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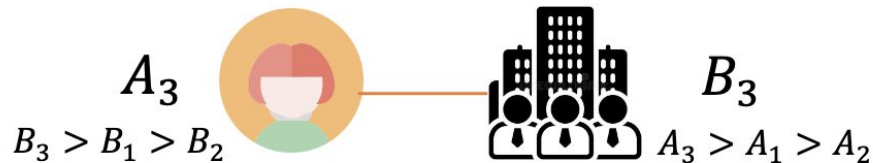
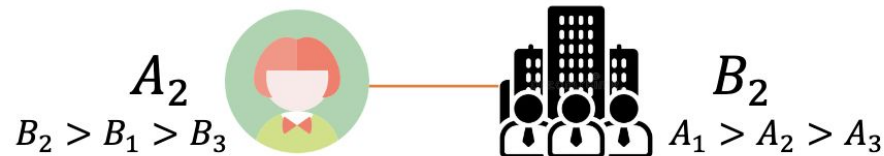
Putting Gale & Shapley to Work: Guaranteeing Stability Through Learning

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Leeds

Matching Markets

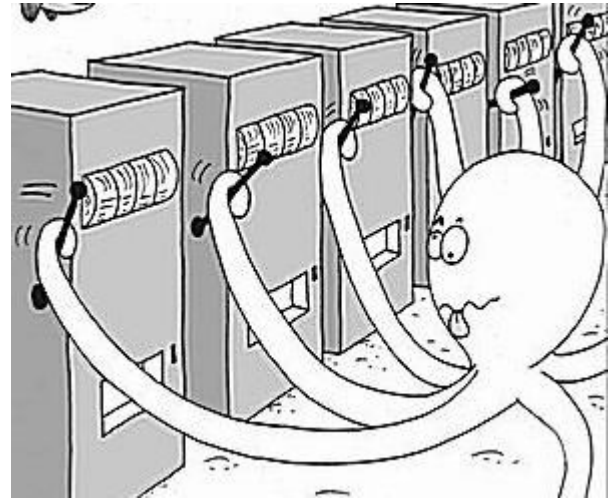
- Examples: labor markets, school application.
- Welfare: how good a partner is.
- Stability: participants have no incentive to leave the market.



$$m_1 = \{(A_1, B_1), (A_2, B_2), (A_3, B_3)\}$$

Bandit Learning in Matching Markets

- Traditional models assume known preferences.
- In real life, preferences may be unknown and need to be learned, e.g. labor markets.
- Bandits: a decision making problem to find optimal arm.
- Assume that one side of preferences is unknown.



Related Work

Centralized and decentralized markets:

- Liu et al. Competing bandits in matching markets. AISTATS 2020.
- Liu et al. Bandit learning in decentralized matching markets. JMLR 2021
- Kong and Li. Player-optimal stable regret for bandit learning in matching markets. SODA 2023.
- Zhang et al. Matching in multi-arm bandit with collision. NeurIPS 2022.

Special preferences:

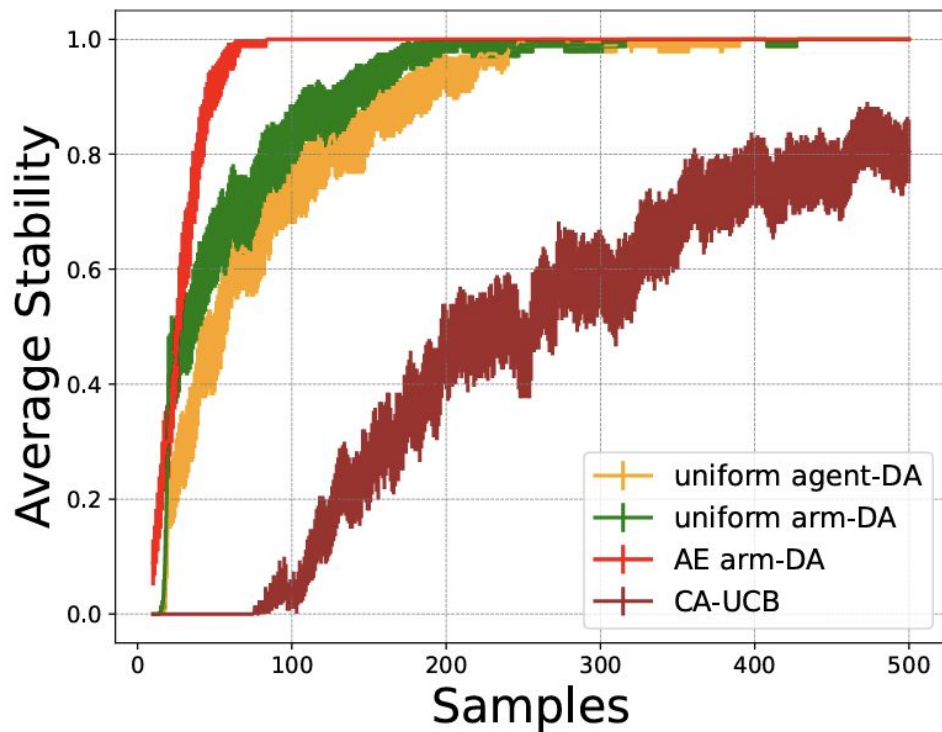
- Das and Kamenica. Two-sided bandits and the dating market. IJCAI 2005
- Basu et al. Beyond $\log^2(t)$ regret for decentralized bandits in matching markets. ICML 2021
- Sankararaman et al. Dominate or delete: Decentralized competing bandits in serial dictatorship. AISTATS 2021
- Maheshwari et al. Decentralized, communication and coordination free learning in structured matching markets. NeurIPS 2022

- However, previous works focused on welfare.
- In this paper, we focus on stability.
- We propose a new algorithm, and show that it could efficiently reach a stable matching.
- We provide both theory and simulated experiments.

Overview of theoretical results

	Uniform agent-DA	Uniform arm-DA	AE arm-DA
Prob. instability	$O(ES(\bar{m}) \gamma)$ (Thm. 2)	$O(ES(\underline{m}) \gamma)$ (Thm. 2)	$O(ES(\underline{m}) \exp\left(-\frac{\Delta^2 T_{min}}{8}\right))$ (Thm. 4)
Sample complexity	$\tilde{O}\left(\frac{NK}{\Delta^2} \log(\alpha^{-1})\right)$ (Thm. 3)	$\tilde{O}\left(\frac{NK}{\Delta^2} \log(\alpha^{-1})\right)$ (Thm. 3)	$\tilde{O}\left(\frac{1}{\Delta^2} ES(\underline{m}) \log(\alpha^{-1})\right)$ (Thm. 5)

Simulated Experiments



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Poster session: 4:30 p.m. - 7:30 p.m., Dec 11

