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Improved Algorithm on Online Clustering of Bandits

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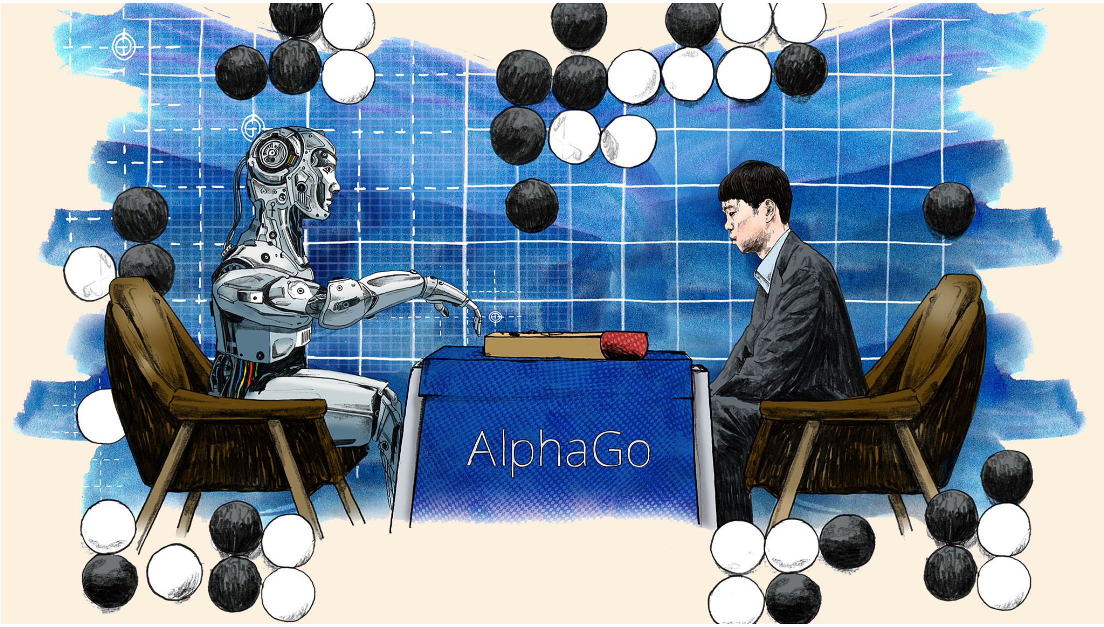
Motivation – Reinforcement Learning



AlphaGo, AlphaStar

Motivation -- Multi-armed Bandits

- A special case of Reinforcement Learning

Multi-armed Bandits

- There are L arms
    - Each arm a has an unknown reward distribution with unknown mean $\alpha(a)$
    - The best arm is $a^* = \text{argmax}_a \alpha(a)$

- At each time t
    - The learning agent selects an arm a_t
    - Observes the reward $X_{a_t,t}$

Multi-armed Bandits (Continued)

- The objective is to minimize the regret in T rounds

$$R(T) = T \cdot \alpha(a^*) - \mathbb{E}\left[\sum_{t=1}^{T} \alpha(a_t)\right]$$

- Balance the trade-off between exploitation and exploration
  - Exploitation: select arms that yield good results so far
  - Exploration: select arms that have not been tried much before

Contextual Multi-armed Bandits

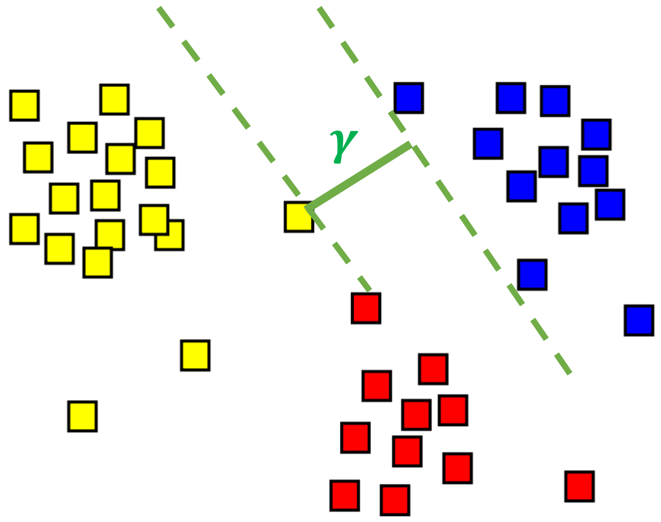
- Contexts
  - User profiles, search key words
  - Important for search, recommendations

- Usually suppose each arm a has a feature representation $x_{a,t} \in \mathrm{R}^d$
  - Contexts could change over time
- The reward mean is $\alpha_t(a) = \theta^\top x_{a,t}$
  - for some fixed but unknown weight vector θ

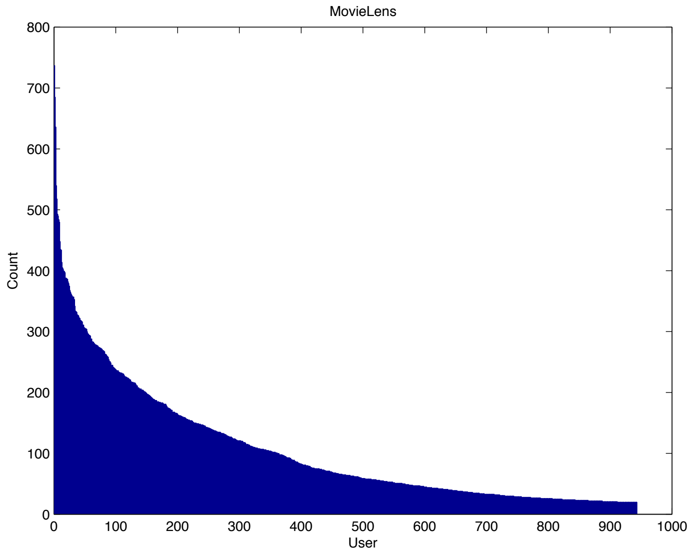
Online Clustering of Bandits

- Drawbacks of simple contextual bandits
  - They assume the weight vector θ is the same for all users

- Online clustering of bandits
  - Users with strong ties (like friendship) usually have similar interests
  - Assume
    - Users within the same cluster have the same θ
    - Users of different clusters have weight gap $\|\theta_i - \theta_j\| \geq \gamma$
  - Find clustering adaptively as well as recommending



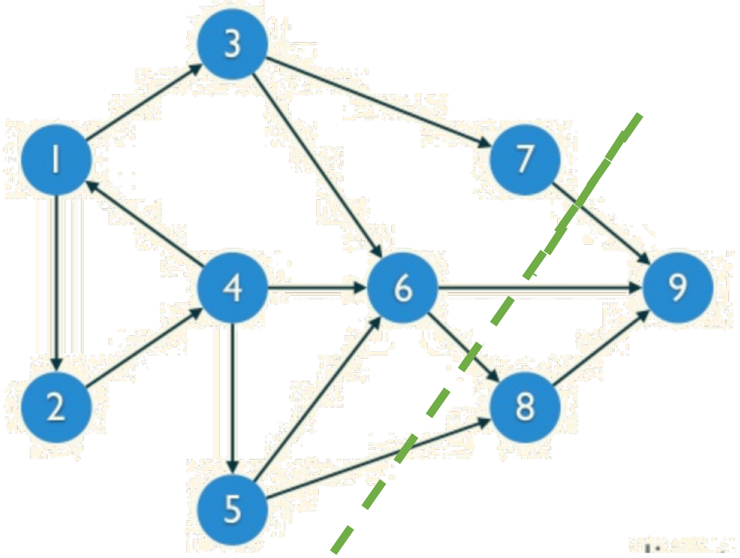
Existing Problems



- They assume the user distribution is uniform

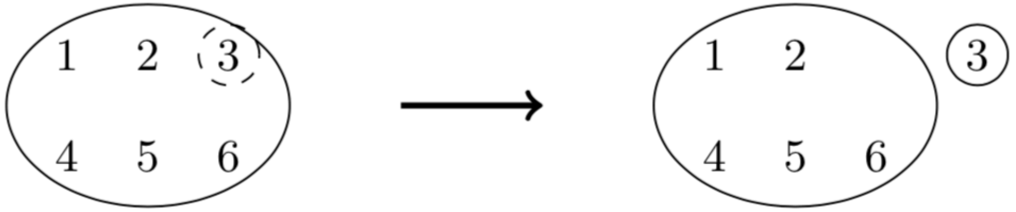
- If generalizing the algorithm to arbitrary distribution over users
  - Their algorithm is much inefficient

  - The regret will depend on the minimal user frequency
  - $R(T) = O\left(d\sqrt{mT}\ln T + \frac{1}{p_{\min}\gamma^2\lambda_x^3}\ln T\right)$

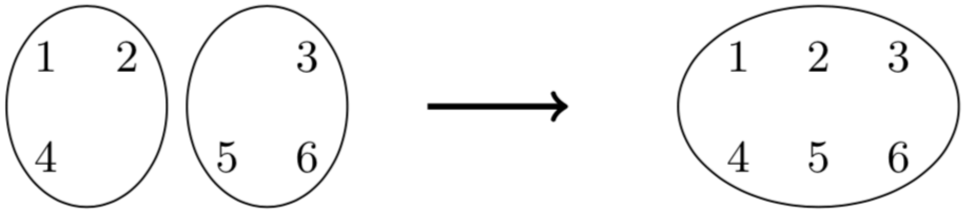


Our Work – SCLUB (set-based clustering of bandits)

- Generalize the setting to allow arbitrary distribution over users
- Split a user out of the current cluster if we finds *inconsistency*



- Merge two *good* clusters together



Results

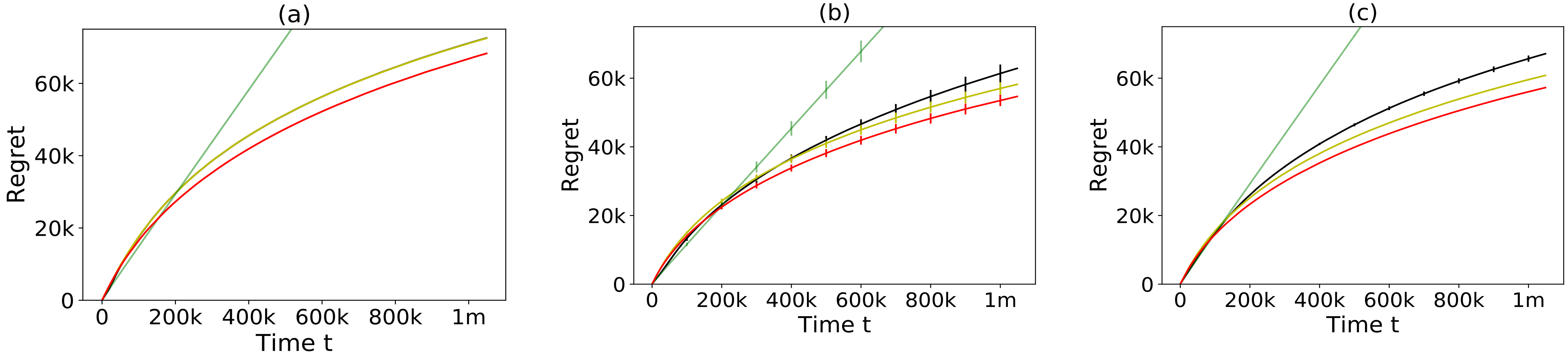
- Regret

$$R(T) = O\left(d\sqrt{mT}\ln T + \left(\frac{1}{\gamma_p^2} + \frac{n_u}{\gamma^2\lambda_x^3}\right)\ln T\right)$$

- compared to $R(T) = O\left(d\sqrt{mT}\ln T + \frac{1}{p_{\min}\gamma^2\lambda_x^3}\ln T\right)$

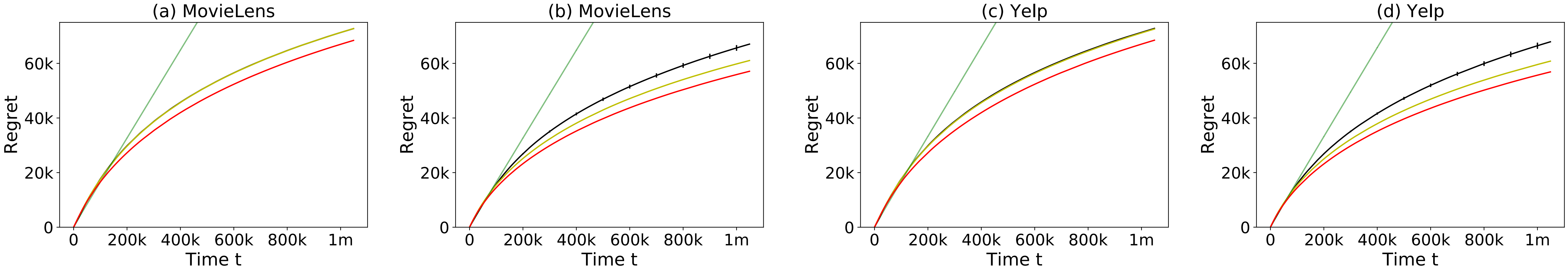
Experiments – Synthetic

- 1000 users, 10 clusters, randomly generated weight vectors, $d = 20$
- (a) uniform distribution over users
- (b) arbitrary distribution over clusters
- (c) arbitrary distribution over users
- ---Ours ---CLUB ---LinUCB-One ---LinUCB-Ind



Experiments – Real Datasets

- 1000 users, $d = 20$
- (a)(c) uniform distribution over users
- (b)(d) arbitrary distribution over users
- ---Ours ---CLUB ---LinUCB-One ---LinUCB-Ind



Future Work

- Asymmetric relationships between users
  - Recommendations for low-frequency users can use information (or feedback) from high-frequency users, but not vice versa
  - Nested clusters

- Use the same idea to improve the collaborative filtering bandits

- Generalize the collaborative filtering bandits to the setting of changing item set

Thanks!

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Questions?