

BEAR: Towards Beam-Search-Aware Optimization for Recommendation with Large Language Models

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Abstract

Recent years have witnessed a rapid surge in research leveraging Large Language Models (LLMs) for recommendation. These methods typically employ supervised fine-tuning (SFT) to adapt LLMs to recommendation scenarios, and utilize beam search during inference to efficiently retrieve B top-ranked recommended items. However, we identify a critical *training-inference inconsistency*: while SFT optimizes the overall probability of positive items, it does not guarantee that such items will be retrieved by beam search even if they possess high overall probabilities. Due to the greedy pruning mechanism, beam search can prematurely discard a positive item once its prefix probability is insufficient.

To address this inconsistency, we propose **BEAR** (BEam-SEarch-Aware Regularization), a novel fine-tuning objective that explicitly accounts for beam search behavior during training. Rather than directly simulating beam search for each instance during training, which is computationally prohibitive, BEAR enforces a relaxed *necessary condition*: each token in a positive item must rank within the top- B candidate tokens at each decoding step. This objective effectively mitigates the risk of incorrect pruning while incurring negligible computational overhead compared to standard SFT. Extensive experiments across four real-world datasets demonstrate

that BEAR significantly outperforms strong baselines. Code will be released upon acceptance.

CCS Concepts

- Information systems → Recommender systems.

Keywords

Recommender Systems; Large Language Models; Beam Search

ACM Reference Format:

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1 Introduction

Large Language Models (LLMs) have exhibited remarkable abilities in natural language understanding [6], generation [44], and reasoning [60], achieving notable successes across a wide range of domains [46, 65, 75]. These advances have sparked growing interest in leveraging LLMs as the backbone for recommender systems, a.k.a. LLM-based RS [12, 17, 23, 30, 47, 72]. This paradigm typically reformulates recommendation as a natural language task, involving three key stages: (i) *Prompt construction*, converting a user's historical interactions into a structured textual prompt to guide the LLMs; (ii) *Supervised fine-tuning* (SFT), pairing prompts with target positive items as training instances to adapt the LLMs for recommendation; and (iii) *Inference*, generating B recommended items via decoding strategies, and selecting the top- K ranked items as final recommendations [4, 14, 33]. Compared with conventional recommenders, LLM-based RS can perform fine-grained preference modeling [31], understand complex contextual information [5], and enhance recommendation interpretability [16], making them a promising and emerging direction.

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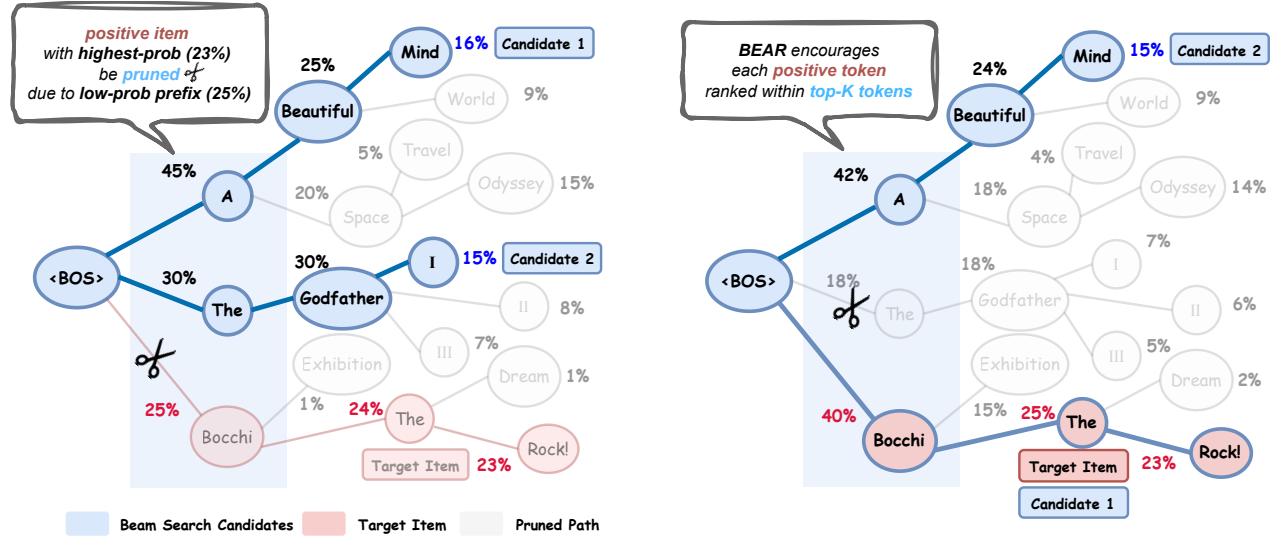
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(a) Beam search example with SFT-trained LLMs.

(b) Beam search example with BEAR-trained LLMs.

Figure 1: Illustration of beam search applied to SFT-trained LLMs vs. BEAR-trained LLMs (beam width $B = 2$). The blue paths represent candidate items retrieved by beam search (e.g., "A Beautiful Mind"), while red circles mark the positive item (e.g., "Bocchi the Rock!"). (a) In the SFT case, although the positive item possesses the highest overall probability, it is pruned at the first step due to the insufficient probability of its prefix (e.g., "Bocchi"). (b) BEAR promotes ranking each positive token within the top- B among all possible tokens, making beam search more likely to retain the positive item.

During inference, beam search is widely adopted to efficiently retrieve items with high probabilities [4, 33, 56]. Beam search incrementally extends sequences token-by-token, retaining only a small number (i.e., the beam width B) of the highest-probability candidates at each step, while discarding the others. This approach is considerably faster than exhaustive retrieval over all items, but it introduces a *greedy pruning* mechanism: if a positive item's prefix has relatively low probability, it may be pruned early, even if its complete sequence has the highest overall item probability.

Challenges. We identify a fundamental *training-inference inconsistency* between SFT optimization and beam search decoding in current LLM-based RS. While SFT targets improving the overall probability of positive items, this objective does not necessarily ensure that the item would be retrieved during beam search. Figure 1(a) illustrates an example: despite the positive item "Bocchi the Rock!" achieving the highest overall probability, its low-probability prefix "Bocchi" causes premature pruning during beam search. Our empirical analysis on real-world datasets reveals that this phenomenon is alarmingly prevalent: over 80% of positive items with top- B overall probability are pruned before reaching the final recommendations of beam search (cf. Figure 3). This striking statistic demonstrates that the training-inference inconsistency constitutes the primary bottleneck in LLM-based RS, demanding urgent resolution.

Our Method. To bridge this gap, we propose a novel fine-tuning objective, termed **BEAR** (Beam-Search-Aware Regularization), which explicitly incorporates the beam search dynamics into training. A straightforward yet naive approach would be to simulate beam search for every instance during training, increasing the *prefix*

probabilities of positive items until they rank in the top- B candidate prefixes at each step. However, this approach entails multiple forward passes per instance during training, making it computationally infeasible (cf. Figure 5). Instead, BEAR optimizes a relaxed *necessary condition* for retrieving positive items via beam search, i.e., ensuring each *token* of the positive items ranks within the top- B candidate tokens. Our motivation stems from an interesting empirical observation: violating this necessary condition constitutes the primary cause of incorrect pruning, accounting for over 70% of cases in real-world datasets (cf. Figure 4). Therefore, optimizing BEAR would naturally and substantially mitigate the risk of incorrect pruning, thereby improving recommendation performance (cf. Figure 3). Moreover, unlike the straightforward solution that simulates beam search, BEAR requires no additional forward passes, achieving high computational efficiency with negligible additional overhead compared to standard SFT, making it highly practical for real-world applications (cf. Figure 5).

To empirically validate the effectiveness of BEAR, we conduct comprehensive experiments on four real-world datasets. Experimental results demonstrate that BEAR surpasses nine state-of-the-art fine-tuning baselines for LLM-based RS (mainly published within the past year), with a *notable average improvement of 12.50%*. Moreover, BEAR is a model-agnostic fine-tuning objective and can be seamlessly integrated into various LLM-based RS backbones. Empirically, we evaluate BEAR on three typical recommendation backbones and obtain consistent performance gains. Additional analyses indicate that BEAR can indeed reduce the ratio of incorrect pruning, thereby validating its effectiveness in addressing the training-inference inconsistency.

Instruction Template	
Instruction:	Given a list of movies the user has watched before, please recommend a new movie that the user likes to the user.
Input:	The user has watched the following movies before: Good Will Hunting , The Man Who Knew Infinity , ... , K-On! , Sound! Euphonium .
Output:	Bocchi the Rock!

Figure 2: Instruction prompt template.

Contributions. In summary, our contributions are as follows:

- We identify and analyze the critical issue of training-inference inconsistency in LLM-based recommendation tasks, and advocate for explicitly incorporating the impact of beam search into the design of fine-tuning objectives.
- We propose BEAR, a novel beam-search-aware fine-tuning objective that optimizes a necessary condition for retrieving positive items via beam search. This objective effectively mitigates the risk of incorrect pruning in beam search with negligible additional computational overhead.
- We conduct extensive experiments to validate the effectiveness of BEAR, with a notable average improvement of 12.50% over state-of-the-art methods.

2 Preliminaries

In this section, we formulate the task of LLM-based RS in Section 2.1, introduce beam search in Section 2.2, and discuss the limitations of SFT due to the training-inference inconsistency in Section 2.3.

2.1 Task Formulation

In this work, we focus on sequential recommendation [21, 25, 51], a widely adopted recommendation scenario that aims to model the temporal dynamics of user preferences. Formally, given a recommender system with the corresponding user set \mathcal{U} and the item set \mathcal{I} , each user $u \in \mathcal{U}$ is associated with a historical interaction sequence $H_u = [h_1, h_2, \dots, h_{N-1}]$, where $h_n \in \mathcal{I}$ is the n -th interacted item. The goal of sequential recommendation is to predict the next item h_N that a user would likely interact with based on the previous interactions H_u .

Recently, given the impressive open-domain knowledge and semantic reasoning capabilities of Large Language Models (LLMs) [1, 2, 52], there has been a surge of interest in leveraging them for sequential recommendation (i.e., LLM-based RS) [3, 4, 26, 32]. In this paradigm, the historical interactions H_u are transformed into a structured prompt x using a predefined template, where each item $h_n \in H_u$ is represented by its textual description (e.g., title or metadata), as illustrated in Figure 2. The prompt x is subsequently employed to instruct LLMs to generate the textual description y of the predicted item, where the generation is driven by the probability $P_\theta(y|x)$ estimated by LLMs with parameters θ .

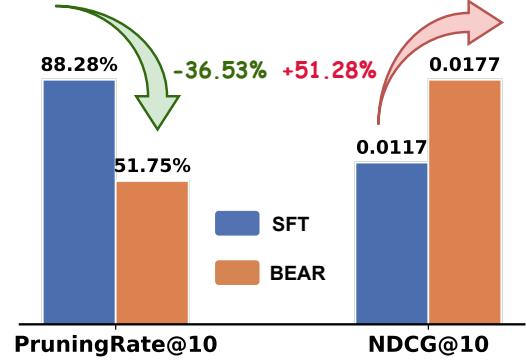


Figure 3: Performance comparison between SFT and BEAR on the Book dataset. PruningRate@10 denotes the pruning rate with beam width $B = 10$, i.e., the proportion of positive items that rank within the top-10 in overall probability yet are pruned during beam search. The complete results are presented in Table 2 and Figure 6.

Notably, LLMs operate at a fine-grained semantic token level, sequentially outputting the tokens of the predicted item y according to the token-wise conditional probability $P_\theta(y_t|y_{<t}, x)$, where y_t denotes the t -th token in y , and $y_{<t}$ denotes the prefix tokens preceding y_t . Consequently, the overall probability of the predicted item y can be factorized as the product of token probabilities, i.e., $P_\theta(y|x) = \prod_{t=1}^{|y|} P_\theta(y_t|y_{<t}, x)$, where $|y|$ is the length of y . Such fine-grained token-level semantic modeling empowers LLMs to capture nuanced user preferences, offering a promising avenue for advancing recommendation performance.

2.2 Beam Search

During the inference stage, LLM-based RS aim to retrieve the top- K items with the highest probabilities $P_\theta(y|x)$. However, given the vast item space and significant computational cost of LLMs, exhaustively enumerating all items and calculating their probabilities is prohibitively expensive. To address this challenge, an efficient approximate decoding strategy, known as *beam search*, is widely adopted in LLM-based RS [4, 33, 56]. This strategy leverages the generative nature of LLMs and incorporates a greedy search principle, achieving a balance between accuracy and efficiency.

Beam Search Procedure. Rather than directly assessing the probabilities $P_\theta(y|x)$ of all items, beam search follows an iterative token-wise extension mechanism. Specifically, at each decoding step, beam search progressively extends the sequences (a.k.a. beams) to their next tokens, and retains only a fixed number (i.e., the beam width B) of the most promising candidate sequences, while pruning the rest. The detailed procedure is as follows (also illustrated in Figure 1):

- **Initialization:** at the initial step $t = 0$, initialize the candidate set $\mathcal{B}_{<1} = \{b_{<1}\}$ with a single candidate $b_{<1} = <\text{BOS}>$, where $<\text{BOS}>$ is a special token denoting the beginning of the sequence.
- **Expansion:** at step $t \geq 1$, for each candidate sequence $b_{<t}$ from the previous step's candidate set $\mathcal{B}_{<t}$, extend it with all possible next tokens b_t to form the extended candidates $b_{<t+1}$. The probabilities of the extended candidates are computed as $P_\theta(b_{<t+1}|x) = P_\theta(b_{<t}|x) \cdot P_\theta(b_t|b_{<t}, x)$.

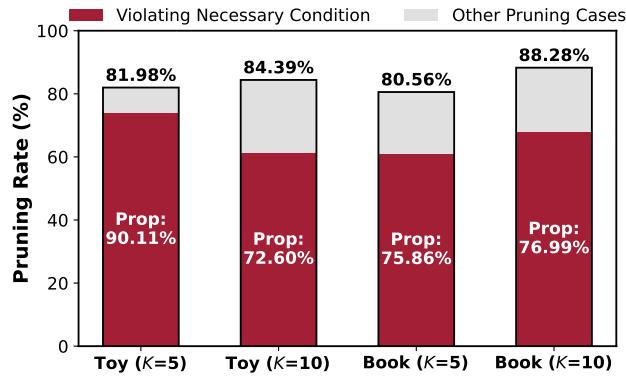


Figure 4: An overwhelming majority of positive items with high overall probabilities (i.e., top- K ranked among candidates) are pruned during beam search, where failure to meet the necessary condition (3.2) is the primary cause (marked as red rectangles). Here, we set beam width $B = 10$ and number of recommended items $K \in \{5, 10\}$. “Prop” denotes the proportion of pruning cases attributable to necessary condition violations (red), consistently accounting for over 70% of all pruning cases (red and gray) across all settings.

- **Pruning:** sort all extended candidates $b_{<t+1}$ by their probabilities $P_\theta(b_{<t+1}|x)$, and retain only the top- B candidates with the highest probabilities as the new candidate set $\mathcal{B}_{<t+1}$ for the next step. All other candidates are pruned.
- **Termination:** repeat the expansion and pruning steps until all candidates are completed by generating a special end-of-sequence token <EOS> or reaching the predefined maximum length. This results in a final candidate set with B completed sequences, from which the top- K items with the highest overall probabilities are selected as the final recommendations.

Suboptimal Pruning in Beam Search. Despite its efficiency, beam search is inherently a locally greedy decoding strategy and is therefore not guaranteed to yield the optimal retrieval results [14]. Specifically, at each decoding step, it retains only the top- B candidates $b_{<t}$ with the highest prefix probabilities $P_\theta(b_{<t}|x)$, potentially pruning candidates that could lead to higher overall probabilities $P_\theta(y|x)$ after generating subsequent tokens. For example, as illustrated in Figure 1(a), at the first decoding step, the candidate sequence “Bocchi” is pruned because its prefix probability (25%) is lower than that of the other two candidates, i.e., “The” (30%) and “A” (45%). However, one of the complete items starting with this prefix, i.e., “Bocchi the Rock!”, indeed has the highest overall probability (23%) among all items. In this case, the positive items with high probability are incorrectly pruned early due to the greedy nature of beam search, which can significantly hinder retrieval accuracy and lead to low-relevance recommendations [55, 70].

2.3 Limitations of SFT

To adapt LLMs to recommendation scenarios, existing LLM-based RS typically employ supervised fine-tuning (SFT) [4, 33, 39, 56]. In this process, the recommendation data is organized into a training dataset consisting of multiple prompt-response pairs (x, y) as

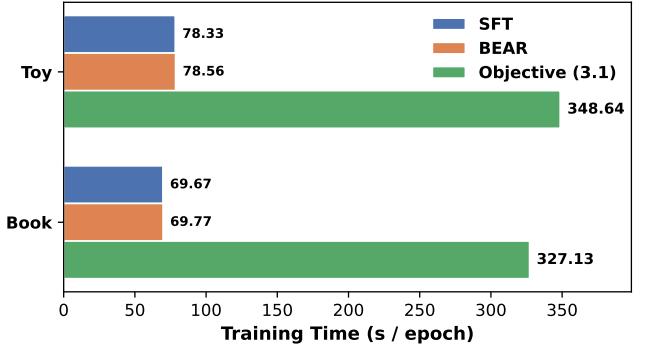


Figure 5: Running time comparison of three training objectives: SFT, BEAR, and objective (3.1). While SFT and BEAR have comparable training time, optimizing the objective (3.1) is significantly more time-consuming due to the need for beam search simulation during training. Refer to Figure 9 for complete results in training efficiency.

training instances, where x is the constructed prompt and y is the textual description of the positive item (cf. Figure 2). Subsequently, the LLM is adapted by optimizing the following SFT objective:

$$\min_{\theta} \mathcal{L}_{\text{SFT}}(x, y; \theta) = -\log P_\theta(y|x) = -\sum_{t=1}^{|y|} \log P_\theta(y_t|y_{<t}, x). \quad (2.1)$$

By minimizing this loss, the model is guided to maximize the overall probability $P_\theta(y|x)$ of the positive item y conditioned on the prompt x , thereby aligning the LLM with recommendation tasks. More importantly, the SFT objective can be decomposed into a sum of token-wise cross-entropy losses (i.e., $-\log P_\theta(y_t|y_{<t}, x)$), which can be efficiently optimized through one forward pass of the LLM per training instance, facilitating scalable training.

Training-Inference Inconsistency. While SFT has shown promising results, this conventional strategy could be suboptimal for LLM-based RS due to the *training-inference inconsistency* between SFT learning and beam search decoding. Specifically, the SFT objective is to maximize the overall probability of positive items. However, **during beam search, a high overall probability does not necessarily ensure successful retrieval**. As discussed in Section 2.2, the greedy pruning behavior of beam search can easily eliminate positive items whose prefixes do not exhibit sufficiently high local probability, regardless of their global high probability. As exemplified in Figure 1(a), the positive item “Bocchi the Rock!” is pruned due to the relatively low probability of its prefix “Bocchi”, despite having the highest overall probability among all items. Critically, this situation is alarmingly common rather than exceptional. Our empirical analysis, as exhibited in Figures 4 and 6, reveals a striking finding: **among positive items with high overall probabilities, an overwhelming majority (e.g., 88.28% in Book and 84.39% in Toy datasets) are pruned by beam search and consequently fail to appear in the final recommendations**. This remarkable percentage underscores that the training-inference inconsistency represents a fundamental bottleneck in LLM-based RS, severely compromising their effectiveness and demanding immediate attention. Thus, this work explores a novel beam-search-aware fine-tuning approach to mitigate this critical inconsistency.

3 Methodology

To bridge the training-inference inconsistency, we present **BEAR** (Beam-Search-Aware Regularization), a novel *beam-search-aware* objective that explicitly considers the impact of beam search. We first present a straightforward yet time-costly solution in Section 3.1, then introduce our BEAR objective in Section 3.2.

3.1 A Straightforward Solution

In Section 2.3, we have identified the limitations of SFT due to its beam search unawareness. Since SFT merely maximizes the overall probability of the positive item, it cannot prevent its low-probability prefixes from being pruned during beam search inference, which may lead to degraded recommendation performance.

Straightforward Objective. To address this issue, a straightforward idea is to directly optimize the objective for retaining the positive item throughout the beam search process, i.e., ensuring that every prefix $y_{<t}$ of the positive item y is always ranked within the top- B candidates at each beam search step t , where B is the beam width. Formally, this requirement can be expressed as:

$$\max_{\theta} \prod_{t=1}^{|y|+1} \mathbb{I}\left(P_{\theta}(y_{<t}|x) \geq P_{\theta}(b_{<t}^B|x)\right), \quad (3.1)$$

where $b_{<t}^B$ denotes the beam search candidate ranked exactly in the B -th position at decoding step $t - 1$ (cf. Section 2.2), and $\mathbb{I}(\cdot)$ is the indicator function. The right-hand term $P_{\theta}(b_{<t}^B|x)$ can be understood as a threshold — if the probability of the prefix $y_{<t}$, i.e., the left-hand term $P_{\theta}(y_{<t}|x)$, exceeds this threshold $P_{\theta}(b_{<t}^B|x)$, the prefix will be preserved by beam search; otherwise, it will be pruned immediately. Optimizing the objective (3.1) systematically elevates the probability of each positive prefix above the corresponding threshold, thereby reducing the risk that the positive item will be incorrectly pruned during beam search.

Limitations on Computational Efficiency. Despite its conceptual simplicity, this straightforward solution is computationally impractical in real-world settings. Specifically, calculating the threshold $P_{\theta}(b_{<t}^B|x)$ in objective (3.1) necessitates simulating the entire beam search procedure during training for each instance (x, y) . This involves token-by-token expansion of candidate sequences and requires up to B times additional forward passes of the LLM per training instance compared to SFT. Worse still, the strictly sequential dependency makes this process inherently difficult to parallelize and thus heavily time-consuming. Even with a relatively small beam width (e.g., $B = 10$), our empirical analysis shows that optimizing (3.1) incurs over $4.45\times$ runtime cost compared to basic SFT in practice, making it unsuitable for real-world applications (cf. Figure 5). This motivates the development of an efficient surrogate strategy to approximate the objective while avoiding the full beam search simulation during training.

3.2 BEAR: Beam-Search-Aware Regularization

Necessary Condition Objective. While directly optimizing the objective (3.1) is challenging, we empirically observe an intriguing phenomenon: ***the majority of incorrect pruning cases are in fact caused by the violation of a necessary condition***, as illustrated in Figure 4. This condition stipulates that the token-wise probability

Table 1: Dataset statistics.

Dataset	#Users	#Items	#Interactions	Density
Office	4895	2414	53149	0.4498%
Book	16559	6344	151928	0.1446%
Toy	19124	11758	165247	0.0735%
Clothing	39230	22948	277534	0.0308%

$P_{\theta}(y_t|y_{<t}, x)$ of each positive token y_t must rank within the top- B among all possible next tokens; otherwise, it will be pruned immediately by the beam search, since only the top- B extended candidates are retained at each decoding step (cf. Section 2.2). Formally, this necessary condition can be expressed as:

$$\max_{\theta} \prod_{t=1}^{|y|} \mathbb{I}\left(P_{\theta}(y_t|y_{<t}, x) \geq \beta_t^B\right), \quad (3.2)$$

where $\beta_t^B = \text{top-}B\{P_{\theta}(\cdot|y_{<t}, x)\}$ denotes the B -th highest token-wise probability among all possible next tokens at step t . In contrast to the original objective (3.1), which enforces that *every positive prefix* is retained within the top- B beam search candidates, this formulation operates at the granularity of *individual positive tokens*. The goal of objective (3.2) is to raise the probability of each positive token $P_{\theta}(y_t|y_{<t}, x)$ above the token-wise threshold β_t^B , thereby ensuring that the extended positive prefix $y_{<t+1}$ at least remains within the top- B among all possible continuations extended from the prefix $y_{<t}$, which is a necessary condition for finally retaining this positive prefix in the next step of beam search.

Notably, although this objective is a *weaker constraint* than (3.1), it remains a strong enough constraint and serves as an *effective and computationally efficient surrogate* for optimization. On the one hand, as shown in Figure 4, failure to satisfy this necessary condition is the *primary cause* of incorrect pruning, accounting for over 70% of all cases. Therefore, directly optimizing this necessary condition can substantially mitigate the training-inference inconsistency and improve recommendation performance. On the other hand, unlike (3.1), this objective does not require simulating the beam search procedure and only involves computing the token-wise top- B threshold β_t^B . Note that the probabilities $P_{\theta}(\cdot|y_{<t}, x)$ for all valid next tokens of each positive prefix $y_{<t}$ can be efficiently calculated by applying a softmax operation to the output logits of LLMs, while these logits are already computed during SFT. Therefore, calculating this top- B threshold β_t^B incurs no additional forward passes of LLMs. As a result, its computational cost is comparable to standard SFT and is significantly more efficient than directly optimizing (3.1), as evidenced by our empirical results in Figures 5 and 9.

Beam-Search-Aware Regularization (BEAR). Despite the potential benefits of optimizing the necessary condition (3.2), it poses significant challenges due to its inherent *discontinuity*, which hinders gradient-based optimization. To tackle these issues, we follow the principle of Empirical Risk Minimization [53] and formulate the risk indicating the violation of this necessary condition as:

$$\mathcal{R}_t(x, y; \theta) = \log \mathbb{I}\left(\log \beta_t^B - \log P_{\theta}(y_t|y_{<t}, x) > 0\right). \quad (3.3)$$

Table 2: Overall performance comparison with various baselines. The LLM-based RS methods are applied ("+" on the BIGRec [3] backbone. N@K and H@K denote NDCG@K and HitRatio@K metrics, respectively. The best results are highlighted in bold, and the best baselines are underlined. "Imp.%" indicates the relative improvement of BEAR over the best baseline.

Methods	Office				Book				Toy				Clothing			
	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10
SASRec	0.0127	0.0196	0.0223	0.0447	0.0061	0.0080	0.0100	0.0157	0.0089	0.0109	0.0148	0.0211	0.0022	0.0033	0.0036	0.0072
BERT4Rec	0.0164	0.0206	0.0264	0.0396	0.0100	0.0121	0.0158	0.0223	0.0101	0.0118	0.0137	0.0188	0.0028	0.0034	0.0033	0.0053
DROS	0.0195	0.0240	0.0265	0.0405	0.0072	0.0096	0.0116	0.0192	0.0105	0.0126	0.0148	0.0213	0.0038	0.0046	0.0048	0.0074
LLM-CF	0.0161	0.0200	0.0306	0.0426	0.0077	0.0100	0.0141	0.0212	0.0077	0.0101	0.0148	0.0223	0.0022	0.0034	0.0042	0.0078
DLLM2Rec	0.0166	0.0231	0.0322	0.0530	0.0068	0.0094	0.0112	0.0194	0.0080	0.0110	0.0156	0.0248	0.0028	0.0045	0.0056	0.0106
BIGRec	0.0105	0.0226	0.0213	0.0587	0.0068	0.0101	0.0128	0.0228	0.0122	0.0157	0.0200	0.0307	0.0043	0.0071	0.0086	0.0172
+ D ³	0.0142	0.0237	0.0291	0.0592	0.0057	0.0093	0.0112	0.0221	0.0163	0.0202	0.0257	0.0375	0.0045	0.0072	0.0088	0.0172
+ CFT	0.0183	0.0272	0.0306	0.0582	0.0051	0.0090	0.0107	0.0224	0.0138	0.0173	0.0217	0.0325	0.0045	0.0076	0.0086	0.0182
+ D ² LR	0.0243	0.0311	0.0395	0.0603	0.0070	0.0089	0.0128	0.0183	0.0142	0.0177	0.0227	0.0338	0.0051	0.0081	0.0098	0.0194
+ IGD	0.0187	0.0266	0.0312	0.0566	0.0061	0.0095	0.0125	0.0228	0.0191	0.0239	0.0273	0.0421	0.0059	0.0084	0.0098	0.0178
+ MSL	0.0346	0.0388	0.0504	0.0634	0.0087	0.0117	0.0137	0.0228	0.0239	0.0301	0.0359	0.0551	0.0075	0.0115	0.0136	0.0260
+ S-DPO	0.0209	0.0292	0.0374	0.0629	0.0082	0.0102	0.0125	0.0189	0.0181	0.0227	0.0288	0.0432	0.0054	0.0093	0.0110	0.0232
+ RosePO	0.0266	0.0338	0.0436	0.0660	0.0117	0.0127	0.0153	0.0185	0.0114	0.0174	0.0194	0.0378	0.0066	0.0110	0.0138	0.0272
+ SPRec	0.0249	0.0326	0.0416	0.0655	0.0072	0.0110	0.0130	0.0244	0.0148	0.0175	0.0234	0.0317	0.0047	0.0069	0.0082	0.0152
+ BEAR	0.0365	0.0421	0.0545	0.0717	0.0146	0.0177	0.0203	0.0297	0.0254	0.0316	0.0380	0.0574	0.0082	0.0127	0.0148	0.0290
Imp.%	+5.49%	+8.51%	+8.13%	+8.64%	+24.79%	+39.37%	+28.48%	+21.72%	+6.28%	+4.98%	+5.85%	+4.17%	+9.33%	+10.43%	+7.25%	+6.62%

Here, the $\Delta_t^B = \log \beta_t^B - \log P_\theta(y_t|y_{<t}, x)$ term¹ can be interpreted as the *pruning margin* at step t . A positive pruning margin indicates that the token-wise probability of y_t falls below the top- B threshold β_t^B , which corresponds to the violation of the necessary condition (3.2) and leads to immediate pruning at step t . Therefore, minimizing this risk for each step is fundamentally equivalent to optimizing the necessary condition for beam search survival.

To enable gradient-based optimization and effectively minimize the risk (3.3), we surrogate the indicator function $\mathbb{I}(\Delta_t^B > 0)$ with the sigmoid function $\sigma_\xi(\Delta_t^B) = 1/(1 + \exp(-\Delta_t^B/\xi))$, where ξ is a temperature hyperparameter that controls the smoothness² [66, 67]. This surrogate provides a smooth and tight approximation to the discontinuous indicator function, resulting in the following differentiable *beam-search-aware regularization* term³:

$$\mathcal{L}_{\text{reg}}(x, y; \theta) = \sum_{t=1}^{|y|} \log \sigma_\xi \left(\log \beta_t^B - \log P_\theta(y_t|y_{<t}, x) \right). \quad (3.4)$$

By minimizing this regularization term, the model is guided to minimize the pruning margin Δ_t^B at each step, thereby effectively reducing the risk of incorrect pruning during beam search. Notably, while the standard SFT objective (2.1) also increases the probabilities of positive tokens, it treats all tokens equally without considering the beam search dynamics, leading to massive premature pruning and noteworthy training-inference inconsistency (cf. Section 2.3). In contrast, regularization (3.4) explicitly takes the pruning margin into account, dynamically evaluating the probabilities of positive tokens $P_\theta(y_t|y_{<t}, x)$ based on their different top- B thresholds β_t^B , thus effectively mitigating the training-inference inconsistency.

¹In objective (3.2), the indicator function $\mathbb{I}(P_\theta(y_t|y_{<t}, x) \geq \beta_t^B)$ is equivalent to $\mathbb{I}(\log \beta_t^B - \log P_\theta(y_t|y_{<t}, x) \leq 0)$, which operates on the difference of log-probabilities and thus facilitates optimization.

²As the temperature $\xi \rightarrow 0$, the sigmoid function $\sigma_\xi(\Delta_t^B)$ converges to $\mathbb{I}(\Delta_t^B > 0)$.

³In objectives (3.3) and (3.4), we take the logarithm to convert maximization of the product into minimization of the sum of risks, facilitating token-wise optimization. For mathematically rigorousness, we assume that the token probabilities are lower bounded by a small positive constant, ensuring the well-definedness of the logarithm operation [62, 66, 67].

Finally, by incorporating the regularization term (3.4) into the SFT objective (2.1), we obtain the proposed **BEAR objective**:

$$\min_{\theta} \mathcal{L}_{\text{BEAR}}(x, y; \theta) = \mathcal{L}_{\text{SFT}}(x, y; \theta) + \lambda \mathcal{L}_{\text{reg}}(x, y; \theta), \quad (3.5)$$

where $\lambda > 0$ is a weight hyperparameter that controls the regularization strength. By incorporating beam-search awareness with SFT, BEAR not only improves the overall probability of positive items (cf. Table 2), but also effectively reduces the risk of incorrectly pruning positive items during beam search (cf. Figure 6). These effects collectively alleviate the training-inference inconsistency and enhance recommendation performance, leading to an effective and efficient fine-tuning objective for LLM-based RS.

4 Experiments

In this section, we conduct extensive experiments to evaluate the effectiveness of the proposed BEAR objective. Our aim is to answer the following research questions (RQs):

- **RQ1:** How does BEAR perform in recommendation tasks compared to existing methods?
- **RQ2:** How does BEAR mitigate the training-inference inconsistency and alleviate the incorrect pruning during beam search?
- **RQ3:** How does BEAR generalize to different LLM-based RS backbones, LLM sizes, and fine-tuning objectives?
- **RQ4:** How does the computational efficiency of BEAR compare to other methods?
- **RQ5:** How do the hyperparameters λ and ξ of BEAR affect its performance?

4.1 Experimental Setup

Datasets. To ensure a fair comparison with existing methods, we conduct experiments on four widely used Amazon datasets [20, 40], including Office, Book, Toy, and Clothing. The dataset preprocessing conforms to the standard procedure in previous studies [3, 56], where the users and items with fewer than 5 interactions are filtered out (i.e., 5-core), and a sliding window of size 11 is applied to segment the user interaction sequences. The resulting sequences

Table 3: Performance comparison using different recommendation backbones, including LLaRA [32] and A-LLMRec [26]. We adopt MSL [56] as the representative SFT method. N@K and H@K denote NDCCG@K and HitRatio@K metrics, respectively. The best results are highlighted in bold. "Imp.%" indicates the relative improvement of BEAR over the best baseline.

Methods	Office				Book				Toy				Clothing			
	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10
LLaRA	0.0110	0.0234	0.0234	0.0618	0.0068	0.0113	0.0135	0.0267	0.0129	0.0163	0.0204	0.0309	0.0036	0.0071	0.0074	0.0184
+ MSL	0.0380	0.0423	0.0561	0.0696	0.0078	0.0105	0.0132	0.0217	0.0230	0.0290	0.0346	0.0534	0.0082	0.0116	0.0146	0.0254
+ BEAR	0.0407	0.0457	0.0592	0.0748	0.0123	0.0157	0.0212	0.0315	0.0259	0.0315	0.0386	0.0559	0.0089	0.0129	0.0156	0.0284
Imp.%	+7.11%	+8.04%	+5.53%	+7.47%	+57.69%	+38.94%	+57.04%	+17.98%	+12.61%	+8.62%	+11.56%	+4.68%	+8.54%	+11.21%	+6.85%	+11.81%
A-LLMRec	0.0125	0.0247	0.0265	0.0639	0.0077	0.0111	0.0153	0.0256	0.0126	0.0160	0.0198	0.0305	0.0036	0.0068	0.0072	0.0172
+ MSL	0.0332	0.0373	0.0525	0.0655	0.0094	0.0118	0.0151	0.0224	0.0247	0.0302	0.0361	0.0532	0.0081	0.0124	0.0140	0.0276
+ BEAR	0.0392	0.0444	0.0561	0.0722	0.0106	0.0149	0.0189	0.0317	0.0255	0.0312	0.0373	0.0549	0.0087	0.0128	0.0164	0.0288
Imp.%	+18.07%	+19.03%	+6.86%	+10.23%	+12.77%	+26.27%	+23.53%	+23.83%	+3.24%	+3.31%	+3.32%	+3.20%	+7.41%	+3.23%	+17.14%	+4.35%

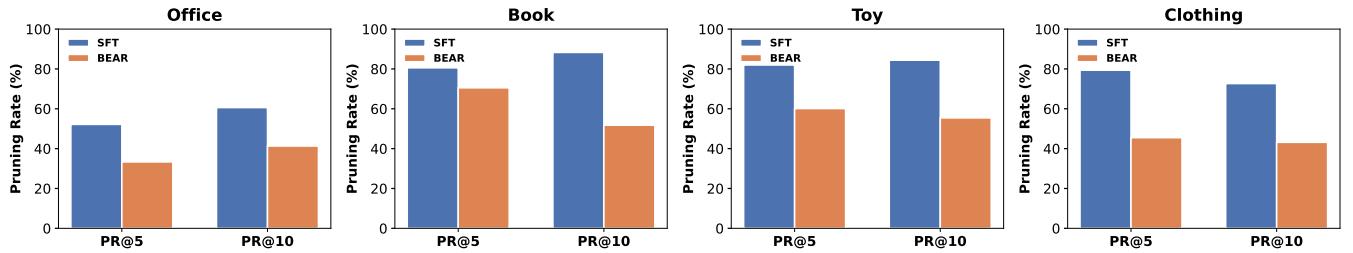


Figure 6: Pruning Rate (PR@K) comparison between SFT and BEAR. During beam search with beam size B , PR@K measures the proportion of incorrectly pruned positive items with high overall probabilities (i.e., top- K ranked among candidates). A lower PR@K indicates better training-inference alignment. Results show that BEAR significantly reduces PR@K compared to SFT.

are then split into training, validation, and test sets with a ratio of 8:1:1 based on the chronological order. The dataset statistics are summarized in Table 1.

Compared Methods. We compare BEAR with the following representative methods:

- **Conventional RS:** traditional methods for sequential recommendation, including SASRec (ICDM '18) [25], BERT4Rec (CIKM '19) [48], and DROS (SIGIR '23) [68].
- **LLM-enhanced RS:** conventional RS models augmented with LLMs as semantic encoder or knowledge enhancer, including LLM-CF (CIKM '24) [49] and DLLM2Rec (RecSys '24) [11].
- **LLM-based RS Backbones:** LLMs directly employed for recommendation. Typical backbones include BIGRec (TORS '25) [3], LLaRA (SIGIR '24) [32], and A-LLMRec (KDD '24) [26].
- **SFT Methods for LLM-based RS:** various SFT optimization methods applied on LLM-based RS, including D³ (EMNLP '24) [4], CFT (CoRR '24) [73], D²LR (SIGIR '25) [39], IGD (CoRR '25) [33], and the state-of-the-art method MSL (SIGIR '25) [56].
- **DPO Methods for LLM-based RS:** direct preference optimization (DPO) [45] methods that model pairwise preferences for LLM-based RS, including S-DPO (NeurIPS '24) [10], RosePO (CoRR '24) [31], and SPRec (WWW '25) [15].

Implementation Details. For conventional sequential recommendation methods, we closely follow their official implementations and default hyperparameters, training a 2-layer and 64-dim transformer for 200 epochs with a batch size of 128 and a learning rate of 1e-3. For LLM-enhanced RS methods, we directly utilize their official code, where SASRec is adopted as the backbone. For LLM-based RS methods, Llama-3.2-3B [19] is employed as the recommendation base model in the main experiments (we also evaluate the performance

of BEAR on other LLM sizes in Table 4, including Llama-3.2-1B and Llama-3-8B [19]). Following the recent works [56], we fine-tune the LLMs for 10 epochs and evaluate the checkpoints with the best NDCCG@10 results on the validation set. During training, the standard LoRA technique [24] and AdamW [38] optimizer are applied, with a rank of 8 and a learning rate of 1e-4 (except for SPRec, which uses 2e-5). The batch size is set to 64 for DPO methods, and 128 for others. During inference, following previous works [3, 4, 56], we use constrained beam search with a beam size B of 10, ensuring that the generated items are valid and non-hallucinated. For evaluation, we adopt the widely-used NDCCG@ K and HitRatio@ K metrics to assess the top- K recommendation performance, with $K \in \{5, 10\}$. For our BEAR method, we search hyperparameters $\lambda \in [0.1, 5.0]$ and $\xi \in [0.25, 3.0]$. For all the baseline SFT and DPO-based fine-tuning methods, we closely follow their official implementations and recommended hyperparameters. For hardware, all experiments are conducted on 8x GeForce RTX 5090 GPUs.

4.2 Experimental Results

In the following, we present and analyze the experimental results to answer the aforementioned research questions.

Overall Performance (RQ1). Table 2 presents the overall recommendation performance comparison of BEAR with baselines. As revealed, BEAR consistently outperforms all compared methods across all datasets, yielding *an average improvement of +12.50%* in NDCCG@ K and HitRatio@ K over the state-of-the-art SFT methods (e.g., MSL) and DPO methods (e.g., RosePO). This demonstrates the effectiveness of BEAR in enhancing recommendation quality, which aligns well with our motivation of bridging the training-inference gap in LLM-based RS (cf. Section 3.2).

Table 4: Performance comparison on different LLMs, including Llama-3.2-1B and Llama-3-8B [19], on the BIGRec [3] backbone. We adopt MSL [56] as the representative SFT method. N@K and H@K denote NDCG@K and HitRatio@K metrics, respectively. The best results are highlighted in bold. "Imp.%" indicates the relative improvement of BEAR over the best baseline.

Methods	Office				Book				Toy				Clothing			
	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10
BIGRec (1B)	0.0095	0.0177	0.0203	0.0447	0.0058	0.0066	0.0114	0.0137	0.0088	0.0133	0.0159	0.0296	0.0032	0.0066	0.0068	0.0176
+ MSL	0.0201	0.0232	0.0322	0.0421	0.0070	0.0089	0.0116	0.0176	0.0165	0.0230	0.0267	0.0465	0.0071	0.0105	0.0136	0.0244
+ BEAR	0.0203	0.0270	0.0343	0.0556	0.0076	0.0096	0.0132	0.0194	0.0176	0.0240	0.0284	0.0484	0.0075	0.0116	0.0144	0.0270
Imp.%	+1.00%	+16.38%	+6.52%	+24.38%	+8.57%	+7.87%	+13.79%	+10.23%	+6.67%	+4.35%	+6.37%	+4.09%	+5.63%	+10.48%	+5.88%	+10.66%
BIGRec (8B)	0.0114	0.0213	0.0213	0.0514	0.0109	0.0137	0.0169	0.0258	0.0142	0.0189	0.0213	0.0357	0.0057	0.0081	0.0104	0.0180
+ MSL	0.0392	0.0417	0.0556	0.0634	0.0103	0.0135	0.0160	0.0260	0.0245	0.0298	0.0373	0.0538	0.0085	0.0128	0.0156	0.0292
+ BEAR	0.0407	0.0438	0.0608	0.0706	0.0140	0.0172	0.0256	0.0356	0.0262	0.0318	0.0401	0.0572	0.0090	0.0135	0.0162	0.0302
Imp.%	+3.83%	+5.04%	+9.35%	+11.36%	+28.44%	+25.55%	+51.48%	+36.92%	+6.94%	+6.71%	+7.51%	+6.32%	+5.88%	+5.47%	+3.85%	+3.42%

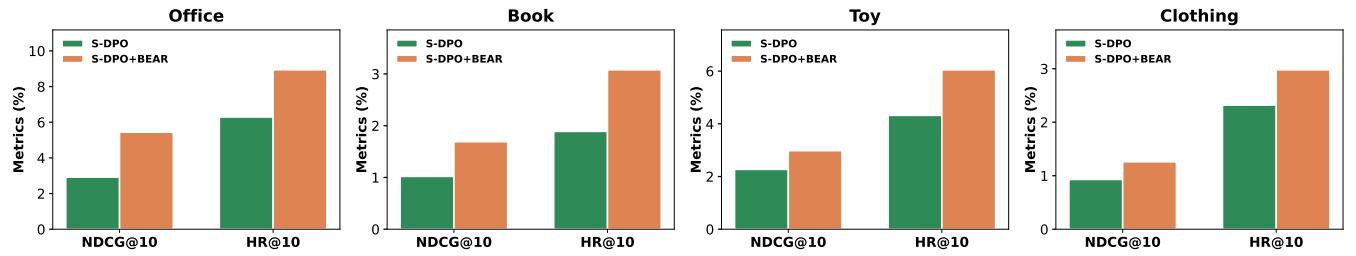


Figure 7: Performance of applying BEAR to S-DPO [10]. In addition to the original S-DPO loss, we apply the positive BEAR regularization to the positive items and the negative BEAR regularization to the sampled negative items. Results show that BEAR significantly enhances the performance of S-DPO across all datasets.

Mitigation of Training-Inference Inconsistency (RQ2). To validate the effectiveness of BEAR in alleviating the incorrect pruning of positive items during beam search, we compare the pruning rate metrics (i.e., PR@K in Figure 6) between BEAR and SFT methods (e.g., MSL). Specifically, PR@K measures the proportion of positive items that are ranked within the top-K based on their overall probabilities but are incorrectly pruned during beam search. As shown in Figure 6, BEAR exhibits a significantly lower PR@K, achieving *an average reduction of -24.86%* compared to SFT methods. This verifies that our beam-search-aware regularization (3.4) can effectively reduce the risk of incorrectly pruning positive items, thereby mitigating the training-inference inconsistency in LLM-based RS.

Generalizability: Backbones and LLM Sizes (RQ3-1). To assess the generalizability of BEAR, we further evaluate its performance on different LLM-based RS backbones (e.g., LLaRA [32] and A-LLMRec [26]) with different base LLM sizes (e.g., Llama-3.2-1B and Llama-3-8B [19]). As illustrated in Table 3 and Table 4, BEAR consistently outperforms the SFT methods across different backbones and LLM sizes, demonstrating its versatility and effectiveness.

Generalizability: Fine-tuning Objectives (RQ3-2). Given that the training-inference inconsistency is a common challenge in fine-tuning LLMs for recommendation, exploring the applicability of BEAR to other fine-tuning objectives, e.g., DPO-based methods, is also of great interest. Therefore, we also apply BEAR to the widely-adopted S-DPO [10]. Specifically, in addition to the original S-DPO loss, we apply the *positive* BEAR regularization in (3.4) (i.e., \mathcal{L}_{reg}) to the positive items, while applying the *negative* regularization (i.e., $-\mathcal{L}_{\text{reg}}$) to the sampled negative items. This encourages the model to retain positive items during beam search and prune negative items, thus aligning the DPO training with the inference

process. As shown in Figure 7, BEAR significantly enhances the performance of S-DPO, validating its broad applicability in improving various fine-tuning objectives for LLM-based RS.

Computational Efficiency (RQ4). As illustrated in Figure 9, BEAR demonstrates both comparable training efficiency to SFT methods and optimal recommendation performance among all compared methods. This should be attributed to BEAR’s meticulous design, which avoids additional forward passes of the LLM during training, as discussed in Section 3.2. In contrast, other methods such as CFT [73], S-DPO [10], and SPRec [15] require additional forward passes for each training instance, leading to noteworthy increased computational overhead (typically 2 \times to 10 \times compared to BEAR). This inefficiency hinders their scalability in real-world applications, making BEAR a more practical choice for deploying LLM-based recommender systems.

Hyperparameter Sensitivity (RQ5). In Figure 8, we conduct sensitivity analysis on the hyperparameters λ and ξ of BEAR. As illustrated, the performance for both λ and ξ exhibits a clear peak. Specifically, the regularization weight λ serves to balance the SFT and the regularization: when λ is too small, BEAR degenerates to standard SFT, leading to suboptimal performance due to the training-inference inconsistency; conversely, an excessively large λ overemphasizes the regularization, potentially failing to maximize the overall probability of positive items. For the temperature parameter ξ , it controls the smoothness of the approximation to the indicator function: when ξ is too small, the approximation becomes overly sharp, resulting in gradient saturation; on the other hand, a too-large ξ leads to an overly smooth approximation, diluting

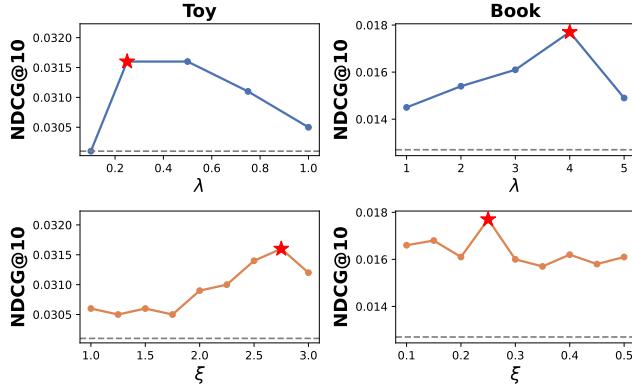


Figure 8: Sensitivity analysis of BEAR’s hyperparameters λ (blue) and ξ (orange). The best result is highlighted with a star, and the baseline result is indicated with a dashed line.

the regularization signal. In addition, we observe that BEAR is relatively robust to hyperparameter variations within a reasonable range, which is beneficial for practical applications.

5 Related Work

Sequential Recommendation. Sequential recommendation [8, 9, 28, 57] has long been a central task in recommendation research, aiming to predict a user’s next interaction based on historical behavior sequences. Classic models such as GRU4Rec [21], Caser [51], SASRec [25], and BERT4Rec [48] have achieved remarkable success by leveraging different architectures to model temporal dependencies [22, 27, 54]. In recent years, by scaling up model sizes to billions of parameters [71], integrating multi-side information [61, 64, 74], performing contextual reasoning [34, 50], and enabling continual learning [7, 41], modern sequential recommendation models have significantly advanced the capabilities of recommender systems.

LLM-based Recommender Systems. Large Language Models (LLMs) [1, 2, 52] have shown exceptional generative [6], reasoning [60], and generalization [44] abilities, inspiring research on their integration into recommender systems (i.e., LLM-based RS) [13, 16, 23, 35, 36, 58]. In this paradigm, recommendation is typically reformulated as a natural language task, where the LLMs are adapted to generate the textual descriptions of the recommended items based on the user history and instructions, thereby leveraging their powerful capabilities for recommendation [5, 12, 17, 26, 30, 32, 47, 59, 72].

Recently, a series of optimization methods have been proposed to enhance the performance of LLM-based RS. Following the standard practice in NLP, supervised fine-tuning (SFT) [3, 4, 42] is widely adopted, aiming to maximize the positive item likelihood. Various enhancements to the basic SFT have been proposed, focusing on causality [73], popularity [39], entropy [33], and masking [56]. Built upon SFT, some researchers have also explored variants of direct preference optimization (DPO) [45], which contrasts preferred and rejected items to model pairwise preferences, including strategies like multiple negatives ranking [10], negative sampling strategies [31], and self-play mechanism [15].

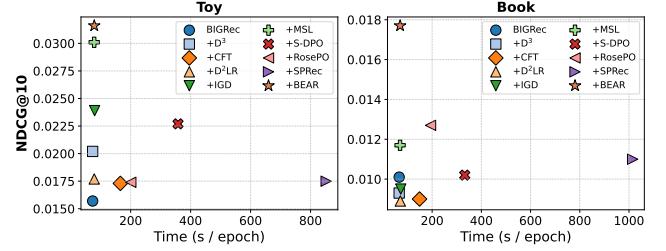


Figure 9: Training efficiency comparison between BEAR and other baselines. The x-axis represents the training time per epoch, and the y-axis represents the NDCG@10 performance.

Despite these promising results, existing fine-tuning strategies still face significant limitations due to the ignorance of the training-inference inconsistency (cf. Section 2.3). Specifically, they typically optimize the overall probability of positive items, which does not guarantee that these items will be retained during the greedy pruning of beam search. This discrepancy can lead to suboptimal recommendation performance, as the final beam search candidates may not include the most relevant items. Targeting this issue, our proposed BEAR method tries to bridge this inconsistency by explicitly considering the beam search process during training, thereby enhancing the recommendation performance of LLM-based RS.

Related Work on Generative Retrieval. Recent studies in other domains, such as generative retrieval [29, 63], have explored the similar training-inference inconsistency issue caused by beam search. These works can be broadly categorized into three main approaches. The first approach, e.g., OTM [76] and DTR [37], focuses on learning a tree model that is Bayes optimal for beam search, or equivalently, satisfies the max-heap property (i.e., each parent node’s preference should be the maximum among its children). The Bayes optimality ensures that the items with top- B overall probabilities will never be pruned. However, transferring this idea to LLM-based RS is non-trivial, as training such a tree model typically requires performing beam search during training, which is computationally impractical for LLMs, as discussed in Section 3.1. The second approach, e.g., RIPOR [69], involves optimizing the prefix probabilities of positive items against negatives to reduce incorrect pruning, which is similar to the objective (3.1). Unfortunately, these methods rely on a large amount of negative sampling, incurring over a 100 \times computational overhead, rendering it impractical for LLM-based RS. The third approach, e.g., ProphetNet-Ads [43] and PAG [70], heuristically incorporates future token or prior item scores to guide beam search. Nonetheless, accurately estimating these look-ahead scores is equivalent to learning a precise recommender, which is inherently difficult. Different from these strategies, our BEAR tackles this issue from a more principled perspective by optimizing a necessary condition for retrieving positive items during beam search, achieving better performance and computational efficiency.

6 Conclusion and Future Directions

In this paper, we identify and address the training-inference inconsistency in LLM-based recommender systems, which arises from the discrepancy between the SFT training objective and the greedy pruning nature of beam search. To bridge this gap, we propose

Table 5: Performance comparison between SFT, BEAR, and the straightforward solution that directly optimizes the objective (3.1), on the BIGRec [3] backbone. Due to the high computational cost of beam search required for optimizing (3.1), experiments are conducted on two small-scale datasets (Toy-S and Book-S) with 2K sampled users.

Methods	Toy-S		Book-S	
	NDCG@10	HR@10	NDCG@10	HR@10
+ SFT	0.0076	0.0200	0.0046	0.0120
+ BEAR	0.0094	0.0260	0.0072	0.0180
+ Obj. (3.1)	0.0103	0.0280	0.0077	0.0200

BEAR, a novel beam-search-aware regularization method that explicitly considers the beam search behavior during training. BEAR optimizes a necessary condition for retaining positive items during beam search, thereby reducing the risk of incorrect pruning and enhancing recommendation performance, while incurring minimal computational overhead compared to standard SFT. For future directions, exploring the integration of BEAR with inference-stage techniques, such as multi-token prediction [18] and diverse beam search [55], would be a promising avenue.

A Appendix: Further Discussions

BEAR vs. Straightforward Solution. As discussed in Section 3.1, a naive solution to alleviate the incorrect pruning issue is directly optimizing the objective (3.1). While this straightforward approach seems "theoretically optimal", it requires performing beam search during training, incurring impractical computational overhead in LLM-based RS. Instead, our proposed BEAR method opts to optimize a necessary condition for retaining positive items, offering a more computationally efficient alternative. A crucial research question naturally arises: *Does optimizing this weaker, necessary condition sacrifice significant effectiveness compared to the "optimal" yet expensive solution?*

To answer this, we conduct experiments comparing BEAR with directly optimizing (3.1) on two datasets in Table 5. As observed, both BEAR and the computationally intensive objective (3.1) significantly outperform standard SFT, validating their ability to mitigate training-inference inconsistency. More importantly, the performance gap between BEAR and objective (3.1) is marginal. This indicates that BEAR is *sufficiently effective* in capturing the core dynamics of beam search pruning, achieving performance parity with the straightforward solution while avoiding its severe computational costs. Notably, these results also align perfectly with our finding in Figure 4: since violating the necessary condition accounts for the vast majority of incorrect pruning cases, effectively targeting this primary cause via BEAR yields the majority of the potential gains, which further explains its strong performance.

References

- [1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774* (2023).
- [2] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. 2023. Qwen technical report. *arXiv preprint arXiv:2309.16609* (2023).
- [3] Keqin Bao, Jizhi Zhang, Wenjie Wang, Yang Zhang, Zhengyi Yang, Yanchen Luo, Chong Chen, Fuli Feng, and Qi Tian. 2025. A bi-step grounding paradigm for large language models in recommendation systems. *ACM Transactions on Recommender Systems* 3, 4 (2025), 1–27.
- [4] Keqin Bao, Jizhi Zhang, Yang Zhang, Xinyue Huo, Chong Chen, and Fuli Feng. 2024. Decoding matters: Addressing amplification bias and homogeneity issue in recommendations for large language models. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*. 10540–10552.
- [5] Keqin Bao, Jizhi Zhang, Yang Zhang, Wenjie Wang, Fuli Feng, and Xiangnan He. 2023. Tallrec: An effective and efficient tuning framework to align large language model with recommendation. In *Proceedings of the 17th ACM conference on recommender systems*. 1007–1014.
- [6] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.
- [7] Guohao Cai, Jieming Zhu, Quanyu Dai, Zhenhua Dong, Xuqiang He, Ruiming Tang, and Rui Zhang. 2022. Reloop: A self-correction continual learning loop for recommender systems. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2692–2697.
- [8] Jianxin Chang, Chen Gao, Yu Zheng, Yiqun Hui, Yanan Niu, Yang Song, Depeng Jin, and Yong Li. 2021. Sequential recommendation with graph neural networks. In *Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval*. 378–387.
- [9] Xu Chen, Hongteng Xu, Yongfeng Zhang, Jiaxi Tang, Yixin Cao, Zheng Qin, and Hongyuan Zha. 2018. Sequential recommendation with user memory networks. In *Proceedings of the eleventh ACM international conference on web search and data mining*. 108–116.
- [10] Yuxin Chen, Junfei Tan, An Zhang, Zhengyi Yang, Leheng Sheng, Enzhi Zhang, Xiang Wang, and Tat-Seng Chua. 2024. On softmax direct preference optimization for recommendation. *Advances in Neural Information Processing Systems* 37 (2024), 27463–27489.
- [11] Yu Cui, Feng Liu, Pengbo Wang, Bohao Wang, Heng Tang, Yi Wan, Jun Wang, and Jiawei Chen. 2024. Distillation matters: empowering sequential recommenders to match the performance of large language models. In *Proceedings of the 18th ACM Conference on Recommender Systems*. 507–517.
- [12] Zeyu Cui, Jianxin Ma, Chang Zhou, Jingren Zhou, and Hongxia Yang. 2022. M6-rec: Generative pretrained language models are open-ended recommender systems. *arXiv preprint arXiv:2205.08084* (2022).
- [13] Sunhao Dai, Ninglu Shao, Haiyuan Zhao, Weijie Yu, Zihua Si, Chen Xu, Zhongxiang Sun, Xiao Zhang, and Jun Xu. 2023. Uncovering chatgpt's capabilities in recommender systems. In *Proceedings of the 17th ACM Conference on Recommender Systems*. 1126–1132.
- [14] Markus Freitag and Yaser Al-Onaizan. 2017. Beam Search Strategies for Neural Machine Translation. In *Proceedings of the First Workshop on Neural Machine Translation*. 56–60.
- [15] Chongming Gao, Ruijun Chen, Shuai Yuan, Kexin Huang, Yuanqing Yu, and Xiangnan He. 2023. Sprec: Self-play to debias llm-based recommendation. In *Proceedings of the ACM on Web Conference 2023*. 5075–5084.
- [16] Yunfan Gao, Tao Sheng, Youlin Xiang, Yun Xiong, Haofei Wang, and Jiawei Zhang. 2023. Chat-rec: Towards interactive and explainable llms-augmented recommender system. *arXiv preprint arXiv:2303.14524* (2023).
- [17] Shijie Geng, Shuchang Liu, Zuohui Fu, Yingqiang Ge, and Yongfeng Zhang. 2022. Recommendation as language processing (rlp): A unified pretrain, personalized prompt & predict paradigm (p5). In *Proceedings of the 16th ACM conference on recommender systems*. 299–315.
- [18] Fabian Gloclekar, Badr Youbi Idrissi, Baptiste Rozière, David Lopez-Paz, and Gabriel Synnaeve. 2024. Better & faster large language models via multi-token prediction. *arXiv preprint arXiv:2404.19737* (2024).
- [19] Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. 2024. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783* (2024).
- [20] Ruining He and Julian McAuley. 2016. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering. In *proceedings of the 25th international conference on world wide web*. 507–517.
- [21] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domonkos Tikk. 2015. Session-based recommendations with recurrent neural networks. *arXiv preprint arXiv:1511.06939* (2015).
- [22] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation* 9, 8 (1997), 1735–1780.
- [23] Yupeng Hou, Junjie Zhang, Zihan Lin, Hongyu Lu, Ruobing Xie, Julian McAuley, and Wayne Xin Zhao. 2024. Large language models are zero-shot rankers for recommender systems. In *European Conference on Information Retrieval*. Springer, 364–381.
- [24] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. 2022. Lora: Low-rank adaptation of large language models. *ICLR* 1, 2 (2022), 3.

- [25] Wang-Cheng Kang and Julian McAuley. 2018. Self-attentive sequential recommendation. In *2018 IEEE international conference on data mining (ICDM)*. IEEE, 197–206.
- [26] Sein Kim, Hongseok Kang, Seungyoon Choi, Donghyun Kim, Minchul Yang, and Chanyoung Park. 2024. Large language models meet collaborative filtering: An efficient all-round lilm-based recommender system. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 1395–1406.
- [27] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems* 25 (2012).
- [28] Jiacheng Li, Yujie Wang, and Julian McAuley. 2020. Time interval aware self-attention for sequential recommendation. In *Proceedings of the 13th international conference on web search and data mining*. 322–330.
- [29] Xiaoxi Li, Jiajie Jin, Yujia Zhou, Yuyao Zhang, Peitian Zhang, Yutao Zhu, and Zhicheng Dou. 2025. From matching to generation: A survey on generative information retrieval. *ACM Transactions on Information Systems* 43, 3 (2025), 1–62.
- [30] Xinyi Li, Yongfeng Zhang, and Edward C Malthouse. 2023. Exploring fine-tuning chatgpt for news recommendation. *arXiv preprint arXiv:2311.05850* (2023).
- [31] Jiayi Liao, Xiangnan He, Ruobing Xie, Jiancan Wu, Yancheng Yuan, Xingwu Sun, Zhanhui Kang, and Xiang Wang. 2024. Roseopo: Aligning lilm-based recommenders with human values. *arXiv preprint arXiv:2410.12519* (2024).
- [32] Jiayi Liao, Sihang Li, Zhengyi Yang, Jiancan Wu, Yancheng Yuan, Xiang Wang, and Xiangnan He. 2024. Llara: Large language-recommendation assistant. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1785–1795.
- [33] Zijie Lin, Yang Zhang, Xiaoyan Zhao, Fengbin Zhu, Fuli Feng, and Tat-Seng Chua. 2025. IGD: Token Decisiveness Modeling via Information Gain in LLMs for Personalized Recommendation. *arXiv preprint arXiv:2506.13229* (2025).
- [34] Enze Liu, Bowen Zheng, Xiaolei Wang, Wayne Xin Zhao, Jinpeng Wang, Sheng Chen, and Ji-Rong Wen. 2025. LARES: Latent Reasoning for Sequential Recommendation. *arXiv preprint arXiv:2505.16865* (2025).
- [35] Junling Liu, Chao Liu, Peilin Zhou, Renjie Lv, Kang Zhou, and Yan Zhang. 2023. Is chatgpt a good recommender? a preliminary study. *arXiv preprint arXiv:2304.10149* (2023).
- [36] Qijiong Liu, Nuo Chen, Tetsuya Sakai, and Xiao-Ming Wu. 2024. Once: Boosting content-based recommendation with both open-and closed-source large language models. In *Proceedings of the 17th ACM International Conference on Web Search and Data Mining*. 452–461.
- [37] Ze Liu, Jin Zhang, Chao Feng, Defu Lian, Jie Wang, and Enhong Chen. 2024. Learning Deep Tree-based Retriever for Efficient Recommendation: Theory and Method. *arXiv preprint arXiv:2408.11345* (2024).
- [38] Ilya Loshchilov and Frank Hutter. 2017. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101* (2017).
- [39] Sijin Lu, Zhibo Man, Fangyuan Luo, and Jun Wu. 2025. Dual Debiasing in LLM-based Recommendation. In *Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2685–2689.
- [40] Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton Van Den Hengel. 2015. Image-based recommendations on styles and substitutes. In *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval*. 43–52.
- [41] Fei Mi, Xiaoyu Lin, and Boi Faltings. 2020. Ader: Adaptively distilled exemplar replay towards continual learning for session-based recommendation. In *Proceedings of the 14th ACM Conference on Recommender Systems*. 408–413.
- [42] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in neural information processing systems* 35 (2022), 27730–27744.
- [43] Weizhen Qi, Yeyun Gong, Yu Yan, Jian Jiao, Bo Shao, Ruofei Zhang, Houqiang Li, Nan Duan, and Ming Zhou. 2020. Prophetnet-ads: A looking ahead strategy for generative retrieval models in sponsored search engine. In *CCF International Conference on Natural Language Processing and Chinese Computing*. Springer, 305–317.
- [44] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog* 1, 8 (2019), 9.
- [45] Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. 2023. Direct preference optimization: Your language model is secretly a reward model. *Advances in neural information processing systems* 36 (2023), 53728–53741.
- [46] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ Questions for Machine Comprehension of Text. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*. 2383–2392.
- [47] Wentao Shi, Xiangnan He, Yang Zhang, Chongming Gao, Xinyue Li, Jizhi Zhang, Qifan Wang, and Fuli Feng. 2024. Large language models are learnable planners for long-term recommendation. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1893–1903.
- [48] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In *Proceedings of the 28th ACM international conference on information and knowledge management*. 1441–1450.
- [49] Zhongxiang Sun, Zihua Si, Xiaoxue Zang, Kai Zheng, Yang Song, Xiao Zhang, and Jun Xu. 2024. Large language models enhanced collaborative filtering. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*. 2178–2188.
- [50] Jiakai Tang, Sunhao Dai, Teng Shi, Jun Xu, Xu Chen, Wen Chen, Jian Wu, and Yuning Jiang. 2025. Think before recommend: Unleashing the latent reasoning power for sequential recommendation. *arXiv preprint arXiv:2503.22675* (2025).
- [51] Jiaxi Tang and Ke Wang. 2018. Personalized top-n sequential recommendation via convolutional sequence embedding. In *Proceedings of the eleventh ACM international conference on web search and data mining*. 565–573.
- [52] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambo, Faisal Azaiez, et al. 2023. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971* (2023).
- [53] Vladimir Vapnik. 2013. *The nature of statistical learning theory*. Springer science & business media.
- [54] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems* 30 (2017).
- [55] Ashwin Vijayakumar, Michael Cogswell, Ramprasaath Selvaraju, Qing Sun, Stefan Lee, David Crandall, and Dhruv Batra. 2018. Diverse beam search for improved description of complex scenes. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 32.
- [56] Bohao Wang, Feng Liu, Jiawei Chen, Xingyu Lou, Changwang Zhang, Jun Wang, Yuegang Sun, Yan Feng, Chun Chen, and Can Wang. 2025. Msl: Not all tokens are what you need for tuning lilm as a recommender. In *Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1912–1922.
- [57] Bohao Wang, Feng Liu, Changwang Zhang, Jiawei Chen, Yudi Wu, Sheng Zhou, Xingyu Lou, Jun Wang, Yan Feng, Chun Chen, and Can Wang. 2025. LLM4DSR: Leveraging Large Language Model for Denoising Sequential Recommendation. *ACM Transactions on Information Systems* (Aug. 2025). Just Accepted.
- [58] Lei Wang and Ee-Peng Lim. 2023. Zero-shot next-item recommendation using large pretrained language models. *arXiv preprint arXiv:2304.03153* (2023).
- [59] Zhefan Wang, Weizhi Ma, and Min Zhang. 2024. To recommend or not: Recommendability identification in conversations with pre-trained language models. In *International Conference on Database Systems for Advanced Applications*. Springer, 19–35.
- [60] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems* 35 (2022), 24824–24837.
- [61] Wei Wei, Chao Huang, Lianghao Xia, and Chuxu Zhang. 2023. Multi-modal self-supervised learning for recommendation. In *Proceedings of the ACM web conference 2023*. 790–800.
- [62] Jiancan Wu, Xiang Wang, Xingyu Gao, Jiawei Chen, Hongcheng Fu, and Tianyu Qiu. 2024. On the effectiveness of sampled softmax loss for item recommendation. *ACM Transactions on Information Systems* 42, 4 (2024), 1–26.
- [63] Shiguang Wu, Zhaochun Ren, Xin Xin, Jiyuan Yang, Mengqi Zhang, Zhumin Chen, Maarten de Rijke, and Pengjie Ren. 2025. Constrained Auto-Regressive Decoding Constrains Generative Retrieval. In *Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2429–2440.
- [64] Xue Xia, Pong Eksombatchai, Nikil Pancha, Dhruvil Deven Badani, Po-Wei Wang, Neng Gu, Saurabh Vishwas Joshi, Nazanin Farahpour, Zhiyuan Zhang, and Andrew Zhai. 2023. Transact: Transformer-based realtime user action model for recommendation at pinterest. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 5249–5259.
- [65] An Yang, Beichen Zhang, Binyuan Hui, Bofei Gao, Bowen Yu, Chengpeng Li, Dayiheng Liu, Jianhong Tu, Jingren Zhou, Junyang Lin, et al. 2024. Qwen2. 5-math technical report: Toward mathematical expert model via self-improvement. *arXiv preprint arXiv:2409.12122* (2024).
- [66] Weiqin Yang, Jiawei Chen, Xin Xin, Sheng Zhou, Binbin Hu, Yan Feng, Chun Chen, and Can Wang. 2024. PSL: Rethinking and Improving Softmax Loss from Pairwise Perspective for Recommendation. *Advances in Neural Information Processing Systems* 37 (2024), 120974–121006.
- [67] Weiqin Yang, Jiawei Chen, Shengjia Zhang, Peng Wu, Yuegang Sun, Yan Feng, Chun Chen, and Can Wang. 2025. Breaking the Top-K Barrier: Advancing Top-K Ranking Metrics Optimization in Recommender Systems. In *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining* V. 2. 3542–3552.
- [68] Zhengyi Yang, Xiangnan He, Jizhi Zhang, Jiancan Wu, Xin Xin, Jiawei Chen, and Xiang Wang. 2023. A generic learning framework for sequential recommendation with distribution shifts. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*.

- Conference on Research and Development in Information Retrieval*. 331–340.
- [69] Hansi Zeng, Chen Luo, Bowen Jin, Sheikh Muhammad Sarwar, Tianxin Wei, and Hamed Zamani. 2024. Scalable and effective generative information retrieval. In *Proceedings of the ACM Web Conference 2024*. 1441–1452.
 - [70] Hansi Zeng, Chen Luo, and Hamed Zamani. 2024. Planning ahead in generative retrieval: Guiding autoregressive generation through simultaneous decoding. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 469–480.
 - [71] Jiaqi Zhai, Lucy Liao, Xing Liu, Yueming Wang, Rui Li, Xuan Cao, Leon Gao, Zhao-jie Gong, Fangda Gu, Michael He, et al. 2024. Actions speak louder than words: Trillion-parameter sequential transducers for generative recommendations. *arXiv preprint arXiv:2402.17152* (2024).
 - [72] Junjie Zhang, Ruobing Xie, Yupeng Hou, Xin Zhao, Leyu Lin, and Ji-Rong Wen. 2025. Recommendation as instruction following: A large language model empowered recommendation approach. *ACM Transactions on Information Systems* 43, 5 (2025), 1–37.
 - [73] Yang Zhang, Juntao You, Yimeng Bai, Jizhi Zhang, Keqin Bao, Wenjie Wang, and Tat-Seng Chua. 2024. Causality-enhanced behavior sequence modeling in LLMs for personalized recommendation. *arXiv preprint arXiv:2410.22809* (2024).
 - [74] Xin Zhou, Hongyu Zhou, Yong Liu, Zhiwei Zeng, Chunyan Miao, Pengwei Wang, Yuan You, and Feijun Jiang. 2023. Bootstrap latent representations for multi-modal recommendation. In *Proceedings of the ACM web conference 2023*. 845–854.
 - [75] Qihao Zhu, Daya Guo, Zhihong Shao, Dejian Yang, Peiyi Wang, Runxin Xu, Y Wu, Yukun Li, Huazuo Gao, Shirong Ma, et al. 2024. Deepseek-coder-v2: Breaking the barrier of closed-source models in code intelligence. *arXiv preprint arXiv:2406.11931* (2024).
 - [76] Jingwei Zhuo, Ziru Xu, Wei Dai, Han Zhu, Han Li, Jian Xu, and Kun Gai. 2020. Learning optimal tree models under beam search. In *International Conference on Machine Learning*. PMLR, 11650–11659.