

Firefly-inspired Synchronization for Improved Dynamic Pricing in Online Markets

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Outline

- Problem: Multi-attribute dynamic pricing
- Solution:
 - Dynamic pricing using distributed synchronization model observed in nature
- Experimental validation
 - while varying system parameters
 - comparison with other dynamic pricing approaches

Problem

- Online market with buyers and sellers
- Simplification: Only one type of product or item is sold/purchased
- Each product is differentiated along a finite set of attributes

Sellers

- Each seller has multiple, infinite number of items in its inventory
- Each seller has a production cost (min threshold) and each buyer has a reservation cost (max threshold)

Buyer Attribute Preference Model

	Time	Insurance	Seller Repu.	A/S support	Cust. serv.
Item	0.2	0.15	0.6	0.0	0.05

- Each buyer differentiates a product along different attributes using a preference vector of probabilities
- Set of preference vectors is finite
- Buyers can be of different types (finite set of types)
 - each type corresponds to one preference vector

Market Operation

	Time	Insur- ance	Seller Repu.	A/S support	Cust. serv.
Item	0.7	0.15	0.1	0.0	0.05

Buyer 1:
Preferred
attribute a_1



Buyer 2:
Preferred
attribute a_3



Get current offer
from sellers

Select Seller

Select Seller

Get current offer
from sellers

Seller 1
<0.8, 0.4, 0.3, 0.5, 0.1>

Seller 2
<0.85, 0.3, 0.6, 0.7, 0.3>

Seller 3
<0.7, 0.1, 0.8, 0.1, 0.2>

Seller 4
<0.6, 0.2, 0.7, 0.4, 0.1>

	Time	Insur- ance	Seller Repu.	A/S support	Cust. serv.
Item	0.2	0.15	0.6	0.0	0.05

<p1, p2, p3, p4, p5> represents seller prices along different product attributes

Market Operation: Over Time

	Time	Insur- ance	Seller Repu.	A/S support	Cust serv.
Item	0.2	0.65	0.1	0.0	0.05

Buyer 1:
Preferred
attribute a_2



Get current offer
from sellers

Select Seller

Select Seller

Buyer 2:
Preferred
attribute a_3



Get current offer
from sellers

Seller 1
<0.8, 0.4, 0.3, 0.5, 0.1>

Seller 2
<0.85, 0.3, 0.6, 0.7, 0.3>

Seller 3
<0.7, 0.1, 0.8, 0.1, 0.2>

Seller 4
<0.6, 0.2, 0.7, 0.4, 0.1>

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Sellers' Knowledge

Item	Time	Insurance	Seller Repu.	A/S support	Cust serv.
	0.7	0.15	0.1	0.0	0.05

Item	Time	Insurance	Seller Repu.	A/S support	Cust serv.
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Buyer 1:
Preferred attribute a_2



?

Buyer 2:
Preferred attribute a_3



Seller 1
~~X~~ $\langle 0.8, 0.4, 0.3, 0.5, 0.1 \rangle$

Seller 2
~~X~~ $\langle 0.85, 0.3, 0.6, 0.7, 0.3 \rangle$

Seller 3
~~X~~ $\langle 0.7, 0.1, 0.8, 0.1, 0.2 \rangle$

Seller 4
 $\langle 0.6, 0.2, 0.7, 0.4, 0.1 \rangle$

Item	Time	Insurance	Seller Repu.	A/S support	Cust serv.
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$\langle p_1, p_2, p_3, p_4, p_5 \rangle$ represents seller prices along different product attributes

Sellers' Knowledge

- A seller knows
 - Set of product attributes
 - Purchase decision of buyer
- A seller does not know
 - How many other sellers are there?
 - What prices other sellers are charging?
 - How many buyers are there?
 - What is the preference distribution of buyers?

Research Question

- How can a seller adjust the prices it charges along different product attributes over time to respond to temporal changes in
 - Buyer demand (Preferences of buyers over different attributes)
 - Competitors' strategies (Prices charged by competing sellers)

Dynamic pricing using distributed synchronization

- Observe competitors' prices
- Goal: Position the price strategically with respect to the competitors
- Problem: Don't know when or by how much other sellers will update their prices
- Solution: Use emergent synchronization model to align the price changes of sellers

Emergent Price Synchronization

- Based on Ermentrout's synchronization model
- Each seller synchronizes its *price-step*, the amount by which it changes its price, with other sellers' price steps
- Price-step corresponds to the frequency of hypothetical oscillator within a pricebot

Price Synchronization Parameters

- Ω – Natural frequency of emitting a flash
- Δ - Natural cycle length for flashing
- φ – Phase of the flashing signal, varies from 0 to 1
- ε – Convergence limit of synchronization between multiple flashes
- δ_u (δ_l) – Max (Min) cycle length of a flash
 - δ_u (δ_l) = $1 / \Omega_u$ (Ω_l)
- Ω_u (Ω_l) – Max (Min) frequency of a flash

Price Synchronization

- When the phase reaches 1, pricebot emits signal (flash) to the market
 - It is ready to change its price by current price step amount
- Other sellers can use perceive the signal emitted by the pricebot and adapt their own price-steps
- When all sellers achieve synchronization, every seller has the same price-step

Price Synchronization Algorithm

1) Update phase φ , $\varphi \leftarrow \varphi + \omega \cdot \text{delayTime}/t$, where ω -current step-size

2) When φ reaches 1:

- Reset phase, $\varphi=0$
- `sendFlash();`
- Update synchronized price:
 $\text{minMarketPrice}_{ai} \leftarrow \text{getMinMarketPrice}(ai)$
if($\text{minMarketPrice}_{ai} \neq p_{ai}$)
 $\text{syncPrice}_{ai} \leftarrow \text{minMarketPrice}_{ai} - \omega \cdot \gamma$, where γ – normalization constant

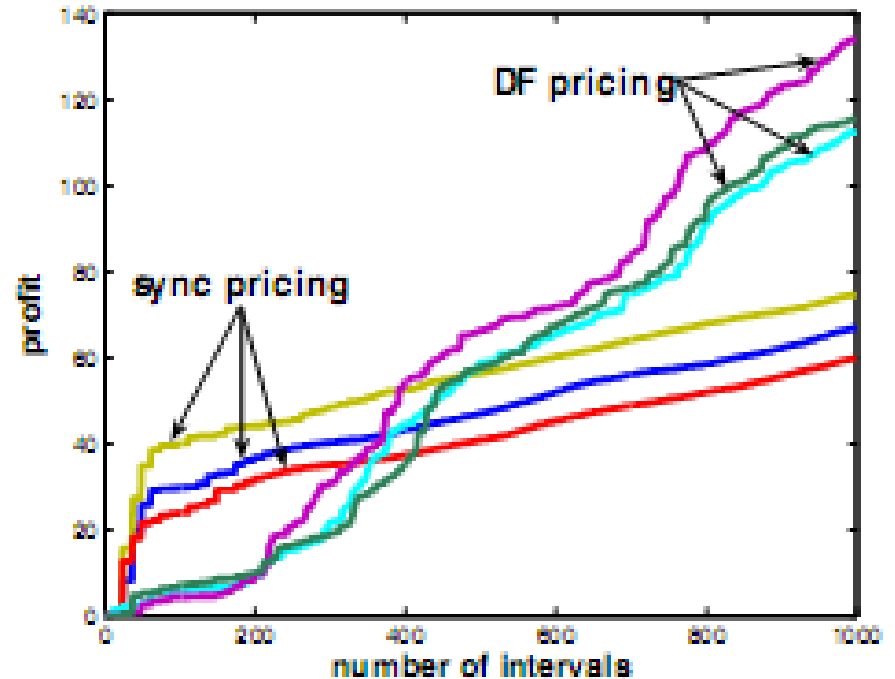
3) If got flash message from other sellers, update phase

$$g^+(\varphi) \leftarrow \max(\sin\pi\varphi/2\pi, 0), g^-(\varphi) \leftarrow -\min(\sin\pi\varphi/2\pi, 0)$$

$$\varphi \leftarrow \varphi + \varepsilon(\Omega - \omega) + g^+(\varphi)(\Omega_l - \omega) + g^-(\varphi)(\Omega_u - \omega)$$

Synchronized pricing vs dynamic pricing

- Inferior performance of synchronized pricing against dynamic pricing
- Combine dynamic pricing with price-step synchronization



Synchronized Dynamic Pricing (SDP)

1) Seller maintains two pricing algorithms:

- Dynamic Pricing
- Synchronized Pricing

2) One of the algorithms is **active**:

- it is used to update prices and calculate the actual profits

and the other one is **latent**:

- it is used to calculate expected profits

Synchronized Dynamic Pricing (SDP)

- 3) At the end of every h intervals, pricebot compares the actual profit and the expected profit
- 4) Pricebot selects an algorithm that yielded higher profits for the next h intervals

Synchronized Dynamic Pricing (SDP)

if ($t < h$)

Strategy ^{$t+1$} = Dynamic Pricing;

else if ($t \bmod h = 0$)

if (expectedCumulativeProfit ^{t} _{ai} >
currentCumulativeProfit ^{t} _{ai})

switch strategies

Simulations

- Number of buyers: 500 or 1000
- Number of sellers: 3 or 5
- Number of product attributes: 5
- Unit production cost: 0.1
- Interval for price updates: 40 quote requests
- Entry price: $U[0.1, 1]$
- Max price step: 0.2
- Min price step: 0.01
- Initial phase: $U[0, 1]$

Variation of Buyer Attribute Preference

- Buyers randomly select a preference vector upon the entrance to the market
- Buyers change the selected preference vector at different random times

Pricing Comparison Strategies

- Fixed Pricing

- Price is randomly selected $U[0.1, 1]$ and is fixed

- Derivative-Follower Pricing

- Price is determined based on the profits obtained

- Goal-Directed Pricing

- Price is determined based on the actual and expected number of products sold

Pricing Comparison Strategies

- Myoptimal Pricing

- Price is determined based on the information about buyer population

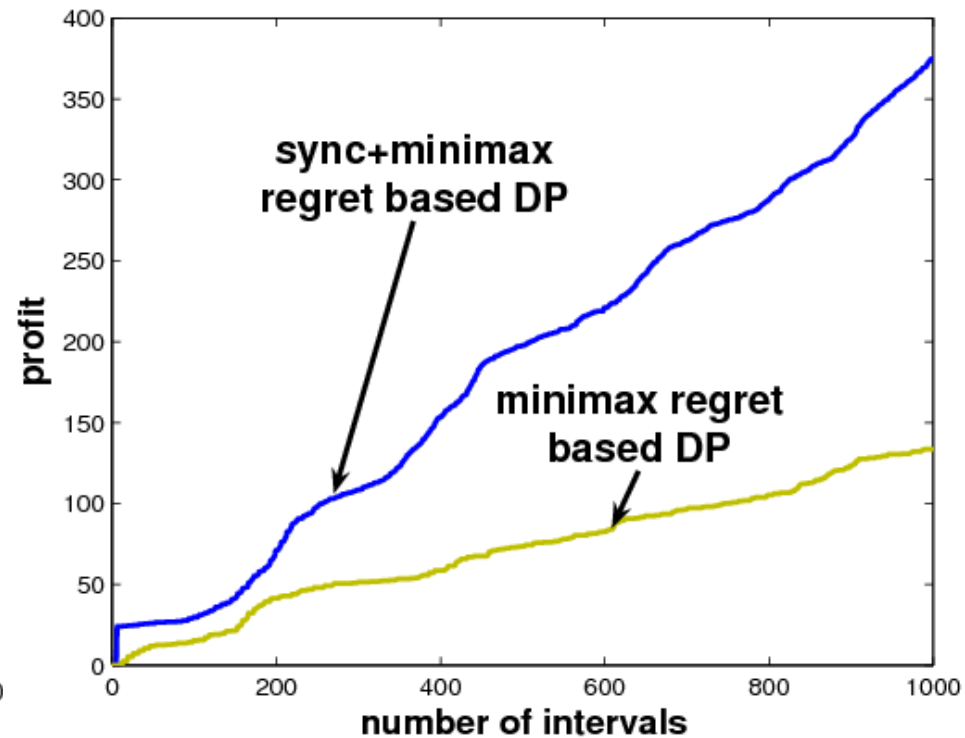
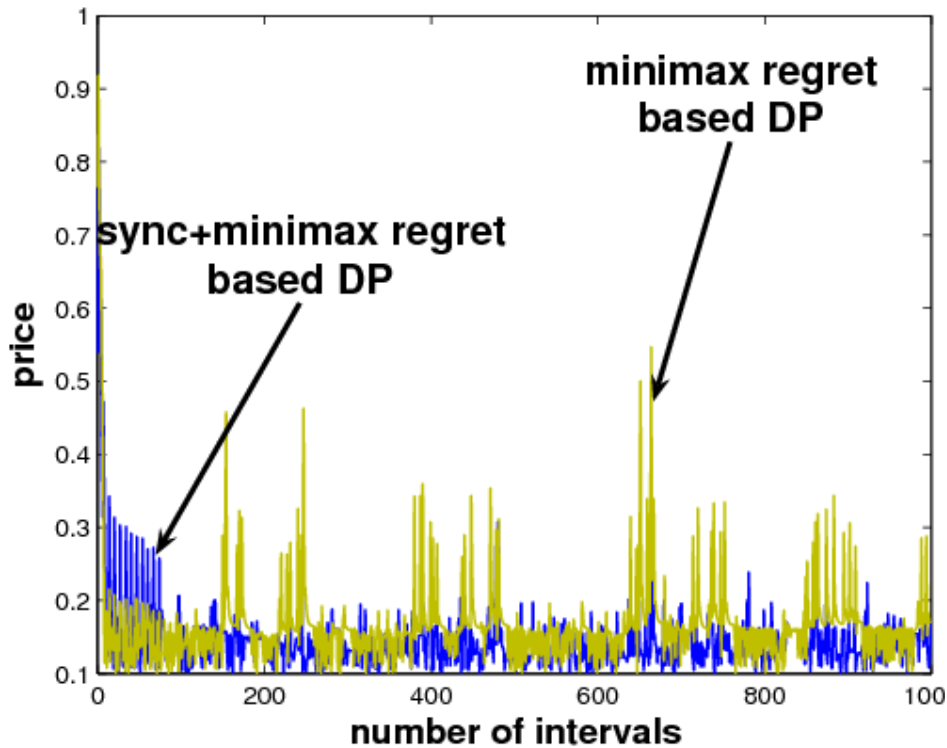
- Game-Theoretic Pricing

- Price is determined based on the information about buyer and seller population

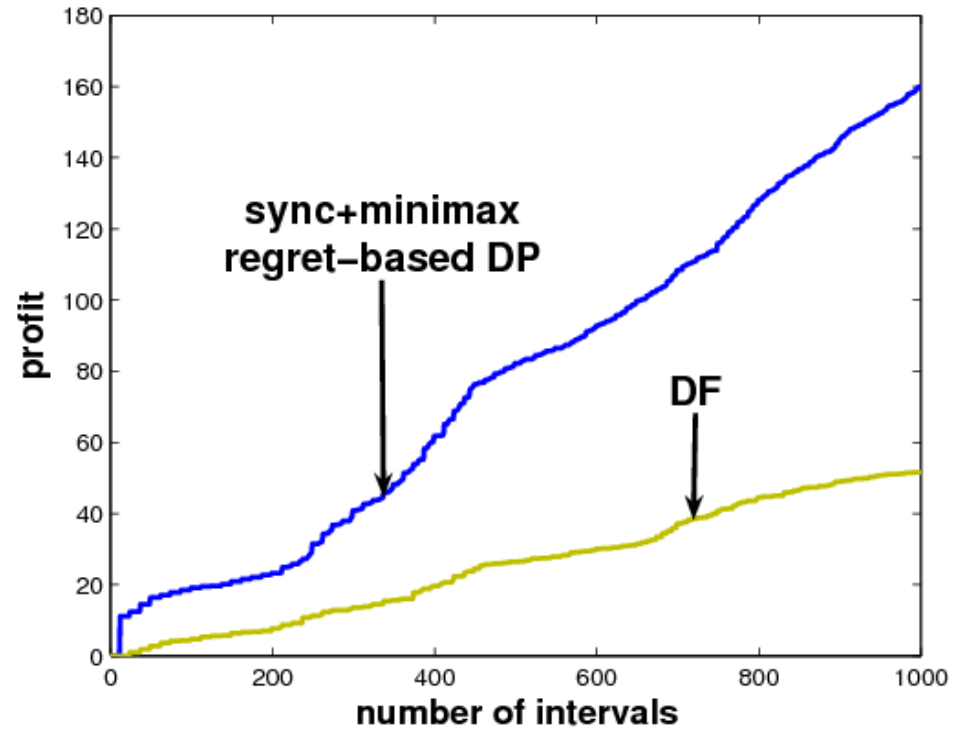
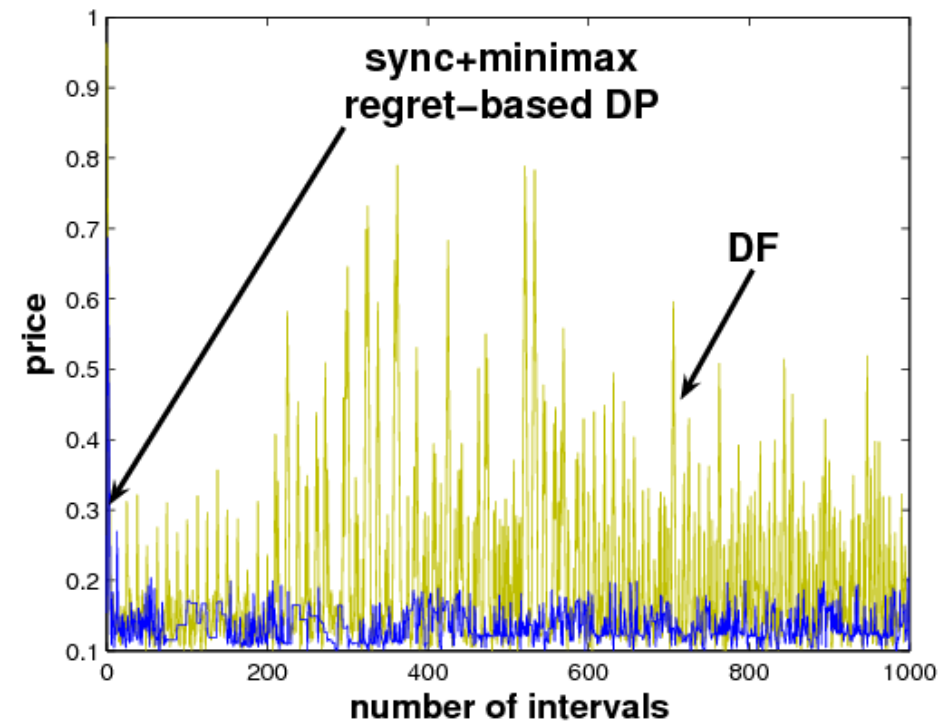
- Minimax Regret Strategy

- Price is determined based on the predicted preferred attributes of the buyers, past profits, and past prices

Experimental Results



Experimental Results



Experimental Results

Seller Strategies	Ave. Cum. Prof. (SDP-X)	Ave. Cum. Prof. _(opponent)	% Perf. Improv.
1 SDP-MMR vs 4 DF	347.89	230.84	50.71
2 SDP-MMR vs 3 DF	274.46	284.2	-3.55
3 SDP-MMR vs 2 DF	237.4	237.91	-0.21
4 SDP-MMR vs 1 DF	236.08	26.89	3.89
1 SDP-MMR vs 4 MMR	773.58	321.96	58.38
2 SDP-MMR vs 3 MMR	451.92	355.67	21.29
3 SDP-MMR vs 2 MMR	538.24	466.68	13.29
4 SDP-MMR vs 1 MMR	398.15	384.8	3.36
2 SDP-MMR vs 3 GD	139.75	127.45	8.85
2 SDP-MMR vs 3 GT	361.33	253.91	29.73
2 SDP-MMR vs 3 MY	506.88	110.98	78.11
1 SDP-DF vs 4 DF	264.42	221.73	16.14
2 SDP-DF vs 3 DF	224.57	201.92	10.09
3 SDP-DF vs 2 DF	211.74	189.71	10.4
4 SDP-DF vs 1 DF	202.79	152.85	24.63
1 SDP-DF vs 4 MMR	316.98	208.67	34.17
2 SDP-DF vs 3 MMR	190.9	187.64	1.71
3 SDP-DF vs 2 MMR	172.73	178.12	-3.12
4 SDP-DF vs 1 MMR	188.79	194.25	-2.89

Experimental Results

- SDP-MMR performs better than DF, MMR, GT, GD, MY
 - 3-78 % improvement in cumulative profits
- SDP-DF performs better than DF, MMR
 - 2-35% improvement in cumulative profits

Conclusion and Future Work

- Synchronized Dynamic Pricing Algorithm
 - Considers changes in competitors' prices and changes in buyer demand and preferences
- Future Work
 - Sellers:
 - Inaccurate price information revelation by sellers
 - Noisy communications
 - Buyers:
 - Sharing information about sellers
 - Competition among buyers to share profits