Pricing and Resource Allocation for Intelligent Trading Agents using Economic Regimes

Wolf Ketter

Dept of Decision and Information Sciences

RSM Erasmus University

ISIS 2007 - Hyderabad - December 22nd

Work done with: John Collins, Maria Gini, Alok Gupta, and Paul Schrater.

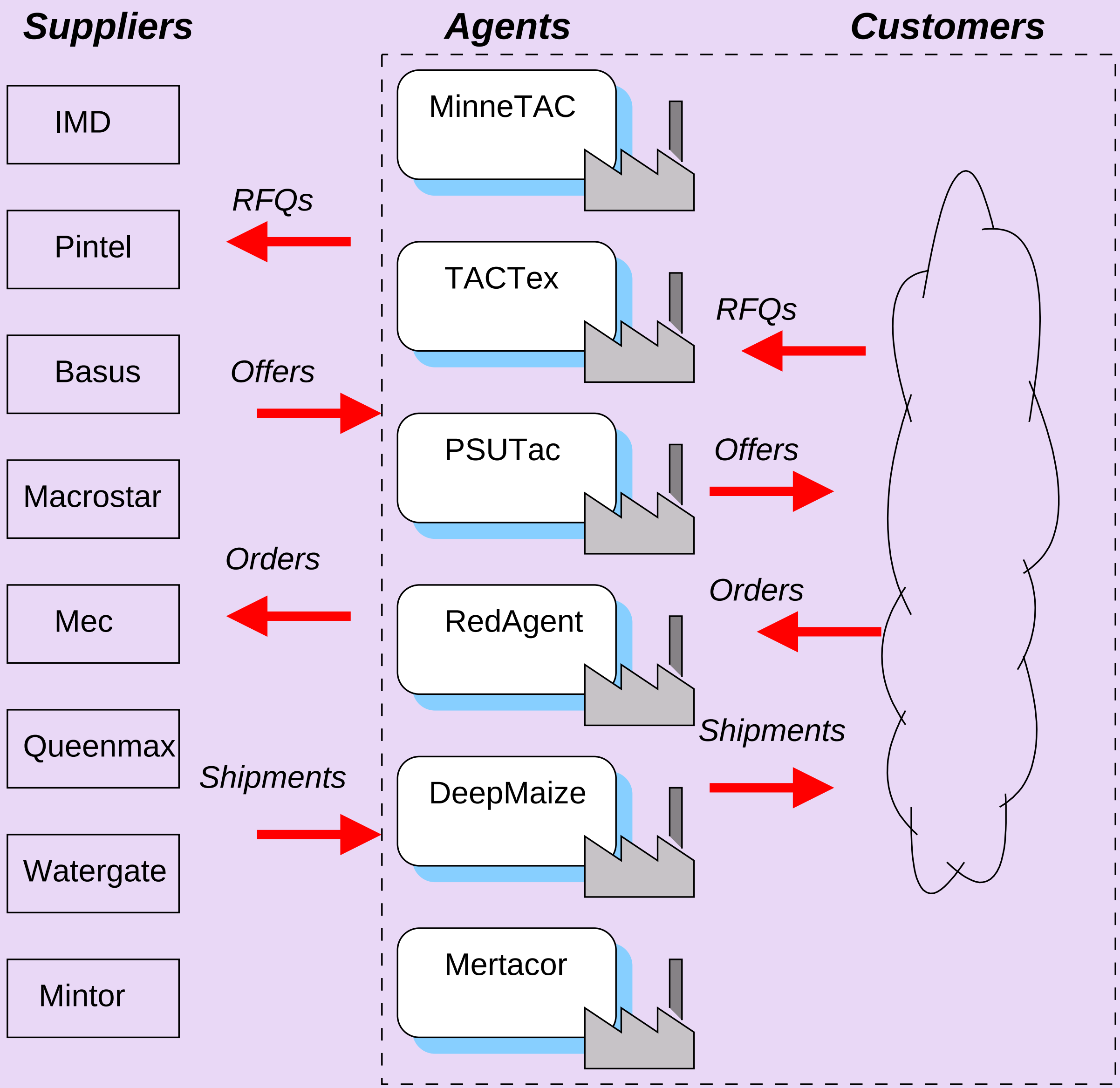
Overview

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

Motivation

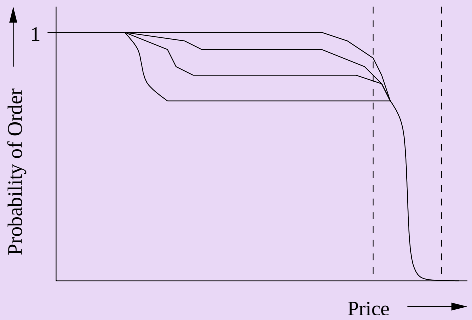
- Economic theory suggests that economic environments exhibit 3 dominant market patterns: scarcity, balanced, and over-supply.
- We call these distinguishable conditions *economic regimes*.
- The objective of our work is to show how knowledge of current and anticipated regimes can enable an agent to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

TAC SCM - Scenario

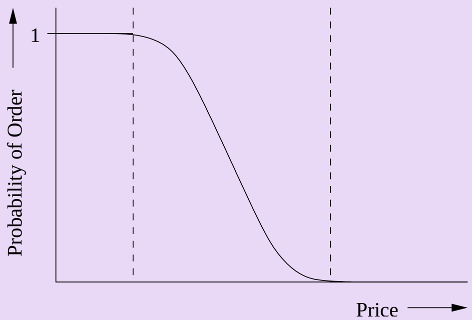


Relationship between Prices, Order Probability, and Regimes

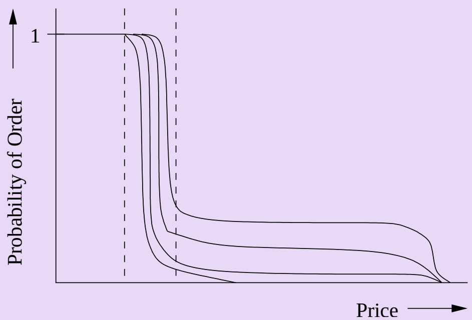
Scarcity:



Balanced:

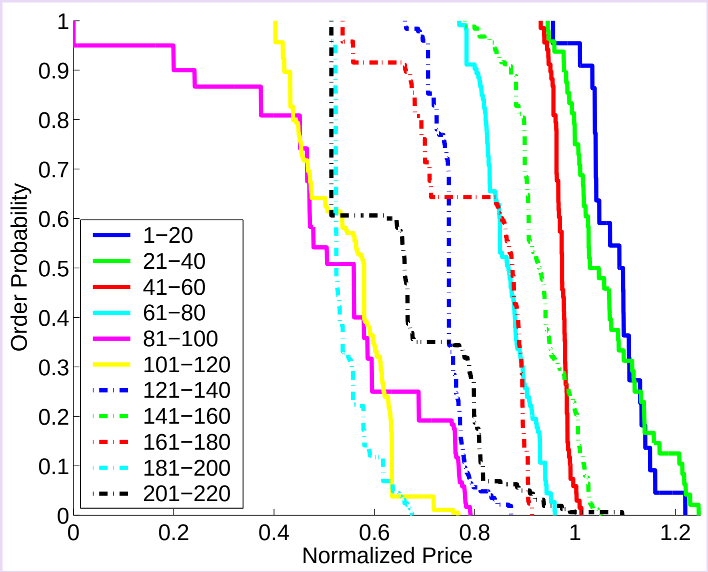


Over-supply:



Reverse cumulative price density function represents probability of order.

Experimental:



Regime Predictions can Drive Sales Strategies

1. Allocation (Strategic Decision):
   - Product mix: Allocating parts and capacity to most profitable products.
   - Sales quotas: Allocating resources 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
   (a) Regime Identification and Prediction
   (b) Sales Pricing

Estimating Price Density Functions

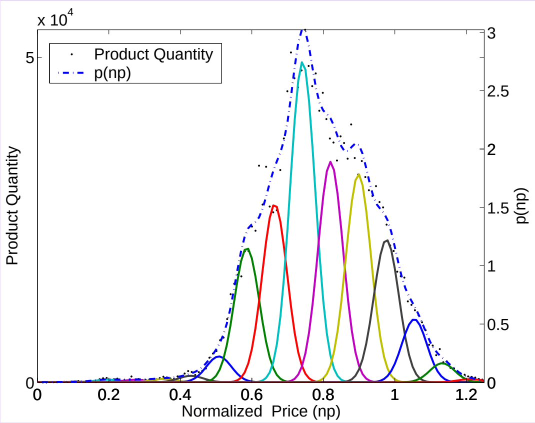
We estimate price density functions using a Gaussian mixture model (GMM)

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

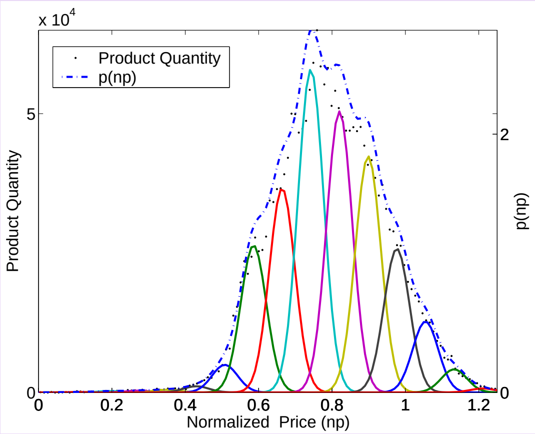
where

- $p(\mathrm{np})$ 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.

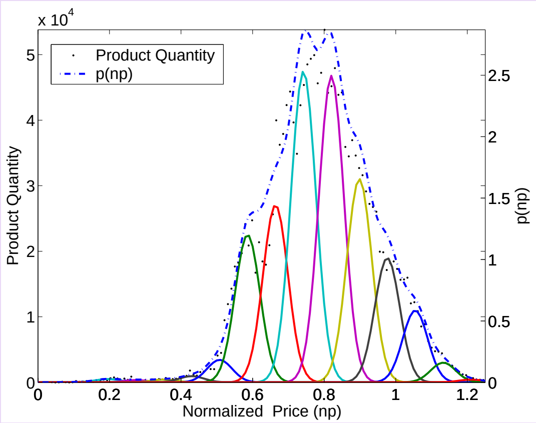
Examples of Estimated Price Density Functions



Low Market



Medium Market



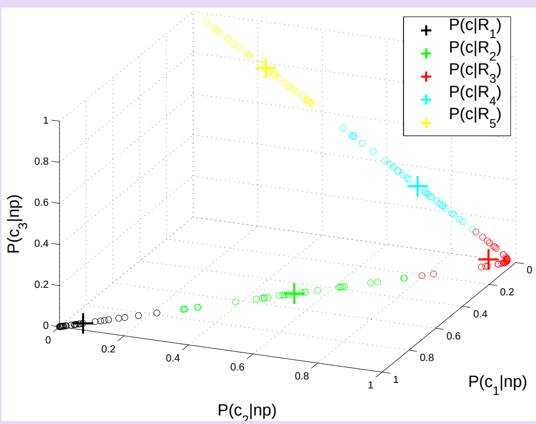
High Market

Definition of Regimes

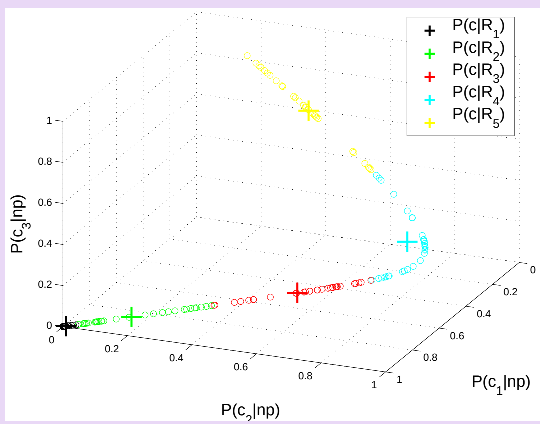
1. We compute at each price np_j the N-dimensional vector

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

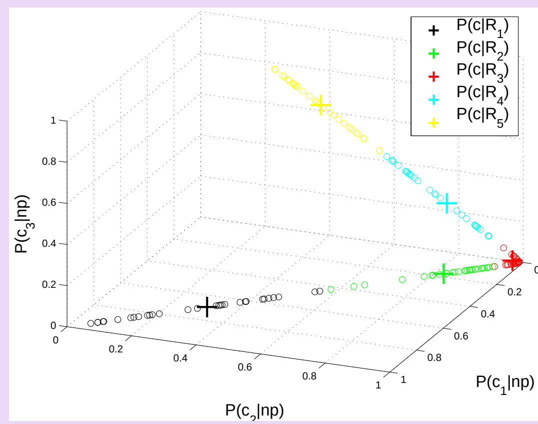
2. We cluster these vectors using k-means.
3. The center of each cluster corresponds to a regime R_k.
4. We compute the posterior probability $P(R_k|\mathrm{np})$



Low Market

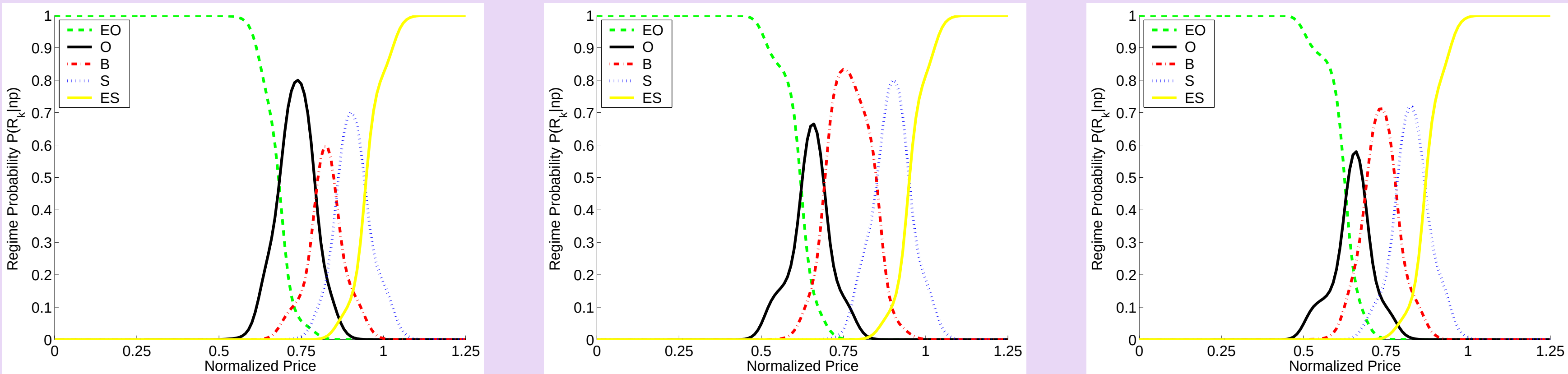


Medium Market



High Market

Regime Probabilities Learned off-line



Low Market

Medium Market

High Market

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

Proposed Approach

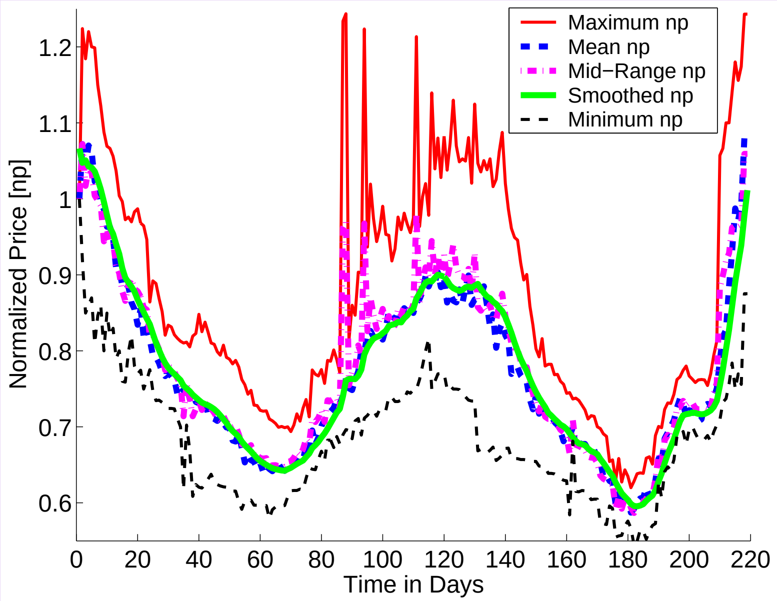
1. Off-line Regime Training
2. Real-time
   (a) Regime Identification and Prediction
   (b) Sales Pricing

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.

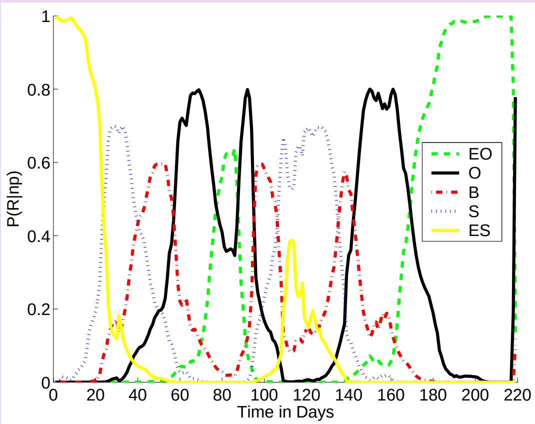
Real-time Identification of Dominant Regime



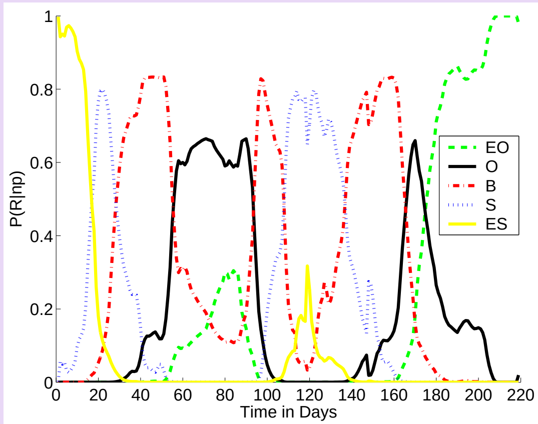
Daily price report 3717@tac3 – low market: Minimum and maximum order prices.

1. Every day we estimate the current regime by calculating the 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. $\mathrm{argmax}_{1 \leq k \leq M} \vec{P}(R_k | \widetilde{\mathrm{np}}_{day})$.

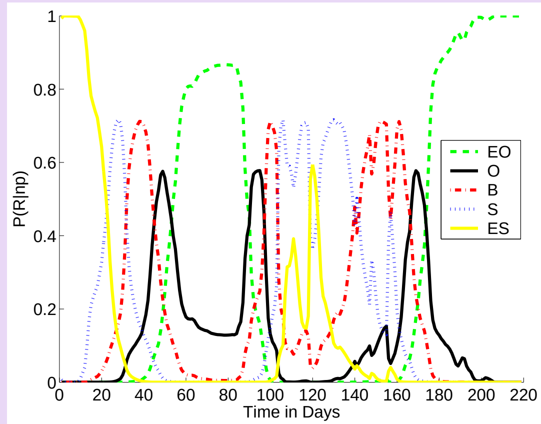
Real-time Computation of Regime Probability



Low Market



Medium Market



High Market

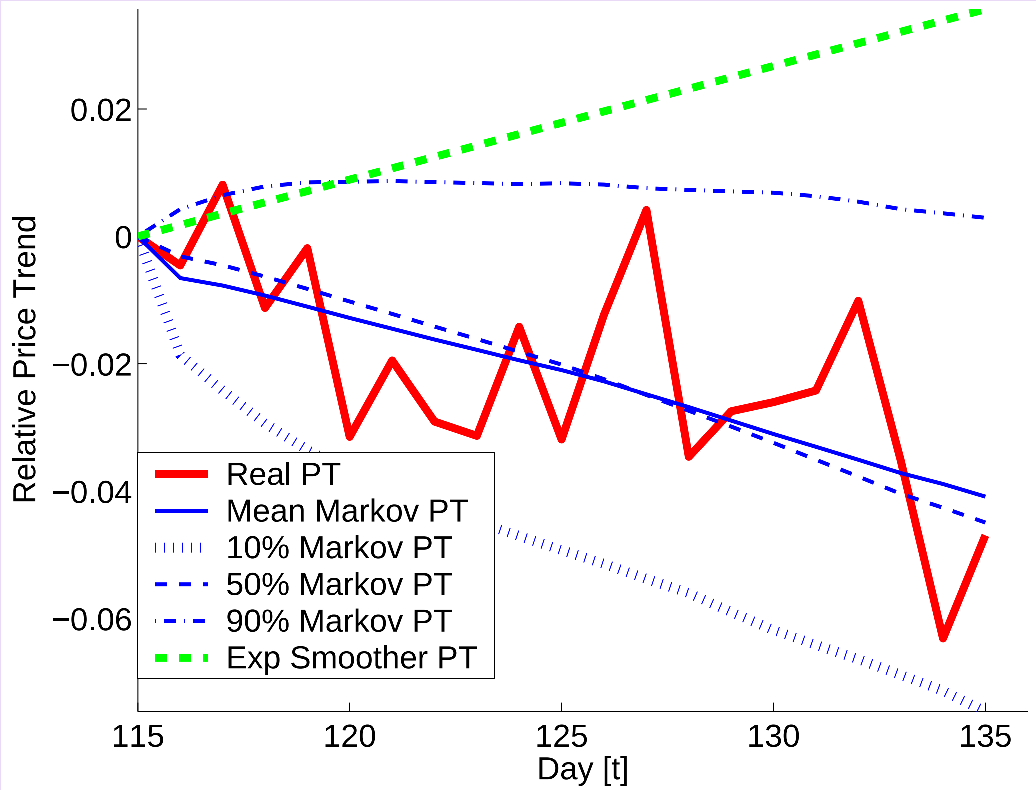
$\vec{P}(R_k|\widetilde{\mathrm{np}}_{day})\ \ \forall k = 1, \cdots, M$ calculated online for game 3721@tac3.

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 $\widetilde{\mathrm{np}}$.

Prediction of Price Trend

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

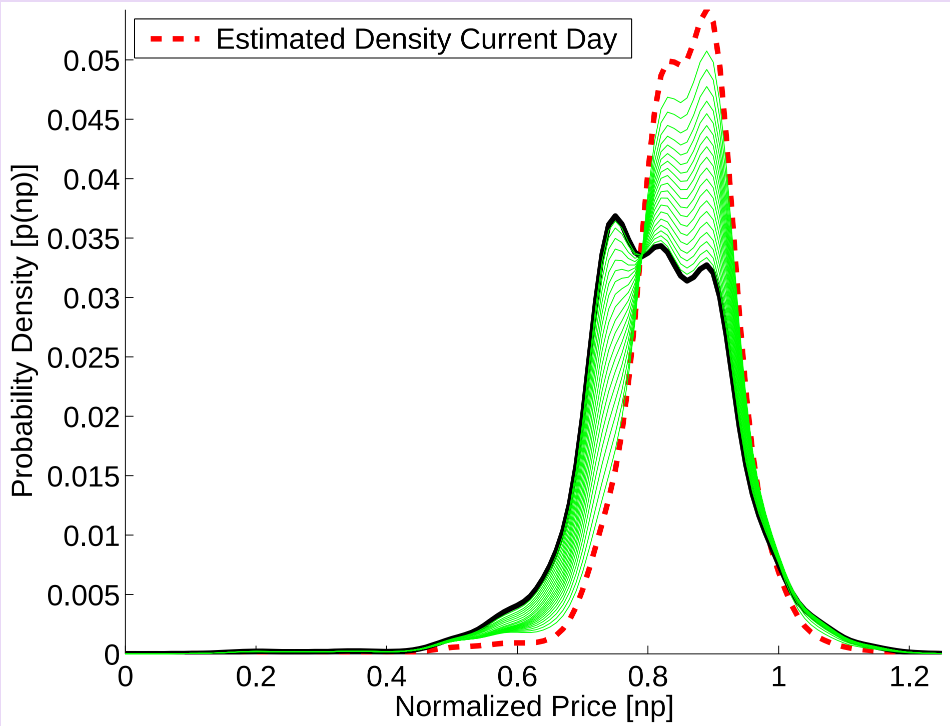


Example: Game 3717tac3

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



$\Rrightarrow$

Prediction of Order Probability

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

where

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

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
   (a) Regime Identification and Prediction
   (b) 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

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

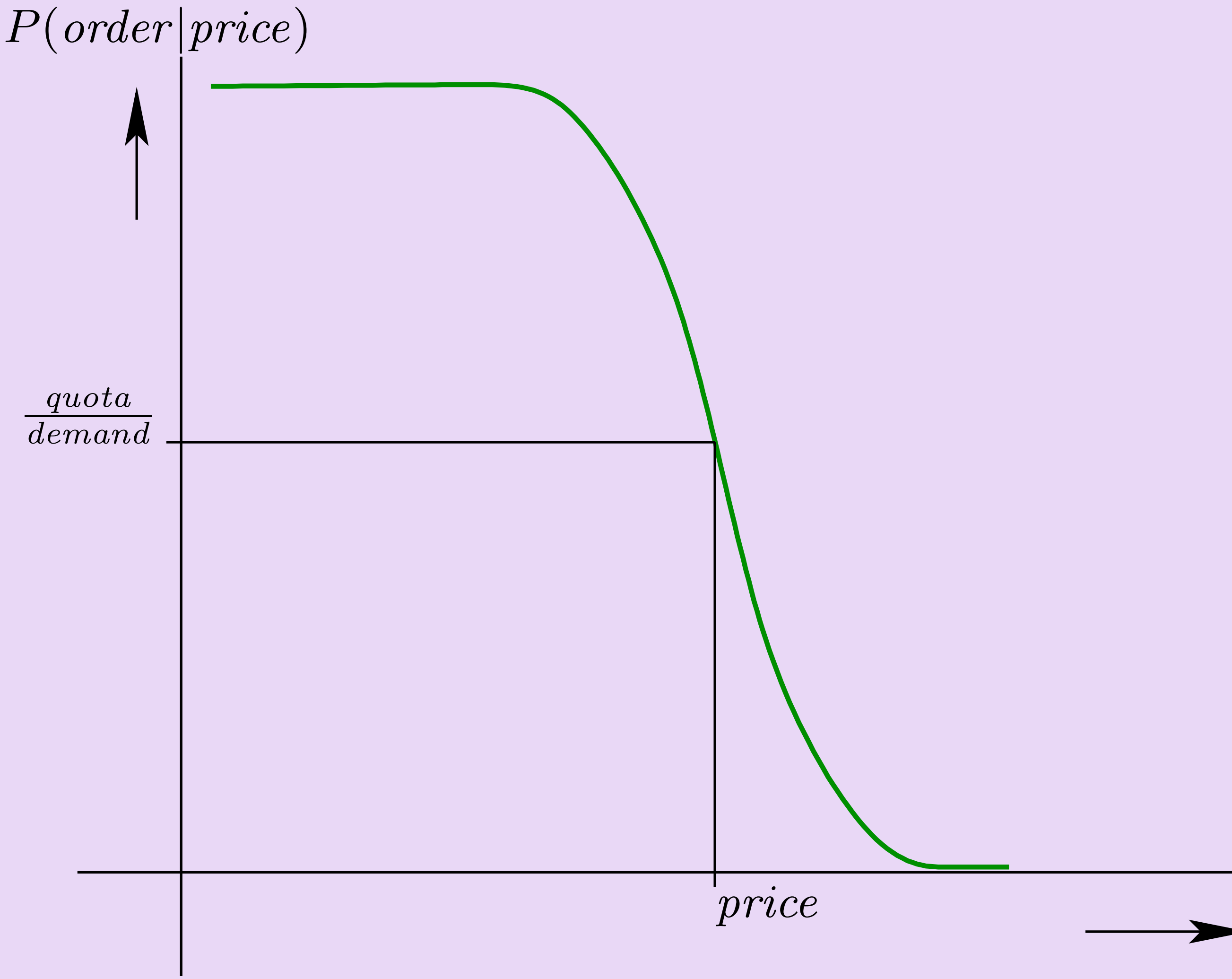
Optimizing sales quotas (2)

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

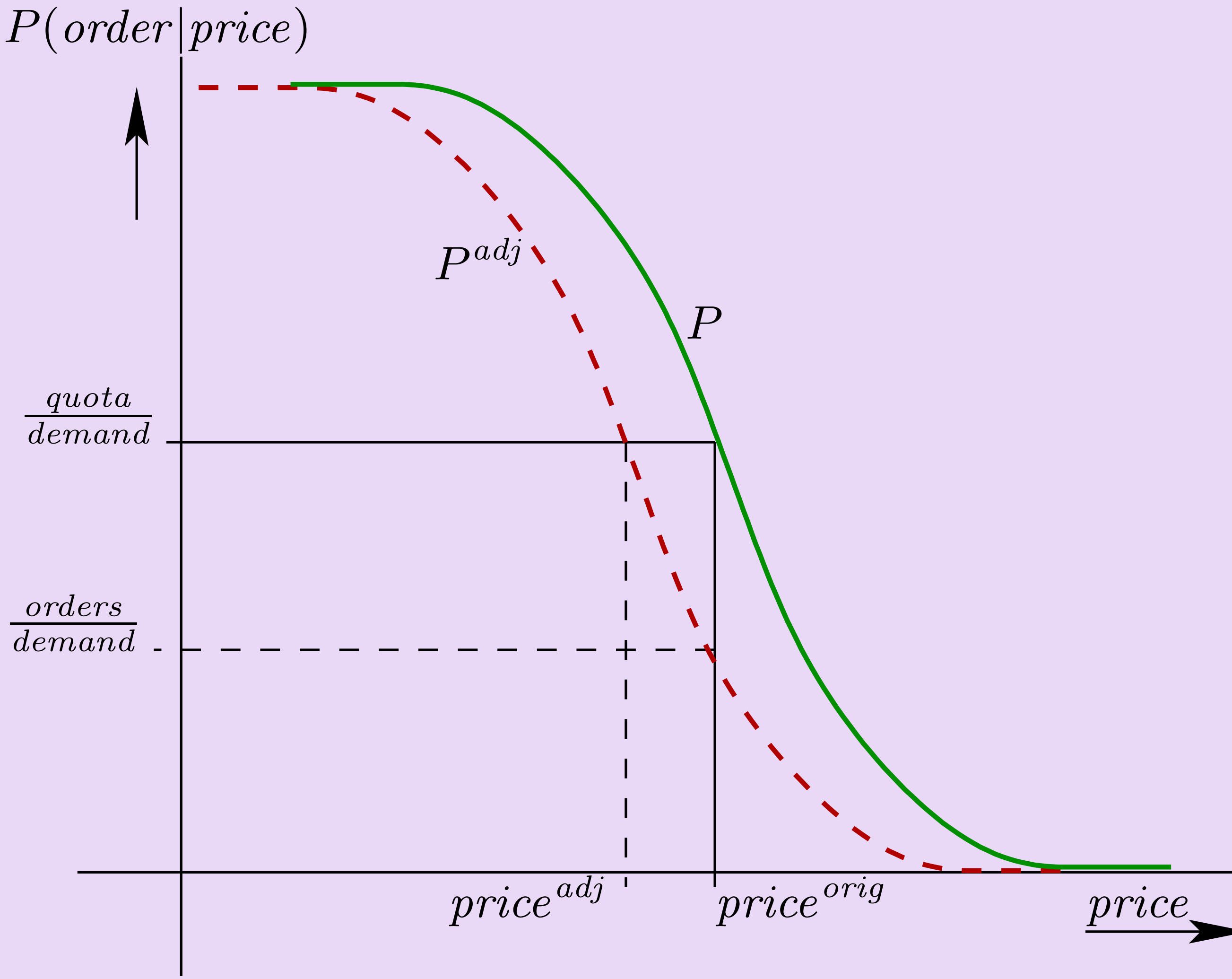
Setting sales prices

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	1	2	3
Strategic:	Follower	Regime-M	Regime-M
Tactical:	Linear	Linear	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)

- Dynamic model selection between the different price prediction approaches.
- 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
  - eBay

Conclusions

- Off-line regime training.
- Real-time identification of dominant regime.
- Real-time prediction of regime transitions, price density, price trends, and order probability.
- Real-time resource allocation and pricing.

Contact
email: `wketter@rsm.nl`
URL: `www.ketter.ws`

Prediction of Price Density

$$p(\widehat{\mathrm{np}}_{t+n}|\widetilde{\mathrm{np}}_{t-1})$$

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

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

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

⇚