# STAR: A Simple Training-free Approach for Recommendations using Large Language Models

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# **Abstract**

Recent progress in large language models (LLMs) offers promising new approaches for recommendation system (RecSys) tasks. While the current state-of-the-art methods rely on fine-tuning LLMs to achieve optimal results, this process is costly and introduces significant engineering complexities. Conversely, methods that bypass fine-tuning and use LLMs directly are less resource-intensive but often fail to fully capture both semantic and collaborative information, resulting in sub-optimal performance compared to their fine-tuned counterparts. In this paper, we propose a Simple Training-free Approach for Recommendation (STAR), a framework that utilizes LLMs and can be applied to various recommendation tasks without the need for fine-tuning. Our approach involves a retrieval stage that uses semantic embeddings from LLMs combined with collaborative user information to retrieve candidate items. We then apply an LLM for pairwise ranking to enhance next-item prediction. Experimental results on the Amazon Review dataset show competitive performance for next item prediction, even with our retrieval stage alone. Our full method achieves Hits@10 performance of +23.8% on Beauty, +37.5% on Toys and Games, and -1.8% on Sports and Outdoors relative to the best supervised models. This framework offers an effective alternative to traditional supervised models, highlighting the potential of LLMs in recommendation systems without extensive training or custom architectures.

#### **CCS Concepts**

ullet Information systems o Recommender systems.

#### **Keywords**

Recommender System, Large Language Models

## 1 Introduction

Personalized recommendation systems have become indispensable tools for enhancing user experiences and driving engagement across Xinyang Yi xinyang@google.com Google DeepMind Mountain View, California, USA

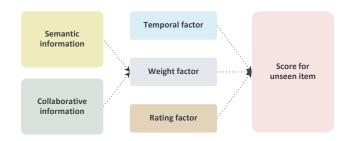


Figure 1: Retrieval pipeline uses scoring rules that combine semantic and collaborative information with temporal, weight, and rating factors to score unseen items without requiring any fine-tuning.

a wide range of online platforms. Recent advances in large language models (LLMs) present new opportunities for addressing recommendation tasks [1–8]. Current strategies primarily involve utilizing LLMs as either feature encoders [9–24] or as scoring and ranking functions [25–31]. When LLMs are employed as feature encoders, there is potential for transfer learning and cross-domain generalization by initializing embedding layers with LLM embeddings, although this approach requires extensive training. On the other hand, using LLMs for scoring and ranking demonstrates the ability to leverage their reasoning capabilities to address recommendation tasks. However, these models still lag behind the performance of fine-tuned models due to a lack of collaborative knowledge.

The primary motivation of this work is to develop a general framework that serves as a generalist across multiple recommendation domains. We demonstrate that recent advancements in LLMs align with this vision, effectively functioning as generalists without requiring any domain-specific fine-tuning. Based on our findings, we present a Simple Training-free Approach for Recommendation (STAR) framework using LLMs. The STAR framework involves two stages: Retrieval and Ranking. The Retrieval stage scores new

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items using a combination of *semantic similarity* and *collaborative commonality* to the items in a user's history. Here, we utilize LLM-based embeddings to determine semantic similarity. Additionally, a *temporal* factor gives priority to user's recent interactions, and a *rating* factor aligns with user preferences to rank items within a specific set (See Figure 1 and Section 3.2). The **Ranking** stage leverages the reasoning capabilities of LLMs to adjust the rankings of the initially retrieved candidates. Specifically, we assess various LLM-based ranking approaches, including point-wise, pair-wise, and list-wise methods, while also determining the key information needed for the LLM to better understand user preferences and make accurate predictions (Section 3.3). Our experimental evaluation shows competitive performance across a diverse range of recommendation datasets, all without the need for supervised training or the development of custom-designed architectures.

We present extensive experimental results on the Amazon Review dataset [32, 33]. Our findings are as follow: (1) Our retrieval pipeline, comprised of both semantic relationship and collaborative information, demonstrates competitive results compared to a wide range of fine-tuned methods. LLM embeddings allow for an effective method to calculate semantic similarity; (2) We show that pair-wise ranking further improves upon our retrieval performance, while point-wise and list-wise methods struggle to achieve similar improvements; and (3) We illustrate that collaborative information is a critical component that adds additional benefits to the semantic information throughout our system, in both the retrieval and ranking stages.

# 2 Related Works

LLM as a Feature Encoder for RecSys. Recommendation systems typically leverage feature encoders to transform item and user profiles into suitable representations for model training. Traditionally, ID-based systems relied on one-hot encoding for structured features [34, 35]. However, recent advancements in LLMs have enabled the utilization of text encoders to capture rich semantic information from item metadata and user profiles [36-39] To further optimize these representations for specific applications, researchers have explored several approaches: (1) mapping continuous LLM embeddings into discrete tokens using vector quantization and training a subsequent generative model [12, 13, 21, 22]; (2) training sequential models by initializing the embedding layer with LLM embeddings [9, 14, 24]; and (3) training models to directly compute the relevance between item and user embeddings (i.e., embeddings of user selected items) [10, 11, 16-20, 23]. While optimizing representations can improve recommendation performance, this often comes at the cost of increased training expenses and reduced generalizability. In this work, we demonstrate that LLM embeddings can be directly used as effective item representations, yielding strong results in sequential recommendation tasks without requiring extensive optimization. This finding aligns with those of [15], but differs by usage of novel scoring rules that incorporates collaborative and temporal information.

LLM as a Scoring and Ranking function for RecSys. Recent studies show that LLMs can recommend items by understanding user preferences or past interactions in natural language. This is achieved through generative selection prompting, where the model ranks

and selects top recommended items from a set of candidates [25–31]. However, these studies show that LLMs alone are less effective than models fine-tuned on user-item interaction data, which leverage collaborative knowledge. To bridge the gap between collaborative knowledge and the semantic understanding of LLMs, recent efforts have focused on fine-tuning the models with interaction data, though this approach is also costly [40–45].

LLM as a Ranker for Information Retrieval. Ranking using LLMs has been widely adopted in document retrieval [46, 47]. Recent studies indicate that LLMs surpass traditional supervised cross-encoders in zero-shot passage ranking. Three prompting approaches have emerged: (1) **point-wise**: LLMs directly evaluate relevance using numerical scores or binary judgments [48, 49], but this method struggles with capturing the relative importance of passages; (2) **pair-wise**: LLMs express preferences between item pairs, which is effective but inefficient due to the high number of calls required [50]; (3) **list-wise**: LLMs compare multiple passages simultaneously [51], but performance heavily relies on the model's semantic prior and reasoning capabilities [50]. In this paper, we investigate the potential of LLM ranking for recommendation tasks, which are subjective in nature, unlike the deterministic nature of document retrieval.

# 3 STAR: Simple Training-Free Approach

This section initially outlines the problem formulation (Section 3.1). Subsequently, we detail the proposed retrieval (Section 3.2) and ranking pipelines (Section 3.3).

### 3.1 Sequential Recommendation

The sequential recommendation task aims to predict the next item a user will interact with based on their interaction history. For a user  $u \in U$ , where U is the set of all users, the interaction history is represented as a sequence of items  $S_u = \{s_1, s_2, \ldots, s_n\}$ , with each  $s_i \in I$  belonging to the set of all items I. Each user history item  $s_i$  is associated with a rating  $r_i \in \{1, 2, 3, 4, 5\}$  given by the user u. The goal is to predict the next item  $s_{n+1} \in I$  that the user is most likely to interact with.

# 3.2 Retrieval Pipeline

The retrieval pipeline aims to assign a score to an unseen item  $x \in I$  given the sequence  $S_u$ . To achieve this, we build two scoring components: one that focuses on the semantic relationship between items and another that focuses on the collaborative relationship.

Semantic relationship. Understanding how similar a candidate item is to the items in a user's interaction history  $s_i \in S_u$  is key to accurately gauging how well candidate items align with user preferences. Here we leverage LLM embedding models, where we pass in custom text prompts representing items and collect embedding vectors of dimension  $d_e$ . We construct a prompt based on the item information and metadata, including the title, description, category, brand,  $sales\ ranking$ , and price. We omit metadata fields like  $Item\ ID$  and URL, as those fields contain strings that can contain spurious lexical similarity (e.g., IDs: "000012", "000013' or URLs: "https://abc.com/uxrl", "https://abc.com/uxrb") and can reduce the uniformity of the embedding space and make it difficult to distinguish between semantically different items (See Appendix A.1

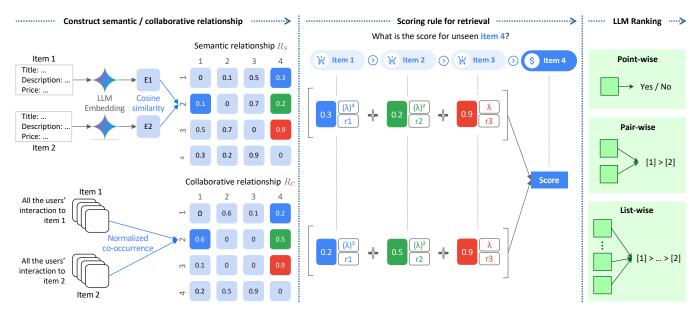


Figure 2: STAR Framework overview. We use the semantic relationship scores in  $R_{\rm S}$  and the collaborative relationship scores in  $R_{\rm C}$  to score the items in the user history compared to new items to recommend. The final score for one new item is a weighted average from the semantic relationship and collaborative relationship scores, with additional weights from the user's ratings r and a temporal decay  $\lambda < 1$  which prioritize recent interactions. The top scoring retrieved items are sent to the LLM Ranking, where we can use point-wise, pair-wise, or list-wise ranking approaches to further improve upon the scoring of recommended items.

for the full prompt). We collect embeddings for each item  $i \in I$ , resulting in  $E \in \mathbb{R}^{n \times d_e}$ , where n is number of items in I.

The semantic relationship between two items  $(i_a, i_b)$  is then calculated using the cosine similarity between their embeddings  $E_{i_a}, E_{i_b} \in E$ . This measure provides a numerical representation of how closely related the items are in semantic space. For our experiments, we precompute the entire semantic relationship matrix  $R_S \in \mathbb{R}^{n \times n}$ . For many domains, this is a practical solution. However, if |I| is very large, Approximate Nearest Neighbor methods [52, 53] are efficient approaches to maintain quality and reduce computation.

Collaborative relationship. Semantic similarity between a candidate item and items in a user's interaction history is a helpful cue for assessing the similarity of items based on the item information. However, this alone does not fully capture the engagement interactions of items by multiple users. To better understand the collaborative relationship, we consider how frequently different combinations of items are interacted with by users. These shared interaction patterns can provide strong indicators of how likely the candidate item is to resonate with a broader audience with similar preferences. For each item  $i \in I$ , we derive an interaction array that represents user interactions, forming a set of sparse user-item interaction arrays  $C \in \mathbb{R}^{n \times m}$ , where m is number of users in U. The collaborative relationship between two items  $(i_a, i_b)$  is then computed by using the cosine similarity between their sparse arrays  $C_{i_a}$ ,  $C_{i_b} \in C$ , capturing the normalized co-occurrence of the items. To streamline the process, we pre-compute and store these

values in a collaborative relationship matrix  $R_C \in \mathbb{R}^{n \times n}$ , which is typically very sparse.

*Scoring rules.* The score for an unseen item  $x \in I$  is calculated by averaging both the semantic and collaborative relationships between items in  $S_u = \{s_1, s_2, \dots, s_n\}$  as follows:

$$score(x) = \frac{1}{n} \sum_{j=1}^{n} r_j \cdot \lambda^{t_j} \cdot \left[ a \cdot R_S^{xj} + (1-a) \cdot R_C^{xj} \right]$$
 (1)

where  $R_S^{xj}$  and  $R_C^{xj}$  represent the semantic and collaborative relationships between the unseen item x and item  $s_j \in S_u$ , respectively. In this equation,  $r_j$  is the rating given by user u to item  $s_j$ , and  $\lambda^{t_j}$  is an exponential decay function applied to the temporal order  $t_j$  of  $s_j$  in the sequence  $S_u$ . Here,  $t_j$  is set to 1 for the most recent item in  $S_u$  and increments by 1 up to n for the oldest item. The framework, illustrated in Figure 2, outputs the top k items in descending order based on their scores.

## 3.3 Ranking Pipeline

After retrieving the top k items, denoted as  $I_k$ , from the initial retrieval process, a LLM is employed to further rank these items to enhance the overall ranking quality. The items in  $I_k$  are already ordered based on scores from the retrieval framework, which reflect semantic, collaborative, and temporal information. We intentionally incorporate this initial order into the ranking process to enhance both efficiency and effectiveness. This framework then leverages the capabilities of the LLM to better capture user preference, complex relationships and contextual relevance among the items.

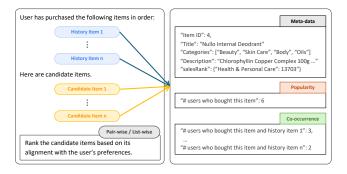


Figure 3: Prompt overview for the ranking pipeline. The prompt includes history items, candidate items, and instructions for the ranking strategy. Each item is represented by metadata, along with additional details such as popularity and co-occurrence, formatted in JSON. Full prompt is available in Appendix A.2.

3.3.1 Rank schema. We present three main strategies for ranking: (1) **Point-wise** evaluates each item  $x \in I_k$  independently, based on the user sequence  $S_u$ , to determine how likely it is that user u will interact with item x. If two items receive the same score, their rank follows the initial order from  $I_k$ ; (2) **Pair-wise** evaluates the preference between two items  $x_i, x_j \in I_k$  based on the user sequence  $S_u$ . We adopt a sliding window approach, starting from the items with the lowest retrieval score at the bottom of the list [50]. The LLM compares and swaps adjacent pairs, while iteratively stepping the comparison window one element at a time. (3) **List-wise** evaluates the preference among multiple items  $x_i, \ldots, x_{i+w} \in I_k$  based on the user sequence  $S_u$ . This method also uses a sliding window approach, with a window size w and a stride d to move the window across the list, refining the ranking as it passes [51]. In this setup, **pair-wise** is a special case of **list-wise** with w = 2 and d = 1.

3.3.2 Item information. We represent the metadata (e.g., Item ID, title, category, etc.) for each item in the user sequence  $s_j \in S_u$  and each candidate item to be ranked  $x \in I_k$  as JSON format in the input prompt. Additionally, we incorporate two more types of information that can help the reasoning capabilities of the LLM: (1) **Popularity** is calculated as the number of users who have interacted with the item x, simply by counting the occurrences in the training data. This popularity value is then included in the prompt for both the items in the user sequence  $s_j \in S_u$  and the candidate item to be ranked  $x \in I_k$  as "Number of users who bought this item: ###"; (2) **Co-occurrence** is calculated as the number of users who have interacted with both item x and item  $s_j \in S_u$ . The resulting value is then included for candidate items  $x \in I_k$  as "Number of users who bought both this item and item  $s_j$ : ###".

#### 4 Experimental Setup

Datasets. We evaluate the performance using public 2014 Amazon review datasets [32, 33]. Specifically, we select the Beauty, Toys and Games, and Sports and Outdoors categories, as these have been used in previous studies [40, 44] and provide data points for comparison (see Table 1). We follow the same data processing steps as

Dataset	# Users	# Items	# Interactions	Density
Beauty	22,363	12,101	198,502	0.0734%
Toys and Games	19,412	11,924	167,597	0.0724%
Sports and Outdoors	35,598	18,357	296,337	0.0453%

Table 1: Dataset statistics. Density is the percentage of actual user-item interactions amongst all possible user-item interactions.

in prior work, filtering out users and items with fewer than five interactions, maintaining consistent baseline settings.

Dataset Construction and Evaluation Metrics. We follow conventional supervised models, where the last item,  $s_n$ , is reserved for testing and the second to last item,  $s_{n-1}$ , is used for validation. The remaining items are used for training. For the final predictions of  $s_n$ , all training and validation items are used as input. Although our method does not train model parameters, we only use the training data to calculate the collaborative user interaction values used for  $R_C$  in retrieval and for **popularity** and **co-occurence** in ranking. We report Normalized Discounted Cumulative Gain (NDCG) and Hit Ratio (HR) at ranks 5 and 10.

Compared Methods. We compare our model with following supervised trained models: (1) KNN is a user-based collaborative filtering method that finds the top 10 most similar users to a given user and averages their ratings to score a specific item; (2) Caser uses convolution neural networks to model user interests [54]; (3) HGN uses hierarchical gating networks to capture both long and short-term user behaviors [55]; (4) GRU4Rec employs GRU to model user action sequences [56]; (5) FDSA uses a self-attentive model to learn feature transition patterns [57]; (6) SASRec uses a self-attention mechanism to capture item correlations within a user's action sequence [58]; (7) BERT4Rec applies a masked language modeling (MLM) objective for bi-directional sequential recommendation [9]; (8) S<sup>3</sup>-Rec extends beyond the MLM objective by pre-training with four self-supervised objectives to learn better item representations [59]. (9) P5 fine-tunes a pre-trained LM for use in multi-task recommendation systems by generating tokens based on randomly assigned item IDs [40]; (10) TIGER also fine-tunes LMs to predict item IDs directly, but these IDs are semantic, meaning they are learned based on the content of the items [21]; and (11) IDGenRec goes further by extending semantic IDs to textual IDs, enriching the IDs with more detailed information [44].

Implementation Details. Unless otherwise specified, we use Gecko text-embedding-004 [39]<sup>1</sup> to collect LLM embeddings for retrieval, and we use gemini-1.5-flash<sup>2</sup> for LLM-based ranking. All API calls were completed as of September 1, 2024.

# 5 Experimental Results

In this section, we present a multifaceted performance analysis of our retrieval (Section 5.1) and ranking pipeline (Section 5.2).

 $<sup>^1\</sup>mbox{https://cloud.google.com/vertex-ai/generative-ai/docs/model-reference/text-embeddings-api}$ 

<sup>&</sup>lt;sup>2</sup>https://deepmind.google/technologies/gemini/flash/

Category Method / Model		Train	Beauty			Toys and Games				Sports and Outdoors				
Salegory Wellow Wood	Wichiou / Wiodel	114111	H@5	N@5	H@10	N@10	H@5	N@5	H@10	N@10	H@5	N@5	H@10	N@10
	KNN	1	0.004	0.003	0.007	0.004	0.004	0.003	0.007	0.004	0.001	0.001	0.002	0.001
	Caser [54]	✓	0.021	0.013	0.035	0.018	0.017	0.011	0.027	0.014	0.012	0.007	0.019	0.010
	HGN [55]	1	0.033	0.021	0.051	0.027	0.032	0.022	0.050	0.028	0.019	0.012	0.031	0.016
	GRU4Rec [56]	1	0.016	0.010	0.028	0.014	0.010	0.006	0.018	0.008	0.013	0.009	0.020	0.011
	BERT4Rec [9]	1	0.020	0.012	0.035	0.017	0.012	0.007	0.020	0.010	0.012	0.008	0.019	0.010
Baseline	FDSA [57]	1	0.027	0.016	0.041	0.021	0.023	0.014	0.038	0.019	0.018	0.012	0.029	0.016
	SASRec [58]	1	0.039	0.025	0.061	0.032	0.046	0.031	0.068	0.037	0.023	0.015	0.035	0.019
	S <sup>3</sup> -Rec [59]	1	0.039	0.024	0.065	0.033	0.044	0.029	0.070	0.038	0.025	0.016	0.039	0.020
	P5 [59]	1	0.016	0.011	0.025	0.014	0.007	0.005	0.012	0.007	0.006	0.004	0.010	0.005
	TIGER [40]	1	0.045	0.032	0.065	0.038	0.052	0.037	0.071	0.043	0.026	0.018	0.040	0.023
	IDGenRec [44]	1	0.062	0.049	0.081	0.054	0.066	0.048	0.087	0.055	0.043	0.033	0.057	0.037
STAR-Retrieval	-	Х	0.068	0.048	0.098	0.057	0.086	0.061	0.118	0.071	0.038	0.026	0.054	0.031
	point-wise	Х	0.068	0.047	0.096	0.056	0.086	0.061	0.117	0.071	0.037	0.026	0.054	0.031
STAR-Ranking	pair-wise	X	0.072	0.051	0.101	0.060	0.090	0.064	0.120	0.073	0.040	0.028	0.056	0.034
	list-wise	X	0.065	0.047	0.090	0.055	0.083	0.060	0.111	0.069	0.036	0.026	0.052	0.031

Table 2: Performance (Hits@K, NDCG@K) comparison among supervised models, and STAR retrieval & ranking pipeline. The first group in the table represents supervised models; The second group shows the retrieval pipeline with parameters set to an exponential decay rate of  $\lambda = 0.7$ , history length of l = 3, and a weight factor of a = 0.5; The third group consists of ranking pipeline which use gemini-1.5-flash. The best model for each dataset is shown in bold, and the second best is underlined.

# 5.1 Retrieval Pipeline

The second group of Table 2 presents the performance of our retrieval framework. STAR-Retrieval alone achieves the best or second-best results compared to all baselines and fine-tuned methods. There is a significant improvement across all metrics for *Toys and Games*, ranging from +26.50% to +35.3%. In *Beauty*, all metrics besides NDCG@5 (-1.2%) are improved from a range of +6.1% to +20.0%. In *Sports and Outdoors*, the results are second best to ID-GenRec, trailing from a range of -19.6% to -5.57%. Furthermore, we conduct more studies to answer the following research questions:

Q1. How do semantic and collaborative information affect predictions? To evaluate the impact of semantic information ( $R_S$ ) and collaborative information ( $R_C$ ) on retrieval performance, we conducted an analysis by adjusting the weighting factor a between these two components. As shown in the left panel of Figure 4, the optimal performance is achieved from a range of 0.5 to 0.6. We choose 0.5 for other experiments as a simple, equal weighting. Furthermore, we see that when we only use one of the two components (a = 0.0 or a = 1.0) then the results are significantly worse than the combination. This validates our hypothesis that it is better to include both semantic and collaborative information and that having both types of information is additive to the overall system.

Q2. How does the number of user history items l and recency factor  $\lambda$  affect predictions? To assess the impact of the number of user history items l and the recency factor  $\lambda$  on retrieval performance, we conducted an analysis by varying both parameters. As depicted in the right panel of Figure 4, we see that having more user history items can help up to a certain point (l=3), but after that performance can be impacted. The middle panel of Figure 4 shows that setting an appropriate recency factor ( $\lambda=0.7$ ) to prioritize recent history items is more effective than not applying any recency factor

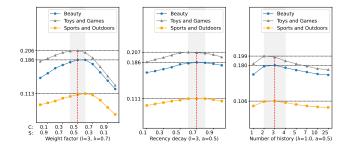


Figure 4: Retrieval performance (Hits@50) with different weighting factor a between  $R_{\rm S}$  and  $R_{\rm C}$  (left), recency factor  $\lambda$  (middle), number of history l (right). The shaded regions show the best range of parameters. We choose  $a=0.5, \lambda=0.7$ , and l=3 in our experiments.

Rating	Bea	uty	Toys an	d Games	Sports and Outdoors		
	H@10	N@10	H@10	N@10	H@10	N@10	
w/ rating	0.095	0.056	0.115	0.069	0.052	0.030	
w/o rating	0.098	0.057	0.118	0.071	0.054	0.031	

Table 3: Retrieval performance (Hits@10, NDCG@10) comparison between w/ and w/o rating.

 $(\lambda=1)$ . However, using a very small recenty factor can discount past items too much, which is similar to only using 1 user history item.

Q3. Does incorporating more user feedback improve results? In Equation 1, we propose using the user ratings to help score items.

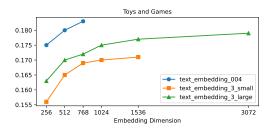


Figure 5: Retrieval performance (Hits@50) comparison by embedding APIs for Toys and Games. The models text-embedding-004, text-embedding-3-small, and text-embedding-3-large each have a maximum dimension of 768, 1536, and 3072, respectively.

Scoring method	Bea	uty	Toys an	d Games	Sports and Outdoors		
<b>g</b>	H@10	N@10	H@10	N@10	H@10	N@10	
Average Pooling	0.060	0.033	0.080	0.043	0.033	0.017	
STAR - Retrieval ( $S = 1.0, C = 0.0$ )	0.072	0.042	0.095	0.055	0.039	0.022	
STAR - Retrieval ( $S = 0.5, C = 0.5$ )	0.098	0.057	0.118	0.071	0.054	0.031	

Table 4: Retrieval performance (Hits@10, NDCG@10) comparison between STAR retrieval pipeline and average embedding pooling. Here, S=Semantic Information and C=Collaborative Information weightings.

Here we test how helpful it is to provide this user feedback information. We compare the results when we score items using rating r versus when we exclude this rating (by setting r=1 for all items). Surprisingly, ignoring the rating information consistently produced better results (See Table 3). This is likely due to a mismatch between tasks, where our analysis focuses on predicting next item *interaction* and we are not concerned about how a user will rate the next item. In our main evaluation and the rest of the analysis, we ignore user ratings (by setting all ratings to 1). This finding is also quite practical, because in real recommendation systems most user-item interactions do not have ratings.

Q4. Are some LLM embedding models better than others? We test different LLM embedding APIs with different embedding size to understand the impact of LLM embeddings capturing item semantic similarity. Figure 5 illustrates the performance differences between the Gecko text-embedding-004 [39], OpenAI text-embedding-3-small, and text-embedding-3-large models<sup>3</sup>. Overall, higher-dimensional embeddings and larger models performed better, indicating that enhanced semantic representation capabilities lead to improved semantic relationship capture.

Q5. Are there other ways to score items? Other studies use LLM embeddings of items within a user sequence ( $S_u$ ) to retrieve candidate items [15, 31]. These methods typically involve generating a "user embedding" by performing average pooling over the LLM embeddings of the items in the user sequence. The most similar item from the candidate pool is then identified by calculating the

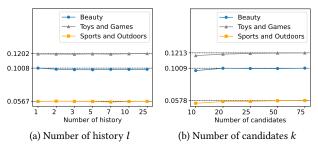


Figure 6: Pair-wise ranking performance (Hits@10) trend by different number of history l and number of candidates k

similarity between this user embedding and the LLM embedding of each candidate item. To demonstrate the effectiveness of our scoring rule, we compare its performance against the pooling approach. As shown in Table 4, our scoring rule, even without using collaborative information for a fair comparison (*i.e.*, S = 1.0, C = 0.0), outperforms the pooling approach solely using embeddings. Furthermore, incorporating collaborative information further enhances the performance (*i.e.*, S = 0.5, C = 0.5).

# 5.2 Ranking Pipeline

The third group of Table 2 highlights the performance of the ranking framework, which improves upon the retrieval stage results. Pairwise ranking improves all metrics over STAR-Retrieval performance by +1.7% to +7.9%. This further improves the results over other baselines for *Beauty* and *Toys and Games*, while closing the gap on IDGenRec in *Sports and Outdoors*. Point-wise and list-wise methods struggle to achieve similar improvements. We answer the following research questions:

Q1. Is ranking an effective approach? How do window size and stride impact performance? Previous approaches use a selection prompt, instructing the LLM to choose the top k items in ranked order from a set of candidates [25, 27, 28]. In contrast, our method uses a ranking prompt, which explicitly instructs the LLM to rank all items within the available context window. We assess the effectiveness of the ranking approach in comparison to the selection approach and a point-wise prompt. Table 5 illustrates the performance differences when varying window size and stride. The results show that ranking with a small window size (such as pair-wise or list-wise with a window size of 4) consistently outperforms the selection and pair-wise methods. Furthermore, the pair-wise and selection prompts often fail to improve performance compared to the retrieval stage, ultimately harming overall effectiveness. These findings align with previous research in document retrieval, where list-wise ranking with large window sizes or reasoning prompts requires specific task knowledge, while pair-wise ranking can be effectively performed by much smaller language models [50].

Q2. How does number of candidates k and number of history l affect predictions? As shown in Figure 6, varying the number of historical items included in the model, denoted as l, does not significantly impact prediction performance. On the other hand, increasing the number of candidate items, k, can be somewhat beneficial because it raises the likelihood of including the correct item among the

<sup>&</sup>lt;sup>3</sup>https://platform.openai.com/docs/guides/embeddings/

Prompt Style	Window Size Stride		Beauty			Toys and Games				Sports and Outdoors				
	,, iiido (, bizo	ourue	H@5	N@5	H@10	N@10	H@5	N@5	H@10	N@10	H@5	N@5	H@10	N@10
None (STAR-Retrieval)	-	-	0.0684	0.0480	0.0977	0.0574	0.0857	0.0606	0.1176	0.0709	0.0379	0.0262	0.0542	0.0314
Selection	-	-	0.0691	0.0484	0.0958	0.0570	0.0841	0.0613	0.1109	0.0699	0.0376	0.0269	0.0520	0.0316
Point-wise	1	1	0.0685	0.0472	0.0956	0.0558	0.0855	0.0611	0.1170	0.0713	0.0370	0.0257	0.0539	0.0312
Pair-wise	2	1	0.0716	0.0506	0.1008	0.0600	0.0899	0.0639	0.1196	0.0734	0.0401	0.0283	0.0564	0.0335
	4	2	0.0724	0.0502	0.1002	0.0592	0.0894	0.0634	0.1195	0.0732	0.0406	0.0282	0.0559	0.0331
**	8	4	0.0688	0.0484	0.0988	0.0581	0.0874	0.0625	0.1202	0.0731	0.0388	0.0276	0.0556	0.0330
List-wise	10	5	0.0676	0.0480	0.0981	0.0578	0.0853	0.0616	0.1201	0.0728	0.0379	0.0270	0.0558	0.0327
	20	-	0.0653	0.0471	0.0903	0.0551	0.0829	0.0603	0.1113	0.0694	0.0364	0.0262	0.0518	0.0311

Table 5: Ranking performance (Hits@K, NDCG@K) by window size and stride. Here we use 20 candidates from the retrieval stage. The best prompt for each dataset is shown in bold, and the second best is underlined.

Item prompt	Bea	uty	Toys an	d Games	Sports and Outdoors		
	H@10	N@10	H@10	N@10	H@10	N@10	
Metadata	0.1000	0.0567	0.1193	0.0690	0.0544	0.0315	
+ popularity	0.0998	0.0564	0.1174	0.0701	0.0549	0.0316	
+ co-occurrence + popularity, co-occurrence	<b>0.1008</b> 0.0999	<b>0.0600</b> 0.0599	0.1196 <b>0.1203</b>	0.0734 <b>0.0736</b>	0.0564 0.0550	0.0335 0.0322	

Table 6: Pair-wise ranking performance (Hits@10 & NDCG@10) by varying information in the item prompt.

Model	Bea	uty	Toys an	d Games	Sports and Outdoors		
Widde!	H@10	N@10	H@10	N@10	H@10	N@10	
gemini-1.5-flash	0.1008	0.0600	0.1196	0.0734	0.0564	0.0335	
gemini-1.5-pro	0.1000	0.0600	0.1202	0.0754	0.0563	0.0337	
gpt-4o-mini	0.1002	0.0580	0.1197	0.0722	0.0560	0.0326	
gpt-4o	0.1002	0.0602	0.1205	0.0743	0.0560	0.0332	

Table 7: Pair-wise ranking performance (Hits@10 & NDCG@10) comparison by different models.

candidates. However, the improvement in performance is minimal. Considering the high computational cost of processing a larger set of candidate items, this marginal gain may not be worthwhile.

Q3. How does additional item information in the prompt affect predictions? We investigate the impact of adding extra item information—specifically, popularity and co-occurrence data—alongside item metadata in the prompt. To assess this, we conduct an analysis by varying the types of information provided. As shown in Table 6, incorporating co-occurrence data alongside item metadata led to performance improvements in NDCG@10 ranging from +0.2% to +3.4% compared to using metadata alone. In contrast, adding popularity information did not enhance performance and, in some cases, even led to a decline. These findings suggest that introducing popularity bias does not help LLMs make better ranking decisions. This aligns with previous research indicating that simple popularity bias is ineffective in addressing recommendation problems [60–62].

Q4. How much do LLM capabilities affect ranking performance? To evaluate how model capabilities impact ranking performance, we compare four models: gemini-1.5-flash, gemini-1.5-pro,

Shuffle	LLM	Beauty		Toys an	d Games	Sports and Outdoors		
Candidates	Ranking	H@10	N@10	H@10	N@10	H@10	N@10	
Х	Х	0.0977	0.0574	0.1176	0.0709	0.0542	0.0314	
/	X	0.0687	0.0312	0.0779	0.0349	0.0371	0.0169	
×	1	0.1008	0.0600	0.1196	0.0734	0.0564	0.0335	
1	✓	0.0793	0.0485	0.0949	0.0596	0.0452	0.0275	

Table 8: Performance (Hits@10 & NDCG@10) comparison with random shuffling of the retrieval candidate items.

gpt-4o-mini, and gpt-4o. In Table 7, we observe the larger models (gemini-1.5-pro and gpt-4o) tend to outperform their smaller counterparts, although the performance differences are minimal. This finding aligns with results from other studies [50], which suggest that increased model capability has limited influence on pairwise ranking tasks. Despite being more computationally expensive, pairwise ranking methods tend to be more robust than alternative approaches.

Q5. Does the order of candidates affect ranking performance? We investigate whether the order of the retrieval candidate items affects the ranking performance of our recommendation system. To assess this, we conducted an experiment comparing the pairwise ranking outcomes between two sets of top 20 candidates: (1) Random order: Candidates were randomly shuffled; (2) Retrieval Order: Candidates were ordered based on their scores from the retrieval pipeline. As shown in Table 8, ordering the candidates according to their retrieval pipeline scores significantly improves ranking performance compared to a random arrangement. Comparing rows 2 and 4 show that our pair-wise ranking can improve results of a randomly shuffled list. However, the results are even better when the candidate list is ranked by the retrieval score (row 3). More analysis needs to be done to determine if  $O(n \log n)$  or  $O(n^2)$  comparisons could better rank a randomly shuffled candidate list compared to a sliding window approach, although this would come at an even higher computation cost.

## 6 Conclusion

In this paper, we introduced a Simple Training-free Approach for Recommendation (STAR) that uses the power of large language

models (LLMs) to create a generalist framework applicable across multiple recommendation domains. Our method comprises two key stages: a retrieval phase and a ranking phase. In the retrieval stage, we combine semantic embeddings from LLMs with collaborative user information to effectively select candidate items. In the ranking stage, we apply LLMs to enhance next-item prediction and refine the recommendations. Experimental results on a largescale Amazon review dataset demonstrate that our retrieval method alone outperforms most supervised models. By employing LLMs in the ranking stage, we achieve further improvements. Importantly, our study highlights that incorporating collaborative information is critical in both stages to maximize performance. Our findings reveal that LLMs can effectively function as generalists in recommendation tasks without requiring any domain-specific fine-tuning. This opens up exciting possibilities for developing versatile and efficient recommendation systems that are readily adaptable across diverse domains.

### 7 Limitations & Future Work

The **STAR** framework presents an effective alternative to traditional supervised models, showcasing the potential of LLMs in recommendation systems without the need for extensive training or custom architectures. However, several limitations remain, which also indicate directions for future improvement:

Importance of item modality and enriched item meta-data. The STAR framework's ability to capture semantic relationships between items relies significantly on the presence of rich item text meta-data. Without such meta-data and with only user-item interaction data available, the framework's semantic relationship component will be less effective. To maximize the use of semantic relationships between items, future work should explore incorporating additional modalities, such as visual or audio data, to generate more comprehensive semantic representations of items, fully utilizing all the available information.

Improving Retrieval Simplicity and Scalability. Although our work demonstrates the effectiveness of a general training-free framework, the current method requires different choices for parameters. In future work, we will explore ways to either reduce the number of parameters choices or select values more easily. In our current implementation, we compute the full set of item-item comparisons for both the semantic and collaborative information. This computation is infeasible if the item set is too large. In future work, we will run experiments to measure how effective approximate nearest neighbor methods are at reducing computation and maintaining retrieval quality.

Beyond LLM ranking. The importance of our work highlights that high quality results can be achieved without additional fine-tuning. However, in the current method, our **STAR** ranking pipeline utilizes costly LLM calls that would result in high latency. This may be a suitable solution to use in offline scenarios, but would be prohibitive to serve large-scale and real-time user traffic. Future work needs to explore how we can improve efficiency, such as using a mix of pair-wise and list-wise ranking. Our work shows a promising first step to creating high quality, training-free, and general recommendation systems.

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# A Appendix

# A.1 Item Encoding Prompt for Retrieval Example

Below is an example of an item prompt for encoding with an LLM embedding API.

```
description:
   LENGTH: 70cm / 27.55 inches
   Color: Mix Color
   EST. SHIPPING WT.: 310g
   Material: Synthetic High Temp Fiber
   Cap Construction: Capless
   Cap Size: Average
   1. The size is adjustable and no pins or tape should be required. It should fit most people.
       Adjust the hooks inside the cap to suit your head.
    2. Please be aware that colors might look slightly different in person due to camera quality and monitor settings.
       Stock photos are taken in natural light with no flash.
   3. Please ask all questions prior to purchasing. I will replace defective items.
       Indicate the problem before returning. A 30-day return/exchange policy is provided as a satisfaction guarantee.
title: 63cm Long Zipper Beige+Pink Wavy Cosplay Hair Wig Rw157
salesRank: {'Beauty': 2236}
categories: Beauty > Hair Care > Styling Products > Hair Extensions & Wigs > Wigs
price: 11.83
brand: Generic
```

# A.2 Ranking Prompt Example

Below is an example of a single pass in a list-wise ranking pipeline with a window size of 4 and a stride of 2 (w = 4 and d = 2) assuming there are 3 history items (l = 3).

System: You are an intelligent assistant that can rank items based on the user's preference.

```
User: User 1656 has purchased the following items in this order:
    "Item ID": 1069,
    "title": "SHANY Professional 13-Piece Cosmetic Brush Set with Pouch, Set of 12 Brushes and 1 Pouch, Red",
    "salesRank_Beauty": 248,
    "categories": [
        ["Beauty", "Tools & Accessories", "Makeup Brushes & Tools", "Brushes & Applicators"]
    "price": 12.95,
    "brand": "SHANY Cosmetics"
    "Item ID": 2424,
    "title": "SHANY Eyeshadow Palette, Bold and Bright Collection, Vivid, 120 Color",
    "salesRank_Beauty": 1612,
    "categories": [
        ["Beauty", "Makeup", "Eyes", "Eye Shadow"]
    "price": 16.99,
    "brand": "SHANY Cosmetics"
},
    "Item ID": 2856,
    "title": "SHANY Studio Quality Natural Cosmetic Brush Set with Leather Pouch, 24 Count",
    "salesRank_Beauty": 937,
    "categories": [
        ["Beauty", "Tools & Accessories", "Bags & Cases", "Cosmetic Bags"]
```

```
"price": 26.99,
"brand": "SHANY Cosmetics"
}
```

I will provide you with 4 items, each indicated by number identifier []. Analyze the user's purchase history to identify preferences and purchase patterns. Then, rank the candidate items based on their alignment with the user's preferences and other contextual factors.

Assistant: Okay, please provide the items.

```
User:[1]
{
    "title": "SHANY Cosmetics Intense Eyes Palette 72 Color Eyeshadow Palette, 17 Ounce",
    "salesRank_Beauty": 181358,
    "categories": [
        ["Beauty", "Makeup", "Makeup Sets"]
    ],
    "price": 26.4,
    "brand": "SHANY Cosmetics",
    "Number of users who bought both this item and Item ID 1069": 18,
    "Number of users who bought both this item and Item ID 2424": 0,
    "Number of users who bought both this item and Item ID 2856": 16
}
```

#### Assistant: Received item [1].

```
User:[2]
{
    "title": "SHANY Cosmetics Carry All Train Case with Makeup and Reusable Aluminum Case, Cameo",
    "salesRank_Beauty": 2439,
    "categories": [
        ["Beauty", "Makeup", "Makeup Sets"]
],
    "price": 39.99,
    "brand": "SHANY Cosmetics",
    "Number of users who bought both this item and Item ID 1069": 27,
    "Number of users who bought both this item and Item ID 2424": 1,
    "Number of users who bought both this item and Item ID 2856": 29
}
```

## Assistant: Received item [2].

```
User: [3]
{
    "title": "SHANY COSMETICS The Masterpiece 7 Layers All-in-One Makeup Set",
    "salesRank_Beauty": 2699,
    "categories": [
        ["Beauty", "Makeup", "Makeup Sets"]
    ],
    "price": 41.89,
    "brand": "SHANY Cosmetics",
    "Number of users who bought both this item and Item ID 1069": 23,
    "Number of users who bought both this item and Item ID 2424": 2,
    "Number of users who bought both this item and Item ID 2856": 25
}
```

#### Assistant: Received item [3].

```
User: [4]
{
    "title": "SHANY Silver Aluminum Makeup Case, 4 Pounds",
    "salesRank_Beauty": 16605,
    "categories": [
        ["Beauty", "Tools & Accessories", "Bags & Cases", "Train Cases"]
    ],
```

```
"price": 59.95,
"brand": "SHANY Cosmetics",
"Number of users who bought both this item and Item ID 1069": 32,
"Number of users who bought both this item and Item ID 2424": 1,
"Number of users who bought both this item and Item ID 2856": 40
}
```

# Assistant: Received item [4].

User: Analyze the user's purchase history to identify user preferences and purchase patterns. Then, rank the 4 items above based on their alignment with the user's preferences and other contextual factors. All the items should be included and listed using identifiers, in descending order of the user's preference. The most preferred recommendation item should be listed first. The output format should be [] > [], where each [] is an identifier, e.g., [1] > [2]. Only respond with the ranking results, do not say any word or explain. Output in the following JSON format:

```
"rank": "[] > [] .. > []"
}
```