

Towards *Human-like* Preference Profiling in Sequential Recommendation

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Abstract

Sequential recommendation systems aspire to profile users by interpreting their interaction histories, echoing how humans make decisions by weighing experience, relative preference strength, and situational relevance. Yet, existing large language model (LLM)-based recommenders often fall short of mimicking the flexible, context-aware decision strategies humans exhibit, neglecting the structured, dynamic, and context-aware mechanisms fundamental to human behaviors. To bridge this gap, we propose RecPO, a preference optimization framework that models structured feedback and contextual delay to emulate human-like prioritization in sequential recommendation. RecPO exploits adaptive reward margins based on inferred preference hierarchies and temporal signals, enabling the model to favor immediately relevant items and to distinguish between varying degrees of preference and aversion. Extensive experiments across five real-world datasets demonstrate that RecPO not only yields performance gains over state-of-the-art baselines, but also mirrors key characteristics of human decision-making: favoring timely satisfaction, maintaining coherent preferences, and exercising discernment under shifting contexts. Code: <https://anonymous.4open.science/r/RecPO-020A/>

1 Introduction

In modern social media, recommender systems are ubiquitous in shaping user experiences by delivering personalized content across various online platforms (Schafer et al., 1999; Sarwar et al., 2000; Ma et al., 2008; Davidson et al., 2010; Jamali and Ester, 2010; Fan et al., 2019; Deldjoo et al., 2020; Ouyang et al., 2024, 2025). Sequential recommendation, as a specialized form, predicts the next item a user is likely to interact with based on his/her

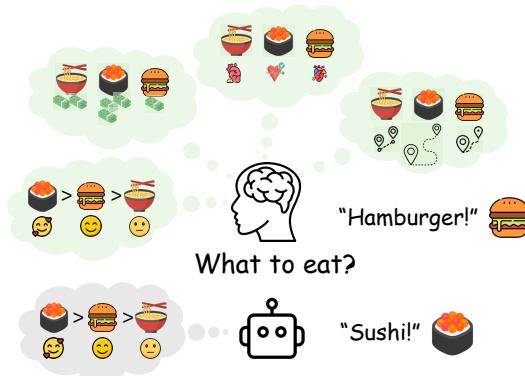


Figure 1: Human-like decision behavior in preference-based choices, involving fine-grained trade-offs among reward, delay, effort, and risk.

historical behaviors. This form plays a crucial role in the real world, such as movie recommendations on streaming platforms like Netflix, or curating the next song on Spotify based on listening history. Sequential recommenders (Sun et al., 2019; Tang and Wang, 2018; Chang et al., 2021) originally leverage neural models such as RNNs (Hidasi, 2016) and Transformers (Kang and McAuley, 2018). These models encode user/item IDs and contextual features (e.g., item descriptions, interaction timestamps) for sequential pattern modeling. More recently, the emergence of large language models (LLMs), has sparked interest in their use for sequential recommendation (Harte et al., 2023; Li et al., 2023; Yang et al., 2024; Bao et al., 2023; Zhang et al., 2023), owing to their broad world knowledge and advanced reasoning capabilities.

As central to sequential recommendation, user preference profiling reflects how humans adapt choices based on prior experience, personalized relevance, and evolving goals (Astington and Jenkins, 1995). However, current LLM-based solutions often fall short in emulating the flexible decision patterns exhibited by humans. Existing preference modeling approaches, such as direct preference op-

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timization (DPO) (Rafailov et al., 2024) and its derivatives (Chen et al., 2024; Meng et al., 2024; Amini et al., 2024), rely on static pairwise comparisons that abstract away the layered and situational nature of real-world preferences. This modeling overlooks the hierarchical structure of human preference (e.g., mild vs. strong affinity) and fails to account for factors like satisfaction delay, decision effort, and perceived risk, as illustrated in Figure 1. For instance, a moderately preferred item that is immediately relevant may be favored over a highly rated item that becomes relevant much later. Such prioritization, common in human decision-making, is rarely reflected in LLM-based systems, limiting their alignment with real user decision dynamics.

To explore this, we begin with a proof-of-concept experiment to demonstrate that leveraging comprehensive and structured user feedback substantially improves preference modeling in sequential recommendation. Building on this insight, we then introduce RecPO, a framework designed to enhance LLM-based recommenders by emulating human-like decision patterns observed in structured and context-aware feedback. RecPO is distinguished by four key components:

- (i) It retains all user interactions, including those with negative feedback, to build a fuller picture of preferences and aversions;
- (ii) It incorporates structured preference inferred from explicit or implicit feedback;
- (iii) It calibrates preferences data using satisfaction immediacy reflected in humans; and
- (iv) It generates adaptive reward margins to guide alignment based on both preference hierarchy and temporal context.

Through experiments across five datasets with either implicit or explicit feedback, we show that RecPO more faithfully mirrors human-like behavior: consistently promoting preferred items, suppressing dispreferred ones, and adapting to context that aligns with real-world user decision patterns.

2 Related Work

Sequential recommendation models temporal user preferences in interaction sequences. Early methods adopt structures such as recurrent neural networks (GRU4Rec (Hidasi, 2016)) and self-attention mechanisms such as SASRec (Kang and

McAuley, 2018). Recent advances integrate LLMs for their rich semantic understanding and contextual reasoning capabilities (Liao et al., 2024; Bao et al., 2023; Geng et al., 2022; Yuan et al., 2023).

LLM preference alignment techniques aim to align language models’ outputs with human preferences, have inspired significant advancements beyond general-purpose tasks such as recommendations. Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022) and DPO (Rafailov et al., 2024) suggest fine-tuning based on human preference data. Building on DPO, methods like IPO (Azar et al., 2024), CPO (Xu et al., 2024), KTO (Ethayarajh et al., 2024), SimPO (Meng et al., 2024), and ODPO (Amini et al., 2024) further refine alignment with improved model efficiency and robustness. Most recently, S-DPO adapts alignment for user-item sequences, optimizing personalization by comparing with list-wise negative items. We provide a more detailed related work in Appendix D.

Our approach differs from previous efforts in that we calibrate structured implicit or explicit preference feedback based on satisfaction delay to refine preference alignment margins, without obtaining them computationally (Amini et al., 2024).

3 Preliminaries

Existing LMs are adapted to sequential recommendation tasks through a two-stage training paradigm, namely *supervised fine-tuning (SFT)* (Ouyang et al., 2022; Liao et al., 2024; Bao et al., 2023), which adapts general-purpose LLMs into task-specific models, and *preference alignment* (Ouyang et al., 2022; Schulman et al., 2017), which further aligns model output to human preference¹.

In *SFT*, models are trained to predict the target item given users’ historical interacted items along with their related contextual information. Specifically, let \mathbf{x}_u^t be the task prompt that encompasses user u ’s interaction history up to time t , information of items to be inquired, and other task-related descriptions. Also let \mathbf{y}_p^t be the text mapping of the target item that best aligns with \mathbf{x}_u^t ’s description. The objective of *SFT* that optimizes π_θ is:

$$\min_{\theta} -\mathbb{E}_{(\mathbf{x}_u^t, \mathbf{y}_p^t) \sim \mathcal{D}_{\text{SFT}}} [\log \pi_\theta(\mathbf{y}_p^t | \mathbf{x}_u^t)]. \quad (1)$$

The LM fine-tuned with this objective on \mathcal{D}_{SFT} is denoted as π_{SFT} . For brevity, we omit the times-

¹More detailed preliminaries in Appendix A.

tamp signs in all subsequent equations unless its inclusion is essential for clarity.

While optimizing the SFT objective effectively adapts LMs to the downstream task, recent studies indicate that models still struggle to align outputs with human judgments of quality (Ziegler et al., 2019; Stiennon et al., 2020; Rafailov et al., 2024). To address this, models undergone SFT require further processing through the *preference alignment* process. One of the most prominent techniques is named DPO (Rafailov et al., 2024), which employs the Bradley-Terry (BT) model (Bradley and Terry, 1952) to model the probability of human preference data. Specifically, let $(\mathbf{y}_p, \mathbf{y}_d)$ be the relatively preferred and dispreferred textual output in a pairwise preference data, respectively. The objective is:

$$\min_{\theta} - \mathbb{E}_{(\mathbf{x}, \mathbf{y}_p, \mathbf{y}_d) \sim D} \left[\log \sigma \left(\beta \log \frac{\pi_{\theta}(\mathbf{y}_p | \mathbf{x})}{\pi_{\text{ref}}(\mathbf{y}_p | \mathbf{x})} \right. \right. \\ \left. \left. - \beta \log \frac{\pi_{\theta}(\mathbf{y}_d | \mathbf{x})}{\pi_{\text{ref}}(\mathbf{y}_d | \mathbf{x})} \right) \right], \quad (2)$$

where π_{ref} is commonly set to π_{SFT} , π_{θ} is the aligned model, and β is a hyperparameter.

Building upon DPO, a recent effort named S-DPO (Chen et al., 2024) has been proposed specifically for LLM-based recommenders. They pair each positive item with multiple negative items generated by random sampling as preference data, and revise the alignment objective as:

$$\min_{\theta} - \mathbb{E}_{(\mathbf{x}, \mathbf{y}_w, \mathcal{T}_d) \sim D} \left[\log \sigma \left(- \log \sum_{\mathbf{y}_d \in \mathcal{T}_d} \exp \left(\beta \log \frac{\pi_{\theta}(\mathbf{y}_d | \mathbf{x})}{\pi_{\text{ref}}(\mathbf{y}_d | \mathbf{x})} - \beta \log \frac{\pi_{\theta}(\mathbf{y}_p | \mathbf{x})}{\pi_{\text{ref}}(\mathbf{y}_p | \mathbf{x})} \right) \right) \right], \quad (3)$$

where \mathcal{T}_d contains the item titles of multiple dispreferred items².

4 Comprehensive and Structured Feedback Grounds Preference Profiling

We design a proof-of-concept experiment to assess how comprehensive and structured preference feedback, captured by user-item ratings, impacts predicting the next preferred item. We devise four-tier input configurations that progressively integrate preference signals:

- (i) *Filtered Items*: Excluding negative feedback items and no explicit ratings are provided, mimicking S-DPO’s setup;

²We use positive/negative, as well as preferred/dispreferred interchangeably in the following content.

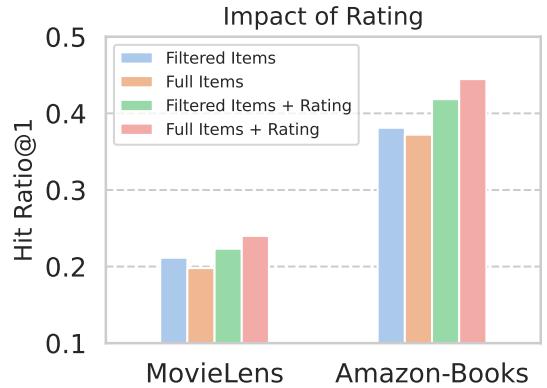


Figure 2: Hit@1 in next favorable item prediction with comprehensive and structured preference feedback.

- (ii) *Full Items*: Retaining all historical items, yet no explicit ratings are provided;
- (iii) *Filtered Items + Rating*: Providing explicit ratings yet excluding negative-feedback items;
- (iv) *Full Items + Rating*: Retaining all items and their corresponding explicit ratings.

We fine-tune LLaMA3-8B on MovieLens and Amazon-Books (described Section 6.1) using the four input configurations. The experimental results are reported using Hit Ratio@1 (see Section 6.1, where higher values indicate better performance) and are shown in Figure 2.

We observe that maintaining comprehensive and structured feedback in the form of ratings consistently improves performance. While it seems counterintuitive to include negatively interacted items when the task is to predict the next favorable items, having structured feedback in the user history proves beneficial, as aversion modeling is crucial for constructing a more accurate user preference profile. Notice that the *Full Items* (without ratings) underperforms the *Filtered Items*, as the absence of explicit annotations for negative items introduces noise into the learning process. These results highlight that structured feedback helps resolve ambiguity, enabling LLMs to differentiate between preferences and aversions.

5 Methodology

In this section, we first lay out the prompt design that establishes the foundation for preference modeling in LLM-based recommendations. We then introduce RecPO, a novel preference optimization framework for sequential recommendation that dynamically calibrates reward margins between pair-

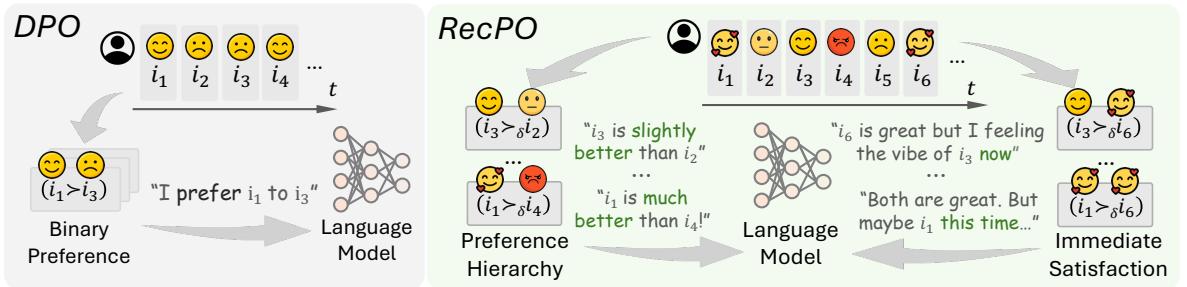


Figure 3: Illustrations for DPO and our framework: DPO assigns rigid preference margin across pairwise preference data, while ours adaptively adjusts preference margin (δ) based on preference structures and contextualization.

wise preference data based on contextualized and structured preference feedback, shown in Figure 3.

5.1 Comprehensive and Structured Preference Feedback as the Foundation

Unlike existing approaches (Liao et al., 2024; Chen et al., 2024) which remove items with negative feedback from interaction histories to construct homogeneous sequences (i.e., items with only positive feedback), building on the observations from Section 4, We preserve the complete interaction sequence for each user, explicitly retaining all historical items along with their associated preference feedback. We use explicit ratings or ratings converted from implicit feedback to construct a hierarchical preference profile. Following prior work (Chen et al., 2024), the input prompts are composed of the following parts:

User historical interaction \mathcal{H}_u Each item in the user history is formatted as "[ItemTitle] | Rating: [ItemRating]". For example, "Toy Story | Rating: 4". All historical items are concatenated with "\n" being the separator.

Candidate item set \mathcal{C} We format all candidate items in a similar format as the historical items, except that no rating attributes are provided.

Task Description We prepend the history-specific prefixes (e.g., "Given the user's recent viewing and rating history") and candidate-specific prefixes (e.g., "recommend a movie they'll likely watch next and rate generously from following candidates") to their respective sequences.

The three prompt components are concatenated as the final textual input \mathbf{x}_u to the LMs. Concrete examples are demonstrated in Appendix C.

5.2 Adaptive Reward Margin Emulates Complex Human Preferences

Current DPO-based methods simplify preference modeling to maximizing the reward difference between pairwise preferred and dispreferred responses/items, exposing them to two key limitations: (i) Neglecting preference hierarchy, where in reality, users may strongly prefer certain items while only slightly prefer others, compared to either the same or different negative items; (ii) Neglecting contextual factors, among which we specifically consider that users typically prioritize immediate satisfaction over delayed rewards. To incorporate both factors into preference modeling, We define an adaptive target reward margin γ_r , dynamically determined by the structured preference between the two compared items and their relative recency with respect to the current timestamp. Specifically, a utility function $\phi(\cdot)$ is utilized to evaluate the reward of an item wrt two perspectives—the stronger the preference of more recent interaction, the larger the utility. The margin of a pairwise data $(\mathbf{y}_p, \mathbf{y}_d)$ is defined as:

$$\gamma_r = \lambda \frac{\phi(s_p, \Delta_{tp})}{\phi(s_d, \Delta_{td})} \quad (4)$$

where \mathbf{y}_p is preferred over \mathbf{y}_d , s_p and s_d are their structured preference score respectively, λ controls the margin's magnitude, and $\Delta_{tp} = t_p^+ - t$ indicates the time latency of the interaction. In this work, we set $\phi(s, \Delta_t) = s / (\Delta_t)^{0.5}$. Note that the choice of score function is customizable as long as it reflects the above preference rules. That is, $\phi(s, \Delta_t) \propto s / (\Delta_t)^\alpha$, where $\alpha > 0$ indicates the temporal decay factor. For dispreferred items from either negative sampling or historical interactions where no user-assigned feedback is available, we set a default preference score and time latency to facilitate the training. More details about the default

$$\begin{aligned} \mathcal{L}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(\mathbf{x}_u, \mathbf{y}_p, \mathcal{T}_d) \sim \mathcal{D}} \left[\log \sigma \left(-\log \sum_{\mathbf{y}_d \in \mathcal{T}_d} \exp \left(\beta \log \frac{\pi_\theta(\mathbf{y}_d | \mathbf{x}_u)}{\pi_{\text{ref}}(\mathbf{y}_d | \mathbf{x}_u)} \right. \right. \right. \\ \left. \left. \left. - \beta \log \frac{\pi_\theta(\mathbf{y}_p | \mathbf{x}_u)}{\pi_{\text{ref}}(\mathbf{y}_p | \mathbf{x}_u)} - \lambda \frac{\phi(s_p, \Delta_{t_p})}{\phi(s_d, \Delta_{t_d})} \right) \right) \right]. \end{aligned} \quad (7)$$

value can be found in Section 6.

5.3 Complex Preference Pattern Emerges from Adaptive Reward Margins

We plug Equation 4 into the BT model to derive the distribution for pairwise preference data:

$$P^*(\mathbf{y}_p \succ \mathbf{y}_d | \mathbf{x}_u) = \sigma(r(\mathbf{x}_u, \mathbf{y}_p) - r(\mathbf{x}_u, \mathbf{y}_d) - \gamma_r), \quad (5)$$

where $r(\cdot)$ is the reward function. We pair each preferred item with multiple dispreferred items, and leverage the Plackett-Luce (PL) model (Plackett, 1975; Luce, 1959) to generalize pairwise comparisons to a list-wise ranking framework. Formally, given the prompt x_u^t encompassing all the historical interactions of user u , a candidate set \mathcal{C} containing K items (one preferred item and $K - 1$ dispreferred items), and a permutation σ representing the predicted ranking of these candidates based on user preference for the next item (denote $\sigma(j)$ as the item ranked at position j), the probability of observing the candidates' preference ranked as $[\mathbf{y}_{\sigma(1)}, \mathbf{y}_{\sigma(2)}, \dots, \mathbf{y}_{\sigma(K)}]$ is:

$$P(\sigma | \mathbf{x}_u, \mathcal{T}_c) = \prod_{j=1}^K \frac{\exp(r(\mathbf{x}_u, \mathbf{y}_{\sigma(j)}))}{\sum_{m=j}^K \exp(r(\mathbf{x}_u, \mathbf{y}_{\sigma(m)}))), \quad (6)$$

where \mathcal{T}_c contains K item descriptions. Building upon Equation 6, we derive the final objective shown in Equation 7. Note that our method is reduced to S-DPO when $\lambda = 0$. For brevity, the detailed derivation process is provided in Appendix B. Optimizing the derived objective effectively integrates structured preference feedback with temporal decay factors to refine implicit preference modeling, adapting LLM recommenders to better fit preference patterns in real-world scenarios.

6 Experiment

6.1 Setup

Datasets. We select five publicly available representative recommendation benchmark datasets

for our experiments: We use five widely used real-world sequential recommendation datasets for evaluation, including *MovieLens-1M* (Harper and Konstan, 2015), *Amazon-books* (Ni et al., 2019), *Steam* (Kang and McAuley, 2018), *BeerAdvocate* (Leskovec and McAuley, 2012), and *LastFM* (Celma, 2010)³.

For each dataset, we apply k -core filtering (He and McAuley, 2016) to remove users and items with less than $k = 5$ interactions. We construct a candidate set of 20 items from which the model selects. During training, this set is composed of 10 subsequent interactions (ensuring that the correct item is always included) and 10 randomly sampled non-interacted items. For validation and testing, the candidate set consists of the correct item plus 19 randomly sampled non-interacted items. For ML-1M, Amazon-books, and BeerAdvocate, we utilize ratings as the structured preferences to adjust the preference margins, and for Steam and LastFM, where explicit ratings are unavailable, we rely on play-hours and play-count as proxies for user structured preferences. For each user, we order the interactions chronologically, using the second-last target interaction for validation, the last one for testing, and the rest for training.

Baselines. We compare RecPO with two types of baseline models: (i) *Traditional* methods leverage sequential patterns in user behaviors to predict the next interacted item, using various modeling architectures such as recurrent neural networks (GRU4Rec (Hidasi, 2016)), convolutional neural networks (Caser (Tang and Wang, 2018)), or multi-head self-attention frameworks (SASRec (Kang and McAuley, 2018)). (ii) *LM-based* methods utilize LMs to process historical interactions and predict the next interacted item. We select two LM backbones, LLaMA3 (Dubey et al., 2024) and Qwen (?), and compare between the standard preference optimization baseline DPO (Rafailov et al., 2024), SimPO (Meng et al., 2024), a reference-free method that enhances DPO with length regulariza-

³More dataset details in Appendix E.1

Model Type	Bkbn	Method	MovieLens		Amazon-Books		BeerAdvocate		Steam		LastFM	
			HR@1	ValidRatio	HR@1	ValidRatio	HR@1	ValidRatio	HR@1	ValidRatio	HR@1	ValidRatio
Feedback Type			Explicit Feedback						Implicit Feedback			
Trad.	-	GRU4Rec	0.2664	1.0000	0.1310	1.0000	0.3708	1.0000	0.4584	1.0000	0.6630	1.0000
	-	Caser	0.2714	1.0000	0.1538	1.0000	0.3757	1.0000	0.4394	1.0000	0.6716	1.0000
	-	SASRec	0.2671	1.0000	0.1559	1.0000	0.3800	1.0000	0.4587	1.0000	0.6659	1.0000
LLM	LLaMA3-8B	LLaMA3	0.0929	0.7351	0.0654	0.6165	0.0686	0.6617	0.0852	0.8672	0.1264	0.6147
		SFT	0.2478	0.9985	0.4447	0.9974	0.2645	0.9936	0.3122	0.9990	0.5076	1.0000
		DPO	0.2809	0.9970	0.5049	0.9887	0.4412	0.9875	0.3340	0.9980	0.5719	1.0000
		SimPO	0.2974	0.9725	0.5129	0.9564	0.4020	0.9250	0.3401	0.9766	0.5759	0.9419
		S-DPO	0.2902	0.9983	0.5065	0.9880	0.4698	0.9903	0.3588	0.9990	0.5719	0.9990
		RecPO	0.3451	0.9969	0.5802	0.9851	0.5771	0.9887	0.4672	0.9985	0.6830	0.9959
	Qwen-7B	Qwen	0.1204	0.7471	0.1013	0.7194	0.0583	0.4223	0.1477	0.6293	0.2148	0.6860
	Qwen-7B	SFT	0.2060	0.9983	0.3659	0.9967	0.2044	0.9849	0.2081	0.9950	0.3119	0.9969
	Qwen-7B	DPO	0.2610	0.9983	0.4412	0.9930	0.2600	0.9724	0.2457	0.9960	0.4046	0.9969
	Qwen-7B	SimPO	0.2888	0.9531	0.4644	0.9880	0.4044	0.9529	0.3706	0.9940	0.5209	0.9796
	Qwen-7B	S-DPO	0.2706	0.9957	0.4623	0.9910	0.3253	0.9798	0.3062	0.9970	0.4495	0.9959
	Qwen-7B	RecPO	0.3446	0.9896	0.5307	0.9880	0.4320	0.9729	0.4143	0.9912	0.5973	0.9980

Table 1: Overall model performance comparison on five real-world recommendation datasets. The best performance is bolded, and runner-ups are underlined. Datasets are grouped by explicit and implicit feedback.

tion and a fixed margin term, and S-DPO (Chen et al., 2024), which adapts DPO specifically for sequential recommendation⁴.

Note that we exclude GPT-4o (OpenAI, 2024), DeepSeek-V3 (et al., 2025), and other similar-sized LLMs from our baselines, as their substantially greater scale renders direct comparisons unfair and risks conflating model size with alignment quality. Our objective is to demonstrate the effectiveness of RecPO as a general preference optimization framework, which is orthogonal to model scaling and broadly applicable across backbone architectures.

Implementation. All experiments were performed on no more than 8 NVIDIA RTX A6000 with 48GB of VRAM. For all the preference learning approaches, we first conduct SFT for task adaptation, and then post-train models initialized from SFT checkpoints by optimizing the alignment loss in Equation 7⁵.

Evaluation Metrics. We follow S-DPO and evaluate models using two metrics: Hit Ratio@1, which measures the proportion of test cases where the top-ranked item matches the ground-truth target, and Valid Ratio, which captures instruction compliance by quantifying the fraction of outputs that follow formatting rules and remain within the candidate set. The latter ensures outputs are valid and in-distribution. Together, they assess both recommendation accuracy and practical deployability.

⁴More baseline details in Appendix E.2

⁵More implementation details in Appendix E.3

6.2 Main Results and Ablations

Overall Performance. Table 1 compares RecPO with the baselines across the five datasets, revealing the following key findings:

- **SFT bridges the gap between LLMs and recommendation constraints.** While LLMs possess open-world knowledge, their raw outputs often violate practical requirements (e.g., recommending non-candidate items or exceeding item limits). SFT significantly improves valid output rates, matching traditional recommenders and demonstrating the necessity to align general-purpose LLMs with specific behavioral requirements in real-world applications.
- **Preference alignment further unlocks the potential of LLMs in recommendation.** All preference learning methods, including our proposed RecPO, DPO, SimPO, and S-DPO, significantly outperform SFT in Hit Ratio@1, suggesting the alignment between complex preferences and ranking-centric recommendation objectives. Notably, RecPO and S-DPO surpass the standard DPO, demonstrating that multi-negative preference learning better captures nuanced user preference patterns in recommendation scenarios. Although SimPO achieves an impressive improvement in Hit Ratio@1, it exhibits a noticeable degradation in Valid Ratio compared to other approaches, which highlights the limitations of reference-free optimization in mitigating distributional discrepancies between recommendation tasks and general NLP tasks.

Dataset	Log Diff	Log Ratio	RecPO
MovieLens	0.3160	0.3247	0.3451
Amazon-Books	0.5370	0.5455	0.5802
BeerAdvocate	0.5023	0.5257	0.5771
Steam	0.4284	0.4517	0.4672
LastFM	0.5912	0.6388	0.6830

Table 2: Ablation study on the margin function, Hit Ratio@1 is reported for comparison.

- **RecPO enhances backbone-irrelevant preference modeling.** By integrating structured preference with contextualization adaptive reward margins, RecPO universally improves Hit Ratio@1 over other LLM-based approaches across both of the language backbones. This can be attributed to its human-aligned preference modeling grounded in cognitive science principles that generalize well across instructive learning tasks. Compared to traditional recommenders on implicit feedback datasets, the performance gains of RecPO are relatively modest. We posit that this narrower gap arises from proxy-derived preference signals, which exhibit homogeneous interaction patterns that even simple traditional models can effectively capture.

Ablation Study on Margin Functions. We denote ϕ_p and ϕ_d as the scores for the preferred and dispreferred items respectively, for brevity. By default, RecPO defines the margin term γ_t as the ratio of preference scores ϕ between positive and negative item pairs, as formalized in Equation 4. To evaluate the impact of this design choice, we introduce two alternative margin functions: (i) *Log Diff*, $\gamma_r = \lambda \log(\phi_p - \phi_d)$; (ii) *Log Ratio*, $\gamma_r = \lambda (\log \phi_p - \log \phi_d)$. As shown in Table 2, both variants outperform the strongest LLM-based recommender baseline, confirming the general utility of margin-aware optimization. RecPO’s default ratio-based margin achieves the best overall performance by amplifying training gradients, especially when historical user ratings show low volatility. By directly contrasting ϕ_p and ϕ_d via division, it provides stronger learning signals that help the model prioritize subtle but critical preference patterns.

6.3 Probing Aligned Preference from Multiple Perspectives

We further evaluate whether the learned preferences align with human-like decision patterns by probing the model from multiple perspectives. Specifically, we ask:

- **Contextual adherence:** When the candidate set includes other future highly-rated items, does the model still prioritize the correct next item, reflecting sensitivity to temporal context?

- **Aversion under temptation:** When the candidate set includes future low-rated items that may appear contextually tempting, can the model avoid recommending them?

- **Dispreference recognition:** When directly prompted, can the model correctly identify the item least aligned with the user’s preferences?

- **Robustness to interaction length:** Does the model maintain stable performance across users with varying lengths of interaction history?

RecPO adheres to contextualized preferences.

To assess RecPO’s ability to model contextualized preferences, we construct more challenging test sets for MovieLens and Amazon-Books by augmenting the candidate pool with other highly-rated items from users’ future interactions. This setup tests whether the model can prioritize the correct next item when competing items, though eventually preferred, are not immediately relevant. We quantify this behavior using the *Adherence Rate* (detailed in Appendix E.4), which measures how often the model recommends the next immediately preferred item over delayed but highly rated alternatives. As shown in Figure 4(a), RecPO consistently outperforms both SFT and S-DPO, more reliably ranking the temporally appropriate item at the top. This suggests improved sensitivity to short-term intent and temporal alignment. In contrast, S-DPO fails to consistently outperform SFT, indicating a failure to fully capture context-dependent user goals. Overall, RecPO’s adaptive reward margins leads to recommendations that more faithfully reflect temporally grounded human preferences.

RecPO avoids recommending undesirable items under temptation.

Beyond modeling contextualized user preferences, we evaluate the model’s ability to avoid recommending items that are ultimately dispreferred, even when they appear contextually relevant. To this end, we construct test sets from MovieLens and Steam by augmenting candidate sets with low-rated items from users’ future interactions. While these items are rated poorly in hindsight, their later occurrence, often driven by exposure or curiosity, makes them superficially

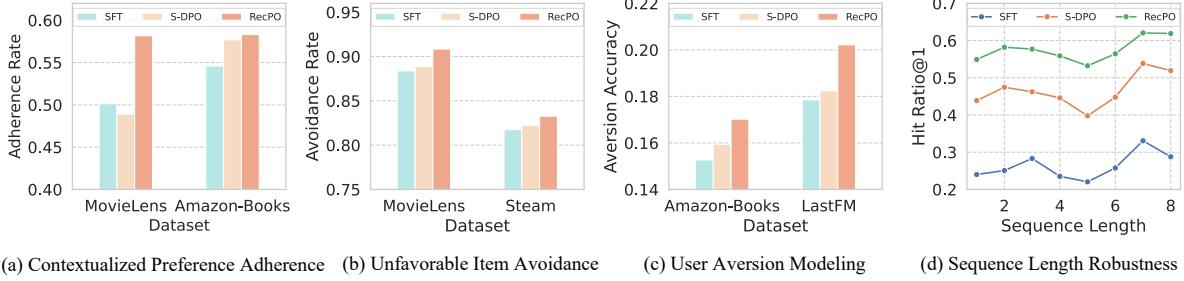


Figure 4: Comparing between SFT, S-DPO, and RecPO from the perspectives of adhering to contextual preference (a), avoiding unfavorable items under temptation (b), identifying dis-preferred items (c), and consistently performing across varying user history lengths (d). The adherence rate and avoidance rate are defined in Section 6.3.

plausible as next-item recommendations, thus posing a form of contextual temptation. We use the *Avoidance Rate* (detailed in Appendix E.4) to measure the model’s ability to reject such items when predicting the next interaction. As shown in Figure 4(b), RecPO consistently achieves the highest avoidance rates across benchmarks, outperforming all baselines. These results indicate that incorporating structured feedback enables the model to internalize both positive and negative preference signals—reducing the likelihood of recommending irrelevant or disliked items, and thereby enhancing overall alignment with user intent.

RecPO implicitly models aversion. While most preference alignment focuses on promoting desirable items, an essential aspect of human-like decision-making is the ability to deliberately avoid dispreferred options. To evaluate this capacity, we construct a test set querying the model directly at inference time to identify the item least aligned with a user’s preferences, without providing any explicit supervision for aversion. This setup tests whether the model’s learned preference representation implicitly encodes negative signals alongside positive ones. As shown in Figure 4(c), RecPO consistently achieves higher aversion accuracy across both datasets, outperforming SFT and S-DPO. This suggests that RecPO internalizes a more complete structure of user preferences, capable of both attraction and avoidance. Notably, **this behavior emerges without explicit aversion labels:** through alignment with structured and contextualized feedback alone, RecPO learns to infer which items users are likely to reject.

RecPO performs consistently better across varying interaction lengths.. In Figure 4(d), we investigate RecPO’s robustness to variations in his-

torical interaction lengths using the BeerAdvocate dataset. We partition the test set into subsets based on the number of past interactions and evaluate performance within each group. RecPO exhibits sustained efficacy, consistently outperforming SFT and S-DPO with larger margins. While all models follow similar performance trends as history length increases, RecPO exhibits the greatest stability, with the lowest variance in Hit Ratio@1 (8.7% vs. 17.8% for S-DPO). These results highlight RecPO’s adaptability to diverse context lengths—a critical trait for real-world systems where user histories vary widely.

7 Conclusion

In this paper, we address the challenge of aligning recommendation objectives with human-like decision behavior by proposing RecPO, a preference alignment framework that models structured feedback and contextual delay to emulate key aspects of human preference reasoning. RecPO introduces adaptive reward margins based on inferred preference hierarchies and interaction latency, enabling LLM-based recommenders to capture fine-grained, context-aware user preferences. Experiments across multiple benchmarks show that RecPO not only improves performance but also better reflects human-like prioritization and aversion in sequential recommendation.

More broadly, this work invites a shift in how preference is modeled: not as a fixed outcome to be predicted, but as a process to be understood. Effective recommendations should not only reflect what users have chosen, but also begin to listen: to intent, uncertainty, and change. RecPO takes a step in this direction, offering a path toward systems that move alongside users, adapting not only to what they prefer, but to how their preferences evolve.

Limitations

While our results demonstrate that incorporating comprehensive and structured interaction feedback improves user preference profiling, this work adopts a simplified, sequential preference structure and considers only satisfaction delay as the contextual factor. In reality, human decision-making reflects more complex hierarchies and richer contextual influences. Future research should explore how to model cognitively plausible preferences across broader preference-based tasks, extending beyond recommendations. Even within the recommendation domain, evaluations should move beyond single metrics, aiming to capture more holistic and behaviorally grounded patterns of user preference.

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A Preliminaries

We begin by formalizing the sequential recommendation task within the LM framework. Next, we outline a two-stage training paradigm that adapts existing LMs to the recommendation task, including *supervised fine-tuning (SFT)* and *preference alignment*. Centering around the alignment stage, we briefly introduce direct preference optimization (DPO) (Rafailov et al., 2024), a technique that aligns LMs using pairwise preference data; We then present S-DPO (Chen et al., 2024), a recent adaptation of DPO designed specifically for sequential recommendation.

Sequential Recommendation with LMs. Let $\mathcal{H}_u = [i^1, i^2, \dots, i^{N_u}]$ represent the chronologically ordered sequence of historical interactions for user u , where each element i^k encapsulates contextual details of the k -th interaction (e.g., item title, style, rating), and N_u denotes the total number of interactions. We define $\mathcal{H}_u^t = \mathcal{H}_u[: t]$ as the subset of interactions up to time t , and let i_p^{t+} denote the **next recent favorable (highly-rated)** item following the interaction history at t . Let π_θ be the LM performing the task, parameterized by θ . The sequential recommendation task within the LM framework is formulated as follows: given user u 's interaction history \mathcal{H}_u^t up to time t and a candidate item set $\mathcal{C} = \{i^{(j)}\}_{j=1}^K$, where $\mathcal{H}_u^t \cap \mathcal{C} = \emptyset$ and $i_p^{t+} \in \mathcal{C}$, the model π_θ is required to predict the item that most likely be favorable to user, i.e., i_p^{t+} .

Supervised Fine-tuning LMs for Sequential Recommendation. Supervised fine-tuning (Ouyang et al., 2022) (SFT) is widely adopted to adapt general-purpose LMs to recommendation tasks (Liao et al., 2024; Bao et al., 2023). Let \mathbf{x}_u^t be the task prompt that encompasses user u 's interaction history \mathcal{H}_u^t up to time t , the candidate item set \mathcal{C} , and other task-related descriptions. We define \mathbf{y}_p^{t+} as the text mapping of item $i_p^{t+} \in \mathcal{C}$ that best aligns with \mathbf{x}_u^t 's description. We construct the SFT training dataset \mathcal{D}_{SFT} using pairwise data $(\mathbf{x}_u^t, \mathbf{y}_p^{t+})$, $\forall u, \forall t < N_u$, and frame the sequential recommendation as a sentence completion task. The objective that optimizes π_θ is:

$$\max_{\theta} \mathbb{E}_{(\mathbf{x}_u^t, \mathbf{y}_p^{t+}) \sim \mathcal{D}_{\text{SFT}}} [\log \pi_\theta(\mathbf{y}_p^{t+} | \mathbf{x}_u^t)]. \quad (7)$$

The LM fine-tuned with this objective on \mathcal{D}_{SFT} is denoted as π_{SFT} . For brevity, we omit the timestamp signs in all subsequent equations unless their inclusion is essential for clarity.

Aligning LLM with Human Preference Feedback. While optimizing the SFT objective effectively adapts LMs to the downstream task, recent studies indicate that models still struggle to align outputs with human judgments of quality (Ziegler et al., 2019; Stiennon et al., 2020; Rafailov et al., 2024). To address this, a reward model $r(\mathbf{x}, \mathbf{y})$ is introduced to estimate output quality assessed by humans, aiming to maximize the expected reward.

To train the reward model, a dataset of comparisons $D = \{\mathbf{x}^{(i)}, \mathbf{y}_w^{(i)}, \mathbf{y}_l^{(i)}\}_{i=1}^N$ is constructed, where $\mathbf{y}_w^{(i)}$ and $\mathbf{y}_l^{(i)}$ denotes the preferred and dispreferred output generated based on $\mathbf{x}^{(i)}$, respectively. The alignment objective with the learned reward function is then defined as:

$$\begin{aligned} \max_{\theta} & \mathbb{E}_{x \sim \mathcal{D}, y \sim \pi_{\theta}(\cdot | x)} \left([r(\mathbf{x}, \mathbf{y})] \right. \\ & \left. - \beta D_{\text{KL}} [\pi_{\theta}(\mathbf{y} | \mathbf{x}) \| \pi_{\text{ref}}(\mathbf{y} | \mathbf{x})] \right), \end{aligned} \quad (8)$$

where β is the parameter controlling the deviation from the reference model π_{ref} , and π_{SFT} is commonly used as the reference model. Based on Equation 8, a recent work DPO (Rafailov et al., 2024), employs the Bradley-Terry (Bradley and Terry, 1952) (BT), $P(\mathbf{y}_w \succ \mathbf{y}_l | \mathbf{x}) = \sigma(r(\mathbf{x}, \mathbf{y}_w) - r(\mathbf{x}, \mathbf{y}_l))$, to express the probability of human preference data in terms of the optimal policy rather than the reward model, they derive the objective based on pairwise preference data as:

$$\begin{aligned} \min_{\theta} & -\mathbb{E}_{(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_l) \sim D} \left[\log \sigma \left(\beta \log \frac{\pi_{\theta}(\mathbf{y}_w | \mathbf{x})}{\pi_{\text{ref}}(\mathbf{y}_w | \mathbf{x})} \right. \right. \\ & \left. \left. - \beta \log \frac{\pi_{\theta}(\mathbf{y}_l | \mathbf{x})}{\pi_{\text{ref}}(\mathbf{y}_l | \mathbf{x})} \right) \right]. \end{aligned} \quad (9)$$

The above preference modeling paradigm aligns naturally with recommendation tasks, with both being preference-based decision-making. Building upon DPO, a recent effort named S-DPO (Chen et al., 2024) has been proposed to further align LLM-based recommenders to user preference. They propose to pair each positive item with multiple negative items generated by random sampling as preference data, and revise the alignment objective as:

$$\begin{aligned} \min_{\theta} & -\mathbb{E}_{(\mathbf{x}, \mathbf{y}_w, \mathcal{T}_d) \sim D} \left[\log \sigma \left(-\log \sum_{\mathbf{y}_d \in \mathcal{T}_d} \exp \left(\right. \right. \right. \\ & \left. \left. \left. \beta \log \frac{\pi_{\theta}(\mathbf{y}_d | \mathbf{x})}{\pi_{\text{ref}}(\mathbf{y}_d | \mathbf{x})} - \beta \log \frac{\pi_{\theta}(\mathbf{y}_p | \mathbf{x})}{\pi_{\text{ref}}(\mathbf{y}_p | \mathbf{x})} \right) \right) \right], \end{aligned} \quad (10)$$

where \mathcal{T}_d contains the item titles of multiple dispreferred items⁶.

B Derivation of Preference Distribution

In the standard Bradley-Terry model, the probability that candidate i beats candidate j is

$$\begin{aligned} P(\mathbf{y}_i \succ \mathbf{y}_j) &= \sigma(r(\mathbf{x}, \mathbf{y}_w) - r(\mathbf{x}, \mathbf{y}_l)) \\ &= \frac{\exp(r(\mathbf{x}_u, \mathbf{y}_i))}{\exp(r(\mathbf{x}_u, \mathbf{y}_i)) + \exp(r(\mathbf{x}_u, \mathbf{y}_j))}, \end{aligned} \quad (11)$$

where $r(\cdot)$ is the reward model. We will only use w_i to represent the candidate-specific probability $\exp(r(\mathbf{x}_u, \mathbf{y}_i))$ in subsequent equations for brevity. Now, suppose we wish to include a margin term γ_{ij} , then the pairwise probability is defined as

$$P(\mathbf{y}_i \succ \mathbf{y}_j) = \frac{w_i \exp(-\gamma_{ij})}{w_i \exp(-\gamma_{ij}) + w_j} \quad (12)$$

where we assume $\gamma_{ij} = -\gamma_{ji}$. Specifically, we can use the Plackett-Luce model to decompose a ranking $i_1 \succ i_2 \succ i_k \succ \dots \succ i_K$ into sequential choices competition. Therefore, at each step t , the winning (got selected) probability i_k is proportional to its weight, i.e., $w_k = \exp(r(\mathbf{x}_u, \mathbf{y}_k))$. Now the added margin term γ_{ij} modifies the competition by giving each candidate an extra boost (or penalty) when facing an opponent. In other words, when candidate i competes against candidate j (within the remaining set) its effective strength is boosted by the factor $\exp(-\gamma_{ij})$. Then, by an extension of Luce's choice axiom, we can get the probability of choosing candidate i from the set \mathcal{C} is proportional to its effective weight:

$$P(i \text{ chosen from } \mathcal{C}) = \frac{w_i \exp \left(- \sum_{j \in \mathcal{C} \setminus \{i\}} \gamma_{ij} \right)}{\sum_{k \in \mathcal{C}} w_k \exp \left(- \sum_{j \in \mathcal{C} \setminus \{k\}} \gamma_{kj} \right)}. \quad (13)$$

Let $\sigma = (\sigma(1), \sigma(2), \dots, \sigma(K))$ be a full ranking of K candidates. We construct the ranking sequentially. At step r , let

$$\mathcal{C}_r = \mathcal{C} \setminus \{\sigma(1), \sigma(2), \dots, \sigma(r-1)\} \quad (14)$$

be the remaining set. Then the probability that candidate $\sigma(r)$ is selected at step r will be,

$$\begin{aligned} P(\sigma(r) | \sigma(1), \dots, \sigma(r-1)) &= \\ & \frac{w_{\sigma(r)} \exp \left(- \sum_{j \in \mathcal{C}_r \setminus \{\sigma(r)\}} \gamma_{\sigma(r)j} \right)}{\sum_{k \in \mathcal{C}_r} w_{\sigma(k)} \exp \left(- \sum_{j \in \mathcal{C}_r \setminus \{k\}} \gamma_{kj} \right)}. \end{aligned} \quad (15)$$

⁶We use positive/negative, as well as preferred/dispreferred interchangeably in the following content.

We can thereby get the likelihood of the full ranking by the chain rule,

$$P(\sigma | \mathcal{C}) = \prod_{r=1}^{K-1} \frac{w_{\sigma(r)} \exp \left(- \sum_{j \in \mathcal{C}_r \setminus \{\sigma(r)\}} \gamma_{\sigma(r)j} \right)}{\sum_{k \in \mathcal{C}_r} w_{\sigma(k)} \exp \left(- \sum_{j \in \mathcal{C}_r \setminus \{k\}} \gamma_{kj} \right)} \quad (16)$$

In the recommendation setting, we are especially interested in penalizing the positive item’s “win” relative to each negative, which means one might only apply a margin from the positive item to each negative. Therefore, we can derive the preference distribution of the recommendation case given interactions \mathbf{x}_u of user u , multiple negative items $\mathbf{y}_d \in \mathcal{T}_d$, and the positive item \mathbf{y}_p :

$$P(\mathbf{y}_p \succ \mathbf{y}_d, \forall \mathbf{y}_d \in \mathcal{T}_d | \mathbf{x}_u, \mathbf{y}_p, \mathcal{T}_d) = \frac{w_p \exp \left(- \sum_{j=1}^{K-1} \gamma_{p,d_j} \right)}{w_p \exp \left(- \sum_{j=1}^{K-1} \gamma_{p,d_j} \right) + \sum_{j=1}^{K-1} w_d_j}. \quad (17)$$

Notably, the ranking likelihood would reduce to the standard Plackett–Luce model if the margin term $\gamma = 0$ for all pairs.

C Prompt Examples

We refer to the prompts used in previous works (Chen et al., 2024; Liao et al., 2024) to construct prompts utilized in our work. Examples in Figure 5 demonstrate the prompts for sequential recommendation.

D Related Work

Sequential Recommendation. Sequential recommendation aims to model user preferences by capturing temporal patterns in interaction sequences. Early approaches, such as GRU4Rec (Hidasi, 2016), leveraged recurrent neural networks (RNNs) to encode sequential dependencies, while SASRec (Kang and McAuley, 2018) introduced self-attention mechanisms to better capture long-range dependencies. Convolution-based methods like Caser (Chang et al., 2021) explored local patterns in sequences using convolutional filters. Recent state-of-the-art methods have further advanced the field by incorporating graph-based structures (Yu et al., 2020), contrastive learning (Xie et al., 2022; Chen et al., 2022), and hybrid architectures (Li et al., 2020; Zhou et al., 2020; Fan et al., 2021) for improved accuracy and robustness.

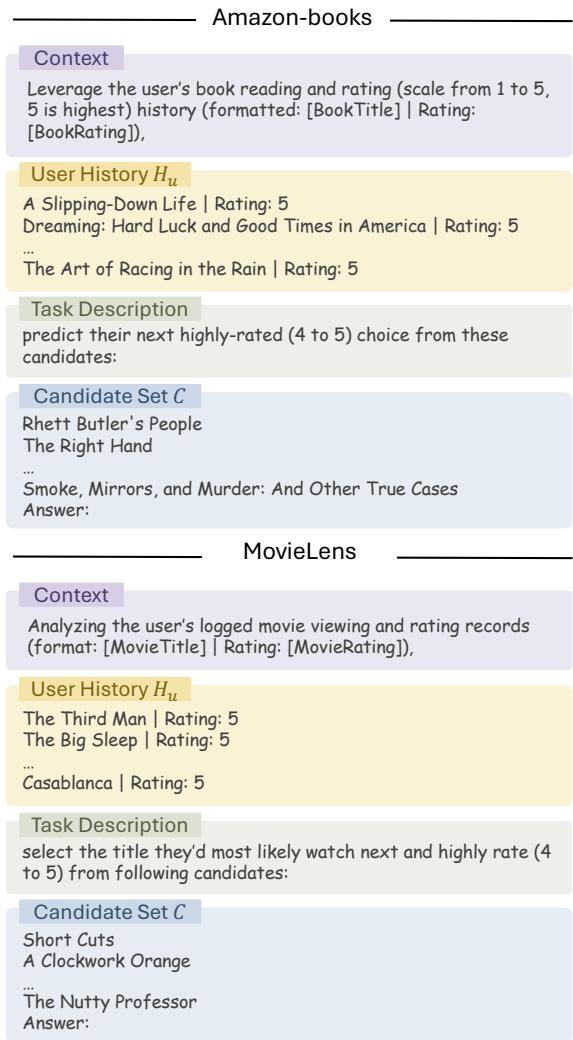


Figure 5: Textual prompt examples for Amazon-books and MovieLens.

LLMs for Recommendation. The integration of LLMs into sequential recommendation has gained momentum due to their ability to leverage rich semantic knowledge and contextual understanding. LLMs are typically integrated by encoding item descriptions, user reviews, or interaction histories as textual inputs, enabling the model to capture nuanced item characteristics and user preferences. For instance, LLaRA (Liao et al., 2024) employs classical sequential recommender systems to generate item embeddings, which are then fused with sequential interaction data to improve recommendation accuracy. TALLRec (Bao et al., 2023) fine-tunes LLMs on user-item interaction sequences, treating recommendations as a text generation task to predict the next item. Other approaches tackles the task from prompting (Geng et al., 2022; Gao et al., 2023; Lyu et al., 2023) or multi-modal data exploitation (Yuan et al., 2023). These methods demonstrate the potential of LLMs to bridge the

Dataset	# Sequence	# Items	# Interactions
MovieLens	6,040	3,952	994,169
Amazon-Books	5,103	38,203	62,290
Steam	3,171	4,251	82,072
BeerAdvocate	4,724	6,105	91,207
LastFM	982	107,296	307,829

Table 3: Statistics of datasets

gap between natural language understanding and sequential recommendation, enabling more interpretable and context-aware recommendations.

LLM Alignment. LLM alignment techniques aim to align general-purpose LMs’ outputs with human preferences, ensuring that generated content is both useful and safe. While not specifically designed for recommendation tasks, these methods have inspired advancements in preference modeling. Early approaches like Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022) and Proximal Policy Optimization (Schulman et al., 2017) laid the foundation by using reinforcement learning to fine-tune models based on human feedback. DPO (Rafailov et al., 2024) emerged as a simpler and more efficient alternative, directly optimizing preference data without requiring explicit reward modeling. Building on DPO, methods like IPO (Azar et al., 2024), CPO (Xu et al., 2024), KTO (Ethayarajh et al., 2024), SimPO (Meng et al., 2024), and ODPO (Amini et al., 2024) further refine alignment by addressing limitations such as capturing fine-grained preference hierarchies, reducing reward hacking, improving robustness to noisy feedback, and enhancing generalization across diverse user contexts. Most recently, S-DPO (Chen et al., 2024) adapts alignment techniques specifically for recommendation tasks, focusing on sequential user preferences and improving the personalization of LLM-based recommenders.

E Experimental Settings

E.1 Datasets

We use five widely used real-world sequential recommendation datasets for evaluation, including *MovieLens-1M*⁷ (Harper and Konstan, 2015), *Amazon-books*⁸ (Ni et al., 2019), *Steam*⁹ (Kang

and McAuley, 2018), *BeerAdvocate*¹⁰ (Leskovec and McAuley, 2012), and *LastFM*¹¹ (Celma, 2010). We demonstrate the dataset statistics in Table 3. The MovieLens-1M dataset is sourced from the MovieLens platform and contains 1 million ratings from 6,000 users on 4,000 movies. The Amazon-Books dataset is a subset of the Amazon Review dataset and comprises 22 million user interactions, reviews, and ratings for 2 million books from 8 million users. The Steam dataset includes user interactions with games, such as purchases, playtime, and reviews, from the Steam platform. The Beer-Advocate dataset collects beer reviews that cover multiple sensory aspects along with overall ratings. The LastFM dataset comprises detailed music listening records for nearly 1,000 users, including user profiles with demographic information, artist and track identifiers, and precise timestamps for each listening event.

For each dataset, we filter out items and users with fewer than 20 interactions. To prevent information leakage during training and evaluation, we adopt the leave-last-two splitting method to divide the datasets into training, validation, and test sets. We build a candidate set of 20 items for each user sequence, from which the model selects the next item. During training, this set comprises 10 subsequent interactions (ensuring that the correct item is always included) and 10 randomly sampled non-interacted items. For validation and testing, the candidate set consists of the correct item plus 19 randomly sampled non-interacted items. To align with the task objective of recommending the most likely favorable item as the next interaction, we follow classical sequential recommendation settings by considering only highly rated items (ratings 4 to 5 on a scale of 1 to 5) from subsequent interactions as the positive item (i.e., the correct answer) (Li et al., 2024). The same process is applied to the validation and test sets; we only retain user sequences whose next item is highly rated. Meanwhile, we preserve all historical interactions and their corresponding ratings in the user history sequence for comprehensive user preference profiling.

For Steam and LastFM, since they lack explicit rating signals, we convert play-hours and play-count, respectively, to a 1-to-5 scale structured rating based on their percentile ranking. For example,

⁷<https://grouplens.org/datasets/movielens/1m/>

⁸<https://nijianmo.github.io/amazon/index.html>

⁹<https://github.com/kang205/SASRec>

¹⁰https://cseweb.ucsd.edu/~jmcauley/datasets.html#multi_aspect

¹¹<http://ocelma.net/MusicRecommendationDataset/lastfm-1K.html>

if a user’s playtime for a game falls within the top 20% compared to other players, the corresponding user-item pair is assigned a rating of 5.

E.2 Baselines

We include the following baseline models for performance comparison:

- GRU4Rec ([Hidasi, 2016](#)) is a recurrent neural network-based model that captures sequential patterns in user interaction sequences for session-based recommendation.
- Caser ([Tang and Wang, 2018](#)) is a convolutional neural network-based model that learns both local and sequential patterns in user-item interactions using convolutional filters.
- SASRec ([Kang and McAuley, 2018](#)) is a transformer-based model that leverages self-attention to capture long-range dependencies and dynamic user preferences in sequential recommendation.
- LLaMA-3 ([Dubey et al., 2024](#)) is a general-purpose LLM with strong semantic reasoning capabilities. We adapt it to sequential recommendation by treating it as a text prediction problem.
- Qwen2.5 (?) is a recent LLM developed by Alibaba, optimized for instruction-following and multi-turn dialogue tasks.
- DPO ([Rafailov et al., 2024](#)) is a preference alignment technique that fine-tunes models using pairwise preference data. In this work, we construct preference data based on explicit preference feedback.
- SimPO ([Meng et al., 2024](#)) is an extension of DPO that directly optimizes pairwise preferences without requiring explicit reward models or complex sampling strategies for improved efficiency and scalability.
- S-DPO ([Chen et al., 2024](#)) is a variant of DPO specifically adapted for sequential recommendation that incorporates list-wise negative items in preference alignment.

E.3 Implementation Details

All experiments were conducted on a maximum of 8 NVIDIA RTX A6000 GPUs, each with 48GB of VRAM. Our framework is implemented using Python 3.10.6, PyTorch 2.2.2, and Huggingface Transformers 4.43.3. For all LLM-based recommenders, we employ LLaMA 3.1 8B ([Dubey et al., 2024](#)) and Qwen2.5-7B (?) as the base models for both SFT and alignment. During training, we set the learning rate to 1e-5 for all LLM-based recommenders and use the AdamW optimizer. Additionally, we apply a 5% warm-up strategy and adjust the learning rate using a cosine scheduler. A global batch size of 128 is used to balance training efficiency and memory consumption. The maximum sequence length is tailored to each dataset based on the features involved and the average title lengths. We set $\beta = 1$ for all preference optimization approaches. For multi-negative preference learning, including S-DPO and our proposed RecPO, we adopt the S-DPO settings and fix the number of negatives at 3. In particular, we set the margin term in SimPO as 2 and set the parameter λ in our method as 2. Finally, following the prompt format provided in Appendix C, we create several additional prompt templates and randomly sample one for each user sequence during training and evaluation to ensure model flexibility and generality. For all traditional recommenders, we follow the settings from previous work ([Chen et al., 2024](#)) by setting the learning rate to 0.001, the batch size to 256, and using the Adam optimizer for model optimization.

E.4 Evaluation Metrics

As mentioned in Section 6.1, we primarily employ two metrics to evaluate model effectiveness: Hit Ratio@1, which measures how accurately the model recommends the correct item, and Valid Ratio, which assesses whether the model follows instructions to generate outputs in the required format. In Section 6.3, we introduce two additional metrics—**Adherence Rate** and **Avoidance Rate**—both derived from Hit Ratio@1. These metrics evaluate the model’s ability to adhere to contextualized user preferences and avoid recommending unfavorable (unsatisfactory) items for the next interaction, with higher values indicating better performance.

In our main experiment, the candidate sets during testing include the last item from the user’s full

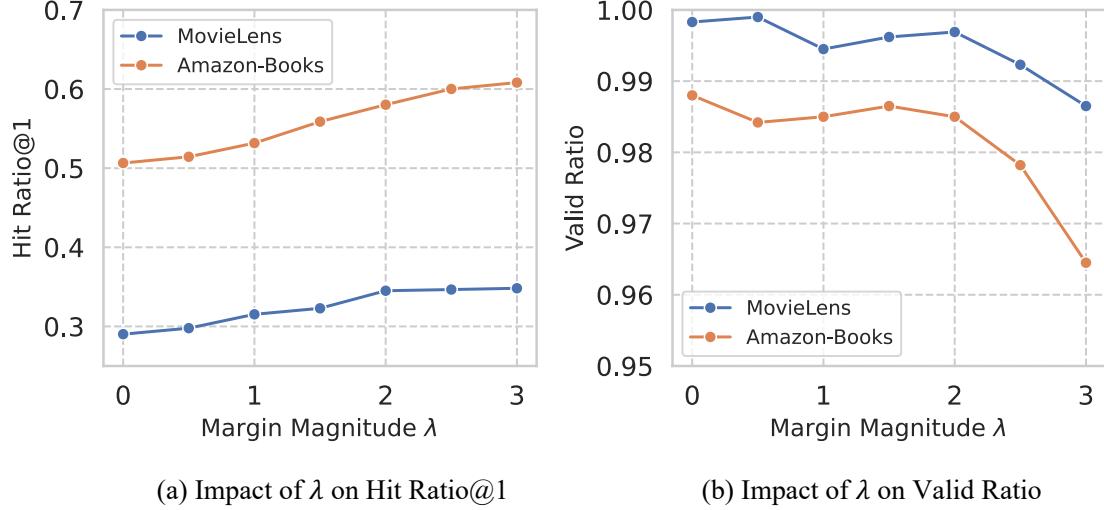


Figure 6: Sensitivity analysis of the margin parameter λ on recommendation performance: (a) Hit Ratio@1 and (b) Valid Ratio across MovieLens and Amazon-Books datasets.

sequence, typically a highly rated item (rating 4 to 5 on a scale of 1 to 5), with the remaining candidates randomly sampled from the non-interacted set. Note that we use rating to denote the preference hierarchy, yet it can be derived from either implicit or explicit feedback. **In the contextualized preference adherence experiment, the candidate set for testing includes at least two highly-rated items from the subsequent sequence.** We follow the rule described in Section 3 to designate the positive item as the one with the smallest time latency Δ_t relative to the prediction timestamp t . A high **Adherence Rate** indicates that the model consistently recommends the positive item among all highly-rated candidates.

For the unfavorable item avoidance experiment, we construct the test set by selecting user sequences where the last interaction is low-rated (rating 1 to 2). Instead of measuring whether the model recommends this low-rated item, we assess whether it favors the randomly sampled candidates over the unfavorable item. Thus, a high **Avoidance Rate** signifies that the model successfully avoids recommending unfavorable items to users.

F Analysis on Margin Magnitude

As detailed in Section 5, the parameter λ controls the extent of the margin term γ_r on preference learning. We adopt $\lambda = 2$ as the default value to balance Hit Ratio@1 (recommendation accuracy) and Valid Ratio (instruction-following capability). To further study the impact of λ on model effectiveness, we conduct sensitivity analyses on MovieLens and Amazon-Books, with results visualized

in Figure 6. Increasing λ consistently elevates Hit Ratio@1, though the rate of improvement diminishes at higher values (e.g., $\lambda = 3$). However, excessively large λ values degrade the Valid Ratio, which quantifies the model’s adherence to user instructions. While Hit Ratio@1 reflects recommendation accuracy, maintaining a robust Valid Ratio ensures alignment with user intent. We recommend $\lambda \approx 2$ to harmonize both metrics.