Comparison-based Conversational Recommender System with Relative Bandit Feedback

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ABSTRACT

With the recent advances of conversational recommendations, the recommender system is able to actively and dynamically elicit user preference via conversational interactions. To achieve this, the system periodically queries users' preference on attributes and collects their feedback. However, most existing conversational recommender systems only enable the user to provide absolute feedback to the attributes. In practice, the absolute feedback is usually limited, as the users tend to provide biased feedback when expressing the preference. Instead, the user is often more inclined to express comparative preferences, since user preferences are inherently relative. To enable users to provide comparative preferences during conversational interactions, we propose a novel comparison-based conversational recommender system. The relative feedback, though more practical, is not easy to be incorporated since its feedback scale is always mismatched with users' absolute preferences. With effectively collecting and understanding the relative feedback from an interactive manner, we further propose a new bandit algorithm, which we call *RelativeConUCB*. The experiments on both synthetic and real-world datasets validate the advantage of our proposed method, compared to the existing bandit algorithms in the conversational recommender systems.

CCS CONCEPTS

• **Information systems** → **Recommender systems**; *Users and interactive retrieval*; • **Computing methodologies** → *Online learning settings.*

KEYWORDS

Conversational Recommender System; Online Learning; Bandit Feedback; Relative Feedback

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1 INTRODUCTION

Recommender systems have received enormous attention in this age of big data. In many scenarios, for a recommender system to interact adaptively and optimally with users, it must learn effectively from user feedback. However, for cold-start users with little historical data, it is very challenging to recommend optimally in an online manner. Moreover, the data collected from users during recommendation can be extremely skewed, as users only express their preference on the recommended item. To better elicit users' preference, the idea of conversational recommender system (CRS) was proposed [5]. In addition to collecting responses (e.g., click behaviors) on recommended items, the system also periodically conducts conversations with the user to better elicit preference. This allows the system to provide personalized recommendations based on the responses.

Despite the success of CRSs in recent years, we argue that current conversation mechanism is still limited. Most existing CRSs only allow the user to provide absolute feedback, from which it can be hard to collect useful and accurate information in practice [2, 10, 17, 27]. For example, in a movie recommendation scenario, the agent may query about the user's preference on a particular category: "*Do you like Nolan's movies?*". As a big fan of Nolan, the user would answer positively. But for a similar question "*What about Michael Bay's movies?*", it could be difficult to answer as the user holds a very mixed attitude towards the director's works. The love felt for the series of Transformers would eventually induce another positive answer. The contradictory feedback misleads the agent to believe that the user admires both directors equally. To address this issue, we consider asking relative questions to elicit the user's preference. We argue that relative feedback can be more accurate, since user preferences are inherently relative.

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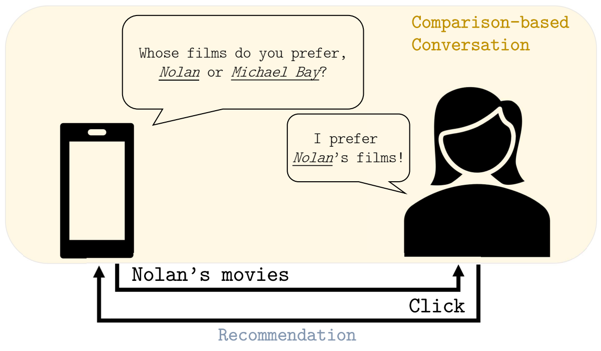

Comparison-based Conversation
Whose films do you prefer, Nolan or Michael Bay?
I prefer Nolan's films!
Nolan's movies
Click
Recommendation

Figure 1: An illustrative example of a comparison-based conversational recommender system.

Motivated by the above considerations, we propose to build a comparison-based conversational recommender system. To the best of our knowledge, few works have reached this topic. The system follows the conventional CRS scenario, recommending items sequentially to the user based on contextual information. Compared to existing CRSs, the proposed framework differs on how to conduct conversations. The comparison-based conversational recommender asks relative questions over key-terms, and then receives relative feedback inferring the user's comparative preference. Similar to that in [29], a key-term is a category-like concept, representing a specific group of items. Movies directed by Nolan is an example of a key-term in the mentioned scenario.

In spite of the mentioned superiority of relative feedback, it could be difficult to incorporate relative feedback due to the mismatch between comparative signals and the underlying user preferences. With effectively collecting and understanding the relative feedback from an interactive manner, we further propose a new bandit algorithm, which we call *RelativeConUCB*. RelativeConUCB formulates conversation and recommendation as a two-stage learning process. When conducting conversations, RelativeConUCB selects the pair of key-terms which maximizes error reduction, and queries the user's comparative preference over it. To incorporate relative feedback, we develop three different mechanisms. The experiments show that our algorithm performs competitively well compared to existing bandit algorithms in the conversational recommender systems.

In summary, we make three major contributions:

- We present a novel comparison-based CRS, which allows users to provide relative feedback to the comparisons of key-terms. This extends the framework of existing CRSs.
- We propose a new bandit algorithm RelativeConUCB to build a comparison-based CRS.
- Experiments on both synthetic and real-world datasets clearly show the advantages of our method.

The rest of the paper is organized as follows. We specify the considered comparison-based conversational recommender system in Section 2. In Section 3 we introduce the RelativeConUCB algorithm in details. The experimental setup and results for evaluation are presented in Section 4. Finally, we discuss some related works in Section 5 and then conclude our work in Section 6.

2 SYSTEM OVERVIEW

In this section we will formulate how our comparison-based conversational recommender system works. We start by introducing the conventional contextual bandit scenario, and then extend the system, equipping it with the power to conduct comparison-based conversations.

2.1 Contextual Bandit

Contextual bandits' objective is to optimize the expected cumulative rewards in a long run. To achieve this, they need to acquire enough information about arms while simultaneously utilizing the available knowledge to choose the best arm.

Suppose there is a finite set of arms (e.g., movies in the domain of movie recommendation) denoted by an index set $\mathcal{A}$ in the system. The agent will interact with a user with unknown feature $\boldsymbol{\theta}^* \in \mathbb{R}^d$ consecutively for T rounds. At each round t, the agent only has access to a subset of arms $\mathcal{A}_t \subseteq \mathcal{A}$, from which the agent needs to choose an arm a_t based on its observed contextual vector $\boldsymbol{x}_{a_t} \in \mathbb{R}^d$ and recommend it to the user. The agent will then receive a binary reward representing the click behavior:

$$r_{a_t,t} \sim \text{Bernoulli}(\boldsymbol{x}_{a_t}^\top \boldsymbol{\theta}^*). \tag{1}$$

The target of the agent is to maximize the cumulative reward or, equivalently, to minimize the cumulative regret in $T \in \mathbb{N}_+$ rounds of interaction:

$$R \triangleq \mathbb{E}\left[\sum_{t=1}^{T} \max_{a \in \mathcal{A}_t} \boldsymbol{x}_a^\top \boldsymbol{\theta}^* - \sum_{t=1}^{T} r_{a_t,t}\right], \tag{2}$$

where regret accumulates as sub-optimal arms are selected.

2.2 Comparison-based CRS

A recent work [29] extends the contextual bandit scenario for conversational recommendation. It allows the agent to occasionally conduct conversations with users, asking the user's preference over *key-terms*. Specifically, a key-term can be a category or a common attribute (e.g., the category of comedy movies in movie recommendation). Key-terms in the system are denoted by an index set $\mathcal{K}$. The relationship between arms and key-terms are defined by a weighted bipartite graph $(\mathcal{A}, \mathcal{K}, \mathbf{W})$, where key-term k is associated to arm a with weight $\mathbf{W}_{a,k} \geq 0$. To normalize, we assume $\sum_{k \in \mathcal{K}} \mathbf{W}_{a,k} = 1$, $\forall a \in \mathcal{A}$. The contextual vector for key-term k is then formulated as $\tilde{\boldsymbol{x}}_k = \sum_{a \in \mathcal{A}} \frac{\mathbf{W}_{a,k}}{\sum_{a' \in \mathcal{A}} \mathbf{W}_{a',k}} \boldsymbol{x}_a$.

2.2.1 Relative Feedback. In the above conversational recommender system, the agent is only allowed to ask the user absolute questions like "*Are you interested in Nolan's films?*" We argue that it is usually unpractical, as the user may have very biased attitudes towards the key-terms, in which case the agent can only collect limited information. Comparative preferences in the meanwhile are potentially more informative and cheaper to collect. Therefore, we design the comparison-based conversation scenario. To conduct conversations, the agent queries relative questions over pairs of key-terms. For example, as illustrated in Figure 1, the agent may ask "*Whose films*

Algorithm 1: Comparison-based Conversational Recommender System

```
Input: Arms $\mathcal{A}$, key-terms $\mathcal{K}$, weight $\mathbf{W}$, users $\mathcal{U}$, and
       conversation frequency function $b(\cdot)$.
1  Initialize the numbers of users' interaction $t_u = 0, \forall u \in \mathcal{U}$;
2  for $i = 1, 2, \ldots, N$ do
3      An arbitrary user $u \in \mathcal{U}$ arrives with $t = t_u$ rounds of
         historical interaction;
4      Set the conversation budget $q_t$ according to Equation 4;
5      Determine the candidate arms $\mathcal{A}_t$ and the candidate
         key-terms $\mathcal{K}_t$ (e.g., by sampling);
       /* An agent starts to interact with $u$          */
6      for $j = 1, 2, \ldots, q_t$ do
7          Select a pair of key-terms $k_1, k_2 \in \mathcal{K}_t$ to query the
             user preference;
8          Receive the conversational feedback $\tilde{r}_{k_1,k_2,t} \in \{0, 1\}$;
9          Update the model parameters;
10     Select an arm $a_t \in \mathcal{A}_t$ to recommend;
11     Receive the reward $r_{a_t,t} \in \{0, 1\}$;
12     Update the model parameters;
13     Update $t_u = t_u + 1$;
```

do you prefer, Nolan or Michael Bay?". It then receives the feedback inferring the user's comparative preference. To simplify, we assume no abstention, making the feedback binary. Furthermore, we assume the feedback may be corrupted by Gaussian noise. Suppose the user has an internal valuation towards key-term k:

$$\tilde{r}_{k,t} = \tilde{\boldsymbol{x}}_k^\top \boldsymbol{\theta}^* + \epsilon_{k,t},$$

where $\epsilon_{k,t} \sim \mathcal{N}(0, \sigma_g^2)$ denotes the random noise. The relative feedback for key-term k_1 and k_2 is:

$$\tilde{r}_{k_1,k_2,t} = \mathbf{1}\left[\tilde{r}_{k_1,t} > \tilde{r}_{k_2,t}\right]. \tag{3}$$

2.2.2 Conversation Frequency. Similarly to [29], we model the conversation frequency by a function $b(\cdot)$. Specifically, if $b(t) - b(t-1) > 0$, the agent will conduct

$$q_t = b(t) - b(t-1) \tag{4}$$

conversations with user at the t-th round of interaction. In such a manner, the agent will conduct $b(t)$ conversations with the user up to round t.

2.2.3 Long-run Interaction. To simulate the long-run process of interaction with multiple users, we consider a sequence of N iterations described in Algorithm 1. Assume there is an arbitrary distribution p over users indicating the user frequency. At each iteration[1], an arbitrary user drawn randomly from p will arrive. The agent, unknowing the user's real feature, will then interact with the user as described in Line 6-12 of Algorithm 1. This framework extends the original contextual bandit scenario by considering one particular user may not arrive consecutively.

[1]It needs to clarify that 'iteration' considers interaction with multiple users, while 'round' refers to interaction with a specific user.

Algorithm 2: RelativeConUCB

```
Input: 1) User $u$ with $t = t_u$ rounds of historical interaction,
          parameters $\mathbf{M}_u$, $\boldsymbol{b}_u$, $\tilde{\mathbf{M}}_u$ and $\tilde{\boldsymbol{b}}_u$;
       2) candidate arms $\mathcal{A}_t$, candidate key-terms $\mathcal{K}_t$,
          weight $\mathbf{W}$, and conversation budget $q_t$;
       3) hyper-parameters $\lambda$, $\tilde{\lambda}$, $\sigma$, $\alpha$, and $\tilde{\alpha}$.
1  if $t = 0$ then
2      Initialize $\mathbf{M}_u = (1-\lambda)\mathbf{I}, \boldsymbol{b}_u = \mathbf{0}, \tilde{\mathbf{M}}_u = \tilde{\lambda}\mathbf{I}, \tilde{\boldsymbol{b}}_u = \mathbf{0}$;
3  for $j = 1, 2, \ldots, q_t$ do
4      Select a pair of key-terms $k_1, k_2 \in \mathcal{K}_t$ according to
         Section 3.1.1 or Section 3.1.2;
5      Receive the conversational feedback $\tilde{r}_{k_1,k_2,t}$ according to
         Equation 3;
6      Update $\tilde{\mathbf{M}}_u$ and $\tilde{\boldsymbol{b}}_u$ according to Algorithm 3;
7  Update $\tilde{\boldsymbol{\theta}}_u = \tilde{\mathbf{M}}_u^{-1}\tilde{\boldsymbol{b}}_u, \boldsymbol{\theta}_u = \mathbf{M}_u^{-1}\left(\boldsymbol{b}_u + (1-\lambda)\tilde{\boldsymbol{\theta}}_u\right)$;
8  Select an arm $a_t \in \mathcal{A}_t$ according to Equation 9;
9  Receive the reward $r_{a_t,t}$ according to Equation 1;
10 Update $\mathbf{M}_u = \mathbf{M}_u + \lambda \boldsymbol{x}_{a_t}\boldsymbol{x}_{a_t}^\top, \boldsymbol{b}_u = \boldsymbol{b}_u + \lambda r_{a_t} \boldsymbol{x}_{a_t}$;
```

The overall objective for an agent in the comparison-based CRS is to minimize the cumulative regret induced by all interacted users in a long run:

$$R(N) \triangleq \sum_{u \in \mathcal{U}_N} R_u, \tag{5}$$

where index set $\mathcal{U}_N$ denotes the users that have interacted with the agent for at least one round and R_u denotes the cumulative regret induced by the historical interaction with user u defined in Equation 2.

3 ALGORITHM

To build a comparison-based conversational recommender system, we propose the RelativeConUCB algorithm.

Algorithm 2 describes the proposed RelativeConUCB which implements Line 6-12 of Algorithm 1. Following the work [29], we model the arms and key-terms separately. Specifically, for user u the agent has two sets of estimated features $\boldsymbol{\theta}_u$ and $\tilde{\boldsymbol{\theta}}_u$. $\boldsymbol{\theta}_u$ models the user's preference on arms, whereas $\tilde{\boldsymbol{\theta}}_u$ models the user's preference on key-terms.

At each iteration i, user u with unknown feature $\boldsymbol{\theta}^*$ will interact with the agent. The agent then decides whether to conduct conversation based on the user's historical interactions and the system's preset conversational frequency function. When conducting conversations, RelativeConUCB selects the pair of key-terms which maximizes error reduction, and queries the user's comparative preference over them. The received feedback will then be utilized to update $\tilde{\boldsymbol{\theta}}_u$, which helps the agent to quickly capture users' preference and, as the result, to recommend the user's desired item. To efficiently incorporate feedback, three update mechanisms are proposed. We will discuss them thoroughly in Section 3.1. Finally, RelativeConUCB recommends an item to the user, and receives a reward. The recommendation process relies on a upper-confidence-based strategy. The detailed methods for item recommendation can be found in Section 3.2.

3.1 Comparison-Based Conversation

In this section we will discuss how to conduct comparison-based conversations (Line 4-6 of Algorithm 2). In each conversation, the agent needs to ask a relative question. Once the user expresses comparative preference over the question, our estimation of the user's parameters can then be updated. To be specific, two key problems will be discussed in details and conquered: 1) how to select key-terms to conduct comparison-based conversations (Line 4 of Algorithm 2); and 2) how to update the model effectively with relative feedback (Line 6 of Algorithm 2).

In this work, we propose three variants of the RelativeConUCB algorithm: **Pos**, **Pos&Neg**, and **Difference**.

3.1.1 ***Pos** and **Pos&Neg**.* On the first attempt, we adopt an absolute model for relative questions inspired by [5]. The insight behind the model is that relative feedback inferring the user's comparative preference can be interpreted as two individual observations of key-term. For example, if the user shows more inclination to comedy movies than sci-fi ones, the agent will translate it into absolute information: 1) the user likes comedy movies; and 2) the user dislikes sci-fi movies. In this manner, we estimate the key-term level preference of user u by:

$$\tilde{\boldsymbol{\theta}}_u = \arg\min_{\tilde{\boldsymbol{\theta}}} \sum_{(\tilde{\boldsymbol{x}},\tilde{r})\in\mathcal{D}_u} \left(\tilde{\boldsymbol{\theta}}^\top \tilde{\boldsymbol{x}} - \tilde{r}\right)^2 + \tilde{\lambda}\|\tilde{\boldsymbol{\theta}}\|_2^2, \tag{6}$$

where $(\tilde{\boldsymbol{x}}, \tilde{r})$ stands for an absolute observation of key-term with $\tilde{\boldsymbol{x}} \in \mathcal{K}$ and $\tilde{r} \in \{0, 1\}$, and $\mathcal{D}_u$ denotes the collected observation dataset of user u. Equation 6 has a closed-form solution $\tilde{\boldsymbol{\theta}}_u = \tilde{\mathbf{M}}_u^{-1}\tilde{\boldsymbol{b}}_u$, where

$$\tilde{\mathbf{M}}_u = \sum_{(\tilde{\boldsymbol{x}},\tilde{r})\in\mathcal{D}_u} \tilde{\boldsymbol{x}}\tilde{\boldsymbol{x}}^\top + \tilde{\lambda}\mathbf{I},$$
$$\tilde{\boldsymbol{b}}_u = \sum_{(\tilde{\boldsymbol{x}},\tilde{r})\in\mathcal{D}_u} \tilde{\boldsymbol{x}}\tilde{r}.$$

Based on the above model, we formulate two variants of the proposed algorithm **Pos** and **Pos&Neg**. They use the same mechanism to select relative questions. Suppose at t-th round of interaction with user u, the agent has access a subset of arms $\mathcal{A}_t$ and a subset of key-term $\mathcal{K}_t$. The contextual vectors for arms are denoted by $\mathbf{X}_t$, whose rows are composed of $\{\boldsymbol{x}_a^\top : a \in \mathcal{A}_t\}$. To collect the most informative observations, we expect to select key-terms that minimize the estimation error $\mathbb{E}\left[\left\|\mathbf{X}_t\boldsymbol{\theta}_u - \mathbf{X}_t\boldsymbol{\theta}_u^*\right\|_2^2\right]$. To select the optimal key-term to observe, we can approximately choose:

$$k = \arg\max_{k'\in\mathcal{K}_t} \frac{\left\|\mathbf{X}_t\mathbf{M}_u^{-1}\tilde{\mathbf{M}}_u^{-1}\tilde{\boldsymbol{x}}_{k'}\right\|_2^2}{1 + \tilde{\boldsymbol{x}}_{k'}^\top\tilde{\mathbf{M}}_u^{-1}\tilde{\boldsymbol{x}}_{k'}}, \tag{7}$$

according to Theorem 2 in [29]. The essence behind Equation 7 is to greedily choose an key-term that could reduce the most uncertainty in the upcoming round of recommendation.

In this manner, we apply the following mechanism to choose the pair of key-terms: 1) we select a key-term k_1 with feature $\tilde{\boldsymbol{x}}_{k_1}$ according to Equation 7; 2) then, we conduct a pseudo update by updating the model with $\tilde{\boldsymbol{x}}_{k_1}$ according to Algorithm 3; 3) finally, we select another key-term k_2 according to Equation 7 with the updated model.

```
Algorithm 3: Key-term Level Updating
  Input: user $u$ with parameters $\tilde{\mathbf{M}}_u, \tilde{\boldsymbol{b}}_u$; observation $(\tilde{\boldsymbol{x}}, \tilde{r})$
1 $\tilde{\mathbf{M}}_u = \tilde{\mathbf{M}}_u + \tilde{\boldsymbol{x}}\tilde{\boldsymbol{x}}^\top$;
2 $\tilde{\boldsymbol{b}}_u = \tilde{\boldsymbol{b}}_u + \tilde{r}\tilde{\boldsymbol{x}}$;
```

The only difference between two variants is how to interpret relative feedback to update the model or, equivalently, how to construct observation samples.

Suppose during the conversation at round t, user u expresses that k_1 is preferred rather than k_2. The agent will therefore receive relative feedback $\tilde{r}_{k_1,k_2,t} = 1$. Then the agent will update the model for user u according to Algorithm 3. For **Pos**, it incorporates only positive information $(\tilde{\boldsymbol{x}}_{k_1}, 1)$. For **Pos&Neg**, the relative feedback is interpreted as two observations of absolute feedback: a positive observation $(\tilde{\boldsymbol{x}}_{k_1}, 1)$ for the preferred key-term and a negative observation $(\tilde{\boldsymbol{x}}_{k_2}, 0)$ for the less preferred key-term.

3.1.2 ***Difference**.* The above updating methods deal with relative feedback the same as with absolute feedback, which may not fully utilize the advantages of relative feedback. To improve, we consider training a linear classifier directly on paired data, and develop the updating method **Difference**.

We still apply the estimation of $\tilde{\boldsymbol{\theta}}_u$ according to Equation 6. But for **Difference**, we incorporate the relative feedback as a single observation $(\tilde{\boldsymbol{x}}_{k_1} - \tilde{\boldsymbol{x}}_{k_2}, 1)$. This is essentially training a linear classifier of feature difference using ridge regression. Note that the unknown parameters can not be fully identified by relative feedback, as $\boldsymbol{\theta}^*$ and $2\boldsymbol{\theta}^*$ induce the same comparison results for any pair $\tilde{\boldsymbol{x}}_{k_1}, \tilde{\boldsymbol{x}}_{k_2}$ in expectation. Rather, what the linear classifier actually estimates is the normalized feature vector $\frac{\boldsymbol{\theta}^*}{\|\boldsymbol{\theta}^*\|_2}$. On the other hand, in the arm-level recommendation, the agent learns the norm of the feature $\|\boldsymbol{\theta}^*\|_2$. In this manner, RelativeConUCB learns users' preferences effectively in the sense of both absolute correctness and relative relationship.

To design relative questions, we follow the maximum error reduction strategy which leads us to choose the pair based on the feature difference $\Delta\tilde{\boldsymbol{x}}_{k_1,k_2} = \tilde{\boldsymbol{x}}_{k_1} - \tilde{\boldsymbol{x}}_{k_2}$:

$$k_1, k_2 = \arg\max_{k_1,k_2\in\mathcal{K}_t} \frac{\left\|\mathbf{X}_t\mathbf{M}_u^{-1}\tilde{\mathbf{M}}_u^{-1}\Delta\tilde{\boldsymbol{x}}_{k_1,k_2}\right\|_2^2}{1 + \Delta\tilde{\boldsymbol{x}}_{k_1,k_2}^\top\tilde{\mathbf{M}}_u^{-1}\Delta\tilde{\boldsymbol{x}}_{k_1,k_2}}. \tag{8}$$

The key-term selection strategy described above induces the standard **Difference** variant. However, since the number of key-terms can be extremely large, the strategy may not be practical as it has a quadratic time complexity. To eschew the problem, we further propose an optimized variant called **Difference** (*fast*). When selecting key-terms, it first selects a key-term k_1 by Equation 7. Then, with the first key-term fixed, it chooses another key-term k_2 based on Equation 8. In Section 4, we will compare these two variants, showing that **Difference** (*fast*) only suffers little decrease of performance.

3.2 Item Recommendation

The arm-level recommendation (Line 8-10 of Algorithm 2) is essentially similar to that of LinUCB [13]. The difference is that, to accelerate the process of arm preference learning, the agent utilizes $\tilde{\boldsymbol{\theta}}_u$ as a guidance of $\boldsymbol{\theta}_u$ by penalizing the difference between $\boldsymbol{\theta}_u$ and $\tilde{\boldsymbol{\theta}}_u$:

$$\boldsymbol{\theta}_u = \arg\min_{\boldsymbol{\theta}} \lambda \sum_{\tau=1}^{t_u} \left(\boldsymbol{x}_{a_\tau}^\top \boldsymbol{\theta} - r_{a_\tau,\tau} \right)^2 + (1-\lambda) \left\| \boldsymbol{\theta} - \tilde{\boldsymbol{\theta}}_u \right\|_2^2 .$$

The hyper-parameter λ balances arm-level and key-term level learning. The closed-form solution for $\boldsymbol{\theta}_u$ is $\mathbf{M}_u^{-1} \left(\boldsymbol{b}_u + (1-\lambda)\tilde{\boldsymbol{\theta}}_u \right)$, where

$$\mathbf{M}_u = \lambda \sum_{\tau=1}^{t_u} \boldsymbol{x}_{a_\tau} \boldsymbol{x}_{a_\tau}^T + (1-\lambda)\mathbf{I},$$

$$\boldsymbol{b}_u = \lambda \sum_{\tau=1}^{t_u} \boldsymbol{x}_{a_\tau} r_{a_\tau,\tau}.$$

To balance exploration and exploitation, RelativeConUCB selects an arm to recommend in a upper-confidence based strategy:

$$a_t = \arg\max_{a \in \mathcal{A}_t} \boldsymbol{x}_a^\top \boldsymbol{\theta}_u + \lambda\alpha \left\| \boldsymbol{x}_a \right\|_{\mathbf{M}_u^{-1}} + (1-\lambda)\tilde{\alpha} \left\| \mathbf{M}_u^{-1} \boldsymbol{x}_a \right\|_{\tilde{\mathbf{M}}_u^{-1}}, \quad (9)$$

where $\alpha, \tilde{\alpha} \in \mathbb{R}$ are hyper-parameters, and $\|\boldsymbol{x}\|_{\mathbf{M}} = \sqrt{\boldsymbol{x}^\top \mathbf{M} \boldsymbol{x}}$.

The strategy exploits the current estimation on the reward of arm a (the first term of Equation 9). A higher value of the first term indicates that in the previous interaction user u has expressed more inclination to arm a. On the other hand, in order to eschew being misled by wrong perception, the strategy needs to choose some sub-optimal arms for exploration. This is achieved by including uncertainty estimation (the second and third term of Equation 9). The second term estimates the uncertainty in the arm-level, while the third term estimates the uncertainty from key-term level parameters. Please refer to [29] for more insights.

3.3 Feedback Sharing

In the former sections, we have made no assumption on users' features. However, in practice, groups of users usually share some similar preferences. A rich body of methods has been proposed to model and exploit users' similar behaviors such as collaborative filtering [7]. We take a step further and claim that, compared to absolute preferences, comparative preferences could be more consistent among users. The reason is that user biases can be eliminated from the feedback when making comparisons. Therefore, no matter how biased each user is, we can still consider users with similar comparative preferences are of the same type.

Based on the hypothesis, we propose to utilize the similarity by feedback sharing. Suppose the agent interacts with user u at iteration i. Once we receive relative feedback from u, we can update parameters of the similar users all at once:

$$\tilde{\mathbf{M}}_u = \tilde{\mathbf{M}}_u + \tilde{\boldsymbol{x}}\tilde{\boldsymbol{x}}^\top,$$

$$\tilde{\boldsymbol{b}}_u = \tilde{\boldsymbol{b}}_u + \tilde{r}\tilde{\boldsymbol{x}}, \forall u \in \mathcal{U}.$$

In this manner, conversation and recommendation actually form a two-stage learning process. When conducting conversations, the agent learns common preferences of a group of users. In the meantime, the received rewards from item recommendation imply users' individual bias. In section 4, we will compare the performance of sharing absolute feedback and relative feedback. We leave more comprehensive study of sharing mechanism as future work.

4 EXPERIMENTS

To validate our proposed RelativeConUCB algorithm empirically, we evaluate and compare the performances of several state-of-the-art algorithms on both synthetic and real-world datasets[2].

4.1 Experimental Setup

In this section we describe our experimental setup. We start with the baselines to compare. Then we describe how the simulation environment is constructed and the evaluation metrics. Finally, we list several research questions that we seek to answer.

4.1.1 Baselines. The following algorithms are selected as the representative baselines to be compared with:

- **LinUCB** [13]: A state-of-the-art non-conversational contextual bandit approach.
- **ConUCB** [29]: A recently proposed conversational contextual bandit approach. When conducting conversations with user u, it chooses the key-term k which maximizes error reduction, queries the user's preference on it, and receives absolute feedback $\tilde{r} \sim \text{Bernoulli}(\tilde{\boldsymbol{x}}_k^\top \boldsymbol{\theta}_u^*)$.

For LinUCB, we set hyper-parameters $\lambda = 1, \alpha = 0.5$. For both ConUCB and RelativeConUCB, we set hyper-parameters $\lambda = 0.5$, $\tilde{\lambda} = 1$, $\sigma = 0.05$, $\alpha = 0.25$, $\tilde{\alpha} = 0.25$ according to the default configuration in ConUCB's public source code.

4.1.2 Simulation. For all experiments, we sequentially simulate $N = 400 \times |\mathcal{U}|$ iterations. At each iteration i, the incoming user u with $t = t_u$ rounds of historical interaction is chosen randomly from the user set $\mathcal{U}$. For item recommendation, the agent can select one out of 50 arms in the candidate set $\mathcal{A}_t$, which is randomly drawn from $\mathcal{A}$ without replacement. The key-term candidate set $\mathcal{K}_t$ contains those key-terms that are related to any arm in $\mathcal{A}_t$. Furthermore, we set the conversation frequency function $b(t) = 5\lfloor \log(t) \rfloor$ which induces more conversations at the early stage to quickly capture preferences [29]. The reward for arms and relative feedback for key-terms are generated by Equation 1 and Equation 3 where $\sigma_g = 0.1$. The distribution p over users is set uniform, suggesting that each user will averagely interact with the agent for 400 rounds. The final results are reported by conducting 10 repeated runs.

4.1.3 Metrics. We mainly use *cumulative regret* in Equation 5 to measure the performance of algorithms. As a widely used metric in the multi-armed bandit scenario, it captures the degree of satisfaction the user feels towards recommendation in a long run. Besides, in Section 4.2, we report *averaged reward* over iterations $A(N) \triangleq \frac{1}{N} \sum_{i=1}^{N} r_i$ to help clearly show the gap between different algorithms.

[2]The source code is available at https://github.com/fffffarmer/RelativeConUCB.

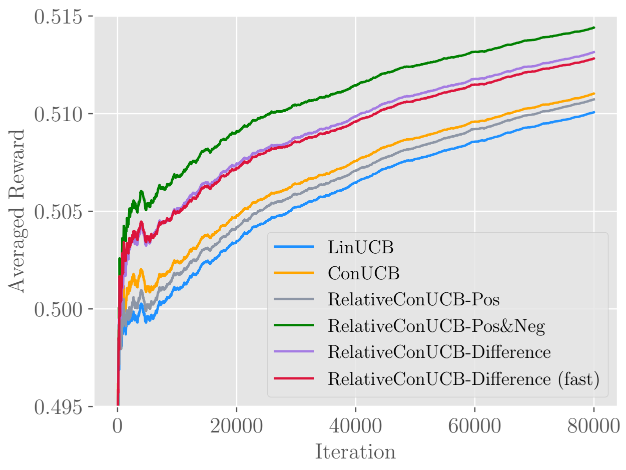


Figure 2: Averaged reward on synthetic data.

4.1.4 Research Questions. The designed experiments aim to answer the following evaluation questions:

RQ1. Can relative feedback be incorporated well to help preference learning, and which variant of our algorithm is more effective?
RQ2. Can we observe the benefit brought from feedback sharing?
RQ3. Under which circumstances will relative feedback be more superior to absolute feedback?

4.2 Synthetic Data

To answer **RQ1**, we first evaluate the algorithms on the synthetic data.

4.2.1 Data Generation. We consider a setting of a user set $\mathcal{U}$ with $|\mathcal{U}| = 200$, an arm set $\mathcal{A}$ with $|\mathcal{A}| = 5,000$ and a key-term set $\mathcal{K}$ with $|\mathcal{K}| = 500$. The relation matrix $\mathbf{W} \in \mathbb{R}^{|\mathcal{A}|\times|\mathcal{K}|}$ between arms and key-terms is constructed by the following procedures: 1) for each key-term k, we uniformly sample a subset of n_k related arms $\mathcal{A}_k \subseteq \mathcal{A}$ without replacement, where n_k is an integer drawn uniformly from $[1, 10]$; 2) we assign $\mathbf{W}_{a,k} = 1/n_a$, assuming arm a is related to a subset of n_a key-terms $\mathcal{K}_a$.

To generate the arms' feature vector, we follow similar procedures in [29]: 1) we first sample a pseudo feature in $d-1$ dimension $\dot{\boldsymbol{x}}_k \sim \mathcal{N}\left(\mathbf{0}, \sigma^2\mathbf{I}\right)$ for each $k \in \mathcal{K}$, where $d = 50$ and $\sigma = 1$; 2) for each arm a, its feature vector $\boldsymbol{x}_a$ is drawn from $\mathcal{N}\left(\sum_{k\in\mathcal{K}_a} \dot{\boldsymbol{x}}_k/n_a, \sigma^2\mathbf{I}\right)$; 3) finally, feature vectors are normalized and added one more dimension with constant 1: $\boldsymbol{x}_a \leftarrow (\frac{\boldsymbol{x}_a}{\|\boldsymbol{x}_a\|_2}, 1)$.

Table 1: Statistics of the datasets used in our experiments.

	Synthetic	Last.FM	Movielens
# of key-terms	500	2,726	5,585
avg. # of related key-terms	0.521	16.55	11.37
avg. # of related items	5.214	12.14	4.071

For the ground-truth feature of each user u, we first randomly sample a feature vector $\boldsymbol{\theta}_u^* \in \mathbb{R}^{d-1}$ from $\mathcal{N}\left(\mathbf{0}, \sigma^2\mathbf{I}\right)$. Then we introduce two parameters: c_u and b_u They are drawn uniformly from $[0, 0.5]$ and $[c_u, 1 - c_u]$ respectively, controlling the variance and mean of expected reward. The final feature vector of user u is $\boldsymbol{\theta}_u^* \leftarrow (c_u \frac{\boldsymbol{\theta}_u^*}{\|\boldsymbol{\theta}_u^*\|_2}, b_u)$. Note that the normalization step on both item features and user features aims to bound the expected reward $\boldsymbol{x}_a^\top \boldsymbol{\theta}_u^* \in [0, 1], \forall a \in \mathcal{A}, u \in \mathcal{U}$.

4.2.2 Results. The results are given in Figure 2, which plots the averaged reward over 80,000 iterations. We can first notice that all other algorithms outperform LinUCB, indicating the advantage of conducting conversations. The improvements are mainly reflected in the early stage, when the agent frequently converses with users.

Answer to RQ1. We can clearly observe that variant **Pos&Neg** and **Difference** have significant improvements over ConUCB. **Pos**, on the other hand, performs similarly to LinUCB.

Besides, the performances of **Difference** (*fast*) and **Difference** are very close. This validates that **Difference** (*fast*), as an approximation of **Difference**, can significantly reduce time complexity with little performance decrease.

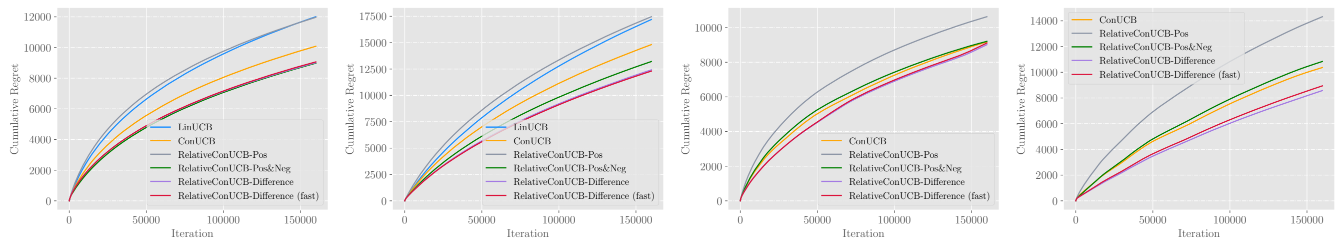
4.3 Real-world Datasets

We next evaluate RelativeConUCB on two real-world datasets from different domains, which are released in [1]: Last.FM[3] for music artist recommendation and Movielens[4] for movie recommendation. Last.FM dataset contains 186,479 interaction records between 1,892 users and 17,632 artists. Movielens dataset, which extends the original MovieLens10M dataset to include tagging information in IMDb[5] and Rotten Tomatoes[6], contains 47,957 interaction records between 2,113 users and 10,197 movies. Artists and movies are treated as items in our setting. We then infer users' real feedback on items based on the interaction records: if the user has assigned attributes to the item, the feedback is 1, otherwise the feedback is missing. For each dataset, we extract 2,000 items with most assigned attributes and 500 users who have assigned most attributes. For each item, we only leave at most 20 attributes that are associated with most items, and consider them as the related key-terms of the item. The statistics of processed data is shown in Table 1, where the average number of related key-terms for items and the average number of related items for key-terms are also reported.

4.3.1 Data Generation. Before we start, we randomly choose 100 users and formulate a binary matrix $H \in \{0, 1\}^{100\times 2\mathrm{k}}$ which stands for the interaction history. We derive feature vectors in $d-1$ ($d = 50$) dimension for items by applying one-class matrix factorization [4] on H, and then normalize them by $\boldsymbol{x}_a \leftarrow (\frac{\boldsymbol{x}_a}{\|\boldsymbol{x}_a\|_2}, 1), \forall a \in \mathcal{A}$. The constructed features will be used to conduct experiments on the records of the remaining 400 users.

For missing feedback of the remaining users, we again apply the matrix factorization technique to reconstruct the feedback matrix $F \in \{0, 1\}^{400\times 2\mathrm{k}}$. Next, in order to derive the ground truth user features, we use a simple autoencoder [18] with four hidden layers

[3]http://www.lastfm.com
[4]http://www.grouplens.org
[5]http://www.imdb.com
[6]http://www.rottentomatoes.com



(a) Last.FM (without feedback sharing) (b) Movielens (without feedback sharing) (c) Last.FM (with feedback sharing) (d) Movielens (with feedback sharing)

Figure 3: Cumulative regret on real-world datasets.

and ReLU activation function. The autoencoder takes the user's feedback (i.e., the corresponding row of F) as its input, encodes it into a latent representation $\boldsymbol{\theta}_u^* \in \mathbb{R}^{d-1}$, and normalizes it by $\boldsymbol{\theta}_u^* \leftarrow (\frac{\boldsymbol{\theta}_u^*}{\|\boldsymbol{\theta}_u^*\|_2}, 1)/2$. Finally, we reconstruct the feedback by $\boldsymbol{x}_a^\top \boldsymbol{\theta}_u^*$.

When training, we use MSE loss as the criterion and Adam with learning rate 3×10^{-4} as the optimizer. The training runs 200 epochs.

4.3.2 Results. In this experiment, we compare the performance of algorithms both in the original setting and the feedback sharing setting. For ConUCB, it shares conversational absolute feedback to all users. For RelativeConUCB, relative feedback is shared instead. The experimental results on real-world dataset are shown in Figure 3.

*Answer to **RQ1**.* We first evaluate the results with feedback sharing disabled. In Figure 3(a) and 3(b), we again observe the advantage of using relative feedback, comparing all algorithms in terms of cumulative regret. On Last.FM dataset, **Difference** (*fast*) and **Pos&Neg** outperforms ConUCB by 10.12% and 10.93% respectively. On Movielens dataset, **Difference** (*fast*) and **Pos&Neg** outperforms ConUCB by 16.93% and 10.82% respectively.

*Answer to **RQ2**.* As illustrated in Figure 3(c) and 3(d), directly sharing relative feedback among all users may not result in good performance. Compared to ConUCB, **Difference** and **Pos&Neg** do not show any advantage, which suggests that feedback sharing needs to be conducted more carefully by only considering similar users.

4.4 Drifted Real-world Datasets

As previously shown, sharing feedback among various kinds of users can not generally improve the performance of RelativeConUCB. But what if we only share feedback among similar users? Can user biases be effectively eliminated by using relative feedback instead of absolute one?

To take a step further, we design a drifted environment based on the real-world datasets. It models the users to be in some sense similar, sharing common comparative preferences. But individuals have their own bias, viewing items with different criteria. Specifically, for any two items, they may agree on which one is preferred. But the absolute attitude (like or dislike) towards each of them can be quite different among the users, depending on how critical each user is.

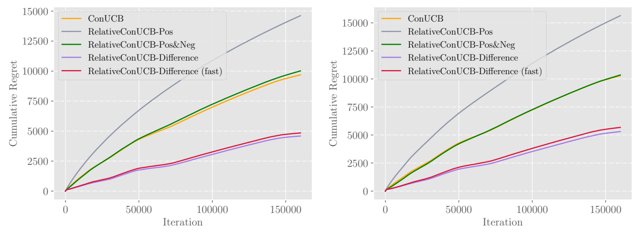
4.4.1 Data Generation. In the drifted environment, we assume the users' comparative preferences are inherently the same. To be specific, we model the feature vectors of user to be different only in the bias term. Following similar procedures in Section 4.3.1, we apply a four-layer autoencoder with two trainable embeddings $\boldsymbol{\theta}_{base} \in \mathbb{R}^{d-1}$ and $c \in [0, 0.5]$ to construct drifted user features. $\boldsymbol{\theta}_{base}$ aims to extract the common preferences of users and c controls the variance of expected reward. Taking the user's feedback as the input, the autoencoder outputs a real number $\tau \in [0, 1]$. The user feature is then constructed by $\boldsymbol{\theta}_u^* \leftarrow (c\frac{\boldsymbol{\theta}_{base}}{\|\boldsymbol{\theta}_{base}\|_2}, b_u)$, where $b_u = c + (1-c)\tau$. In this manner, the autoencoder constructs a drifted user group where preferences only differ in b_u.

When training on the autoencoder, we use MSE loss as the criterion and Adam with learning rate 3×10^{-3} as the optimizer. The training runs 1,000 epochs.

4.4.2 Results. The results are shown in Figure 4.

*Answer to **RQ1**.* As illustrated in the figures, **Difference** outperforms other algorithms by a substantial degree. Based on the result, we argue that **Difference** can better capture the intrinsic common preferences of users.

*Answer to **RQ2**.* As we can observe, among a group of similar users, sharing relative feedback can bring significant improvements. Compared to ConUCB, **Difference** (*fast*) outperforms by 49.96% and 44.75% on Last.FM and Movielens dataset respectively. The result demonstrates that relative feedback can conquer the problem of user bias, which makes it more effective to utilize user feedback.



(a) Last.FM (with feedback sharing) (b) Movielens (with feedback sharing)

Figure 4: Cumulative regret on real-world datasets in a drifted setting.

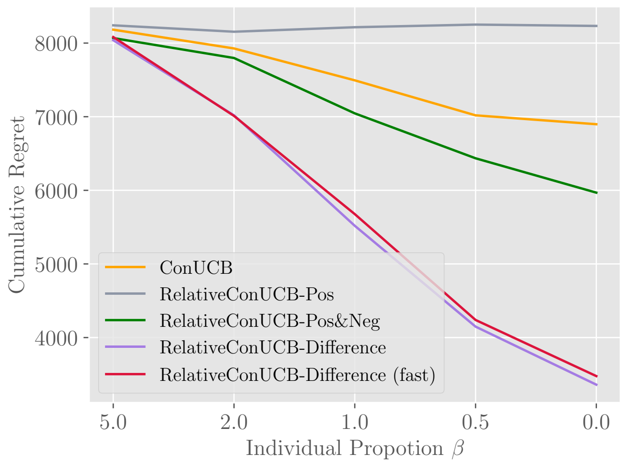


Figure 5: Effect of feedback sharing on different user groups.

4.5 Different User Groups

In Section 4.4, we have observed that when users have similar but biased preferences, relative feedback can be greatly utilized by sharing among users to better help recommendation. To explore the superiority in a fine-grained prospective, we setup another set of experiments to answer **RQ3**.

4.5.1 Data Generation. We modify the procedures of user feature generation based on the synthetic experiment. For each user u, we consider the ground-truth feature is composed of three parts: users' common feature $\boldsymbol{\theta}_{base}$, the user's individual feature $\boldsymbol{\theta}_u$[7], and the user's bias b_u. $\boldsymbol{\theta}_{base}$ and $\boldsymbol{\theta}_u$ are both in $d-1$ dimension, and are drawn randomly from $\mathcal{N}\left(\mathbf{0}, \sigma^2\mathbf{I}\right)$. We introduce two parameters $c \in [0, 0.5]$ and $\beta \in [0, +\infty)$ to control the reward variance and user similarity. The final feature vector of user u is $\boldsymbol{\theta}_u^* \leftarrow (c\frac{\boldsymbol{\theta}_{base}+\beta\boldsymbol{\theta}_u}{\|\boldsymbol{\theta}_{base}+\beta\boldsymbol{\theta}_u\|_2}, b_u)$, where b_u is drawn uniformly from $[c, 1-c]$. In this experiment we set $c = 0.4$.

4.5.2 Results. Figure 5 shows the outcome of the experiment, a comparison of the performances of algorithms under different user individual partitions (i.e., β). As the value of β gets smaller, users share more similarity in preferences. Meanwhile, the scale of user bias over the user group remains the same.

*Answer to **RQ3**.* From Figure 5 we can clearly observe a trend of increasing performance over all algorithms when we decrease the proportion β of users' individual feature. However, for ConUCB, the benefit brought from smaller β is limited. The main reason is that absolute feedback is contaminated by user biases, which makes it difficult to share. On the contrary, the improvement of **Difference** over other algorithms gets larger as β gets smaller. The trend validates our intuition that, compared to absolute feedback, relative feedback can better capture the intrinsic similarity by eliminating user biases. This allows the comparison-based algorithms to further utilize feedback information.

[7]It is a slight abuse of notion, as $\boldsymbol{\theta}_u$ usually stands for the estimated user feature.

5 RELATED WORK

There are mainly two lines of research that are related to and motivate our work: conversational recommender system and preference-based learning.

5.1 Conversational Recommender System

The most related works are a series of studies on conversational recommender systems. Although traditional recommender systems have shown significant success in practice [7, 16, 21], there are still several shortages. One of the shortages is that the user's preference estimated from the historical interaction data by the traditional recommender system is static and thus the dynamic changes of user preference can not be well captured in this manner. As an emerging topic in the community of recommender system, the conversational recommender system (CRS) is an appealing solution which aims to tackle the cold-start problem as well as the dynamic changes of user preferences [9, 11].

Due to the significant developments of deep learning, many CRS equipped with natural language processing techniques have been emerging in recent years [8]. Li et al. [14] propose a hierarchical recurrent encoder-decoder to address the cold-start problem in conjunction with classification of sentiment of dialogues. Yu et al. [26] devise a visual dialog augmented model utilizing the user feedback presented in natural language. Zhou et al. [32] adopt knowledge graphs to eliminate the semantic gap between natural language expression and item-level user preferences for more accurate recommendations. Lei et al. [12] make conversations on graphs to enhance the model's explainability. Other works [3, 30] utilize natural language understanding and generation to improve the accuracy of recommendations.

Some other works adopt reinforcement learning (RL) methods to address when and what to ask as the agent interacts with the users. Sun and Zhang [23] incorporate a deep policy network into the CRS to decide whether to conduct conversations or to recommend. Zhang et al. [28] design a constraint-augmented reinforcement learning framework to avoid recommendations violating user historical preferences. Zhou et al. [31] integrate the CRS, knowledge graph and bandit-based algorithm in order to face the fast-changing preferences and rich user expressions in music recommendation. Christakopoulou et al. [5] first introduce the multi-armed bandits into CRS. And one of our main baselines, ConUCB [29] gives a clear and theoretically supported integration of linear contextual bandits and CRS. A follow-up [15] proposes another bandit-based method for CRS using Thompson Sampling.

5.2 Preference-Based Learning

Another line that is closely related to our work is preference-based learning [25]. In many RL scenarios such as games [6] and robotics [24], the success of applications is highly dependent on a well-designed reward function. However, users usually have difficulties in providing their absolute feedback explicitly, which makes it hard to define such a reward function. In the meanwhile, the comparative preferences could better capture the user's intentions. Therefore, a rich body of methods has been proposed to directly learn from users' preference.

Christiano et al. [6] use comparison feedback provided by humans rather than absolute numerical scores to train an agent without a well-defined reward function in a complex environment. In the area of robotics, Tucker et al. [24] and Sadigh et al. [19] also use users' pairwise preferences for trajectories rather than numerical feedback to instruct the learning of robots. In the field of information retrieval, Joachims et al. [10] and Radlinski et al. [17] find that user's clicks are sometimes biased and conclude that paired comparisons can be more accurate than absolute numerical scores to evaluate retrieval quality. To address the exploration-exploitation dilemma with constrained relative feedback, dueling bandits [22] have been proposed and well-studied. Saha and Gopalan [20] further explore the topic of combinatorial bandits with relative feedback provided instead of absolute bandit feedback.

6 CONCLUSION

In this paper, we introduce a comparison-based conversation framework for item recommendation, utilizing relative feedback to better understand user preferences. Within the framework, we develop the RelativeConUCB algorithm to effectively collect and incorporate relative bandit feedback. To further explore the advantages of relative feedback, we propose to share relative feedback among similar users. Extensive experiments on both synthetic and real-world datasets demonstrate the competitiveness of RelativeConUCB. With relative feedback, our recommender system can efficiently elicit user preferences, especially among similar users, and provide satisfactory recommendations.

In the future, we plan to explore the following directions: 1) to improve the applicability of our framework, one may consider a more flexible system that can seamlessly query relative questions and absolute questions; or 2) one may focus on the feedback sharing mechanism to make it more robust and adaptive by incorporating techniques such as online clustering.

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