Large Language Models for Recommendation with Deliberative User Preference Alignment

Yi Fang¹, Wenjie Wang¹, Yang Zhang², Fengbin Zhu², Qifan Wang³, Fuli Feng¹, and Xiangnan He¹

¹University of Science and Technology of China, ²National University of Singapore, ³Meta AI

peterfang@mail.ustc.edu.cn,{wenjiewang96,zyang1580,zhfengbin}@gmail.com

wqfcr@meta.com,{fulifeng93,xiangnanhe}@gmail.com

Abstract

While recent advancements in aligning Large Language Models (LLMs) with recommendation tasks have shown great potential and promising performance overall, these aligned recommendation LLMs still face challenges in complex scenarios. This is primarily due to the current alignment approach focusing on optimizing LLMs to generate user feedback directly, without incorporating deliberation. To overcome this limitation and develop more reliable LLMs for recommendations, we propose a new Deliberative Recommendation task, which incorporates explicit reasoning about user preferences as an additional alignment goal. We then introduce the Deliberative User Preference Alignment framework, designed to enhance reasoning capabilities by utilizing verbalized user feedback in a step-wise manner to tackle this task. The framework employs collaborative step-wise experts and tailored training strategies for each expert. Experimental results across three real-world datasets demonstrate the rationality of the deliberative task formulation and the superior performance of the proposed framework in improving both prediction accuracy and reasoning quality.

CCS Concepts

Information systems → Recommender systems.

Keywords

Large Language Model, Deliberative Recommendation, User Preference Alignment, Multi-step Reasoning

ACM Reference Format:

Yi Fang, Wenjie Wang, Yang Zhang, Fengbin Zhu, Qifan Wang, Fuli Feng, and Xiangnan He. 2018. Large Language Models for Recommendation with Deliberative User Preference Alignment. In *Proceedings of Make sure to enter the correct conference title from your rights confirmation email (Conference acronym 'XX)*. ACM, New York, NY, USA, 11 pages. https://doi.org/XXXXXXXXXXXXXXXXX

1 INTRODUCTION

Large Language Models are increasingly utilized and aligned with recommendation task through supervised fine-tuning [4, 6, 55] or

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Conference acronym 'XX, Woodstock, NY

© 2018 Copyright held by the owner/author(s). Publication rights licensed to ACM. ACM ISBN 978-1-4503-XXXX-X/2018/06 https://doi.org/XXXXXXXXXXXXXXX

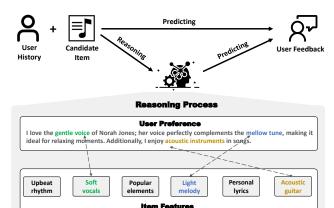


Figure 1: Comparison between the alignment objective of existing research, which optimizes LLMs to directly predict user feedback; and the objective of *Deliberative Recommendation*, which optimizes LLMs to conduct explicit reasoning about user preferences before generating the prediction.

direct preference optimization [10] for predicting the user feedback. Although these recommendation LLMs (RecLLMs) generally achieve performance gains in different scenarios [44, 47, 51], they can still fail in some complex cases, resulting in valueless even disappointing recommendations. For instance, a RecLLM would present a video on vanilla attention mechanisms to a user who has watched several videos on self-attention and its enhanced variants.

Recent insights from OpenAI regarding the limitations of general LLMs [14] suggest that failures of current RecLLMs come from their alignment objective, *i.e.*, optimizing the LLM to directly generate user feedback given the user history and candidate item. This pattern-based learning makes the model susceptible to data biases [5] and spurious correlations [19, 57], hindering their ability to generalize to low-frequency or cold-start items. Moreover, this label-oriented optimization objective pushes the LLM to make prediction instantly, discouraging thorough reasoning about user preferences. Consequently, it is crucial to investigate alternative alignment objectives for RecLLMs.

Inspired by the recent advancements in enhancing the reliability of general LLMs through explicit reasoning [1, 11, 20, 25, 52], we introduce a new *Deliberative Recommendation* task. This task is designed to train LLMs to engage in reasoning about user preferences and item features prior to predicting user feedback. As illustrated in Figure 1, the RecLLM will explicitly generate a reasoning process, using this process to augment its predictions. To achieve this goal while adhering to commercial restrictions, the

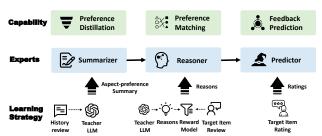


Figure 2: Illustration of the Deliberative User Preference Alignment framework.

key of this formulation is seeking user generated and freely available rationale behind the user feedback as guidance for training the LLM in reasoning generation. Consequently, we incorporate verbalized user feedback such as reviews or conversations, into our task formulation as supervisory signals for reasoning, setting our work apart from previous studies [23, 30, 41].

To effectively address the Deliberative Recommendation task, it is crucial to decompose the highly personalized and diverse reasoning process [45] into distinct steps, and equipping the LLM with specialized reasoning capabilities for each step. In this way, we highlight three fundamental capabilities: 1) *Preference Distillation*, which analyzes the user history to identify aspect-level user preferences [16] and examines existing verbalized user feedback on the candidate item to recognize positive and negative features; 2) *Preference Matching*, which matches distilled user preferences with item features and generates rationales for why the user might like or dislike the candidate item; and 3) *Feedback Prediction*, which predicts the user feedback with consideration of the generated raionales.

In this light, we propose a Deliberative User Preference Alignment (DeliRec) framework to teach LLMs with the recognized reasoning capabilities with the guidance of verbalized user feedback (e.g., user reviews [18]). As illustrated in Figure 2, DeliRec employs three collaborative experts, each dedicated to a specific reasoning step, to hone step-specific reasoning capabilities. To reduce the computational and memory cost, these experts are implemented using separate QLoRA [13] adapters on the same LLM. Recognizing that each reasoning step necessitates extracting distinct signals from the verbalized user feedback, each expert is equipped with a uniquely tailored training strategy. Taking rating prediction [27] as an example, we conduct extensive experiments across three real-world datasets, validating the effectiveness of DeliRec regarding prediction accuracy and reasoning quality, and the rationality of the framework design. The code and datasets are available at https://anonymous.4open.science/r/OurDeliRec-F4B5.

To summarize, our contributions are threefold:

- We formulate the *Deliberative Recommendation* task, which pursues LLMs conducting reasoning before making prediction by learning from verbalized user feedback.
- We propose a *Deliberative User Preference Alignment* framework, which achieves the reasoning process with step-wise experts associated with specifically designed training strategies.
- We conduct extensive experiments on three datasets, validating the effectiveness and rationality of the proposed DeliRec framework, showing the potential of slow thinking in recommendation.

2 TASK FORMULATION

• Deliberative Recommendation. We formulate the task of deliberative recommendation, which performs thoughtful reasoning regarding user preference and item features before predicting user feedback as illustrated in Figure 1. To guide the reasoning process, we propose incorporating verbalized user feedback for LLM optimization. In this work, we adopt user reviews due to fine-grained user preferences described in reviews [18]. Besides, we investigate deliberative recommendation on the classic rating prediction task, following prior work [23, 41].

Formally, let $\mathcal U$ denote a set of users and I a set of items. The interaction between user u and item i can be represented as (r_{ui}, c_{ui}) , where r_{ui} is the rating of user u for item i, and c_{ui} is the corresponding review, which exists in many datasets [17, 31]. For a user-item pair (u, i), the historical interactions of user u and item i are defined as:

$$\mathcal{H}_u = \{(i, r_{ui}, c_{ui}) \mid i \in \mathcal{I}_u\}, \quad \mathcal{H}_i = \{(u, r_{ui}, c_{ui}) \mid u \in \mathcal{U}_i\},$$

where I_u represents items previously rated by user u, and \mathcal{U}_i denotes users who rated item i. Given \mathcal{H}_u and \mathcal{H}_i , the LLM is tasked to predict the rating \hat{r}_{ui} after performing explicit reasoning:

reason_{*ui*},
$$\hat{r}_{ui} = LLM(\mathcal{H}_u, \mathcal{H}_i)$$
,

where reason u_i denotes the reasoning process and \hat{r}_{ui} is the predicted rating.

Considering the reasoning process is highly personalized and diverse across users, we decompose the complex reasoning into multiple steps, as shown in Figure 2, to achieve different objectives: Preference Distillation, Preference Matching, and Feedback Prediction. To emphasize the alignment between the reasoning process and the user's true preference, we incorporate the target item review c_{ui} of user u for item i as additional supervision during training. Notably, it is excluded in testing to prevent data leakage.

• Justification for explicit reasoning in RecLLMs. Incorporating explicit reasoning into RecLLMs holds significant potential, despite it potentially increases the prediction time and computational cost. Specifically, it enables RecLLMs to: 1) fully leverage the reasoning capabilities of LLMs to improve prediction accuracy and reliability; 2) enhance interpretability through step-by-step reasoning as explanations, thereby enhancing user trust; 3) possibly facilitate user-controllable recommendation for human-AI collaboration [53], since users can adjust the reasoning process to generate new recommendations. Notably, explicit reasoning is particularly beneficial in scenarios where real-time recommendation requirements are less critical, but accuracy is paramount, such as E-commerce product, movie, and medication recommendations [2]. These items typically involve long usage periods and require careful deliberation before purchase or viewing. Furthermore, as LLMs efficiency continually improves [26], the computational costs will decrease accordingly, enhancing the feasibility of wide applications.

3 METHOD

In this section, we present DeliRec with three experts to collaboratively perform multi-step reasoning before recommendation. To supervise the reasoning process, DeliRec incorporates user reviews, directly aligning the reasoning with user preferences rather than only inferring preferences through users' numerical or binary feedback (*e.g.*, ratings and clicks). We then detail the three experts, *i.e.*, summarizer, reasoner, and predictor, with their fine-tuning strategies. An overview of DeliRec is illustrated in Figure 2.

3.1 Summarizer for Preference Distillation

DeliRec leverages a summarizer to distill the user's preferences and the item's positive and negative features from their historical reviews. It filters out noise from the reviews, captures nuanced user preferences, and enriches item features with the LLM's inherent knowledge. The distillation output is formatted as an aspect-preference summary, *i.e.*, concise and representative keywords that encapsulate essential user preferences and item features, providing a reasoning foundation for the subsequent reasoning process.

• **Summarizer Instantiation.** Formally, given a historical interaction (r_{ui}, c_{ui}) between user u and item i, the summarizer will generate an aspect-preference summary. We instantiate the summarizer by fine-tuning a QLoRA adapter [13] on an LLM and the summarizer's prompt is illustrated in the following, which uses the Music dataset as an example.

Summarizer Prompt

Task: Summarize the reasons behind the given rating of a Music based on the customer review.

Music: iRating: r_{ui} Review: c_{ui}

Analyze the above customer review for the Music i and summarize the reasons behind the given rating of r_{ui} . Please consider the positive and negative aspects mentioned in the review and provide the keywords of reasons and user preference elements.

The user's preferences and the item's features are outputted as an aspect-preference summary. A template example is as follows:

Positive Aspects: Catchy Melody, Unique Instrumentation, ... Negative Aspects: Repetitive Lyrics, Overuse of Autotune, ... User Preference Elements: Harmony, Emotional Resonance, ...

- Summarizer Fine-tuning. Considering ChatGPT [33] has shown strong performance in various summarization tasks [7], we employ closed-source ChatGPT as a teacher model to generate aspect-preference summaries, guiding the learning of open-source LLMs. With these summaries, we optimize the QLoRA adapter of the summarizer by SFT [35].
- Offline Summarization. Given a summarizer, we can store the generated aspect-preference summaries offline for all the historical interactions between users and items. This step eliminates the need for repeated preference distillation, thereby reducing computational overhead and enhancing efficiency.

3.2 Reasoner for Preference Matching

Given all the aspect-preference summaries of a user and an item, DeliRec adopts a reasoner to evaluate their matching degree, generating reasons for why the user might like or dislike the item. • **Reasoner Instantiation.** Formally, given a user-item pair (u, i), we aggregate the aspect-preference summaries from their historical interactions \mathcal{H}_u and \mathcal{H}_i in chronological order into a single prompt, tasking the reasoner to measure the preference matching between u and i. The reasoner is also implemented by another QLoRA adapter on the same LLM. An example of the reasoning prompt is shown below:

Reasoner Prompt

User Review History ### $\langle \mathcal{H}_u \text{ organized as below} \rangle$

1. Title of Item 1

Positive Aspects: [Aspect 1], [Aspect 2], ... Negative Aspects: [Aspect 1], [Aspect 2], ...

User Preference Elements: [Preference 1], [Preference 2], ...

2. Title of Item 2

Positive Aspects: [Aspect 1], [Aspect 2], ... Negative Aspects: [Aspect 1], [Aspect 2], ...

User Preference Elements: [Preference 1], [Preference 2], \dots

...

Item Review History by Other Users

 $\langle \mathcal{H}_i \text{ organized in the same format as above} \rangle$

Task: Analyze whether the user will like the new Music i based on the user's preferences and the item's features. Provide your rationale in one concise paragraph.

Reasoner Fine-tuning. Given a historical interaction between user u and item i, we propose using target item review c_{ui} to guide the reasoner learning, because users would explicitly explain their preferences in verbalized reviews. However, directly using reviews for supervision suffers from noise issues, since user reviews often contain low-quality comments or preference-irrelevant details (see evidence in Section 4.3.2). Thus, we employ a generation-then-filter strategy: using ChatGPT first generates diverse reasons why user u might like or dislike item i, and a reward model then selects the high-quality reasons based on target item review c_{ui} . The selected high-quality reasons are used for reasoner learning through SFT. Reason Generation. As outlined in Algorithm 1, given a user-item pair, we repeatedly sample candidate reasons from ChatGPT based on the reasoner prompt and evaluate reasons using the reward model until either a high-quality reason is obtained or the maximum iteration count is reached. Particularly, to avoid repeatedly generating reasons that contradict the user's binary preference, we incorporate the user's actual rating as a hint, except for the initial generations. This is implemented by appending the following hint statement to the reasoner prompt:

Hint: The user actually rated the item r_{ui} stars. The star ranges from 1 to 5, with 5 being the best. Use the hint but don't mention the user's rating in your response.

Reason Filter. We introduce a reward model to filter candidate reasons based on their alignment with the target item review c_{ui} . Considering the alignment, the reward model assigns a score of 1 to high-quality reasons and 0 to low-quality reasons. Using this reward model, we can iteratively generate high-quality reasons using ChatGPT for the reasoner fine-tuning. The detailed training and inference of the reward model can be found in Section 3.4.

3.3 Predictor for Feedback Prediction

DeliRec finally introduces a predictor for user feedback prediction. In this work, we investigate the classic rating prediction task [59]. The input for the predictor is the reasoning process generated by the summarizer and reasoner. In addition, considering that the user's historical ratings serve as a valuable reference for rating prediction [24], we also include ratings as input. The user's actual rating for the target item r_{ui} is used for supervision.

• **Predictor Instantiation.** Given a user-item pair (u, i) with historical interactions $(\mathcal{H}_u, \mathcal{H}_i)$, we first aggregate the aspect-preference summaries from \mathcal{H}_u and \mathcal{H}_i in the same format as in the reasoner prompt, supplemented with historical ratings (see the following predictor prompt). Next, following previous work [23], we include the average ratings from all historical interactions in the prompt. Finally, the reason generated by the reasoner is appended to the *Reason Placeholder*. The final prompt is shown below to predict the user ratings. To implement the predictor, we apply another QLoRA on the LLM and utilize the rating r_{ui} for SFT.

Predictor Prompt

User Review History

 $\langle \mathcal{H}_u |$ is organized in the same format as in the reasoner prompt, except that historical ratings are additionally included.

1. Title of Item 1, Rating: 5.0

Positive Aspects: [Aspect 1], [Aspect 2], ...

Negative Aspects: [Aspect 1], [Aspect 2], ...

User Preference Elements: [Preference 1], [Preference 2], ...

•••

Item Review History by Other Users

 $\langle \mathcal{H}_i \text{ organized in the same format as above} \rangle$

Average Past Ratings

User's Average Rating (all previous ratings): 4.5

Item's Average Rating (all ratings by other users): 3.7

Personalized Recommendation Analysis

⟨This section is referred to as **Reason Placeholder**, where we place the generated reason here.⟩

Task: Based on the above information, please predict the user's rating for *i*, (1 being the lowest and 5 being highest, directly give the rating without other content.)

[Output Format] Predicted Rating:[Rating between 1 and 5]

• Logit-weighted Decoding. We adopt logit-weighted decoding for the final prediction, which transforms the predicted rating scores from discrete integer values to continuous scores—a method proven to offer greater precision and adopted in previous work [23].

Specifically, when decoding the rating token, the LLM first obtains the logit values for each possible rating token (e.g., the logits for tokens "1", "2", "3", "4", and "5"), denoted as l_1, l_2, \ldots, l_5 (assuming the rating range is from one to five). These logits are then normalized into probabilities p_k for each rating k using the softmax function: $p_k = \frac{\exp(l_k)}{\sum_{j=1}^5 \exp(l_j)}, k \in \{1,2,\ldots,5\}$. The final prediction

is calculated as the expected value: $r_{ui} = \sum_{k=1}^{5} k \cdot p_k$, where each possible rating is weighted by its corresponding probability.

Algorithm 1 Generation-then-filter strategy

Input: A teacher model LLM, a reward model R, the reasoner prompt P, an iteration count T, a Hint with user's actual rating.

```
1: Initialize a high-quality reason set S_{\text{high}} \leftarrow \emptyset;

2: Initialize a reason s \leftarrow \text{LLM}(P);

3: for all t \in \{1, ..., T\} do

4: Get the reason quality Score \leftarrow R(s);

5: if Score = 1 then

6: Save S_{\text{high}} \leftarrow s;

7: break;

8: else

9: Regenerate a new reason with hint: s \leftarrow \text{LLM}(P, \text{Hint});

10: end if

11: end for
```

Output: the high-quality reason in S_{high} .

• Efficient Rating Prediction. Since the LLM is instructed to output ratings in a fixed format, starting with the phrase "Predicted Rating:" as specified in the predictor prompt, we can skip decoding these predictable and invariant words. We directly decode the final rating using logit-weighted decoding. Only decoding the single rating token significantly reduces inference time and costs.

3.4 Reward Model for Reason Judgment

We use a reward model to select high-quality reasons for the reasoner fine-tuning. Given candidate reasons and the corresponding target item reviews, the reward model assigns a score of 1 if the reason is high-quality and aligns with the target item review; otherwise, it assigns 0.

• **Reward Model Training.** We fine-tune another QLoRA on the LLM as the reward model, which is trained to predict the user ratings based on the user review. The input is the predictor prompt template, where the *Reason Placeholder* is filled by the target item review rather than the generated reasons. The reward model is trained to extract the user's true preferences from the target item review to enhance prediction accuracy.

Separate Training Data. To prevent the reward model from predicting ratings solely by memorizing training data rather than capturing the user's true preferences from target item reviews, we separate the training data for the reward model and the reasoner. This separation ensures that the reward model is evaluated on unseen data, enabling a more reliable assessment of reason quality.

• **Reason Judgment.** Since the reward model is trained to capture the user's true preferences from the target item's review, a reason that better aligns with the user's review can achieve superior prediction accuracy, as evidenced in Section 4.3.3. Based on this insight, we define an evaluation score as:

$$s_{\text{eval}} = |r_{ui} - r_{\text{reason}}| - |r_{ui} - r_{\text{review}}|$$

where r_{ui} represents the ground-truth rating for user u and item i. $r_{\rm review}$ and $r_{\rm reason}$ denote the predicted ratings by the reward model based on the target item review and a generated reason. And $s_{\rm eval}$ measures the prediction difference:

• If $s_{\text{eval}} < 0$, it suggests that the reason surpasses the raw review in rating prediction performance.

• If $s_{\text{eval}} > 0$, a smaller s_{eval} indicates a closer performance between the reason and review, suggesting superior alignment.

By introducing a threshold τ , we identify all reasons of $s_{\rm eval} < \tau$ as high-quality ones with the evaluation score as 1. Treating τ as a hyperparameter can balance the trade-off between the quantity and quality of the reasons.

4 EXPERIMENT

In this section, we conduct a series of experiments to answer the following research questions:

- RQ1: How does DeliRec perform compared to other baseline methods in terms of accuracy in predicting user feedback (i.e., ratings) and the quality of generated reasons?
- RQ2: Why is the multi-step reasoning strategy in DeliRec essential, and how does it compare in effectiveness to one-step reasoning strategies?
- RQ3: How effective is our approach (the reason generation method and proposed reward model) in incorporating user-verbalized preference feedback?

4.1 Experimental Settings

- 4.1.1 **Datasets.** We conduct experiments on three widely-used real-world datasets:
- Amazon Music (Music): This refers to the "Digital Music" subset of the well-known Amazon Product dataset¹, which records rich user reviews, ratings, and textual information about items, such as titles, across a broad range of product categories, on the Amazon platform. We refer to this dataset as "Music" for short.
- Amazon Book (Book): This refers to the "Book" subset of the Amazon Product dataset, shortened "Book".
- Yelp: This refers to the Yelp Open dataset², which includes user reviews, ratings for businesses such as restaurants and retail shops, as well as textual information about the businesses. It is widely used in recommendation tasks [36].

We use the entire Music dataset for experiments, while for the Book and Yelp datasets, we utilize only a subset due to their large size. For the Book dataset, we use data from the last two months, and for the Yelp dataset, we use data from the last six months. For each dataset, we split it into training, validation, and test sets based on the timestamps of interactions, ensuring that test interactions occur after all training and validation interactions to prevent information leakage [21]. Regarding data filtering, following prior work [28], we adopt a 5-core setting to filter the data and exclude cold-start users and items—those not appearing in the training set—from the validation and test sets. The statistical details of the processed dataset are provided in Table 1.

4.1.2 **Evaluation Metrics.** To evaluate the accuracy of rating prediction, we use two standard metrics [23, 29]: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

To evaluate reasoning quality, we employ BLEURT [38] and GPTScore [43] to measure the semantic alignment between the generated reasoning and the target item review. BLEURT³ is an

Table 1: Statistical details of the evaluation datasets.

Dataset	#Train	#Valid	#Test	#User	#Item
Music	43,071	3,271	1,296	4,183	2,660
Book	71,972	6,144	5,541	13,863	13,515
Yelp	51,497	4,757	4,328	8,453	13,426

evaluation metric that leverages contextual embeddings to assess the semantic similarity between text pairs, providing a fine-grained measure of alignment. GPTScore, computed based on GPT-40⁴, analyzes the semantic alignment of the given text pairs and assigns a score between 0 and 100, with higher scores indicating better alignment. These metrics are commonly adopted in explainable recommendation tasks [32].

- 4.1.3 **Baselines.** To comprehensively evaluate performance, we compare DeliRec against three categories of recommendation methods: traditional methods (MF), review-based recommendation methods (DeepCoNN, NARRE, DAML), and LLM-based methods (GPT-40, Rec-SAVER, EXP3TR).
- MF [24]: Matrix Factorization is a classical collaborative filtering method that predicts user ratings based solely on the historical rating matrix.
- DeepCoNN [59]: This method employs a Convolutional Neural Network (CNN) model to jointly learn item properties and user behaviors from review text to assist in rating prediction.
- NARRE [9]: This method employs an attention mechanism to prioritize the most useful reviews, enabling better extraction of user and item features to enhance recommendations.
- DAML [27]: This method models the interaction between user and item review documents to improve the representations of both users and items.
- GPT-4o [29]: This approach uses GPT-4o to directly predict ratings based on the user's rating history. We adopted the same few-shot prompting template as [29].
- Rec-SAVER [41]: This method supplies LLMs with the target item's metadata (e.g., title, categories, description) and the user's historical interactions (e.g., metadata of previously interacted items, user ratings, and raw reviews), and then instructs the LLMs to generate their reasoning process before providing the prediction.
- EXP3RT [23]: This method first constructs user and item profiles from historical reviews and ratings using LLMs. These profiles are then leveraged to reason about user preferences and predict potential ratings in a single step.
- 4.1.4 **Implementation Details.** For review-based methods, we adopt the implementation⁵ from previous work [28]. For all reasoning-enhanced LLMRec methods (*i.e.*, Rec-SAVER, EXP3RT and our DeliRec), we use GPT-3.5-turbo⁶ as the teacher model and fine-tune

 $^{^{1}} https://cseweb.ucsd.edu/{\sim}jmcauley/datasets/amazon/links.html.$

²https://business.yelp.com/data/resources/open-dataset/.

³https://github.com/google-research/bleurt.

⁴https://chatgpt.com/?model=gpt-4o.

⁵https://github.com/ShomyLiu/Neu-Review-Rec.

⁶https://platform.openai.com/docs/models#gpt-3-5-turbo.

the LLama3-8B model 7 using the QLoRA technique. To accelerate the training and inference process, we leverage the Unsloth 8 framework.

To reduce computational costs, we randomly sample 12,000 user-item pairs from the training data to construct the instruct data for LLMs learning, while conventional methods use the full train dataset. This sample size is sufficient to achieve strong performance, as demonstrated in our main results. All reasoning-enhanced LLMRec methods are trained on the same 12,000 user-item pairs. For training the reward model, we use an additional 8,000 user-item pairs, ensuring no overlap with the instruct data. The hyper-parameter reward threshold (τ) is set to 0.1, 0.2, and 0.04 for Music, Book, and Yelp, respectively. More details can be found in our code.

4.2 Main Results (RQ1)

We compare our DeliRec method with baseline methods on the accuracy of user feedback (rating) prediction (Predictor output) and the quality of generated reasons (Reasoner output).

- Accuracy of User Feedback Prediction. The comparison of user feedback prediction performance is summarized in Table 2. As shown in the table, for the MAE metric, our method outperforms all datasets, achieving an average MAE reduction of approximately 0.02 compared to the best baseline results. For the RMSE metric, our method achieves the best performance on the Amazon Music and Amazon Book datasets, while delivering comparable results to the best baseline on the Yelp dataset. These superior performances of DeliRec confirm that incorporating reasoning about user preference and item features before making the final prediction, i.e., applying deliberation, is effective in enhancing RecLLM performance, thereby validating the rationality of our formulation of deliberative recommendation. Notably, although Rec-SAVER and EXP3RT also incorporate reasoning, their reasoning is performed in a single step, unlike our approach, which involves multiple steps-preference distillation, matching, and prediction. This lack of true "deliberation" in a single step may lead to their relatively poorer performance.
- Quality of Generated Reasons. We next analyze the quality of the reasons generated by the Reasoner in DeliRec, compared to two reasoning-aware baselines (i.e., Rec-SAVER and EXP3RT). Table 3 summarizes the results. As shown by the results of the two metrics, whether compared with target item reviews using the BLEURT metric or evaluated using the more powerful GPT model (corresponding to GPTScore metric), the reasons generated by our method significantly outperform those of the two reasoning-aware baselines. Our method achieves an average relative improvement of 7.9% on the GPTScore metric and 7.0% on the BLEURT metric across all datasets. The superiority of our method's reasoning can be attributed to the fact that we teach LLMs with recognized reasoning capabilities, guided by verbalized user feedback (e.g., user reviews [18]), while the baselines fail to leverage this guidance.

Table 2: Comparison of user feedback prediction performance between our DeliRec method and the baselines across the three evaluation datasets. The best results are highlighted in bold and sub-optimal results are underlined.

Туре	Method	Music		Book		Yelp	
Type		MAE ↓	RMSE ↓	,MAE↓	RMSE \	MAE ↓	RMSE ↓
CF-based	MF	0.6188	0.8142	0.6277	0.8565	0.7980	1.0711
	DeepCoNN	0.6034	0.8057	0.6221	0.8403	0.8312	1.0665
Review-based	dNARRE	0.5799	0.7881	0.6242	0.8435	0.8177	1.0785
	DAML	0.5703	$\underline{0.7848}$	0.6214	$\underline{0.8371}$	$\underline{0.7964}$	1.0405
	GPT-40	0.7438	1.1069	0.7591	1.1558	0.8766	1.3005
LLM-based	Rec-SAVER	0.6463	0.9262	0.6645	0.9356	0.8295	1.1282
	EXP3RT	$\underline{0.5608}$	0.8385	$\underline{0.6135}$	0.9370	0.8306	1.2311
Ours	DeliRec	0.5442	0.7722	0.6029	0.8345	0.7586	1.0418

Table 3: Quality evaluation of generated reasons. "GPT" refers to "GPTScore". The best results are highlighted in bold and sub-optimal results are underlined.

Method	Music		Book		Yelp	
1,10111011	GPT	BLEURT	GPT	BLEURT	GPT	BLEURT
Rec-SAVER	75.60	0.3652	72.45	0.4233	66.43	0.4102
EXP3RT	76.22	0.3840	73.60	0.4373	64.28	0.4275
DeliRec	80.53	0.4067	77.31	0.4731	72.70	0.4565

4.3 In-depth Analysis

In the following sections, we present an analysis of the impact of multi-step reasoning and verbalized preference feedback in DeliRec, followed by the evaluation of DeliRec's inference cost. Lastly, we provide detailed cases comparing the reasoning generated by DeliRec with those from baseline methods to demonstrate its superior alignment with the user's true preferences.

- 4.3.1 Impact of Multi-step Reasoning (RQ2). To evaluate the impact of multi-step reasoning in DeliRec, we first conduct an ablation study to analyze the necessity of the component in each step (i.e., Summarizer, Reasoner and Predictor) and then assess the performance changes by replacing the multi-step reasoning mechanism with two alternative single-step reasoning strategies.
- Necessity of Each Step. An ablation study on DeliRec is conducted by removing each step to assess its contribution. Specifically, we make the following changes in each experiment: 1) w/o Step 1 (i.e., Summarizer): Directly using user historical reviews to replace the aspect-preference summaries as input for Step 2 and Step 3; 2) w/o Step 2 (i.e., Reasoner): Remove the Reason Placeholder section from the Step 3 Prompt and instruct the LLMs to directly predict the rating based solely on the aspect-preference summaries and historical ratings; 3) w/o Step 3 (i.e., Predictor): Combine Step 2 and Step 3 into a single step, asking the LLMs to simultaneously generate the match analysis and predicted ratings based on the aspect-preference summaries and the user's historical ratings.

We conduct this study on Amazon Music and Book datasets and present the results in Figure 3, from which we make the following observations:

 $^{^{7}} https://www.llama.com/docs/model-cards-and-prompt-formats/meta-llama-3/. \\$

⁸https://github.com/unslothai/unsloth.

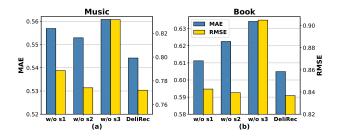


Figure 3: Necessity of each Step. An ablation study on each step in DeliRec.

- The removal of each step results in an increase of the rating prediction errors on both Music and Book datasets, as reflected by higher MAE and RMSE values in the figure.
- The MAE and RMSE increase significantly on both datasets after removing Step 3, underscoring the importance of separately training match analysis and rating prediction. One potential reason is that simultaneously training the LLM to complete the reasoning and rating tasks imposes significant challenges, resulting in degraded performance.
- The removal of Step 2 results in a relatively slight increase in RMSE but a significant increase in MAE on both datasets. This discrepancy can be attributed to the fact that RMSE is overly sensitive to extreme errors (e.g., predicting 1 for a true rating of 5). Without match analysis, LLMs can still predict a roughly correct rating based on the user's aspect-preference summaries and historical ratings, which helps avoid extreme errors and results in only a slight increase in RMSE. In contrast, MAE assigns equal weight to all errors and is better at capturing finer-grained inaccuracies. The significant increase in MAE highlights the critical role of Step 2 in enabling the LLMs to predict user feedback more effectively on a fine-grained scale.
- One-step v.s. Multi-step. To verify the effectiveness of the multi-step reasoning strategy in DeliRec, we compare it with two alternative strategies: (1) One-step reasoning, which generates both an entangled reasoning process and the ratings in a single step, and (2) Chain-of-Thought (CoT) reasoning, which generates the outputs of our three reasoning steps in one single prompt. We prepare the datasets separately based on the two above strategies and train the LLMs accordingly. In Figure 4, we summarize the results and make the following observations: 1) Both one-step reasoning and CoT reasoning strategies lead to a notable increase in prediction errors on both Music and Book datasets, as reflected by the higher MAE and RMSE values. 2) In contrast, the performance of the CoT reasoning strategy is inferior to that of the simpler one-step reasoning strategy. This may be due to the complexity of multiple tasks involved in the CoT reasoning strategy, which poses significant challenges for LLMs to effectively process simultaneously.
- 4.3.2 Effect of Reason Generation Approaches (RQ3). To validate the effectiveness of our reason generation approach in Step 2 of DeliRec, we compare it against four alternative approaches:
 1) Without reason: Remove Step 2 from DeliRec entirely and instruct the LLMs to directly predict the rating based solely on the

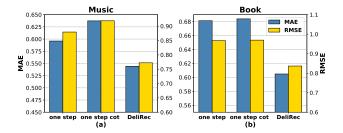


Figure 4: One-Step v.s. Multi-Step. Performance comparison between DeliRec's multi-step reasoning strategy and two alternative one-step reasoning strategies.

Table 4: Effect of different reason generation approaches.

Method	Μι	ısic	Book		
Without	MAE	RMSE	MAE	RMSE	
Without Reason	0.5529	0.7742	0.6225	0.8394	
Review-guide Reason	0.5825	0.7812	0.6376	0.8390	
Review-inferred Reason	0.5723	0.7816	0.6306	0.8420	
History-inferred Reason	0.5640	0.7744	0.6305	0.8376	
DeliRec	0.5442	0.7722	0.6029	0.8345	

aspect-preference summaries and historical ratings, as done in the ablation study; 2) **Review-guided reasons**: Use the target item reviews as direct supervision for the LLMs' learning process in Step 2; 3) **Review-inferred reasons**: Use ChatGPT to generate reasons inferred from the target item reviews and employ these generated reasons as supervision for Step 2; 4) **History-inferred reason**: Use ChatGPT to generate reasons inferred from the aspect-preference summaries using the Step 2 Prompt and directly use them as supervision for Step 2 without applying filtering through our reward model.

In Table 4, we present the results and make the following observations: 1) All four alternative approaches perform worse than our proposed method on both Music and Book datasets, highlighting the advantages of our proposed method in collecting high-quality reasons for training LLMs. 2) The performance of Review-inferred Reason is worse than Without Reason on both datasets in MAE and RMSE. This indicates that directly using reviews to generate reasons can have a negative impact. A possible explanation is that our objective is to train LLMs to perform reasoning based on historical interactions without relying on target item reviews. Using reasons derived directly from these reviews introduces the risk that the reasoning logic may rely on preferences not reflected in the historical data. Such inconsistencies disrupt the training process and ultimately result in suboptimal performance. 3) History-inferred Reason also performs worse than "Without Reason" on most metrics. This indicates that directly supervising with GPT-generated reasons without refinement is ineffective, underscoring the importance of using verbalized preference feedback as supervision.

4.3.3 **Effectiveness of Reward Model (RQ3)**. The reward model should be capable of assessing whether the generated reasons align

Table 5: Rating prediction accuracy of reward model using different types of reasons.

Music		Book	
MAE	RMSE	MAE	RMSE
0.6798	0.9359	0.6186	0.8298
0.294	0.4527	0.3329	0.4597
0.4238	0.568	0.4214	0.5394
0.4879	0.6876	0.5174	0.7137
0.7257	1.071	0.6842	0.9686
	MAE 0.6798 0.294 0.4238 0.4879	MAE RMSE 0.6798 0.9359 0.294 0.4527 0.4238 0.568 0.4879 0.6876	MAE RMSE MAE 0.6798 0.9359 0.6186 0.294 0.4527 0.3329 0.4238 0.568 0.4214 0.4879 0.6876 0.5174

with the ground-truth preferences (as reflected in the target item reviews) by utilizing these reasons for rating prediction. We conduct experiments to verify whether the reward model successfully acquires this capability. Specifically, we construct different types of reasons with known similarity levels to target item reviews to compare the prediction accuracy. We include the four types of reviews defined in Section 4.3.2, along with an additional type: Hint-Inferred Reason. This type generates reasons using ChatGPT, based on aspect-preference summaries and our reasoner's prompt, with the user's actual rating included as a hint. Based on their similarity to ground-truth reviews, the types of reasons are ranked from highest to lowest as follows: Review-Guided, Review-Inferred, Hint-Inferred, and History-Inferred Reason. Table 5 summarizes the reward model's prediction accuracy using each type of reason. The results show that the prediction accuracy ranking aligns with the known similarity ranking, verifying that the reward model effectively evaluates the quality of the generated reviews.

4.3.4 Cost Analysis. To evaluate the efficiency of DeliRec, we compared its inference time and generation cost with those of reasoning-aware baselines (Rec-SAVER and EXP3RT). As shown in Table 6, despite dividing the reasoning process into three steps, DeliRec achieves comparable average inference time and generates a similar number of tokens as the baselines. Specifically, it requires approximately 6 seconds and generates an average of 148 tokens per prediction. This efficiency is primarily attributed to two factors: 1) the preference distillation step in DeliRec is preprocessed in advance, as discussed in Section 3.1, leaving only the last two steps to be executed during inference; and 2) DeliRec only decodes a single token during the final step, as explained in Section 3.3. These designs effectively minimize computation costs.

Table 6: Cost analysis of the average inference time and the average number of tokens generated per prediction. Experiments were conducted on an NVIDIA A800 GPU using 100 data points from the Book dataset. For DeliRec, only the last two steps were measured, and for EXP3RT, profile construction costs were excluded.

Method	Avg. Inference Time (s)	Avg. Tokens Generated
DeliRec	5.86	147.78
Rec-SAVER	6.43	175.59
EXP3RT	5.62	150.74

4.3.5 Case study. We conduct a case study to examine whether the reasons generated by DeliRec better align with true user preferences, as reflected in the target item reviews. We compare the reasoning results of DeliRec with those of EXP3RT and Rec-SAVER. Figure 5 illustrates an example. In this case, the target item review indicates that the user values the book for its practicality and helpfulness. DeliRec accurately identifies these features and aligns them with the user's preferences, as highlighted in green. In contrast, EXP3RT incorrectly attributes the user's preference to the storyline and characters. Rec-SAVER also fails to recognize both the item's key features and the user's actual preferences, despite predicting that the user would like the book.

User Review

This is a very comprehensive guide to strategies and tips as well as medical treatments to alleviate this most bedevilling condition that is associated with shoulder pain. The problems and the instigators of shoulder pain and discomfiture are many and varied. I myself also suffer from right and left shoulder pain caused by a tear of the supraspinatus ligament next to the humerus. This book by Jim Johnson, "Bulletproof Your Shoulder" is just that. I have gained immense relief from practicing what I have read here. Highly Recommended.

DeliRec (Ours)

Based on the user's review history, it is likely that they will enjoy the book "Bulletproof Your Shoulder." The user has shown a preference for informative content, practical examples, and effective strategies in their reviews. The book "Bulletproof Your Shoulder" has been praised for its detailed information, practical expert advice, and effective exercises, which align with the user's preference for informative and practical content. Additionally, the book's focus on preventing surgery and improving shoulder health may appeal to the user's interest in health improvement and avoiding unnecessary procedures. Overall, the user's preference for practicality, and effectiveness suggests that they would appreciate the content and features of "Bulletproof Your Shoulder."

EXP3RT

The user would appreciate the detailed and easy-to-understand format of "Bulletproof Your Shoulder", as they value high-quality writing and detailed world-building. The practical expert advice and emphasis on strengthening the core of the shoulder to prevent pain and injury align with the user's preference for engaging storylines with surprises and twists. The inclusion of studies and statistics to support the program would appeal to the user's appreciation for intricate story arcs. Additionally, the user would find the clear instructions and diagrams for exercises helpful, as they enjoy well-developed characters and intricate story arcs. Overall, the user would likely enjoy and benefit from the detailed information and helpful exercises provided in "Bulletproof Your Shoulder".

Rec-SAVER

The user has a history of enjoying a variety of genres, including mystery, thriller, fantasy, and horror. They have shown a preference for well-written stories with strong character development and engaging plots. The user has also appreciated books that offer a unique perspective or twist on a familiar theme. The new item, "Bulletproof Your Shoulder," falls into the self-help category, which is quite different from the user's past preferences. However, given the user's openness to different genres and their appreciation for well-crafted stories, they may still find value in the self-help aspect of this book.

Figure 5: Case study on whether the reasons generated by our DeliRec and the baselines align with user preferences. The "User Review" includes the ground-truth user preferences.

5 RELATED WORK

In this work, we focus on Deliberative Recommendation, empowering RecLLMs with explicit reasoning abilities and optimizing LLMs through verbalized user feedback. This is highly related to LLM-based recommendation, deliberative alignment, and review-based recommendation.

5.1 LLM-based Recommendation

Recent research has shown growing interest in RecLLMs [44], with many studies exploring the use of LLMs to predict user feedback through in-context learning [12, 29, 37] and fine-tuning [6, 55, 56]. However, these approaches often instruct LLMs to generate predictions directly without disclosing their intermediate reasoning steps, resulting in a limited utilization of the amazing reasoning capabilities of LLMs. To address this limitation, some recent studies explored leveraging LLMs' reasoning capabilities for recommendation tasks through various prompting strategies, such as chain-of-thought (CoT) [49] and self-reflection [46]. For instance, DRDT [46] encourages LLMs to perform sequential recommendation in a divergent thinking manner by prompting them to analyze user preferences from multiple aspects, while simultaneously reflecting on their analysis using a critic prompt [46]. GOT4Rec [30] applies the graph of thought strategy to prompt LLMs to reason through three different directions. However, these in-context learning methods are inherently constrained by the models' existing capabilities, making LLMs often struggle to handle recommendation tasks effectively without task-specific fine-tuning [6].

Some studies have explored fine-tuning LLMs to improve their reasoning ability specifically for RecLLMs [8, 23, 41, 48]. For example, RecSAVER utilizes reasoning generated by a larger LLM as ground truth to fine-tune a smaller LLM, enabling the latter to learn reasoning patterns tailored for recommendation tasks [41]. EXP3RT [23] employs a similar fine-tuning strategy but introduces an additional preparatory step: to construct user and item profiles based on their review histories first. Leveraging these constructed profiles, EXP3RT reasons about user preferences and predicts possible ratings in the same single step. However, these fine-tuning methods face two main limitations. First, they compress the complex reasoning process into a single step and train it jointly, which makes it challenging for LLMs to effectively learn. In contrast, DeliRec decomposes the reasoning process into multiple steps, training each step independently for better performance. Second, they lack finegrained supervision in training data selection, leading models to learn the reasoning patterns misaligned with users' real preferences. DeliRec addresses this limitation by using verbalized user feedback as supervision, resulting in reasons that more accurately reflect users' preferences and enhance the multi-step reasoning abilities of RecLLMs.

5.2 Deliberative Alignment

Existing work has demonstrated the superiority of LLMs combined with multi-step reasoning [42], with OpenAI's O1 showcasing remarkable reasoning capabilities [34]. Meanwhile, Deliberative Alignment [15], a training paradigm that directly teaches LLMs human-written safety specifications and trains them to explicitly

reason about these specifications before responding, has garnered widespread attention in the LLM safety domain.

However, there are significant differences between this and the Deliberative Recommendation task: 1) in the safety domain, alignment specifications are relatively well-defined and consistent, whereas the reasoning process behind user feedback is highly complex, with significant personalization and diverse preferences. Achieving deliberative user preference alignment at the individual level is thus a far more challenging task. 2) Given the complexity of the Deliberative Recommendation task, relying solely on numerical user feedback (*e.g.*, ratings) or pairwise preference data for LLM learning, is insufficient. We propose leveraging verbalized user feedback to supervise reasoning for superior alignment, setting it apart from previous approaches to Deliberative Alignment.

5.3 Review-based Recommendation

Review-based recommendation systems have been widely studied recently to address tasks such as rating prediction [22, 36, 39, 54, 58]. These methods typically adopt a dual tower architecture that employs a user encoder and an item encoder to capture the semantics of reviews as user and item embeddings. Then, the user and item embeddings are combined through a fusion layer to derive joint representations, which are passed to a rating prediction layer to produce the final output [18]. To obtain better embeddings of users and items from reviews, many advanced techniques have been explored. For instance, DeepCoNN [59] employs convolutional neural networks (CNNs) to extract semantic information from historical reviews, achieving excellent results. Furthermore, attention mechanisms [3] are also introduced at both the word and review levels to identify critical words and reviews that are most significant [28, 40, 50]. For example, NARRE [9] employs attention mechanisms to prioritize reviews that are most useful for improving embedding learning. While these methods leverage reviews to represent user preferences implicitly with embeddings, resulting in the lack of interoperability. In contrast, DeliRec generates the reasoning process for each step in explicit textual form, offering clearer and more interpretable explanations of user preferences. Additionally, most review-based recommendation methods primarily leverage reviews as input features for generating embeddings. However, DeliRec also utilizes reviews as supervisory signals on the output side, aligning the LLM's reasoning with the user's true preferences.

6 CONCLUSION AND FUTURE WORK

In this work, we addressed the limitations of existing RecLLMs in complex scenarios by introducing a novel Deliberative Recommendation task, which emphasizes explicit reasoning before predicting user feedback. To achieve Deliberative Recommendation, we proposed the DeliRec framework, which enables multi-step reasoning via three collaborative experts with three core reasoning capabilities: Preference Distillation, Preference Matching, and Feedback Prediction. We aligned the reasoning process with users' true preference by using verbalized user feedback, *i.e.*, reviews. Through

extensive experiments on three real-world datasets, DeliRec demonstrated superior performance in both prediction accuracy and reasoning quality, highlighting the significance of slow thinking in recommendation tasks.

Despite its promising results, DeliRec is an initial attempt on Deliberative Recommendation, leaving many future directions. First, we only adopt user reviews as verbalized user feedback. Exploring multi-turn and diverse forms of verbalized user feedback, *e.g.*, conversations, may further enhance the reasoning process. Second, although DeliRec achieves comparable or even lower inference costs than Rec-SAVER and EXP3RT, there is still significant room to improve its efficiency. Future work could explore designing LLM acceleration algorithms tailored to Deliberative Recommendation. Third, it is promising to design an interactive learning paradigm between DeliRec and users.

References

- [1] Janice Ahn, Rishu Verma, Renze Lou, Di Liu, Rui Zhang, and Wenpeng Yin. 2024. Large Language Models for Mathematical Reasoning: Progresses and Challenges. In Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2024: Student Research Workshop, St. Julian's, Malta, March 21-22, 2024, Neele Falk, Sara Papi, and Mike Zhang (Eds.). 225–237.
- [2] Zafar Ali, Yi Huang, Irfan Ullah, Junlan Feng, Chao Deng, Nimbeshaho Thierry, Asad Khan, Asim Ullah Jan, Xiaoli Shen, Rui Wu, and Guilin Qi. 2023. Deep Learning for Medication Recommendation: A Systematic Survey. Data Intell. 5, 2 (2023), 303–354.
- [3] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural Machine Translation by Jointly Learning to Align and Translate. In ICLR.
- [4] Keqin Bao, Jizhi Zhang, Wenjie Wang, Yang Zhang, Zhengyi Yang, Yancheng Luo, Fuli Feng, Xiangnan He, and Qi Tian. 2023. A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems. *CoRR* abs/2308.08434 (2023).
- [5] Keqin Bao, Jizhi Zhang, Yang Zhang, Xinyue Huo, Chong Chen, and Fuli Feng. 2024. Decoding Matters: Addressing Amplification Bias and Homogeneity Issue for LLM-based Recommendation. CoRR abs/2406.14900 (2024).
- [6] Keqin Bao, Jizhi Zhang, Yang Zhang, Wenjie Wang, Fuli Feng, and Xiangnan He. 2023. TALLRec: An Effective and Efficient Tuning Framework to Align Large Language Model with Recommendation. In Proceedings of the 17th ACM Conference on Recommender Systems, RecSys 2023, Singapore, Singapore, September 18-22, 2023. 1007-1014.
- [7] Lochan Basyal and Mihir Sanghvi. 2023. Text Summarization Using Large Language Models: A Comparative Study of MPT-7b-instruct, Falcon-7b-instruct, and OpenAI Chat-GPT Models. CoRR abs/2310.10449 (2023).
- [8] Millennium Bismay, Xiangjue Dong, and James Caverlee. 2024. ReasoningRec: Bridging Personalized Recommendations and Human-Interpretable Explanations through LLM Reasoning. CoRR abs/2410.23180 (2024).
- [9] Chong Chen, Min Zhang, Yiqun Liu, and Shaoping Ma. 2018. Neural Attentional Rating Regression with Review-level Explanations. In WWW. ACM, 1583–1592.
- [10] Yuxin Chen, Junfei Tan, An Zhang, Zhengyi Yang, Leheng Sheng, Enzhi Zhang, Xiang Wang, and Tat-Seng Chua. 2024. On Softmax Direct Preference Optimization for Recommendation. CoRR abs/2406.09215 (2024).
- [11] Xiaoxue Cheng, Junyi Li, Wayne Xin Zhao, and Ji-Rong Wen. 2025. Think More, Hallucinate Less: Mitigating Hallucinations via Dual Process of Fast and Slow Thinking. arXiv preprint arXiv:2501.01306 (2025).
- [12] Sunhao Dai, Ninglu Shao, Haiyuan Zhao, Weijie Yu, Zihua Si, Chen Xu, Zhongxiang Sun, Xiao Zhang, and Jun Xu. 2023. Uncovering ChatGPT's Capabilities in Recommender Systems. In RecSys. ACM, 1126–1132.
- [13] Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. 2023. QLoRA: Efficient Finetuning of Quantized LLMs. In NeurIPS.
- [14] Melody Y. Guan, Manas Joglekar, Eric Wallace, Saachi Jain, Boaz Barak, Alec Helyar, Rachel Dias, Andrea Vallone, Hongyu Ren, Jason Wei, Hyung Won Chung, Sam Toyer, Johannes Heidecke, Alex Beutel, and Amelia Glaese. 2025. Deliberative Alignment: Reasoning Enables Safer Language Models. arXiv:2412.16339 [cs.CL] https://arxiv.org/abs/2412.16339
- [15] Melody Y Guan, Manas Joglekar, Eric Wallace, Saachi Jain, Boaz Barak, Alec Heylar, Rachel Dias, Andrea Vallone, Hongyu Ren, Jason Wei, et al. 2024. Deliberative alignment: Reasoning enables safer language models. arXiv preprint arXiv:2412.16339 (2024).
- [16] Xinyu Guan, Zhiyong Cheng, Xiangnan He, Yongfeng Zhang, Zhibo Zhu, Qinke Peng, and Tat-Seng Chua. 2019. Attentive aspect modeling for review-aware recommendation. ACM Transactions on Information Systems (TOIS) 37, 3 (2019),

- 1-27
- [17] F. Maxwell Harper and Joseph A. Konstan. 2016. The MovieLens Datasets: History and Context. ACM Trans. Interact. Intell. Syst. 5, 4 (2016), 19:1–19:19.
- [18] Emrul Hasan, Mizanur Rahman, Chen Ding, Jimmy Xiangji Huang, and Shaina Raza. 2024. Review-based Recommender Systems: A Survey of Approaches, Challenges and Future Perspectives. CoRR abs/2405.05562 (2024).
- [19] Xiangnan He, Yang Zhang, Fuli Feng, Chonggang Song, Lingling Yi, Guohui Ling, and Yongdong Zhang. 2023. Addressing Confounding Feature Issue for Causal Recommendation. ACM Trans. Inf. Syst. 41, 3 (2023), 53:1–53:23.
- [20] Shima Imani, Liang Du, and Harsh Shrivastava. 2023. MathPrompter: Mathematical Reasoning using Large Language Models. In Proceedings of the The 61st Annual Meeting of the Association for Computational Linguistics: Industry Track, ACL 2023, Toronto, Canada, July 9-14, 2023, Sunayana Sitaram, Beata Beigman Klebanov, and Jason D. Williams (Eds.). 37-42.
- [21] Yitong Ji, Aixin Sun, Jie Zhang, and Chenliang Li. 2023. A Critical Study on Data Leakage in Recommender System Offline Evaluation. ACM Trans. Inf. Syst. 41, 3 (2023), 75:1–75:27.
- [22] Donghyun Kim, Chanyoung Park, Jinoh Oh, Sungyoung Lee, and Hwanjo Yu. 2016. Convolutional Matrix Factorization for Document Context-Aware Recommendation. In RecSys. ACM, 233–240.
- [23] Jieyong Kim, Hyunseo Kim, Hyunjin Cho, SeongKu Kang, Buru Chang, Jinyoung Yeo, and Dongha Lee. 2024. Review-driven Personalized Preference Reasoning with Large Language Models for Recommendation. CoRR abs/2408.06276 (2024).
- [24] Yehuda Koren, Robert M. Bell, and Chris Volinsky. 2009. Matrix Factorization Techniques for Recommender Systems. Computer 42, 8 (2009), 30–37.
- [25] Chengpeng Li, Guanting Dong, Mingfeng Xue, Ru Peng, Xiang Wang, and Dayiheng Liu. 2024. DotaMath: Decomposition of Thought with Code Assistance and Self-correction for Mathematical Reasoning. CoRR abs/2407.04078 (2024).
- [26] Xinyu Lin, Wenjie Wang, Yongqi Li, Shuo Yang, Fuli Feng, Yinwei Wei, and Tat-Seng Chua. 2024. Data-efficient Fine-tuning for LLM-based Recommendation. In SIGIR. ACM, 365–374.
- [27] Donghua Liu, Jing Li, Bo Du, Jun Chang, and Rong Gao. 2019. DAML: Dual Attention Mutual Learning between Ratings and Reviews for Item Recommendation. In KDD. ACM, 344–352.
- [28] Hongtao Liu, Fangzhao Wu, Wenjun Wang, Xianchen Wang, Pengfei Jiao, Chuhan Wu, and Xing Xie. 2019. NRPA: Neural Recommendation with Personalized Attention. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval. 1233–1236.
- [29] Junling Liu, Chao Liu, Renjie Lv, Kang Zhou, and Yan Zhang. 2023. Is ChatGPT a Good Recommender? A Preliminary Study. arXiv preprint arXiv:2304.10149 (2023).
- [30] Zewen Long, Liang Wang, Shu Wu, Qiang Liu, and Liang Wang. 2024. GOT4Rec: Graph of Thoughts for Sequential Recommendation. CoRR abs/2411.14922 (2024).
- [31] Sichun Luo, Xinyi Zhang, Yuanzhang Xiao, and Linqi Song. 2022. HySAGE: A Hybrid Static and Adaptive Graph Embedding Network for Context-Drifting Recommendations. In CIKM. ACM, 1389–1398.
- [32] Qiyao Ma, Xubin Ren, and Chao Huang. 2024. XRec: Large Language Models for Explainable Recommendation. In EMNLP (Findings). Association for Computational Linguistics, 391–402.
- [33] OpenAI. 2023. ChatGPT: Optimizing Language Models for Dialogue. Blog Post.
- [34] OpenAI. 2024. Learning to reason with LLMs. https://openai.com/index/learningtoreason-with-llms/ (2024).
- [35] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback. In NeurIPS.
- [36] Zhaopeng Qiu, Xian Wu, Jingyue Gao, and Wei Fan. 2021. U-BERT: Pre-training User Representations for Improved Recommendation. In AAAI. AAAI Press, 4320–4327.
- [37] Scott Sanner, Krisztian Balog, Filip Radlinski, Ben Wedin, and Lucas Dixon. 2023. Large Language Models are Competitive Near Cold-start Recommenders for Language- and Item-based Preferences. In RecSys. ACM, 890–896.
- [38] Thibault Sellam, Dipanjan Das, and Ankur P. Parikh. 2020. BLEURT: Learning Robust Metrics for Text Generation. In ACL. Association for Computational Linguistics, 7881–7892.
- [39] Jie Shuai, Kun Zhang, Le Wu, Peijie Sun, Richang Hong, Meng Wang, and Yong Li. 2022. A Review-aware Graph Contrastive Learning Framework for Recommendation. In SIGIR. ACM, 1283–1293.
- [40] Yi Tay, Anh Tuan Luu, and Siu Cheung Hui. 2018. Multi-Pointer Co-Attention Networks for Recommendation. In KDD. ACM, 2309–2318.
- [41] Alicia Tsai, Adam Kraft, Long Jin, Chenwei Cai, Anahita Hosseini, Taibai Xu, Zemin Zhang, Lichan Hong, Ed Huai-hsin Chi, and Xinyang Yi. 2024. Leveraging LLM Reasoning Enhances Personalized Recommender Systems. In Findings of the Association for Computational Linguistics, ACL 2024, Bangkok, Thailand and virtual meeting, August 11-16, 2024. 13176–13188.
- [42] Chaojie Wang, Yanchen Deng, Zhiyi Lyu, Liang Zeng, Jujie He, Shuicheng Yan, and Bo An. 2024. Q*: Improving multi-step reasoning for llms with deliberative

- planning. arXiv preprint arXiv:2406.14283 (2024).
- [43] Jiaan Wang, Yunlong Liang, Fandong Meng, Haoxiang Shi, Zhixu Li, Jinan Xu, Jianfeng Qu, and Jie Zhou. 2023. Is ChatGPT a Good NLG Evaluator? A Preliminary Study. CoRR abs/2303.04048 (2023).
- [44] Qi Wang, Jindong Li, Shiqi Wang, Qianli Xing, Runliang Niu, He Kong, Rui Li, Guodong Long, Yi Chang, and Chengqi Zhang. 2024. Towards Next-Generation LLM-based Recommender Systems: A Survey and Beyond. CoRR abs/2410.19744 (2024).
- [45] Xiting Wang, Kunpeng Liu, Dongjie Wang, Le Wu, Yanjie Fu, and Xing Xie. 2022. Multi-level Recommendation Reasoning over Knowledge Graphs with Reinforcement Learning. In WWW. ACM, 2098–2108.
- [46] Yu Wang, Zhiwei Liu, Jianguo Zhang, Weiran Yao, Shelby Heinecke, and Philip S. Yu. 2023. DRDT: Dynamic Reflection with Divergent Thinking for LLM-based Sequential Recommendation. CoRR abs/2312.11336 (2023).
- [47] Yuling Wang, Changxin Tian, Binbin Hu, Yanhua Yu, Ziqi Liu, Zhiqiang Zhang, Jun Zhou, Liang Pang, and Xiao Wang. 2024. Can Small Language Models be Good Reasoners for Sequential Recommendation?. In Proceedings of the ACM on Web Conference 2024, WWW 2024, Singapore, May 13-17, 2024. 3876–3887.
- [48] Yuling Wang, Changxin Tian, Binbin Hu, Yanhua Yu, Ziqi Liu, Zhiqiang Zhang, Jun Zhou, Liang Pang, and Xiao Wang. 2024. Can Small Language Models be Good Reasoners for Sequential Recommendation?. In WWW. ACM, 3876–3887.
- [49] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. 2022. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. In NeurIPS.
- [50] Chuhan Wu, Fangzhao Wu, Junxin Liu, and Yongfeng Huang. 2019. Hierarchical User and Item Representation with Three-Tier Attention for Recommendation. In NAACL-HLT (1). Association for Computational Linguistics, 1818–1826.
- [51] Likang Wu, Zhi Zheng, Zhaopeng Qiu, Hao Wang, Hongchao Gu, Tingjia Shen, Chuan Qin, Chen Zhu, Hengshu Zhu, Qi Liu, Hui Xiong, and Enhong Chen.

- 2024. A survey on large language models for recommendation. World Wide Web (WWW) 27 (2024), 60.
- [52] Jundong Xu, Hao Fei, Liangming Pan, Qian Liu, Mong-Li Lee, and Wynne Hsu. 2024. Faithful Logical Reasoning via Symbolic Chain-of-Thought. In Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2024, Bangkok, Thailand, August 11-16, 2024, Lun-Wei Ku, Andre Martins, and Vivek Srikumar (Eds.). 13326–13365.
- [53] Diyi Yang, Sherry Tongshuang Wu, and Marti A. Hearst. 2024. Human-AI Interaction in the Age of LLMs. In Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 5: Tutorial Abstracts). 34–38.
- [54] Wei Yang, Tengfei Huo, Zhiqiang Liu, and Chi Lu. 2023. Review-based Multiintention Contrastive Learning for Recommendation. In SIGIR. ACM, 2339–2343.
- [55] Yang Zhang, Keqin Bao, Ming Yan, Wenjie Wang, Fuli Feng, and Xiangnan He. 2024. Text-like Encoding of Collaborative Information in Large Language Models for Recommendation. In Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2024, Bangkok, Thailand, August 11-16, 2024. 9181–9191.
- [56] Yang Zhang, Fuli Feng, Jizhi Zhang, Keqin Bao, Qifan Wang, and Xiangnan He. 2023. CoLLM: Integrating Collaborative Embeddings into Large Language Models for Recommendation. CoRR abs/2310.19488 (2023).
- [57] Yang Zhang, Tianhao Shi, Fuli Feng, Wenjie Wang, Dingxian Wang, Xiangnan He, and Yongdong Zhang. 2023. Reformulating CTR Prediction: Learning Invariant Feature Interactions for Recommendation. In SIGIR. ACM, 1386–1395.
- [58] Guoshuai Zhao, Xiaojiang Lei, Xueming Qian, and Tao Mei. 2019. Exploring Users' Internal Influence from Reviews for Social Recommendation. *IEEE Trans. Multim.* 21, 3 (2019), 771–781.
- [59] Lei Zheng, Vahid Noroozi, and Philip S. Yu. 2017. Joint Deep Modeling of Users and Items Using Reviews for Recommendation. In WSDM. ACM, 425–434.