Algorithmic Collusion with Coarse Memory

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Literature

- Calvano et al. (2020) and Klein (2021): pricing algorithms can learn to collude
- Assad et al. (2020): empirical evidence in the German retail gasoline market
- pricing algorithms are completely unregulated

Algorithmic collusion

- high prices by itself is not collusion
- algorithms learn to sustain supra-competitive outcomes with equilibrium strategies
- Calvano et al. (2020) and Klein (2021): finite phases of punishment

Coarse memory

- I limit the algorithms' memory of their rival's past price
- e.g., can only remember if the price of their rival was low, intermediate, or high

Motivation

- Potentially relevant for two (opposing) reasons:
  - could be useful to prevent algorithmic collusion
  - firms might introduce coarse memory to foster collusion

Economic environment

- two symmetric firms with constant marginal cost
- infinitely repeated Bertrand model
- logit demand, differentiated products

Algorithms

- Q-learning: learn from trial and error
  - initially select actions randomly
  - most successful actions are reinforced
- hyperparameters:
  - learning rate, α
  - exploration intensity, ν

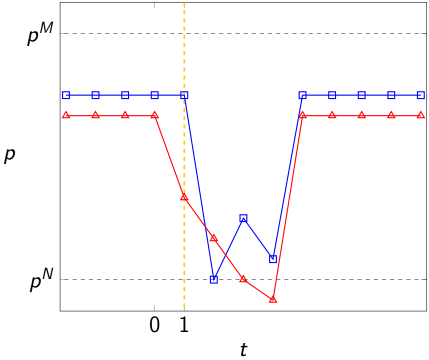
Algorithms (cont'd)

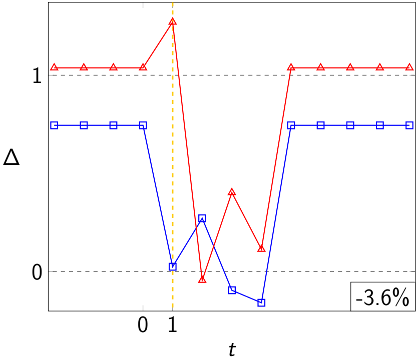
- feasible actions: $a \in A, \quad A = \{p^1, p^N, \ldots, p^M, p^{15}\}$
- state of the environment: $s \in S, \quad s_t = (p_{1t-1}, p_{2t-1})$
- aim is to maximize: $\sum_{t=1}^{\infty} \delta^{t-1} \pi_i$

Perfect Memory

Hyperparameters: $\alpha = 0.15$, $\nu = 25$

- Average profit gain (Δ): 0.856
- Average deviation loss: -2.7%





Coarse memory

- memory (3–3–3–3–3)

$p^1 \mid p^N \mid p^3$	$p^4 \mid p^5 \mid p^6$	$p^7 \mid p^8 \mid p^9$	$p^{10} \mid p^{11} \mid p^{12}$	$p^{13} \mid p^M \mid p^{15}$

- memory (5–5–5)

$p^1 \mid p^N \mid p^3 \mid p^4 \mid p^5$	$p^6 \mid p^7 \mid p^8 \mid p^9 \mid p^{10}$	$p^{11} \mid p^{12} \mid p^{13} \mid p^M \mid p^{15}$

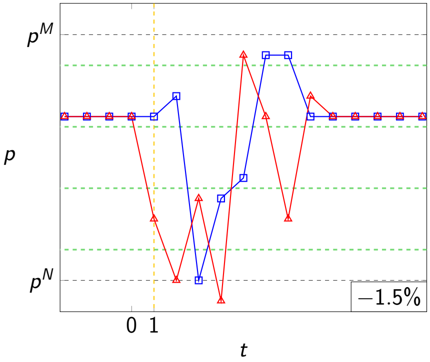
- no memory of rival's past price

Coarse Memory – Results

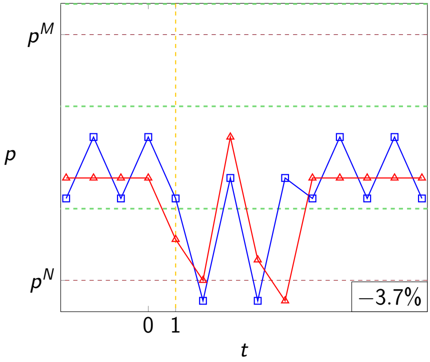
	Profit gain	Deviation gain (loss)
Perfect memory	0.856	-2.7 %
(3–3–3–3–3)	0.802	-2.5 %
(5–5–5)	0.742	-2.1 %
No memory	0.078	0.1 %

Table: Averages across 1000 experiments. Deviation to static best-response.

Coarse Memory – Punishments

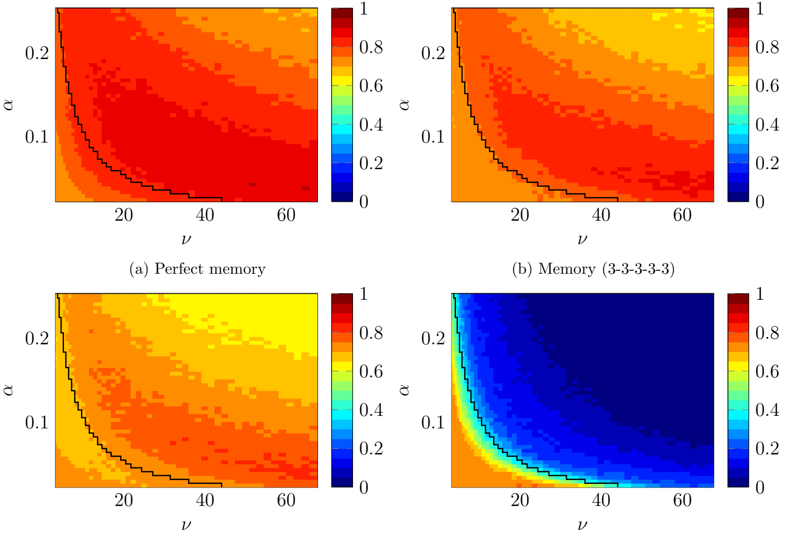


(3–3–3–3–3)



(5–5–5)

Coarse Memory – Hyperparameter grid



(a) Perfect memory (b) Memory (3-3-3-3-3)

(c) Memory (5-5-5) (d) No memory

Figure 4.6: Average profit gain.

Conclusions

- coarse memory does not foster collusion
- partial limitations to the algorithms' memory do not prevent algorithmic collusion either
- with no memory of their rival's past price algorithms price competitively