Tree of Preferences for Diversified Recommendation

Anonymous Author(s)
Affiliation
Address
`email`

Abstract

Diversified Recommendation has attracted increasing attention from both researchers and practitioners, which can effectively address the homogeneity of recommended items. Existing approaches predominantly aim to infer the diversity of user preferences from observed user feedback. Nonetheless, due to inherent data biases, the observed data may not fully reflect user interests, where *underexplored* preferences can be overwhelmed or remain unmanifested. Failing to capture these preferences can lead to suboptimal diversity in recommendations. To fill this gap, this work aims to study diversified recommendation from a data-bias perspective. Inspired by the outstanding performance of large language models (LLMs) in zero-shot inference leveraging world knowledge, we propose a novel approach that utilizes LLMs' expertise to uncover underexplored user preferences from observed behavior, ultimately providing diverse and relevant recommendations. To achieve this, we first introduce the Tree of Preference (ToP), an innovative structure constructed to model user preferences from coarse to fine. ToP enables LLMs to systematically reason over the user's rationale behind their behavior, thereby uncovering their underexplored preferences. To guide diversified recommendations using uncovered preferences, we adopt a data-centric approach, identifying candidate items that match user preferences and generating synthetic interactions that reflect underexplored preferences. These interactions are integrated to train a general recommender for diversification. Moreover, we scale up overall efficiency by dynamically selecting influential users during optimization. Extensive evaluations of both diversity and relevance show that our approach outperforms existing methods in most cases and achieves near-optimal performance in others, with reasonable inference latency. Our code is publicly available at `https://anonymous.4open.science/r/TPRec-7047/`.

1 Introduction

Recommender systems have gained significant value in recent years, powering diverse applications such as social media [1, 2], e-commerce [3, 4], and video streaming platforms [5, 6]. To improve recommendation performance, numerous models have emerged, which are essentially built upon interactions between users and items [4, 7–10], such as shares, likes in social media, ratings in e-commerce, or viewing time in video streaming[11–14]. While these systems aim to better fit user behavior data, it is increasingly recognized that implicit feedback, often based on observed data, carries inherent biases, which can have various impacts on recommendation systems [7, 10, 15]. Among these, recommendation *diversity* is an aspect crucial to user satisfaction.

Recommendation diversity represents the dissimilarity of items recommended to an individual user [16]. Numerous studies have shown that higher diversity can provide users with freshness, meet their diverse interests, and lead to higher engagement [1, 17]. Recent works have explored various methods to enhance recommendation diversity. Some focus on the reranking phase, leveraging

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user-behavior models [17] or graph clustering [1] to capture user interests. Others focus on the matching stage, including multi-vector representations [7], separate matching of categories and items [9], or box embedding [6]. Another set of approaches comes from data perspective, such as node-copying for diverse sample graphs [8], knowledge distillation from diversified teachers [18], or rebalanced neighbor sampling [16]. Although these methods make considerable progress, they rely solely on existing observed user-item interactions, without supplementary knowledge. However, due to inherent biases in the data itself (*e.g.*, exposure bias, selection bias [10]), it may not be sufficient to comprehensively infer user preferences. Consequently, to improve recommendation diversity, these methods can carry a higher risk of irrelevant suggestions, leading to a degradation in recommendation relevance, which contradicts the fundamental goal of accuracy for recommender systems.

Ideally, recommender systems are expected to capture comprehensive aspects of user interests based on observed user behavior, thereby providing a diversified recommendation. Nevertheless, due to biases, user behavior may not accurately reflect user interests. Here, we consider two key scenarios. First, due to limited system recommendations, items matching user's certain interests may not have been interacted with, causing a lack of feedback, known as exposure bias. For example, a user with an interest in travel may like tourism posts on social media, but they may also be interested in photography tips that haven't appeared in their feed yet. Second, due to individual differences, users adopt different interaction strategies, leading to selection bias [10]. For instance, some users may primarily rate the shoes they purchase while leaving everyday items unrated, which does not imply a lack of interest in those items. As such, data bias makes it difficult for conventional methods to fully capture users' *underexplored preferences* without external knowledge, which may be overshadowed by dominant preferences in the observed data or may not yet appear, leading to narrow suggestions that cater only to dominant interests and placing users in "rabbit hole" [17, 19]. To mitigate this issue, we aim to investigate the task of diversified recommendation.

In this paper, we explore the feasibility of enhancing recommendation diversity while minimizing relevance loss by leveraging the domain knowledge provided by large language models (LLMs). As LLMs demonstrate unprecedented capability in zero-shot inference using world knowledge, our key insight is to leverage their expertise to analyze the rationale behind user historical interactions and uncover underexplored preferences, thus addressing the negative impact on diversity from data bias. For instance, a user who frequently browses travel and transportation posts on social media can be profiled as a travel enthusiast by the LLM, which can further infer potential interests in local cuisines or photography. In doing so, we strive to unbiasedly recover user preferences, thereby facilitating *diverse yet relevant* enhancements. Nevertheless, achieving this goal entails several challenges.

The first challenge is how to effectively leverage LLMs to capture a user's underexplored preferences from biased observations. Existing works using LLMs for diversified recommendations often fall short in systematic, fine-grained analysis of user preferences [20–22]. Some approaches directly match user history with items [20] or infer preferences at the category level [21]. We argue that coarse-grained matching is unsuitable for exploring latent preferences in diversity enhancement, as broad preferences may introduce noise, thereby diminishing relevance. To solve this, we design Tree of Preferences (ToP), which models user preferences from coarse to fine, to help the LLM better analyze the rationale behind user historical behaviors and improve the inference of latent interests.

The second challenge is how to leverage the uncovered preferences to guide diverse and relevant recommendations for users. A straightforward solution is to leverage LLMs to generate items in the embedding space [22], such as a two-step grounding paradigm [21, 23], but it suffers from suboptimal inference latency. Another is to have LLM rank items within the candidate set, either the full item set or a subset narrowed by external aids [20, 24], but its performance depends heavily on the size or quality of the candidates. To address this, we adopt a data-centric approach, where candidate items matching latent user preferences are identified via the LLM. We then generate synthetic interactions that best reflect user underexplored interests and integrate them into a general recommender for training. Moreover, we speed up the efficiency by dynamically selecting influential users during the optimization process. Our contributions are as follows:

- We propose ToP-Rec, a novel approach that explores diversified recommendation from a data-bias perspective, aiming to enhance diversity while maintaining relevance with expertise from LLMs.

- We design the Tree of Preferences to model fine-grained user interests, serving as a vehicle for LLMs to uncover underexplored preferences from observed behaviors. Synthetic interactions are generated to supplement existing data, training a general recommender for diversified suggestions.

- Extensive experiments on three real-world datasets show that ToP-Rec achieves advantages in both diversity and relevance in most cases, with a dominant trade-off and efficient inference latency compared to baselines.

2 Preliminary

The recommendation diversity referred to in this paper measures the dissimilarity of items recommended to an individual user [16]. A closely related but orthogonal concept is the novelty of recommendations [25], also referred to as serendipity, popularity bias, or even diversity in some works [15, 26–28]. For consistency, we refer to this concept as novelty in this paper. Novelty measures the proportion of long-tail or unpopular items among the recommendations for different users [15, 25]. Given the fundamental difference between diversity and novelty, this paper focuses on enhancing recommendation diversity, excluding novelty from its scope.

Diversity-relevance trade-off in recommendation. The trade-off between recommendation diversity and relevance has been extensively studied in prior work [1, 6, 8, 16]. In essence, this phenomenon arises from the fact that introducing dissimilarity may lead to additional noisy recommendations that are irrelevant to the user. Nevertheless, we emphasize that dissimilar items are not necessarily irrelevant; they may harbor implicit correlations by sharing common aspects aligned with user potential preferences. For example, a list comprising sneakers, sports socks, a smartwatch, and a yoga mat is generally more relevant to fitness enthusiasts than a list comprising office supplies, home decor, and kitchenware. Therefore, if latent user preferences can be captured, enhancing diversity while preserving relevance becomes feasible. In this work, we investigate the balance between diversity and relevance in recommender systems with the aid of LLMs. With this in mind, we next present a formal definition of the target problem.

Problem formulation. Let $\mathcal{U}$ denote the set of users and $\mathcal{I}$ denote the set of items. $\mathcal{R} \subseteq \mathcal{U} \times \mathcal{I}$ is the interaction set between users and items. In this paper, we assume each user $u \in \mathcal{U}$ is associated with an attribute set $\mathcal{A}_u$, and each item $i \in \mathcal{I}$ is associated with an attribute set $\mathcal{A}_i$, where attributes are described by natural languages. In this context, a recommender system aims to maximize the diversity among the items suggested to each user while promoting their relevance. Formally, we define this as the diversity-relevance aware recommendation problem.

Problem 1 (Diversity-relevance aware recommendation) *Given a user set $\mathcal{U}$ with attributes $\{\mathcal{A}_u | u \in \mathcal{U}\}$, an item set $\mathcal{I}$ with attributes $\{\mathcal{A}_i | i \in \mathcal{I}\}$, and an interaction set $\mathcal{R} \subseteq \mathcal{U} \times \mathcal{I}$, the diversity-relevance aware recommendation aims to learn a scoring function $f : \mathcal{U} \times \mathcal{I} \to \mathbb{R}$ with respect to the following two objectives:*

Objective 1: relevance. *The recommender aims to maximize the relevance of the recommended items for each user u, i.e., $\max_{X \subseteq \mathcal{I}} \mathsf{Rel}(u, \mathcal{X})$, where $\mathcal{X} \subseteq \mathcal{I}$ is the set of recommended items for user u, typically comprising items with the highest scores assigned by the recommender. $\mathsf{Rel}(u, \mathcal{X})$ is a relevance metric for item set $\mathcal{X}$ and user u, such as recall.*

Objective 2: diversity. *The recommender aims to enhance the diversity of the recommended items for each user u, i.e., $\max_{X \subseteq \mathcal{I}} \mathsf{Div}(\mathcal{X})$, where $\mathsf{Div}(\mathcal{X})$ is a diversity metric for item set $\mathcal{X}$, such as category entropy.*

3 Methodology

In this section, we detail the design of ToP-Rec. We begin with an overview, then introduce the two steps of ToP-Rec, where a user's latent preferences are first unveiled (§ 3.2) to guide the generation of synthetic interactions (§ 3.3). We further discuss a strategy for scaling up our approach in § 3.4.

3.1 Overall framework

Given users' textual attributes and their interaction history, ToP-Rec aims to generate diverse and relevant recommendation lists for them. We provide an illustration in Figure 1:

(1) ToP-Rec first uncovers latent user preferences by constructing ToP (black arrows) and inferring latent preferences through systematic reasoning on ToP (dashed lines);

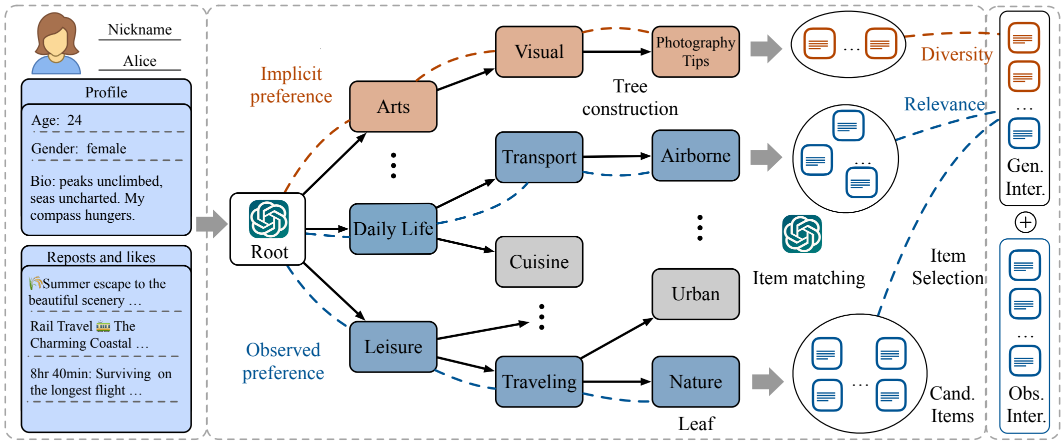


Figure 1: Illustration of our approach: **T**ree **o**f **P**references for diversified **Rec**ommendation (ToP-Rec). Given "Alice" with her attributes and interacted items, ToP-Rec infers her rationale along the constructed ToP by prompting LLMs to comprehensively uncover her preferences until reaching the leaf nodes. Items aligned with her preferences are then matched, and synthesized user-item interactions concerning diversity and relevance are generated and integrated with the observed interactions. The combined data enables the recommender to offer diversified suggestions.

(2) ToP-Rec generates synthetic interactions that recover the true preference distribution by identifying items aligned with inferred preferences and selecting those that enhance diversity and relevance.

(3) Synthetic interactions are integrated with the original, and a general recommender is trained on the combined data. To scale up, ToP-Rec dynamically selects users for synthetic interaction generation.

3.2 Uncovering underexplored preferences

Despite LLMs' domain knowledge, uncovering a user's unexplored preferences from biased historical interactions remains challenging. Existing work uses LLMs to analyze user preferences based on history, yielding promising results [20, 21]. However, these approaches lack a systematic analysis of fine-grained user interests, which are essential for providing diverse recommendations while maintaining relevance. Inspired by ToT [29, 30], we propose establishing a hierarchical user preference structure to enable the LLM to reason the rationale behind user historical behaviors from coarse to fine, ultimately uncovering a user's unexplored preferences.

Constructing tree of preferences over items. First, we discuss how to construct a hierarchy tree representing user preferences. Essentially, this process involves progressively dividing the *space* of user's preferences over items. Figure 1 shows an example partition in a social media context, where user interest in travel posts is initially separated from leisure, and subsequent partitions lead to fine-grained preferences like nature or urban tours. Such a hierarchical structure serves as a vehicle, embodying the LLM's systematic reasoning of the user's rationale behind their behavior.

Starting from the root node, we instruct the LLM to partition the preference space progressively until a fine-grained division is achieved. To ensure sufficient knowledge of item distribution, we use a k-means-based method to sample a smaller, text-rich subset of items $\mathcal{S} \subset \mathcal{I}$ for the LLM. For conciseness, sampling details are in Appendix A.2. Formally, the construction of ToP can be represented as

$$\mathcal{T}(\mathcal{V}, \mathcal{E}) = \mathsf{LLM}(\mathsf{Prompt}_{\mathsf{ToP}}(\mathcal{S})), \tag{1}$$

where $\mathcal{V}$ denotes the node set of hierarchical preferences, $\mathcal{T}$ denotes the tree of preferences, and $\mathcal{E} \subset \mathcal{V} \times \mathcal{V}$ denotes the edge set. Each node $v \in \mathcal{V}$ represents a kind of user preference generated by LLM, denoted by a token sequence $[\mathsf{Token}_0, \mathsf{Token}_1, \ldots]$. Each edge $e \in \mathcal{E}$ represents a finer preference division from its parent node. $\mathsf{Prompt}_{\mathsf{ToP}}$ means the instructions for constructing ToP (see Appendix A.2). In practice, if the item set has a predefined categorization, it will also be provided as a reference in the prompt of ToP.

Capturing user latent preferences via rationale reasoning. Next, we explain the systematic reasoning behind the user's behavior. Given their historical interactions, the LLM performs a top-down exploration of the hierarchical preferences, identifying the coarse-to-fine path that best matches the user's behavior (see dashed lines in Figure 1. This enables a systematic analysis of user rationale and fine-grained preferences. The LLM also reevaluates the exploration with respect to the user's rationale, checking for unobserved preferences not reflected in the interaction history.

Based on user interactions, a breadth-first search algorithm is used. Starting from the root node, the LLM selects preferences v^l that best explain the user behavior at each level, storing the corresponding nodes. As it moves to the next $l+1$-level, only the stored nodes' children are activated, continuing until the leaf node. The LLM then summarizes the user's behavior rationale and revisits the exploration to check for unobserved preferences, which are added if found, following the same root-to-leaf path. Finally, the leaf nodes of all selected paths are returned. The process can be summarized as:

$$\{v_1, ...v_n\} = \mathsf{LLM}(\mathsf{Prompt}_{\mathsf{PR}}(\mathcal{A}_u, \mathcal{R}_u)), \{v_1, ...v_n\} \subset \mathcal{V}_{\mathsf{Leaf}}, \tag{2}$$

where $\{v_1, \ldots, v_n\}$ denote the selected leaf nodes representing user latent preferences, $\mathcal{R}_u \subset \mathcal{R}$ denotes user u's interactions, and $\mathsf{Prompt}_{\mathsf{PR}}$ is the instruction for preference reasoning.

3.3 Generating synthetic interactions

As we uncover underexplored preferences, the next challenge lies in generating unbiased interactions based on them. We adopt a data-centric approach, leveraging data augmentation to mitigate potential biases in the observed feedback while ensuring efficient inference latency. First, candidate items that align with user preferences are identified. Then, items that cover underexplored preferences while considering relevance are selected and incorporated into existing user interactions. The synthetic unbiased interactions are ultimately used to train a diversified recommender.

Matching candidate items with tree of preferences. To find candidate items matching the preferences of any user, we aim to assign items from the entire set to the corresponding leaf nodes in ToP (*cf.* Eq. (2)). To reduce repeated computation, we pre-assign each item to its best matching leaf node by providing the item's textual attributes $\mathcal{A}_i$ to the LLM, which identifies the suitable leaf node in ToP. Finding candidate items that match specific preferences can then be easily achieved. The pre-assignment of each item is represented as follows:

$$v_i = \mathsf{LLM}(\mathsf{Prompt}_{\mathsf{IM}}(\mathcal{A}_i)), v_i \in \mathcal{V}_{\mathsf{Leaf}}, \tag{3}$$

where v_i denotes the assigned leaf node of item i via LLM and $\mathsf{Prompt}_{\mathsf{IM}}$ denote the prompt for item matching. Note that this process can be completed once ToP is constructed (see § 3.2), and we present it here for clarity. To improve load imbalance of leaf , we also incorporate refinement mechanisms after assignment. Please refer to Appendix A.2 for a detailed description.

Data generation for debiasing user interactions. Next, we select items that cover underexplored preferences, which are either overlooked or not yet manifested in the user's behavior. To do this, we calculate each item's contribution to diversity by measuring its impact on debiasing. Intuitively, selecting an item that reflects a latent preference with low (no) occurrence in the user's history has a higher impact. Thus, the diversity score of an item i is defined as $s_{\mathsf{div}}(u,i) \propto 1/\mathsf{freq}_i$, where freq_i represents the frequency of the preference associated with item i in u's history. We also measure the relevance of each item by calculating its semantic alignment with the user: $s_{\mathsf{rel}}(u,i) = \langle \mathsf{Enc}(\mathcal{A}_u), \mathsf{Enc}(\mathcal{A}_i) \rangle$, where $\mathsf{Enc}(\cdot)$ denotes a pretrained language model (*e.g.*, BERT [31]) and $\langle \cdot, \cdot \rangle$ denotes cosine similarity. Finally, the overall score is computed as:

$$s(u,i) = (1-\lambda) \cdot s_{\mathsf{rel}}(u,i) + \lambda \cdot s_{\mathsf{div}}(u,i), \tag{4}$$

where λ is a hyperparameter used to balance relevance and diversity. For a given user, we calculate the scores of all candidate items and select those above a predefined threshold. To reduce bias and better reflect user interests, the selected items are added to the user's interaction history, obtaining synthetic interactions $\mathcal{R}'_u = \mathcal{R}^+ \cup \mathcal{R}_u$, where $\mathcal{R}^+$ represents the selected items. Finally, the synthetic interactions are used for training a general recommender, leading to diverse yet relevant performance.

3.4 Cost-efficient interaction generation

Limited by token throughput and LLM latency, generating interactions for every user can be costly. To address this, we propose a cost-efficient strategy that identifies influential users for interaction generation, balancing improvements with costs. Given the complexity of data and recommender designs, it is infeasible to design a static heuristic to distinguish user importance, so we dynamically quantify each user's influence based on the recommender's feedback during training. To be specific, the recommender is initially trained on the original interactions. As user influence varies during training, we backtrack parameter updates and compute user influence at fixed intervals. The most influential users are selected to generate synthetic interactions, which are integrated into the training set. This continues until the model reaches peak performance. To quantify user influence, we design a custom criterion based on gradient alignment, measuring each user's contribution by the alignment between their local gradient and the model's parameter trajectory.

Assume the recommender is optimized using Bayesian Personalized Ranking (BPR) loss[1] [32], defined as: $\mathcal{L} = -\sum_{u\in\mathcal{U}}\sum_{(u,i)\in\mathcal{R}_u}\sum_{(u,j)\notin\mathcal{R}_u}\ln\sigma(\hat{y}_{ui}-\hat{y}_{uj})$, where $\hat{y}$ denotes similarity scores. The local loss incurred by user u is: $\ell(u;\theta) = -\sum_{(u,i)\in\mathcal{R}_u}\sum_{(u,j)\notin\mathcal{R}_u}\ln\sigma\left(\hat{y}_{ui}-\hat{y}_{uj}\right)$. Based on this, we define a user's influence in the gradient descent process over k steps.

Definition 1 (k-step influence) *Given the local gradient $\nabla\ell(u;\theta)$ of user u, and the gradient descent trajectory of model parameters $\{\theta^0,\ldots\theta^t\}$ backward from step t, the k-step influence of user u is defined as $\mathsf{Inf}_u = \sum_{i=t-k}^{t}\langle\nabla\ell(u;\theta^{i-1}),\theta^i-\theta^{i-1}\rangle$.*

With numerous users or high-dimensional gradients, the computational cost of user influence increases. We apply gradient dimension reduction [33] and group users to compute the group influence. More theoretical and empirical analyses are provided in Appendix A.2 and A.4.

Discussion with existing work. (1) Conventional diversified recommendations adopt various solutions to capture user preferences, such as uncertain masking [6], contrastive context learning [18], and user-category matching [9], which rely solely on observed data. However, due to inherent data bias, they often fail to fully capture preferences. In contrast, our approach moves beyond the scope of observed data, leveraging world knowledge from LLMs to reason about user rationale, offering greater potential to enhance diversity. (2) LLM-based diversified recommenders propose reranking solutions [20], or use LLM fine-tuning [22] to capture user preferences for item genres [21]. However, these approaches focus on a coarse category level, which can lead to noisy recommendations and affect accuracy. In contrast, our ToP models user preferences in a coarse-to-fine manner, facilitating nuanced reasoning over user rationale for better diversity and relevance.

4 Experiments

In this section, we evaluate the performance of ToP-Rec through extensive experiments. Due to space limitations, please refer to Appendix A.3 and A.4 for more experimental settings and results.

4.1 Experimental setup

Datasets. We use the Twitter [11], Weibo [12], and Amazon [14] datasets. Twitter and Weibo are social network datasets with user attributes (e.g., username, location, bio) and posts as items, including metrics like retweets and content. User feedback consists of likes and retweets. Amazon is an e-commerce dataset, where we combine seven categories as in [34]. We follow [16] to extract a subset, applying a 10-core filter (5-core for Twitter) and dropping items with no attributes. The train, validation, and test sets are split as 0.6:0.2:0.2. See Appendix A.3 for details and statistics of datasets.

Evaluation metrics. To evaluate the relevance of recommendations, we follow [16] and adopt the metric Recall@k (R@k), indicating the proportion of relevant items retrieved in the top-k recommendation list. To assess diversity, we use the Category-Entropy@k (CE@k), which measures the distribution of different categories within the top-k list. We report $k = 50$ and 100 in this work.

Baselines. We adopt nine baselines to compare with the proposed approach, categorized into three types: (1) Heuristic methods: Random, MMR [35], and DPP [36]; (2) Conventional diversity-enhancing methods: Box/LCD-UC [6] and CDM [18]; (3) LLM-based diversified recommender: LLM4Rerank-A/LLM4Rerank-AD [20] and LLMRec-MMR [24]. See Appendix A.3 for details.

[1]Note that our method can be applied to other types of losses, such as binary cross-entropy loss.

Table 1: Comparison of performance on diversity (R@k) and relevance (CE@k). * denotes the backbone model, and $^+/^-$ indicates performance improvements or declines compared to the backbone. The optimal performance is in bold, and the suboptimal performance is underlined.

	Twitter				Weibo				Amazon			
	R@50	R@100	CE@50	CE@100	R@50	R@100	CE@50	CE@100	R@50	R@100	CE@50	CE@100
LightGCN*	0.0567	0.0830	1.2841	1.3413	0.1052	0.1669	0.9905	1.0763	0.1362	0.2105	0.5004	0.5609
Random	0.0494^-	0.0730^-	1.2954^+	1.3475^-	0.0988^-	0.1577^-	0.9995^+	1.0801^+	0.1356^-	0.2062^-	0.5184^+	0.5792^+
MMR	0.0540^-	0.0790^-	1.3078^+	1.3550^-	0.0990^-	0.1578^-	1.0081^+	1.1005^+	$\underline{0.1371}^+$	$\underline{0.2115}^+$	0.5141^+	0.5755^+
DPP	0.0467^-	0.0765^-	1.3048^+	1.3532^-	0.0963^-	0.1530^-	$\mathbf{1.0362}^+$	1.1150^+	0.1283^-	0.2035^-	0.5181^+	0.5748^+
CDM	$\underline{0.0562}^-$	0.0814^-	1.2986^+	1.3461^-	0.1014^-	0.1620^-	1.0018^+	1.0912^+	0.1349^-	0.2103^-	$\underline{0.5228}^+$	0.5816^+
Box	0.0527^-	0.0741^-	1.2844^+	1.3407^-	0.0996^-	0.1587^-	1.0238^+	1.1034^+	0.1228^-	0.2019^-	0.5186^+	0.5844^+
LCD-UC	0.0517^-	0.0768^-	$\underline{1.3154}^+$	$\underline{1.3784}^-$	0.1038^-	0.1625^-	1.0211^+	1.0956^+	0.1295^-	0.2065^-	0.5202^+	0.5842^+
LLMRec-MMR	0.0558^-	0.0820^-	1.3056^+	1.3551^-	0.1041^-	$\underline{0.1662}^-$	1.0246^+	$\underline{1.1182}^+$	0.1363^+	0.2113^+	0.5177^+	0.5836^+
LLM4Re-A	$\underline{0.0562}^-$	$\underline{0.0827}^-$	1.2855^+	1.3424^-	0.1032^-	0.1656^-	0.9891^-	1.0745^-	0.1359^-	0.2049^-	0.5028^+	$\underline{0.5863}^+$
LLM4Re-AD	0.0560^-	0.0822^-	1.2864^+	1.3466^-	$\underline{0.1044}^-$	0.1652^-	1.0001^+	1.0823^+	0.1332^-	0.2042^-	0.5131^+	0.5827^+
ToP-Rec	$\mathbf{0.0586}^+$	$\mathbf{0.0841}^+$	$\mathbf{1.3275}^+$	$\mathbf{1.3852}^+$	$\mathbf{0.1054}^+$	$\mathbf{0.1667}^-$	$\underline{1.0333}^+$	$\mathbf{1.1369}^+$	$\mathbf{0.1380}^+$	$\mathbf{0.2120}^+$	$\mathbf{0.5298}^+$	$\mathbf{0.5902}^+$

Implementation details. We implement LightGCN with 2 hidden layers and a hidden size of 32, which is optimized using Adam optimizer with a learning rate of 5e-3. We also evaluate the performance of ToP-Rec on other backbones (see Appendix A.4). We employ a random negative sampling with a 1:50 ratio and use early stopping. For hyperparameters affecting diversity and relevance, we search the number of selected leaves in $[4, 7]$ (step size 1), number of augmentations per user in $[3, 9]$(step size 2), and the item sampling weight λ in $[0.2, 0.8]$ (step size 0.2). We utilize Qwen2.5-32B-Instruct [37] to complete tasks involving LLMs. To ensure fairness, we employ the same LLM for our approach and all baselines involving LLMs. Experiments are repeated 5 times to report the average performance with standard deviation. See Appendix A.3 for more details.

4.2 Evaluation of performance

We first evaluate ToP-Rec's overall performance in terms of diversity and relevance. For fairness, we select a balanced result for methods with adjustable hyperparameters and run other baselines with their original settings. For reranking methods like MMR and DPP, we use 10 times the top-k value as the candidate list, and for LLM4Rerank-A and LLM4Rerank-AD, we use twice the top-k value due to instability. Table 1 presents average recall and category-entropy comparisons, revealing several insights: (1) ToP-Rec dominates in most cases, with only one suboptimal result, showing its advantage in both diversity and relevance. (2) LLM-based methods perform relatively well in relevance, but improvement in diversity is limited, likely due to a lack of fine-grained preference analysis, leading to redundant item selections. (3) LCD-UC and Box struggle with high relevance, as box embeddings increase similarity with irrelevant items. (4) Heuristics like MMR are hard to achieve a balance, excelling in one aspect while underperforming in another, as observed in [16].

Relevance-diversity trade-off. To further demonstrate the robustness of our proposed method, we evaluate the relevance-diversity trade-off of ours and the baselines that support adjustments to balance this trade-off, including Random, MMR, DPP, CDM, LCD-UC, and LLMRec-MMR. We tune the hyperparameters of each method to explore their trade-offs, selecting the best three trade-off points for each method and visualizing them in Figure 2. The upper-right corner represents the ideal performance, with higher recommendation relevance and diversity. The result shows that our approach achieves the best trade-off compared with other baselines. In particular, while the diversity is enhanced with a larger margin, the relevance under our approach is consistently improved upon the backbone LightGCN (shown by a star mark). We also compare the trade-offs on Weibo and Amazon, which can be found in the Appendix A.4.

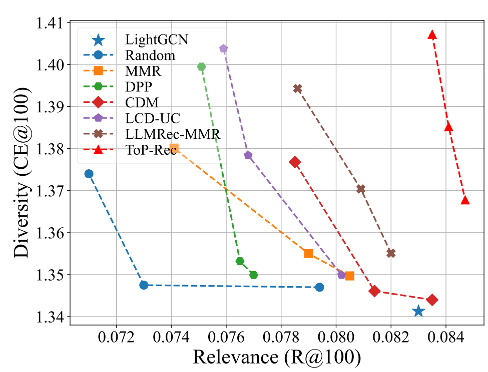
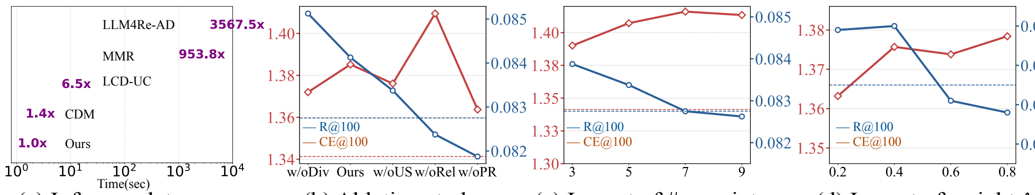


Figure 2: Diversity-relevance trade-off comparison. The upper-right represents the ideal.



(a) Inference latency. (b) Ablation study. (c) Impact of # gen. inter. (d) Impact of weight λ.

Figure 3: (a) Comparison of average time to generate recommendations; (b) Evaluation of each component in ToP-Rec; (c) and (d) Impact of generated interactions per user and selection weight λ. We use dashed lines to represent the performance of the backbone recommender.

Inference latency. To evaluate our method's efficiency, we compare its inference time with other methods, measuring the average time to generate a recommendation list for a user. Figure 3(a) shows that our method achieves similar latency to traditional methods like CDM and LCD-UC, while outperforming the reranking method MMR. Notably, it also shows a significant advantage over LLM-based method LLM4Rerank. In summary, our method can optimize diversity-relevance performance while maintaining efficient inference latency compared to baselines.

4.3 Ablation study

We conduct ablation studies to evaluate the effectiveness of each component in our approach, including four variants: (1) w/o Div and (2) w/o Rel: We ignore the item's contribution to diversity or relevance in item selection (*cf.* Eq.(4)); (3) w/o US: We discard the influential user selection (*cf.* § 3.4) and random select user for augmentation; (4) w/o PR: We avoid LLM to infer user preferences, instead randomly selecting leaf nodes (*cf.* Eq.(2)). Figure 3(b) visualizes their changes in diversity and relevance, ordered by relevance in descending order. First, w/o Div and w/o Rel outperform Ours in relevance and diversity, respectively, but perform poorly in the other aspect due to considering only one factor. Second, w/o US improves both aspects but remains weaker than Ours, showing that augmentation on influential users boosts performance. Finally, w/o PR performs worst in relevance, indicating that ignoring user interests increases the risk of irrelevance.

4.4 Hyperparameter analysis

Next, we evaluate the influence of important hyperparameters in our approach, which impact the diversity-relevance performance. These mainly include: (1) the weight λ for item selection. (2) the number of generated interactions per user. (3) the number of selected leaf nodes per user. We tune the weight λ among $\{0.2, 0.4, 0.6, 0.8\}$ and number of generated interactions among $\{3, 5, 7, 9\}$. The results in Figure 3(d) show that as the weight λ for item selection increases, diversity rises while relevance declines. This is because a higher weight increases the focus on diversity, raising the possibility of irrelevance. Figure 3(c) shows that as the number of generated interactions increases, relevance decreases, while diversity initially rises and then stabilizes. This is due to the decline in item relevance, which reduces recall, while the contribution to diversity also diminishes, stabilizing its growth. Due to page limitations, we analyze the impact of other hyperparameters in the appendix.

5 Literature Review

Diversified recommendation. Research on diversified recommendation has a well-established history. Early works concentrate on re-ranking diversification [35, 36, 38–42]. These approaches often leverage greedy solutions to balance utility and diversity [35, 39, 40], or employ Determinantal Point Processes [43] to generate diverse recommendations by measuring set diversity [36, 41, 42]. Recently, more complex diversified re-ranking methods have been proposed, such as introducing a user-behavior model to maximize knowledge diversity [17], or employing graph clustering to capture user interests and sub-models to assess diversity [1]. Unlike these post-matching works, our framework directly incorporates diversification in the matching stage. Many recent works also focus on the matching stage, with some built upon Bayesian graph convolutional neural networks [8], multi-vector representations [7], two-stage category-item matching [9], or rebalanced sampling techniques [16]. Compared to them, we propose a universal pipeline for use with generic recommender backbones, instead of designing a specific model. Our work is most similar to [6, 18], where they propose a general framework for diversified recommendation via box embedding and uncertainty masking[6], or knowledge distillation learning from MMR [18]. A common limitation of traditional methods is their reliance on observed data, which hinders overcoming diversity decline due to inherent data bias. In contrast, our approach moves beyond the scope of observed data, leveraging world knowledge from LLMs to reason about the user rationale, offering greater potential to enhance diversity.

LLM-based recommendation. With the impressive capabilities demonstrated by LLMs, a growing body of work explores their application in recommender systems [44–46]. Early research primarily focuses on leveraging LLMs to enhance the relevance of recommendations [24, 47–50], utilizing the reasoning abilities of LLMs to analyze potential user interests and generate tailored recommendations. Recently, LLM-based recommendations have expanded beyond relevance, with a growing focus on other performance aspects [51], especially on recommendation diversity [20–22]. To mitigate the homogeneity issue in LLM-based recommendations, the decoding strategy in [22] integrates a text-free assistant model to refine the token scores. However, its effectiveness depends on the assistant model's quality; if the model provides poor suggestions, it may lead to irrelevant or low-quality recommendations. DLCRec [21] introduces a framework for diversity control in LLM-based recommendations by breaking down the recommendation task into three sub-tasks; LLM4Rerank [20] proposes a LLM-based reranking approach that leverages a graph structure to represent accuracy, diversity, and fairness in reranking, allowing for the refinement of the final recommendations. Despite some improvement in diversity, these approaches lack fine-grained user preference analysis and item space partitioning, leading to a higher risk of irrelevant recommendations and affecting accuracy. In contrast, tree of preference hierarchically refines user preferences from coarse to fine, enabling the LLM to uncover underexplored user preferences through nuanced reasoning, thereby facilitating diverse and relevant recommendations.

Influential data selection. Existing research on influential data selection aims to estimate the influence of individual or sets of training records on model performance and select the most influential ones [33, 52]. In this paper, we primarily discuss two widely used approaches: influence function-based methods [52–55] and gradient descent tracing-based methods [33, 56–58]. While influence functions provide insights into how perturbations to certain parts of the training data affect model behavior [59], the computation of the inverse-Hessian limits the effectiveness of the selection process [60]. Furthermore, existing work has pointed out that traditional influence functions may fail on certain types of data and model architectures. For instance, when applied to Graph Neural Networks (GNNs), computing influence requires analyzing the mutual interactions between nodes [61–63], which adds significant computational overhead when using influence functions for user selection in many GNN-based recommendation models [64]. On the other hand, studies [56] utilize first-order approximation to estimate the influence of a training sample on model performance under stochastic gradient descent. [33] extends this assumption to the Adam optimizer. The methods in [57, 58] are closest to ours, calculating the alignment between the local gradient of pretrain samples and the downstream loss gradient. However, the downstream loss gradient may not align with the actual parameter update during fine-tuning. In contrast, we calculate the alignment between the local gradient of a sample and the actual parameter update trajectory, ensuring a more accurate measure.

6 Conclusion

In this paper, we explore diversified recommendation from a data-bias perspective, identifying two key scenarios that may introduce bias affecting diversity. To address this, we propose ToP-Rec, which leverages external knowledge from LLMs to complement data bias. We construct the Tree of Preferences to model user preferences from coarse to fine, helping the LLM analyze user behaviors and improve latent interest inference. To ensure efficient recommendations, candidate items matching latent preferences are identified via the LLM, and synthetic data is generated through a relevance-diversity-aware strategy for training. Additionally, we introduce a dynamic user selection mechanism to reduce costs by selecting influential users based on gradient feedback. We extensively evaluate the performance of ToP-Rec on three real-world datasets, comparing it to nine competitive baselines. The results demonstrate that ToP-Rec outperforms in most cases, achieving second-best performance in others, with the optimal trade-off between diversity and relevance and efficient inference latency.

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