

An α -regret Analysis of Adversarial Bilateral Trade

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Bilateral Trade

We study the *bilateral trade* problem in the framework of **online learning**

Learning Protocol of Sequential Bilateral Trade

- 1: **for** time $t = 1, 2, \dots$ **do**
 - 2: a new seller/buyer pair arrives with (hidden) valuations $(s_t, b_t) \in [0, 1]^2$
 - 3: the learner posts prices $p_t, q_t \in [0, 1]$ with $p_t \leq q_t$
 - 4: the learner receives a (hidden) reward $\text{GFT}_t(p_t, q_t)$
 - 5: a feedback z_t is revealed
-

Gain from trade

$$\begin{aligned} \text{GFT}_t(p_t, q_t) &= \left(\underbrace{(b_t - q_t)}_{\text{buyer's gain}} + \underbrace{(q_t - p_t)}_{\text{platform's gain}} + \underbrace{(p_t - s_t)}_{\text{seller's gain}} \right) \underbrace{\mathbb{I}\{s_t \leq p_t \leq q_t \leq b_t\}}_{\text{trade happens}} \\ &= (b_t - s_t) \mathbb{I}\{s_t \leq p_t \leq q_t \leq b_t\} \end{aligned}$$

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Feedback models and regret

Feedback models

- **Full feedback** (direct revelation): $z_t = (s_t, b_t)$
- **Two-bit feedback** (posted-price): $z_t = (\mathbb{I}\{s_t \leq p_t\}, \mathbb{I}\{q_t \leq b_t\})$
- **One-bit feedback** (minimal): $z_t = \mathbb{I}\{s_t \leq p_t \leq q_t \leq b_t\}$

Prices

- **Single Price** (strong budget balance): $p_t = q_t$
- **Two Prices** (budget balance): $p_t \leq q_t$

Adversaries

- **Stochastic setting**: *i.i.d.* valuations ✓ [Cesa-Bianchi et al. 2021]

• **Adversarial setting**: *(unknown) sequence*

$$= \max_{p \in [0,1]} \mathbb{E} \left[\sum_{t=1}^T \text{GFT}_t(p) - \sum_{t=1}^T \text{GFT}_t(p_t, q_t) \right]$$

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- **Stochastic setting**: *i.i.d.* valuations ✓ [Cesa-Bianchi et al. 2021]

• **Adversarial setting**: (arbitrary) sequence

$$= \max_{p \in [0,1]} \mathbb{E} \left[\sum_{t=1}^T \text{GFT}_t(p) - \sum_{t=1}^T \text{GFT}_t(p_t, q_t) \right]$$

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- **Stochastic setting**: *i.i.d.* valuations ✓ [Cesa-Bianchi et al. 2021]
- **Adversarial setting**: *any* (oblivious) sequence

$$R_T = \max_{p \in [0,1]} \mathbb{E} \left[\sum_{t=1}^T \text{GFT}_t(p) - \sum_{t=1}^T \text{GFT}_t(p_t, q_t) \right]$$

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$$R_T = \max_{p \in [0,1]} \mathbb{E} \left[\sum_{t=1}^T \text{GFT}_t(p) - \sum_{t=1}^T \text{GFT}_t(p_t, q_t) \right]$$

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Adversaries

- **Stochastic setting**: *i.i.d.* valuations ✓ [Cesa-Bianchi et al. 2021]
- **Adversarial setting**: *any* (oblivious) sequence ✓ [This work]

$$R_T^\alpha = \max_{p \in [0,1]} \mathbb{E} \left[\sum_{t=1}^T \text{GFT}_t(p) - \alpha \sum_{t=1}^T \text{GFT}_t(p_t, q_t) \right]$$

The soft spot: $\alpha = 2$

Theorem

For any $\alpha \in [1, 2)$, there is a **linear** lower bound on the α -regret achievable, even with full feedback and posting two different prices.

	Full Feedback	Two-bit feedback	One-bit feedback
Single price	$O(\sqrt{T})$	$\Omega(T)$	
Two prices	$\Omega(\sqrt{T})$	$\Omega(T^{2/3})$	$O(T^{3/4})$

Table: Summary of 2-regret results in various settings.

- **Upper bound** with 1-bit feedback: “Magic” Estimator
- **Lower bounds:** Partial monitoring and feedback structure

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Thank you!

See you in New Orleans