Incentivizing Exploration by Heterogeneous Users

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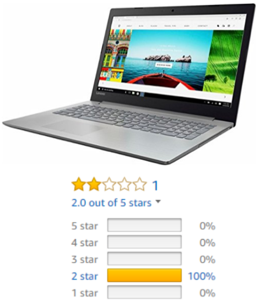
Motivation

Amazon wants users to ***explore***
Each customer only wants to buy one good item



Previous Work

Without Money Transfer:

- Implementing the "Wisdom of the Crowd", Kremer et al. 2014;
- Bayesian incentive-compatible bandit exploration, Mansour et al. 2015;
- $\cdots$

With Money Transfer

- Incentivizing exploration, Frazier et al. 2014;
- Incentivizing exploration with heterogeneous value of money, Han et al. 2015;
- $\cdots$

Heterogeneity presents a new challenge

Customers prefer different kinds of items

Amazon doesn't know which item each user prefers

Heterogeneity Provides Free Exploration

- In the classical MAB: cumulative regret is $O(\log(T))$
- In incentizing exploration with heterogeneous users: we show, with assumptions, cumulative regret is $O(1)$
- Key insight: Heterogeneity provides free exploration
- Our contribution: First algorithm and analysis for incentivizing exploration when users have heterogeneous preferences over arms

Problem Setting

N arms

- Each arm has an unknown feature vector $\boldsymbol{u}_i \in R^d$
- Pulling arm i gives observation of $\boldsymbol{u}_i$, perturbed by independent sub-Gaussian noise
- The agents and principal observe averages $\hat{\boldsymbol{u}}_{i,t}$ of each arm's past pulls

Myopic Agents

- Agents arrive sequentially
- Agent t has linear preferences with weight vector $\boldsymbol{\theta}_t \in R^d$ drawn from known distribution F
- Without incentives, agent t would choose the arm maximizing $\boldsymbol{\theta}_t \cdot \hat{\boldsymbol{u}}_{i,t}$.

Problem Setting

Agents' behavior

- Principal chooses payment $c_{t,i}$ for arm i at time t
- Agent $\boldsymbol{\theta}_t$ pulls arm $i_t = \arg\max_i \{\boldsymbol{\theta}_t \cdot \hat{\boldsymbol{u}}_{i,t} + c_{t,i}\}$

Principal's goal

- Regret $r_t = (\max_i \boldsymbol{\theta}_t \cdot \boldsymbol{u}_i) - \boldsymbol{\theta}_t \cdot \boldsymbol{u}_{i_t}$ and payment $c_t = c_{t,i_t}$
- Incentivize to minimize the cumulative regret while making a small cumulative payment

Key Assumptions

- (**Every arm is someone's best**) Each arm is preferred by at least p fraction of users.
- (**Not too many near-ties**) Let $q(z)$ be the cumulative distribution function of those agents whose utility difference between their best and second best arm is less than or equal to z. Then, there exists a $\hat{z} > 0$, L such that $q(z) \leq L \cdot z$ for all $z \leq \hat{z}$.
- (**Compact Support**) $\boldsymbol{\theta}$ has compact support contained in $[0, D]^d$.

Main Result

Theorem 1

Our policy achieves:

expected cumulative regret $O(Ne^{2/p} + LN\log^3(T))$,

using expected cumulative payments of $O(N^2 e^{2/p})$.

Special case: When agent preferences are discrete, i.e. $L = 0$, regret and payment are bounded by constants in T.

Algorithm

Set the current phase number $s = 1$. {Each arm is pulled once initially "for free."}
for time steps $t = 1, 2, 3, \ldots$ **do**
  Update the current phase number if needed;
  if there is a payment-eligible arm i **then**
    Offer "whatever it takes" payment for pulling arm i (and payment 0 for all other arms).
  else
    Let agent t play myopically, i.e., offer payments 0 for all arms.

Question?

Thanks for your time!