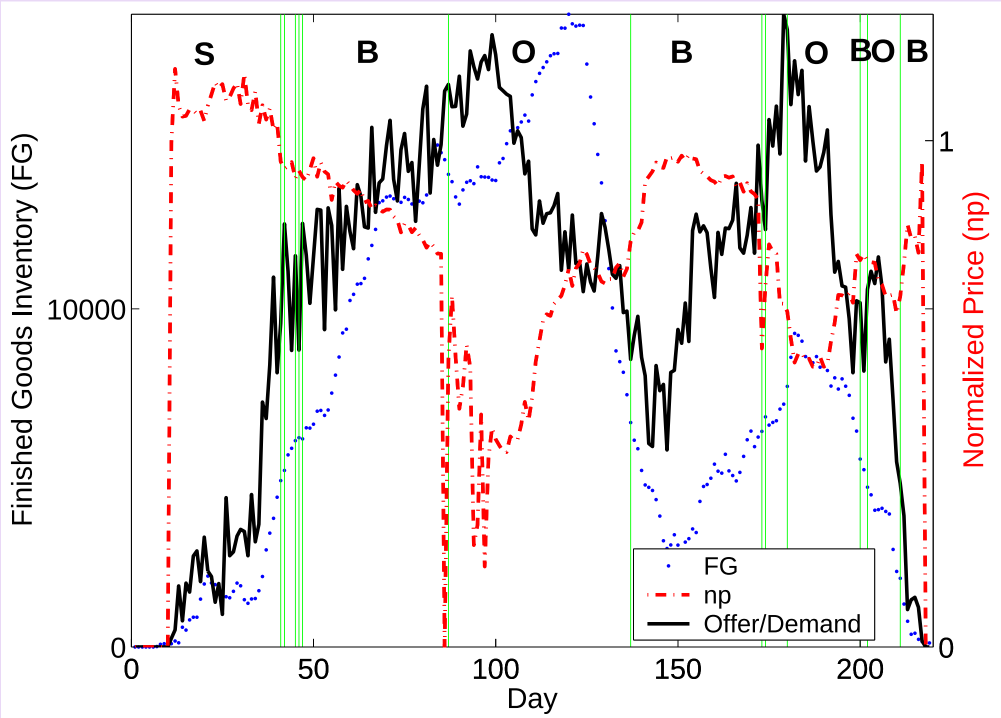
Medium Market



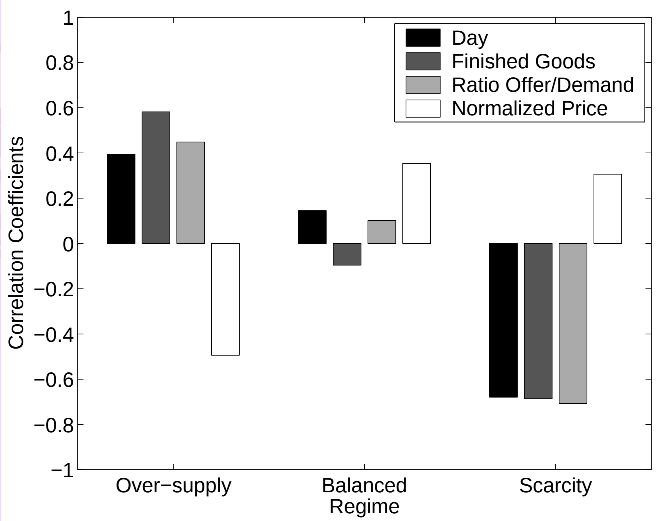
High Market

Example: 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 distributions and trends using regimes.

Prediction of Regimes

Markets exhibit time dependent behavior and agents should be able to predict which regime will the market transition next. We model the prediction of the next regime as a Markov process.

Online Prediction Of Regimes (1)

The prediction of regimes is based on a correction and prediction algorithm:

Correction recursive Bayesian update of posterior regime probabilities based on the history of normalized prices since the last regime change.

Prediction of posterior regime probabilities for the current and future days based on yesterday's normalized prices. The probability transition matrix $\mathbf{T}_{\mathbf{predict}}$ is updated in each prediction step.

Online Prediction Of Regimes (2)

$$
\begin{aligned}
&\vec{P}(r_{t+n}|\{\overline{\mathrm{np}}_{t_0}, \ldots, \overline{\mathrm{np}}_{t-1}\}) \\
&\quad = \sum_{r_{t+n}} \cdots \sum_{r_{t-1}} \vec{P}(r_{t-1}|\{\overline{\mathrm{np}}_{t_0}, \ldots, \overline{\mathrm{np}}_{t-1}\}) \\
&\qquad\quad \cdot \prod_{j=0}^{n} \mathbf{T}_{\mathbf{predict}}(r_{t+j}|r_{t+j-1})
\end{aligned}
$$

Prediction of regimes dependent on yesterday's normalized prices for n days into the future. The probability transition matrix $\mathbf{T}_{\mathbf{predict}}$ is updated in each prediction step.

Prediction Results of Future Regime and Regime Change

	low market	medium market	high market
	avg/stdev	avg/stdev	avg/stdev
# regime changes	9.75/9.85	7.88/4.97	3.69/1.72
correct regime	73.87%	85.30%	97.83%

Results shown are computed every day for the next 20 days from day 1 to day 199 (for a total of 3184 trials).

Proposed Approach

1. Off-line identification of regimes from past game data.
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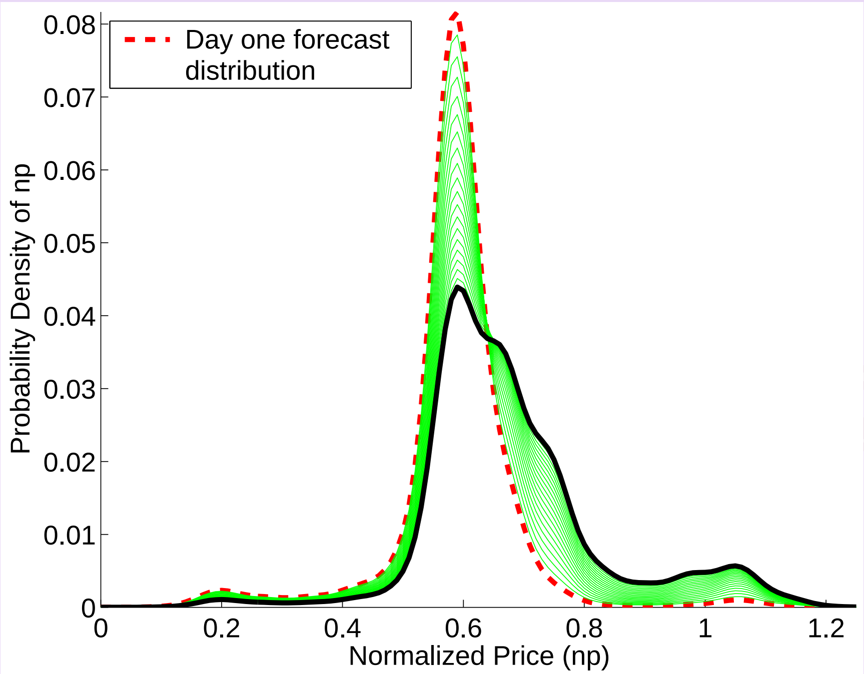
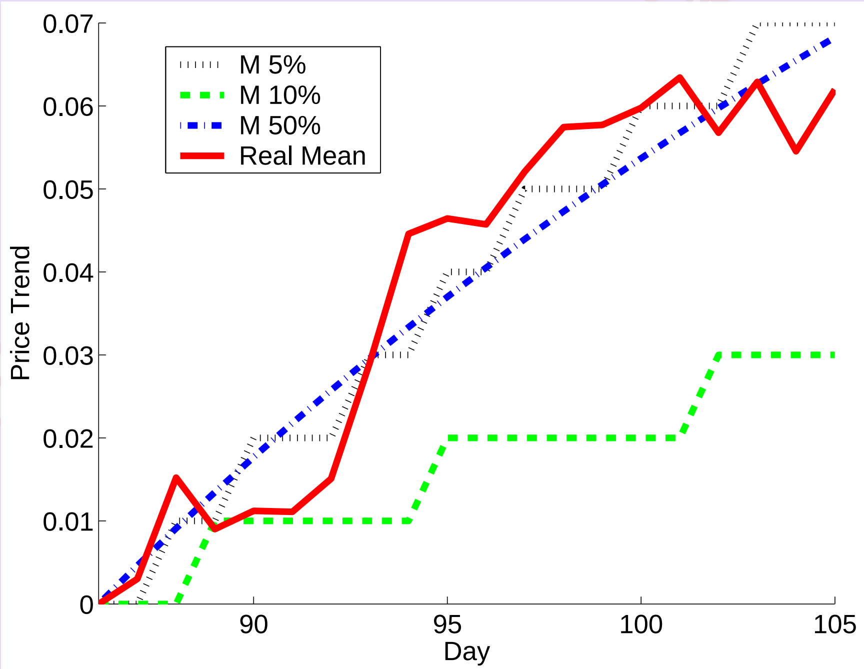
Price Distribution (1)

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

Price Distribution (2)



Price Distribution



Price Trend

Example: Game 3717tac3

Evaluating Prediction Quality

Predictors	*Market Segment*	*Success Rate (%)*							
		Number of Regimes							
		3	4	5	6	7	8	9	
Q Bayes Net	Low	54.93	54.93	54.93	54.93	54.93	54.93	54.93	5
10 % Markov	Low	70.95	71.42	71.32	67.69	68.99	68.34	66.57	7
50 % Markov	Low	67.32	67.04	66.48	67.13	67.04	67.32	65.55	6
Q Bayes Net	Medium	57.45	57.45	57.45	57.45	57.45	57.45	57.45	5
10 % Markov	Medium	71.23	68.62	68.99	68.62	68.62	67.23	63.97	6
50 % Markov	Medium	72.25	72.16	67.78	71.60	67.32	69.65	68.44	6
Q Bayes Net	High	56.70	56.70	56.70	56.70	56.70	56.70	56.70	5
10 % Markov	High	70.11	70.30	73.18	74.49	74.39	72.16	72.35	7
50 % Markov	High	71.14	64.25	70.48	71.23	70.76	69.37	68.53	7
Mean Markov	All	70.48	68.69	70.00	69.70	69.34	68.31	67.55	6

Future Work

- Develop sales strategies that take advantage of regime forecasting.
- Integrate regime forecasting in the decision making process of the agent.
- Evaluate results.

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 distributions and trends.

Contact

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