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

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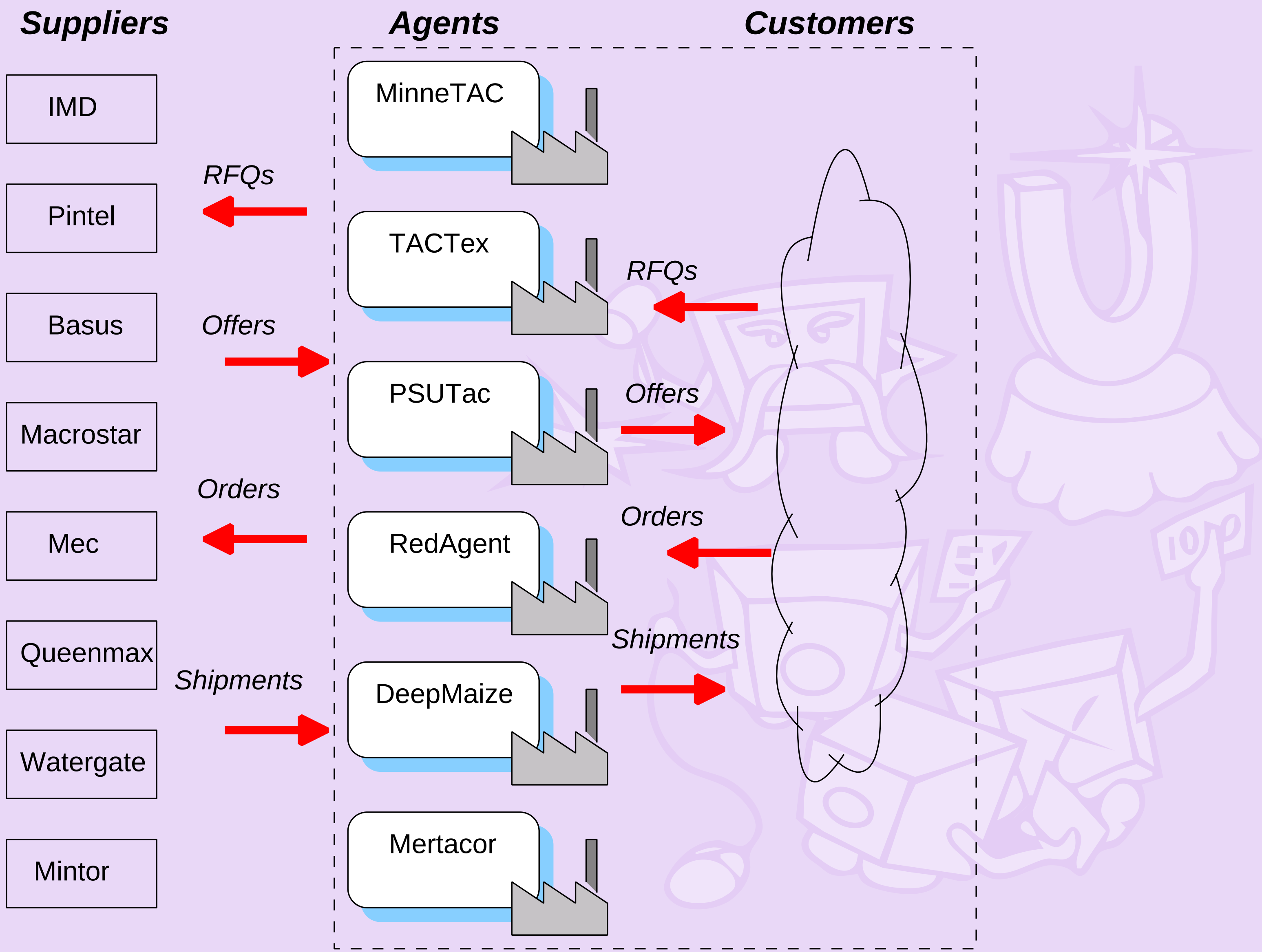
Overview

- TAC SCM - Game Overview
- Problem
- Proposed Solution
- Biggest Remaining Concerns
- Future Work
- Conclusion

TAC SCM - Game Overview

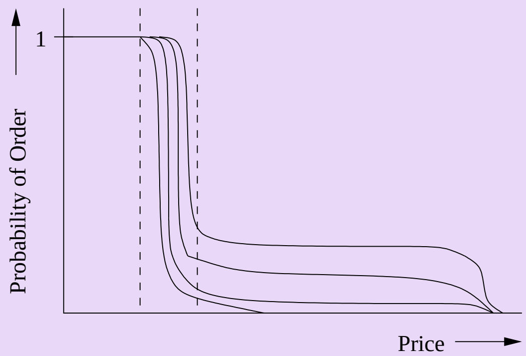
- Six autonomous agents:
  - Compete to acquire parts from suppliers.
  - Assemble parts into computers.
  - Compete for customer orders.
- The simulation takes place over 220 virtual days, each lasting 15 seconds of real time.
- At the end (game/tournament), the agent with the most money in its account is the winner.
- Supply and demand varies randomly through the game and across three market segments (low, medium, and high computer price).

TAC SCM - Scenario

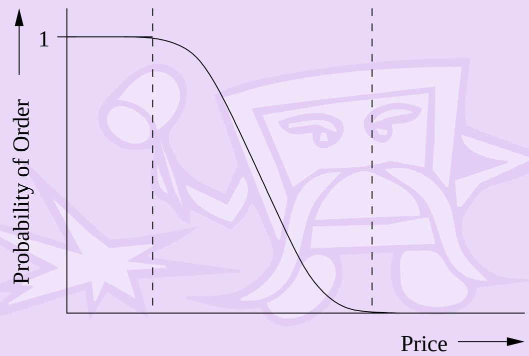


Economic Regimes

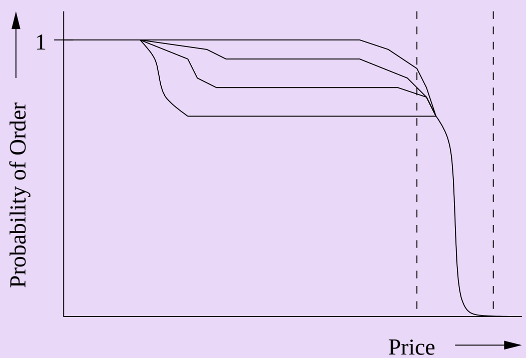
Reverse cumulative density function represents probability of order.



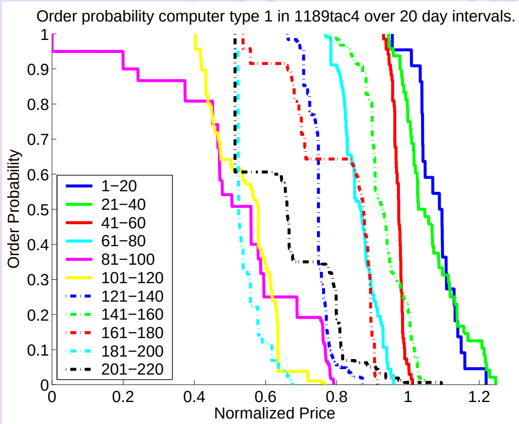
Over-supply



Balanced



Scarcity



Experimental

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. Biggest Remaining Concerns
   (a) Prediction of regime transitions.
   (b) Use regime prediction for sales strategies.

Off-line Regime Identification (1)

We use a Gaussian mixture model (GMM):

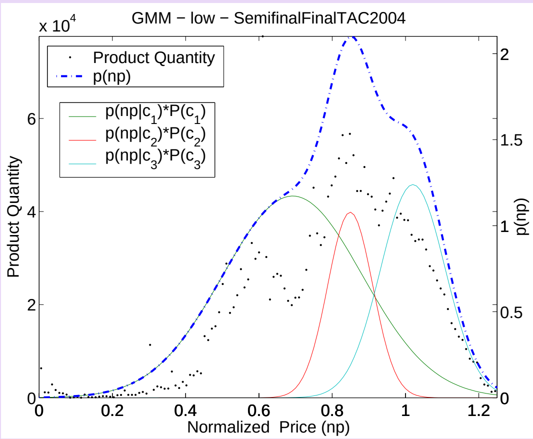
$$p(\mathrm{np}) = \sum_{i=1}^{N} p(\mathrm{np}|c_i)\, P(c_i)$$

where

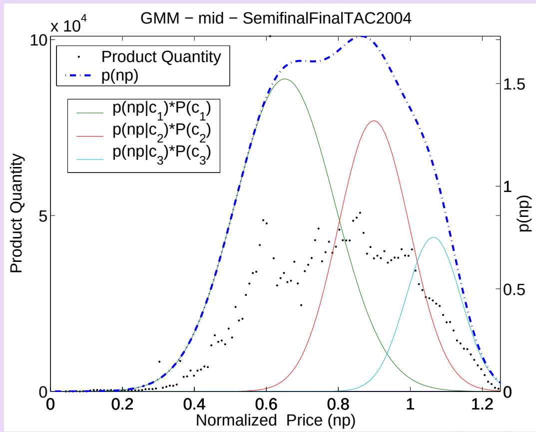
- np is the normalized price.
- $p(\mathrm{np}|c_i) = N[\mu_i, \sigma_i](\mathrm{np})$ is the i-th Gaussian of the normalized price density from the GMM.
- $P(c_i)$ is the prior probability of the i-th Gaussian.

Off-line Regime Identification (2)

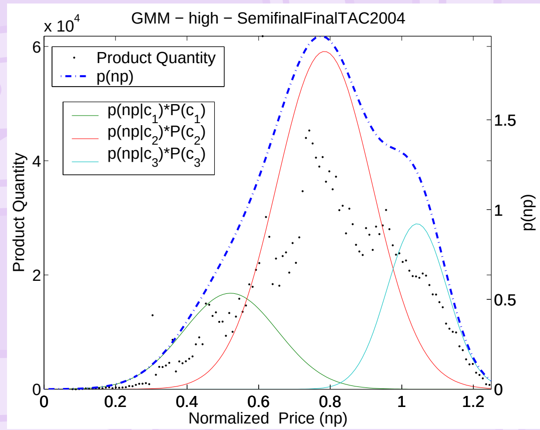
The EM-Algorithm determines the Gaussians (μ_i,σ_i, and $P(c_i)$) of the GMM, where $\forall i = 1, \cdots, N$. Assumption: $N = 3$.



Low Market



Medium Market



High Market

Using Bayes' rule we determine the posterior probability:

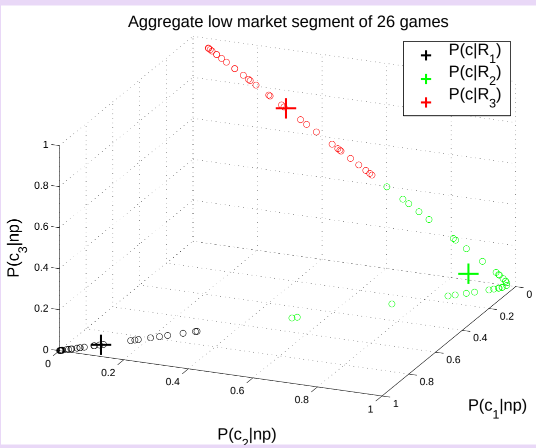
$$P(c_i|\mathrm{np}) = \frac{p(\mathrm{np}|c_i)\,P(c_i)}{\sum_{i=1}^{N} p(\mathrm{np}|c_i)\,P(c_i)} \qquad \forall i = 1, \cdots, N$$

Off-line Regime Identification (3)

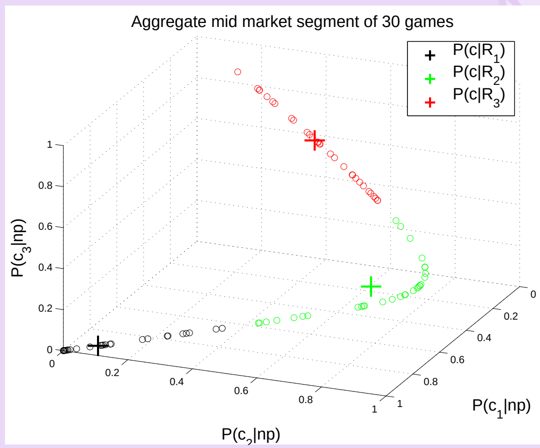
We define the N-dimensional vector

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

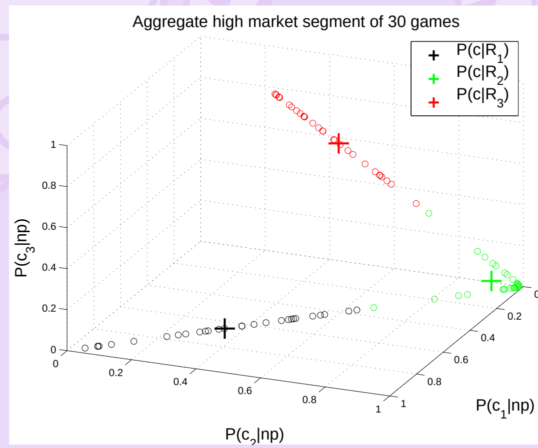
1. Compute $\vec{\eta}(\mathrm{np}_j)$ which is $\vec{\eta}$ evaluated at the np_j price.
2. Cluster these collections of vectors using k-means.
3. The center of each cluster corresponds to a regime R_k.



Low Market



Medium Market



High Market

Off-line Regime Identification (4)

Marginalizing over the components c_i we obtain:

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

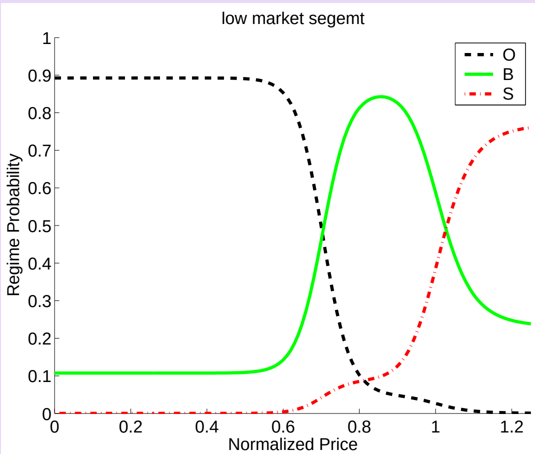
where R_k is a specific regime.

Using Bayes' rule we determine the posterior probability:

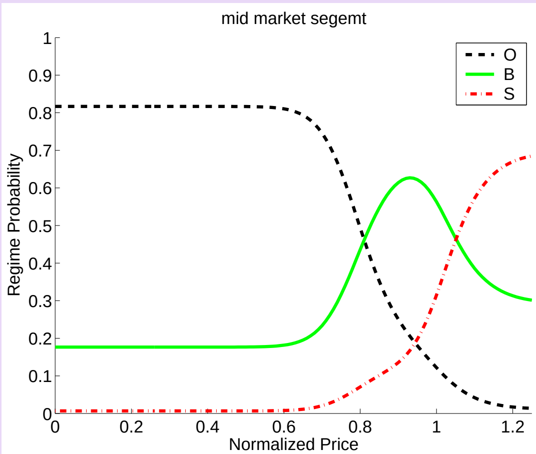
$$P(R_k|\mathrm{np}) = \frac{P(\mathrm{np}|R_k)\, P(R_k)}{\sum_{k=1}^{R} P(\mathrm{np}|R_k)\, P(R_k)} \quad \forall k = 1, \cdots, M$$

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

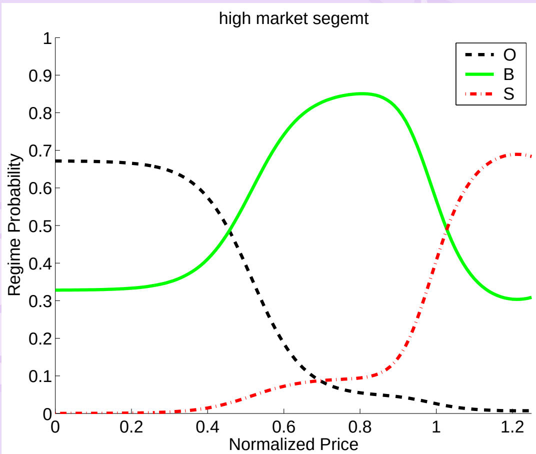
Regime Probability over Price for the 3 Market Segments



Low Market



Medium Market



High Market

Regime probability over price - 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. Biggest Remaining Concerns
   (a) Prediction of regime transitions.
   (b) Use regime prediction for sales strategies.

Available Information in the Customer Market

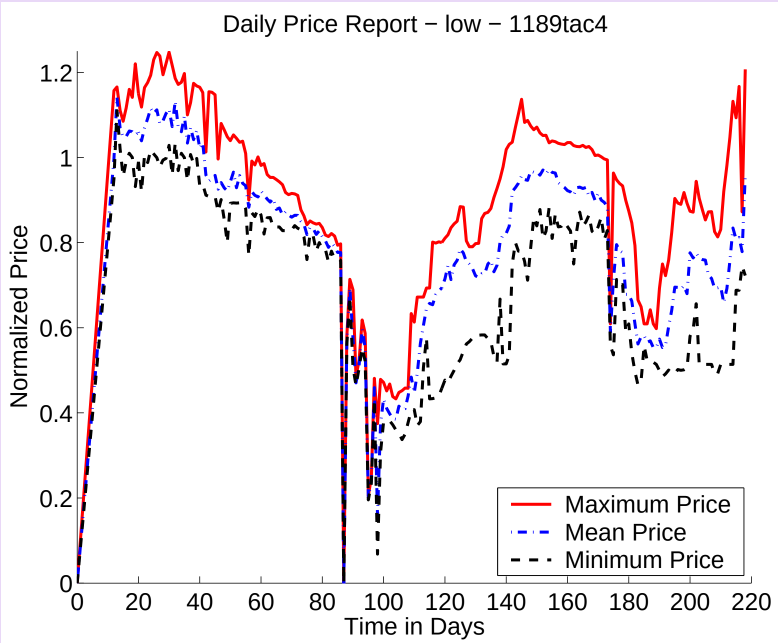
Every day:

1. RFQs (RFQid, computer type, due date, penalty, reserve price)
2. Lowest and highest price paid per computer type from the previous day.

Every 20 days (market report):

1. Total quantity per computer type ordered since the last market report.
2. Average order price per computer type ordered since the last market report.

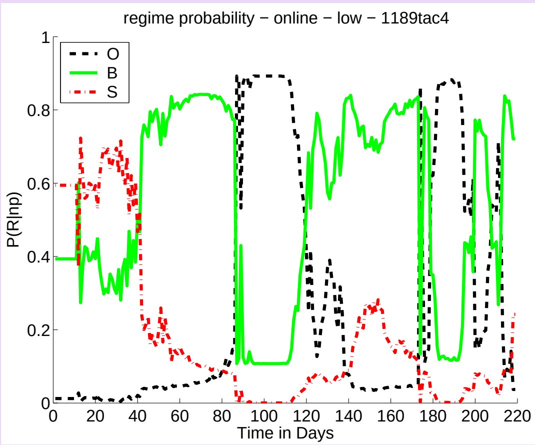
Online Identification of the Current Regime



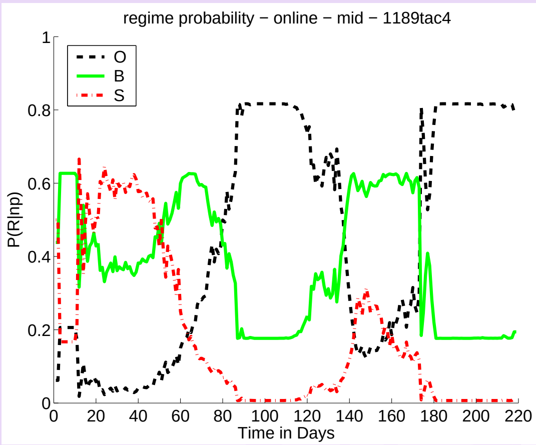
Daily price report: Minimum and maximum order prices.

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

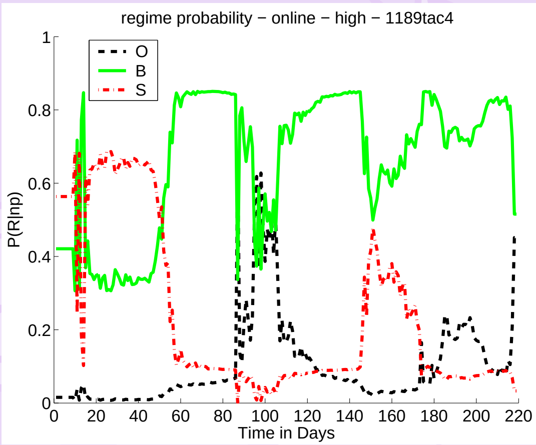
Regime Probability – online for the 3 Market Segments



Low Market



Medium Market

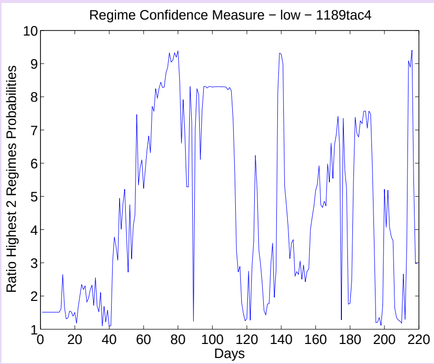


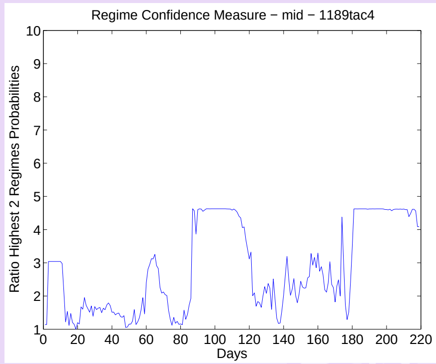
High Market

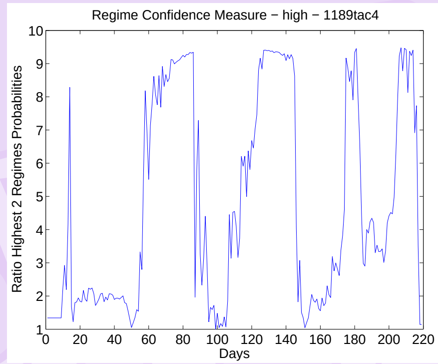
Game 1189@tac4: Regime probability over time.

Regime Confidence Measure

Game 1189@tac4: Ratio of highest and second highest regime probabilities.



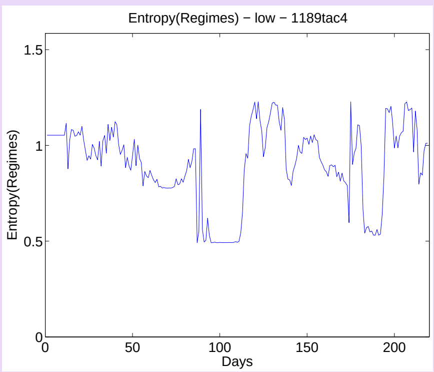


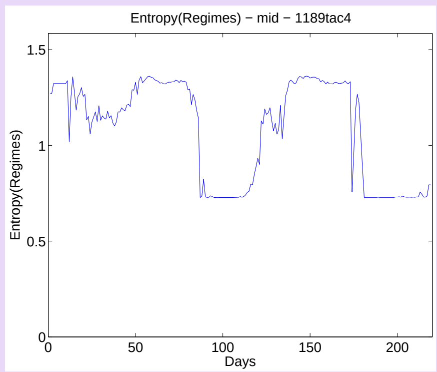


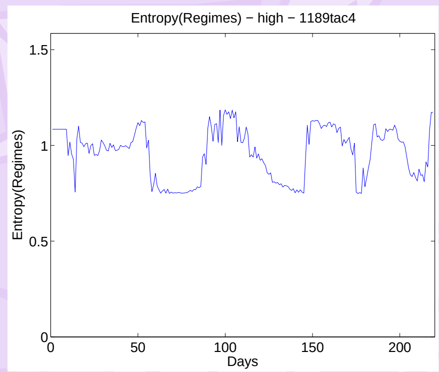
Low Market

Medium Market

High Market

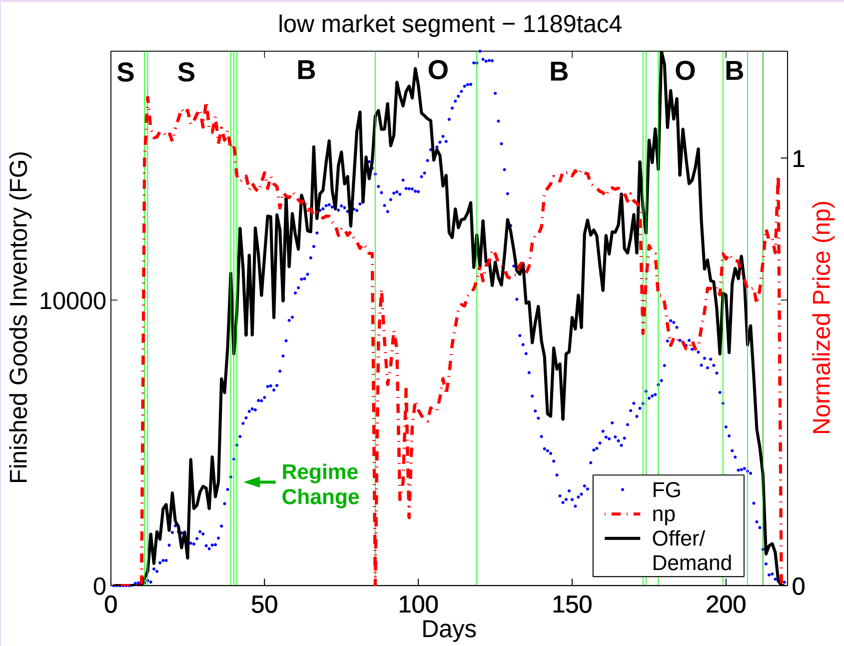


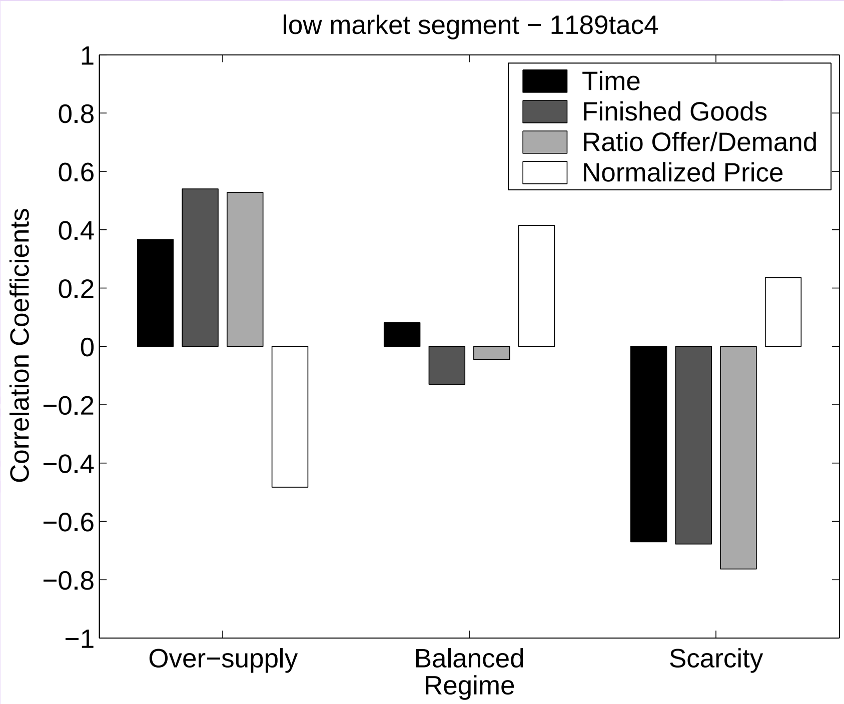




$$Entropy = \sum_{k=1}^{M} -P(R_k|\text{np}) \log_2 P(R_k|\text{np}) \qquad \forall k = 1, \cdots, M$$

Regime Market Parameters for the Low Market Segment





Game 1189@tac4: Ratio $\frac{Offer}{Demand}$, and finished goods inventory (left) and correlation coefficients between regimes and market parameters (right).

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. Biggest Remaining Concerns
   (a) Prediction of regime transitions.
   (b) Use regime prediction for sales strategies.

Prediction of Regimes

Agent behavior should depend on the current market regime and expectation of future regimes.

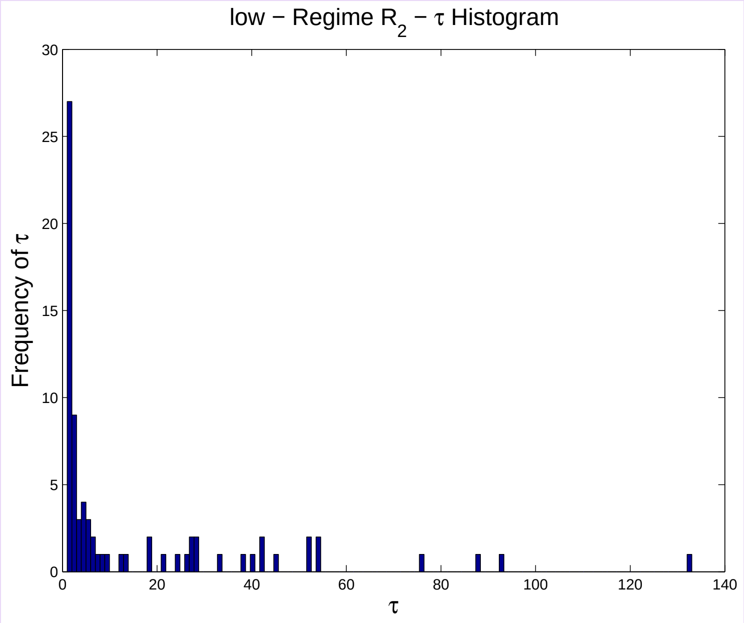
- Market exhibits time dependent behavior – long stable regimes and rapid switches to new regimes.
- Hypothesis: Regimes can be predicted with a discrete, semi-Markov process:
  - It's a continuous time and a discrete space stochastic process.
  - Does not have the memoryless property of a Markov process.

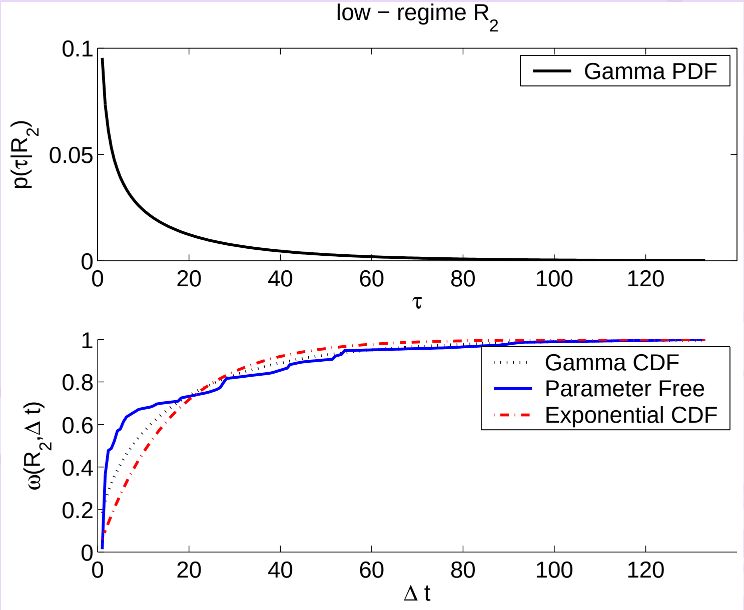
Markov Transition Matrix

$$\mathbf{T}_{\mathbf{predict}}(r_{t+1}|r_t) = (1-\omega(.))\,\mathbf{T}_{\mathbf{steady}}(r_{t+1}|r_t) + \omega(.)\,\mathbf{T}_{\mathbf{change}}(r_{t+1}|r_t)$$

- r_t is the current regime.
- $\omega(.)$ is the probability of a regime change.
- $\mathbf{T}_{\mathbf{steady}}$ is a $M \times M$ identity matrix, where M is the number of regimes.
- $\mathbf{T}_{\mathbf{change}}$ represents the posterior probability of transitioning to a regime given the current regime.

Off-line Regime Transition Probability





Model $p(\tau_i|R_i)$ with the gamma density function:

$$g(t;\alpha,\lambda) = \begin{cases} \frac{\lambda^\alpha}{\Gamma(\alpha)} t^{\alpha-1} e^{-\lambda t} & \text{for } t \geq 0 \\ 0 & \text{for } t < 0 \end{cases},$$

where $\Gamma(x)$ is the gamma function.

Online Regime Transition Probability

Define Δt as the time since the last regime transition at t_0:

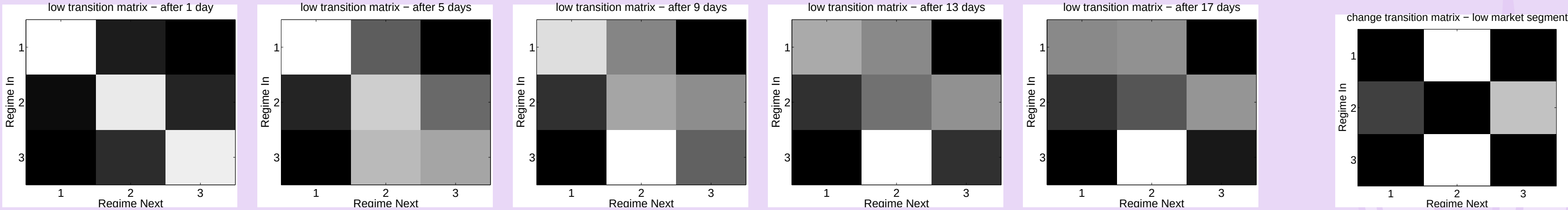
$$\Delta t = t - t_0$$

Probability of a regime transition:

$$\omega(r = R_i, \Delta t) = \int_0^{\Delta t} p(\Delta t | r = R_i)\, \mathrm{d}\Delta t$$

where $p(\Delta t | r = R_i) = g(\Delta t; \alpha_i, \lambda_i)$, and the parameters α_i, λ_i are fitted separately for each regime.

Online Prediction of Regimes for the Low Market Segment



- Probabilities are shown as shades of gray, white = 1 and black = 0.
- Rows: Active regime - Columns: Next regime.
- $\mathbf{T}_{\mathbf{predict}}$ is evaluated for 1, 5, 9, 13 and 17 days from left to right.
- The rightmost matrix represents $\mathbf{T}_{\mathbf{change}}$.

Online Prediction Of Regimes

$$\vec{P}(r_{t+k}|\mathrm{np}_{t-1}) = \sum_{r_{t+k-1}} \cdots \sum_{r_{t-1}} \vec{P}(r_{t-1}|\mathrm{np}_{t-1}) \cdot \prod_{j=1}^{k} \mathbf{T}_{\mathbf{predict}}(r_{t+j}|r_{t+j-1}, \Delta t + j - 1)$$

Prediction of regimes dependent on yesterday's normalized prices for $k-1$ days into the future. The probability transition matrix $\mathbf{T}_{\mathbf{predict}}$ is updated in each prediction step.

Proposed Approach

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Use Regime Prediction For Sales Strategies

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

Remaining Work

- Complete work on prediction
  - Use $\mathbf{T}_{\mathbf{predict}}$ to make
    - current day predictions,
    - long term predictions, and
    - determine prediction accuracy.
- 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.

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