Privacy-Preserving Online Learning for Movie Recommendation

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Outline

- Background Problem
- Online Learning
- Differential Privacy
- Algorithm
- Experiments
Background Problem: Movie Recommendations

#YouTube

#personalized movie recommendation

#How to find the movie that matches a particular user’s preference?

#Privacy issue: Recommendation leaks user’s personal information.
Background Problem: Movie Recommendations

Different users with different preferences

Users are represented by row vectors

Static user database

Actually, recommendation is an online learning task:

Goal: design a learning algorithm that can achieve recommendation and preserve user personal information.
Online Learning/Contextual Bandit

- A gambler faces $k$ slot-machines (arms).
- Each machine provides a random reward from unknown distribution specific to that machine.
- At each time slot, the gambler selects one machine to play, and gets a random reward.
- Goal: how to maximize the sum of rewards over all time slots.

The stochastic bandit problem

*Known parameters:* number of arms $K$ and (possibly) number of rounds $n \geq K$.
*Unknown parameters:* $K$ probability distributions $\nu_1, \ldots, \nu_K$ on $[0, 1]$.

For each round $t = 1, 2, \ldots$

1. the forecaster chooses $I_t \in \{1, \ldots, K\}$;
2. given $I_t$, the environment draws the reward $X_{I_t,t} \sim \nu_{I_t}$ independently from the past and reveals it to the forecaster.
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For \( i = 1, \ldots, K \) we denote by \( \mu_i \) the mean of \( \nu_i \) (mean reward of arm \( i \)). Let

\[
\mu^* = \max_{i=1,\ldots,K} \mu_i \quad \text{and} \quad i^* = \arg\max_{i=1,\ldots,K} \mu_i.
\]

In the stochastic setting, it is easy to see that the pseudo-regret can be written as

\[
\overline{R}_n = n\mu^* - \sum_{t=1}^{n} \mathbb{E}[\mu_{I_t}].
\]

Goal: Design a learning algorithm for the gambler to minimize the regret.
Online Learning/Contextual Bandit

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Formalize Recommendation as a bandit problem:

- At each time slot, recommender receives new user's contextual information.
- Choose a movie (arm) to recommend.
- Receive a random reward of recommended movie.
- Update strategy for next user.
Differential Privacy

\[ M(D) = f(D) + Lap(b) \]

Definition: An algorithm \( M \) is \( \epsilon \)-differentially private if for all pairs of neighboring datasets \( D, D' \), and for all outputs \( x \):

\[
\Pr[M(D) = x] \leq (1 + \epsilon) \Pr[M(D') = x]
\]

Laplace Mechanism to achieve differential privacy:

Directly query the database \( D \)
Algorithm

Part 1. Offline Estimation

1. Partition $n$ users into $m$ groups based on their contextual similarity.
2. Recommend all movies to them and gather rewards.
3. Compute average reward of different movie.

Part 2. Online Recommendation

At each time slot:

1. Receive new user, compute which group it belongs to.
2. Recommend the movie with highest average reward to the user.
3. Observe reward.
4. Add Laplace noise to this reward and update average reward.

Performance Metric:

Minimize the regret:

$$ \overline{R}_n = n\mu^* - \sum_{t=1}^{n} E[\mu_{It}] $$
Experiments: Set Up

1. Dataset: the MovieLens dataset collected by the GroupLens Research Project at the University of Minnesota
   - 943 users
   - 5 movie genres

2. Generate Bernoulli distribution to simulate user's reward/feedback.

3. Plot the regret function to show the performance of the proposed algorithm.
Experiments: Results
References

Thank You!