SEAR: LLM-Powered Sequential Recommendation via Fusion of Collaborative, Semantic, and Rating Information

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Abstract

As users' preferences evolve over time, personalized online services increasingly rely on sequential recommender systems to predict future interactions by modeling patterns in historical user behavior. However, existing methods for sequential recommendation (SR) face two key challenges: they struggle to simultaneously leverage collaborative, semantic, and rating information, and the use of hard labels during training provides limited supervision. In this paper, we introduce SEAR, an LLM-powered Sequential recommEndation framework via fusion of collAborative, semantic, and Rating information. The proposed deep model comprises an embedding layer and a sequence encoder. The embedding layer transforms user-item interactions into three types of embeddings: collaborative, semantic, and rating. The sequence encoder then integrates these embeddings and identifies sequential patterns to model user representations. To enhance the utilization of item semantics, we integrate a large language model (LLM) to extract LLM embeddings. These embeddings are then employed to initialize the semantic embedding layer, collaborative embedding layer, and item embeddings. To capture more nuanced user behavior patterns, we generate preference-weighted soft labels based on the next k interactions. Extensive experiments validate the effectiveness of SEAR, and ablation studies further highlight the distinct contributions of the collaborative, semantic, and rating information. The source code is publicly available at https://github.com/guanwei49/SEAR.

CCS Concepts

• **Information systems** → **Recommender systems**.

Keywords

Sequential recommendation; Large language model; Mamba

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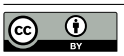

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1 Introduction

Personalized online services increasingly depend on sequential recommender systems to capture users' evolving preferences [29]. These systems are designed to predict future user interactions by modeling the sequential patterns in their past behaviors [25]. Given the pivotal role of sequential recommendation (SR), a wide range of methods have been developed to improve its performance. Typically, three types of information can be utilized during SR: collaborative, semantic, and rating.

Most existing approaches [28, 50, 52], which treat items as categorical IDs, only adopt collaborative information. Although these methods achieve acceptable performance and demonstrate the effectiveness of collaborative information, semantic and rating information are crucial for accurately capturing users' true preferences. As illustrated in Fig. 1, although 'User1' and 'User2' exhibit identical sequences of interacted items, their rating patterns differ, which suggests differing user preferences: 'User1' consistently assigns higher ratings to items with modifier 'A', whereas 'User2' assigns higher ratings to items with modifier 'B'. This disparity suggests differing user preferences, with 'User1' likely to favor items with modifier 'A' in the future, while 'User2' is more inclined to prefer those with modifier 'B'. To leverage semantic information within items, some methods [22, 33, 54] treat item attributes as IDs and incorporate them into the modeling of user preferences. More recent studies [12, 18, 21, 26, 35, 51] embed item attributes into prompts, utilizing either self-designed semantic extractors [18, 51] or LLMs [12, 21, 26, 35] to enhance SR performance. Additionally, a few methods [20, 23] integrate rating information to complement collaborative signals.

However, existing methods face two key challenges. First, while three types of information are beneficial for enhancing SR, most approaches utilize only a single type, typically collaborative [28, 50, 52] or semantic [12, 21, 42], resulting in suboptimal performance.

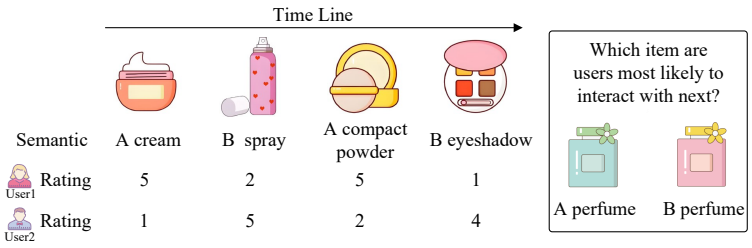


Figure 1: Integrating semantic and rating information can enhance sequential recommendation.

Although some methods attempt to integrate multiple information types, they often struggle to fuse them effectively. For example, Liu et al. [26] combine semantic and collaborative information using cross-attention and feed the result into a single sequence encoder. However, different types of information often have distinct patterns, so using a single encoder can result in poor user representations. In contrast, Zhang et al. [51] encode semantic and collaborative information separately, without any interaction between them. Other studies [20, 23, 54] primarily focus on collaborative information and merely use additional signals to guide the encoding process. Second, during training, most existing methods adopt hard labels, considering only the immediate next interacted item as the target. However, a user may also prefer items within the next k interactions. Although Huang et al. [15] propose a time-dependent soft label for SR, focusing on items from the near future, they overlook the fact that rating scores also reflect the user's degree of preference.

To tackle the aforementioned challenges, we propose SEAR, an LLM-powered **S**equential recomm**E**ndation framework that fully leverages coll**A**borative, semantic, and **R**ating information. SEAR utilizes an LLM to encode the semantic information of items, generating LLM embeddings. The model architecture includes an embedding layer and a sequence encoder for deriving user representations. The embedding layer encodes user-item interactions into three types of embeddings: semantic, collaborative, and rating. The semantic embedding is adapted from LLM embeddings via a trainable adapter, while the collaborative embedding is initialized using principal component analysis (PCA) [34] applied to the LLM embeddings. These embeddings are then passed through the sequence encoder, which consists of a stack of N identical layers. Each layer contains three instances of both the aggregation layer and the Mamba layer—one for each embedding type. The aggregation layer integrates cross-embedding information, while the Mamba layer captures sequential patterns within each type. The user embedding is formed by concatenating the sequence encoder's outputs corresponding to the final item in the sequence. Finally, next-item prediction is performed by computing the dot product between the user embedding and the item embeddings (also initialized via PCA on LLM embeddings). To enhance model training, we construct preference-weighted soft labels, that take into account the next k interactions. These soft labels are designed based on the assumption that users prefer items they have rated highly and interacted with more recently. Therefore, higher probabilities are assigned to more recent items and those with higher rating scores, enabling the model to capture finer-grained insights into user behavior.

The main contributions of this work are as follows:

- We propose SEAR, a framework that fuses collaborative, semantic, and rating information to model user representations. To leverage item semantics, we incorporate an LLM.
- To enhance the training process, we construct preference-weighted soft labels based on the next k interactions, enabling the model to capture finer-grained insights.
- Extensive experiments demonstrate the effectiveness of SEAR. Ablation studies validate the individual contributions of collaborative, semantic, and rating embeddings.

2 Related Work

In this section, we explore related work in the field of sequential recommendation and the soft label for recommendation systems.

2.1 Sequential Recommendation

Existing SR methods can be broadly categorized into three groups: i) collaborative information-based methods, ii) semantic information-involved methods, and iii) rating information-enhanced methods.

Collaborative information-based methods, which treat items purely as categorical IDs, rely solely on collaborative information. Most approaches focus on designing effective model architectures to capture sequential dependencies. For instance, GRUs are employed in [40, 49, 50]. Caser [41] utilizes horizontal and vertical convolutional filters to learn sequential patterns, while RCNN [45] and ADNNet [47] combine RNNs and CNNs for sequential feature extraction. Additionally, methods such as [3, 17, 27, 31, 32] leverage GNNs to model user representations. Self-attention mechanisms are utilized in [16, 19, 37, 39, 44, 52] to capture long-range dependencies, with BERT4Rec [39] directly utilizing the open-source BERT [6] architecture. Mamba4Rec [24] and SIGMA [28] explore the use of Mamba blocks [9] for efficient sequential modeling. Recent advances include CORE [13], which introduces a representation-consistent encoder to align user and item embeddings in the same representation space and a robust distance measuring method to prevent overfitting of embeddings in the consistent representation space, thereby enhancing item representation learning. CPR [2] proposes novel softmax architectures to more effectively leverage the neural encoder's ability to learn when to copy and when to exclude items from the input sequence.

Semantic information-involved methods incorporate various item attributes, such as description text, brand, and price, to better capture user preferences. Some methods [7, 22, 23, 33, 54] treat item attributes as discrete IDs. For example, TransFM [33] learns an embedding and translation space for each attribute dimension, replacing the inner product with squared Euclidean distance to

measure the interaction strength between attributes. DETAIN [22] proposes a 2D attention mechanism to simultaneously capture the importance of items and their attributes within sequences. S^3-Rec [54] introduces a pre-training framework that leverages mutual information maximization to extract correlations from multiple views (e.g., item-attribute, attribute-context).

Recently, researchers have begun to incorporate item attributes into prompts to leverage items' semantic embedding. Recformer [18] and FDSA [51] convert item attributes into sentences, utilizing self-designed semantic extractors for representation learning. Recformer [18] transforms key-value attribute pairs into descriptive sentences, processed by a transformer encoder to model user preferences, while FDSA [51] extracts topical keywords from items' description text, encodes them with Word2Vec [30], and employs feature- and item-based self-attention blocks to process semantic embeddings and collaborative embeddings, respectively. With the rise of LLMs, it has become feasible to exploit their deep semantic understanding [10, 11, 38, 48]. LLMSeqSim [12] uses LLMs to create embeddings from item names, averages these to get user embeddings, and makes recommendations based on the similarity between user and item embeddings. LLM2BERT4Rec [12] initializes the item embedding layer of BERT4Rec with PCA on LLM-derived item embeddings. SAID [14] maps item IDs into embeddings via a projector, feeding them into the LLM to elicit textual tokens, and uses the resulting semantically enriched embeddings within sequential recommenders. LLM-ESR [26] and EIMF [35] integrate semantic embeddings extracted from LLMs with collaborative embeddings to enhance SR. Specifically, LLM-ESR [26] introduces a dual-level fusion strategy: sequence-level fusion via cross-attention and logit-level fusion via concatenation, while EIMF [35] adopts a multi-task learning framework to combine the two types of embeddings. LLMSeqPrompt [12], MLLM4Rec [42], and PatchRec [21] directly leverage LLMs to generate recommendations by incorporating item sequences into prompts and fine-tuning the models for next-item prediction. Specifically, PatchRec [21] proposes a multi-granularity compression framework, which first pre-trains the LLM to understand compressed item patches and then fine-tunes it on time-aware compressed sequences.

Note that although some methods, such as LLM-ESR [26] and LLM2BERT4Rec [12], incorporate item ratings into prompts to obtain item embeddings—thus seemingly considering rating information—they in fact only use the item's average rating score. They do not take into account the specific ratings given by users during interactions. Therefore, we do not regard these methods as truly utilizing rating information.

Rating information-enhanced methods. Li et al. [20] and Liu et al. [23] take into account the rating information, they integrate rating information into self-attention calculation process, to generate better attention distribution. Nevertheless, existing methods fall short in simultaneously exploiting three types of information. In contrast, each layer of our sequence encoder contains three instances of aggregation layers and Mamba layers. The aggregation layers are designed to integrate the three types of information, while the Mamba layer captures sequential patterns within each type, resulting in a more accurate representation of user preferences.

2.2 Soft Label for Recommendation Systems

Recommendation systems often rely on one-hot labels [1, 5, 46], which overlook the inherent uncertainty in user feedback and may hinder model generalization. To mitigate this, recent studies [4, 43, 55] have explored the use of soft labels to provide more informative supervision signals. Most existing methods [4, 43, 53] generate soft labels with the assistance of auxiliary models. For example, SoftRec [4] and CSRec [43] introduce teacher models to guide the student model during training. Specifically, SoftRec [4] synthesizes soft labels from item popularity, user interests, and model predictions, while CSRec [43] extends this idea by leveraging model-, data-, and training-level teacher models. MVS [53] employs a complementary model to construct smoothed interaction contexts for soft label generation. However, the quality of soft labels depends on the performance of auxiliary models and introduces additional time costs. SCLRec [55] utilizes entropy optimal transport to find user-item matches as soft labels for contrastive learning. FENRec [15] proposes time-dependent soft labels that consider items the user will interact with soon as items of interest and assigns higher probabilities to items closer to the next interaction. However, existing methods do not incorporate rating scores, which reflect the intensity of user preferences, when constructing soft labels. We propose preference-weighted soft labels, which take into account the next k interactions, assigning higher probabilities to more recent items and those with higher rating scores.

3 Methodology

The goal of sequential recommendation is to predict the next item a user is likely to interact with, based on their historical interaction records. In this section, we denote the set of users and items as $\mathcal{U} = \{u_1, u_2, \ldots, u_{|\mathcal{U}|}\}$ and $\mathcal{V} = \{v_1, v_2, \ldots, v_{|\mathcal{V}|}\}$, where $|\mathcal{U}|$ and $|\mathcal{V}|$ are the total numbers of users and items, respectively. Each user u has an interaction sequence $\mathcal{S}_u = \langle s_1^u, s_2^u, \ldots, s_{n_u}^u \rangle$, where each interaction $s_i^u = (v_i^u, r_i^u)$ is a tuple consisting of the item v_i^u the user interacted with and the corresponding rating score r_i^u. Here, n_u denotes the number of interactions for user u. For simplicity, we omit the script u in the subsequent sections.

3.1 Framework Overview

The architecture of SEAR is illustrated in Fig. 2. An LLM is employed to encode the semantic information of items, resulting in LLM embeddings. These embeddings are then used to initialize the semantic embedding layer, the collaborative embedding layer, and the item embeddings. The embedding layer encodes user-item interactions into three types of embeddings: semantic, collaborative, and rating. These embeddings are then fed into the sequence encoder, which comprises a stack of N identical layers, each of which includes three instances of both the aggregation layer and the Mamba layer—one for each type of embedding. The aggregation layer integrates information across the embedding type, while the Mamba layer captures sequential dependencies within each embedding type. The user embedding is obtained by concatenating the sequence encoder's outputs corresponding to the last item. Finally, the next-item prediction is obtained by computing the dot product between the user embedding and the item embeddings, followed by applying a softmax function.

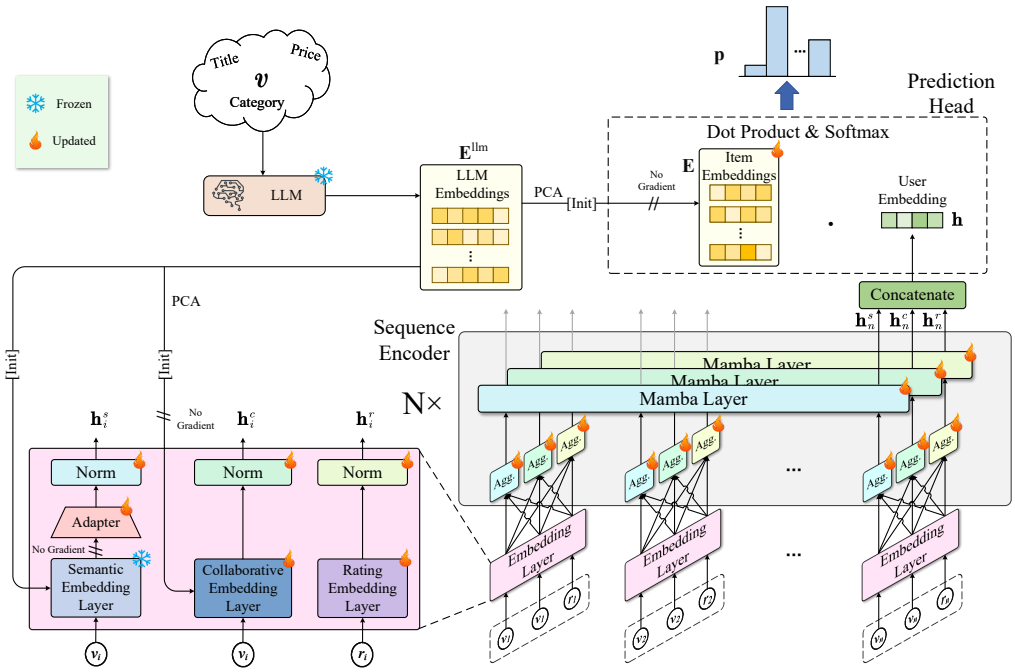


Figure 2: The architecture of SEAR, including the embedding layer, sequence encoder, and prediction head.

3.2 Extraction of LLM Embeddings

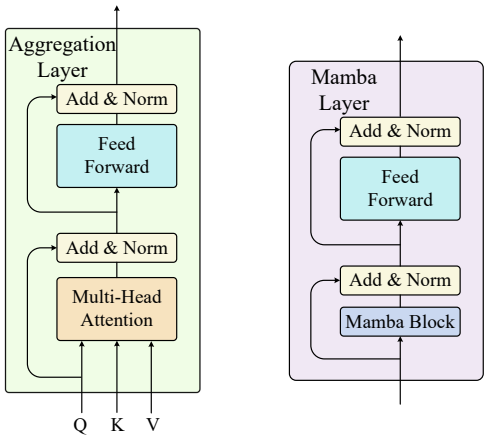
In general, item attributes contain rich semantic information, which is valuable for understanding user preferences. We incorporate item attributes into textual prompts and input them into LLMs to extract LLM embeddings. Specifically, these embeddings can be obtained by retrieving the last hidden states from open-source LLMs such as LLaMA [8], or from models specialized for sentence embeddings, such as Sentence-BERT [36]. The general template of the prompt is as follows: "Below is the item's information: $*Attribute_1*$: $Value_1$; $*Attribute_2*$: $Value_2$; $\cdots$; $*Attribute_n*$: $Value_n$." For example, if an item's title is 'Liquid foundation' and its brand is 'A', the corresponding prompt would be: "Below is the item's information: *Title*: Liquid foundation; *Brand*: A." Let $\mathbf{E}^{llm} \in \mathbb{R}^{|\mathcal{V}| \times d_{llm}}$ denote the LLM embeddings of all items, where d_{llm} represents the hidden state dimension of the LLM. The i-th row of $\mathbf{E}^{llm}$ corresponds to the LLM embedding of the i-th item. After obtaining $\mathbf{E}^{llm}$, the LLM is no longer involved in the subsequent model training and inference, which reduces computational cost and simplifies the overall architecture.

3.3 Embedding Layer

The embedding layer encodes a user-item interaction $s_i = (v_i, r_i)$ into three types of embeddings: semantic, collaborative, and rating. Semantic embedding (SE) captures the content information of items, collaborative embedding (CE) reflects user-item interaction patterns, and rating embedding (RE) represents the intensity of explicit user preferences. The **semantic embedding** $\mathbf{h}_i^s \in \mathbb{R}^{d_h}$ is obtained by feeding the item v_i into a semantic embedding layer followed by an adapter and layer normalization. The semantic embedding layer is initialized with LLM embeddings $\mathbf{E}^{llm}$. To preserve the original semantic information, we freeze the semantic embedding layer during training. To bridge the gap between the raw semantic space (of dimension d_{llm}) and the recommendation space (of dimension d_h), we introduce an adapter implemented as a linear layer. The **collaborative embedding** $\mathbf{h}_i^c \in \mathbb{R}^{d_h}$ is obtained by feeding the item v_i into a collaborative embedding layer, followed by layer normalization. The collaborative embedding layer is initialized by reducing the dimensionality of $\mathbf{E}^{llm}$ using PCA. The dimensionality of the collaborative embedding is also d_h. The **rating embedding** $\mathbf{h}_i^r \in \mathbb{R}^{d_h}$ is obtained by feeding the rating score r_i into a rating embedding layer, followed by layer normalization. Since the rating score is a continuous value, the rating embedding layer is implemented as a linear layer that transforms the scalar input into an embedding vector of dimension d_h. After feeding the interaction sequence into the embedding layer, we obtain the semantic embedding sequence $\langle \mathbf{h}_1^s, \mathbf{h}_2^s, \cdots, \mathbf{h}_n^s \rangle$, the collaborative embedding sequence $\langle \mathbf{h}_1^c, \mathbf{h}_2^c \cdots, \mathbf{h}_n^c \rangle$, and the rating embedding sequence $\langle \mathbf{h}_1^r, \mathbf{h}_2^r, \cdots, \mathbf{h}_n^r \rangle$.

3.4 Sequence Encoder

The sequence encoder comprises a stack of N identical layers, each includes three instances of both the aggregation layer and the Mamba layer—one for each embedding type tp (semantic, collaborative, or rating). The purpose of the **aggregation layer** is to integrate information from the embeddings of three types. The aggregation layer comprises two sub-layers, as shown in Fig. 3a. The first sub-layer utilizes a multi-head attention mechanism, where the queries are derived from the embedding of type tp, denoted as $\mathbf{h}_i^{tp}$. The keys and values are the embeddings of all types, $\{\mathbf{h}_i^s, \mathbf{h}_i^c, \mathbf{h}_i^r\}$. The second sub-layer is a fully connected feed-forward network.



(a) Agg. layer. (b) Mamba layer.

Figure 3: Aggregation layer and Mamba layer.

Each sub-layer is followed by a residual connection and layer normalization. The purpose of the **Mamba layer** is to capture sequential dependencies within each type of embedding. Similar to the aggregation layer, the Mamba layer consists of two sub-layers, as illustrated in Fig. 3b. The first sub-layer employs a Mamba block [9], which leverages input-dependent adaptations and a selective state space model (SSM) to efficiently process sequential information. Unlike transformers, which scale quadratically with input length due to self-attention, Mamba block scales linearly. This makes it highly efficient and practical for long sequences. The second sub-layer is a position-wise fully connected feed-forward network. Each sub-layer is followed by a residual connection and layer normalization. The Mamba layer for tp receives and processes the embedding sequence $\langle \mathbf{h}_1^{tp}, \mathbf{h}_2^{tp}, \cdots, \mathbf{h}_n^{tp} \rangle$ from the aggregation layer.

3.5 Prediction Head

The user embedding is obtained by concatenating the sequence encoder's outputs corresponding to the last item, formally defined as $\mathbf{h} = [\mathbf{h}_n^s; \mathbf{h}_n^c; \mathbf{h}_n^r] \in \mathbb{R}^{3d_h}$. To facilitate next-item prediction, we construct item embeddings for all items, denoted by $\mathbf{E} \in \mathbb{R}^{|\mathcal{V}| \times 3d_h}$, by applying PCA to reduce the dimensionality of $\mathbf{E}^{llm}$. The i-th row of $\mathbf{E}$ represents the embedding of the i-th item. It is worth noting that $\mathbf{E}$ is trainable during the model optimization process. The probability distribution $\mathbf{p} \in \mathbb{R}^{|\mathcal{V}|}$ over the entire item set, representing the likelihood of the user's next interaction, is computed as the dot product between the item embeddings and the user embedding, followed by a softmax function:

$$\text{logits}_i = \mathbf{E}_i \cdot \mathbf{h} = \sum_{j=1}^{3d_h} \mathbf{E}_{ij} \cdot \mathbf{h}_j \tag{1}$$

$$\mathbf{p}_i = \frac{\exp(\text{logits}_i)}{\sum_{l=1}^{|\mathcal{V}|} \exp(\text{logits}_l)} \tag{2}$$

where $\mathbf{E}_i \in \mathbb{R}^{3d_h}$ denotes the embedding of the i-th item, and $\mathbf{E}_{ij}$ refers to its j-th component, which is a scalar. Similarly, $\mathbf{h}_j$ denotes the j-th component of $\mathbf{h}$, also a scalar. $\mathbf{p}_i$ denotes the predicted probability that the user will interact with the i-th item in the next step.

3.6 Model Training

Most existing sequential recommendation methods consider only the immediate next interacted item as the item of interest. However, users may not only favor the next item but also the subsequent k interacted items. Moreover, users tend to prefer items with higher rating scores. To better capture user preferences, we generate **preference-weighted soft labels** based on both temporal proximity and rating scores. Specifically, we treat the next k interacted items as items of interest. We assume that users favor items they have rated highly and interacted with more recently. Consequently, we assign higher probabilities to items that are more recent and have higher rating scores.

Formally, the next k interactions of the user u are given by $(v_{n+1}^u, r_{n+1}^u), \cdots, (v_{n+k}^u, r_{n+k}^u)$. The preference-weighted soft label $\mathbf{y} \in \mathbb{R}^{|\mathcal{V}|}$, where $\mathbf{y}_i$ represents the i-th element of $\mathbf{y}$, that is, the probability that the user will interact with item $v_i \in \mathcal{V}$, can then be constructed as follows:

$$\mathbf{y}_i = \sum_{j=n+1}^{n+k} \mathbb{I}\left(v_j^u = v_i\right)\, p(j), \tag{3}$$

where $\mathbb{I}(\cdot)$ is the indicator function, and

$$p(j) = \frac{e^{-\lambda(j-n-1)} \cdot r_j^u}{\sum_{\ell=n+1}^{n+k} e^{-\lambda(\ell-n-1)} \cdot r_\ell^u}. \tag{4}$$

Here, λ is a hyperparameter that controls the distribution of the preference-weighted soft labels. A higher value of λ imposes a stronger penalty on distant interactions. When an item appears multiple times within the future interaction window, its contributions are accumulated over all corresponding positions.

To align the model's predicted probability distribution $\mathbf{p}$ with the preference-weighted soft label $\mathbf{y}$, we employ the Kullback–Leibler (KL) divergence as the loss function:

$$\mathcal{L}_{\text{KL}} = \sum_i \mathbf{y}_i (\log(\mathbf{y}_i) - \log(\mathbf{p}_i)) \tag{5}$$

This loss encourages the predicted distribution $\mathbf{p}$ to closely match the preference-weighted soft label $\mathbf{y}$, which encapsulates more nuanced supervisory signals compared to hard labels. By minimizing the KL divergence, the model is guided to capture subtle patterns in the data, thereby improving its generalization capability and overall performance.

4 Experiments

In this section, we conduct extensive experiments on five real-life datasets to investigate the following research questions (RQs): i) **RQ1**: How effective is SEAR in sequential recommendation? ii) **RQ2**: How do the three types of information influence SEAR's performance? iii) **RQ3**: How does the PCA-based initialization strategy affect the performance of SEAR? iv) **RQ4**: How do the parameters λ and k in the soft label mechanism impact SEAR's performance? v) **RQ5**: How effective is SEAR in addressing long-tail recommendation challenges?

Table 1: The statistics of datasets. 'Avg. Iter$_x$' denotes the average number of iterations for each x.

	# Users	# Items	# Iterations	Sparsity	Avg. Iter$_{user}$	Avg. Iter$_{item}$
Beauty	22,363	12,101	198,502	99.93%	8.88	16.40
Games	54,955	17,256	494,934	99.95%	9.01	28.68
Supplies	236,506	42,351	2,093,662	99.98%	8.85	49.44
Scientific	10,646	4,991	74,357	99.86%	6.98	14.90
ML-1M	6,040	3,416	999,611	95.16%	165.50	292.63

Table 2: Performance comparison of different methods on five datasets. The best results are in boldface and the second-best results are underlined. '*' indicates the statistically significant improvements (i.e., two-sided t-test with p < 0.05) over the best baseline. 'Improv.' indicates the relative improvement against the best baseline.

Datasets	Metrics	GRU4Rec	SASRec	BERT4Rec	CORE	Mamba4Rec	SIGMA	CPR	FENRec	LLM2BERT4Rec	LLM-ESR	SEAR	Improv.
Beauty	H@10	0.0567	0.0733	0.0377	0.0610	0.0675	0.0602	0.0482	0.0623	0.0621	0.0813	**0.0863***	6.15%
	N@10	0.0332	0.0409	0.0193	0.0243	0.0417	0.0342	0.0255	0.0361	0.0419	0.0483	**0.0525***	8.70%
	M@10	0.0260	0.0278	0.0137	0.0134	0.0338	0.0263	0.0187	0.0324	0.0318	0.0396	**0.0423***	6.82%
Games	H@10	0.1176	0.1328	0.0979	0.1108	0.1269	0.1269	0.1024	0.1092	0.1171	0.1266	**0.1335**	0.53%
	N@10	0.0787	0.0806	0.0644	0.0599	0.0850	0.0843	0.0697	0.0812	0.0793	0.0869	**0.0901***	3.68%
	M@10	0.0669	0.0647	0.0543	0.0444	0.0723	0.0714	0.0598	0.0612	0.0668	0.0746	**0.0770***	3.22%
Supplies	H@10	0.1373	0.1309	0.1172	0.1321	0.1368	0.1361	0.1228	0.1219	0.1256	0.1326	**0.1393***	1.46%
	N@10	0.1144	0.1053	0.0955	0.0834	0.1149	0.1146	0.1050	0.1023	0.1084	0.1096	**0.1169***	1.74%
	M@10	0.1024	0.0974	0.0887	0.0677	0.1082	0.1080	0.0995	0.0971	0.1000	0.1035	**0.1100***	1.66%
Scientific	H@10	0.1029	0.1415	0.0975	0.1320	0.1229	0.1226	0.0724	0.1321	0.1235	0.1373	**0.1447***	2.26%
	N@10	0.0862	0.0985	0.0677	0.0718	0.0994	0.0977	0.0600	0.0976	0.1070	0.0984	**0.1124***	5.05%
	M@10	0.0811	0.0849	0.0583	0.0530	0.0922	0.0900	0.0562	0.0864	0.0957	0.0926	**0.1025***	7.11%
ML-1M	H@10	0.2712	0.2432	0.2725	0.1452	0.2911	0.3114	0.3134	0.2916	0.2998	0.3193	**0.3338***	4.54%
	N@10	0.1531	0.1248	0.1500	0.0621	0.1656	0.1807	0.1779	0.1723	0.1688	0.1924	**0.1985***	3.17%
	M@10	0.1171	0.0888	0.1128	0.0374	0.1273	0.1406	0.1476	0.1452	0.1351	0.1529	**0.1569***	2.62%

4.1 Experimental Setup

Datasets. We conduct comprehensive experiments on five representative real-world datasets: four subsets of Amazon[1] (Beauty, Games, Supplies and Scientific) and MovieLens-1M[2] (ML-1M). Amazon is a large-scale e-commerce dataset that contains user reviews of various products. MovieLens, on the other hand, is a dataset comprising user ratings for a wide range of movies. We follow the same preprocessing procedure as described in [16], discarding users and items with fewer than five interactions. The statistics of the datasets after preprocessing are summarized in Table 1. Regarding the data split, the last item v_{n_u} and the penultimate item v_{n_u-1} in each interaction sequence are used as the test and validation sets, respectively.

Compared Methods. We compare our method with state-of-the-art SR approaches, which can be broadly categorized into three groups: i) Traditional collaborative information-based methods, including GRU4Rec [40], SASRec [16], BERT4Rec [39], CORE [13], Mamba4Rec [24], SIGMA [28], and CPR [2] with GRU4Rec as its backbone; ii) Soft label-enhanced methods, represented by FENRec [15]; iii) LLM-enhanced methods, including LLM2BERT4Rec [12] and LLM-ESR [26] with GRU4Rec as its backbone.

Implementation Details. We conduct all experiments on a server equipped with an Intel Xeon Gold 6330 CPU (38 cores), 256GB of memory, and an NVIDIA A40 GPU with 48 GB of memory. In our experiments, we employ the all-mpnet-base-v2 model[3] to extract LLM embeddings. The hyperparameters k and λ, described in Section 3.6, are set to 4 and 2, respectively. The embedding dimension d_h is set to 64, and N, which is the number of layers in the sequence encoder, is set to 2. We employ the AdamW optimizer with a mini-batch size of 2048, an initial learning rate of 1e-3, and an exponential learning rate scheduler with a decay factor of 0.96. The number of training epochs is set to 200. To prevent overfitting, we employ an early stopping strategy with a patience of 4 epochs, terminating training when no improvement in loss is observed.

Evaluation Metrics. We adopt widely used evaluation metrics, including the top-10 hit rate (H@10), top-10 normalized discounted cumulative gain (N@10), and top-10 mean reciprocal rank (M@10). All experimental results reported are the averages of five independent runs of each method.

4.2 Benchmarking Results (RQ1)

Table 2 presents the performance comparison across five benchmark datasets. From the results, we observe that the proposed SEAR consistently outperforms all competing methods across various evaluation metrics, demonstrating the effectiveness and robustness of our approach. Although LLM2BERT4Rec and LLM-ESR also leverage LLMs to incorporate semantic information into the recommendation process, they overlook two important aspects. First, while both methods consider the item sequences with which users have interacted to infer preferences, they ignore the valuable insights contained in users' explicit ratings on interacted items. Ratings provide an additional, often more direct, signal of user preference that complements behavioral sequences. Second, both methods lack a well-designed mechanism to effectively integrate multiple types of user information (i.e., collaborative and semantic information).

[1] https://cseweb.ucsd.edu/~jmcauley/datasets.html#amazon_reviews
[2] https://grouplens.org/datasets/movielens/
[3] https://huggingface.co/sentence-transformers/all-mpnet-base-v2

Table 3: Time consumption averaged over all five datasets.

	GRU4Rec	SASRec	BERT4Rec	CORE	Mamba4Rec	SIGMA	CPR	FENRec	LLM2Bert4Rec	LLM-ESR	SEAR
Training Time (s)	711.81	739.50	3942.97	691.63	674.24	1809.63	1459.69	785.85	3956.57	1034.73	3415.71
Testing Time (s)	3.34	4.51	23.34	6.50	5.07	7.76	6.06	4.23	23.76	4.34	18.36

Table 4: Ablation studies on three types of embeddings. The best results are in boldface. 'Drop' indicates the average performance drop compared to SEAR across five datasets. 'w/o' and 'w/' denote 'without' and 'with', respectively.

	Beauty		Games		Supplies		Scientific		ML-1M		Drop	
	H@10	N@10	H@10	N@10	H@10	N@10	H@10	N@10	H@10	N@10	H@10	N@10
w/ SE	0.0600	0.0337	0.1066	0.0689	0.1267	0.1053	0.1193	0.0849	0.2975	0.1739	17.63%	21.23%
w/ CE	0.0734	0.0464	0.1299	0.0894	0.1356	0.1154	0.1284	0.1052	0.3227	0.1917	6.98%	4.70%
w/ RE	0.0123	0.0062	0.0096	0.0048	0.0225	0.0157	0.0389	0.0175	0.0349	0.0173	85.01%	89.03%
w/o CE	0.0612	0.0341	0.1065	0.0701	0.1271	0.1057	0.1201	0.0851	0.2994	0.1749	17.07%	20.60%
w/o SE	0.0743	0.0472	0.1269	0.0879	0.1359	0.1154	0.1312	0.1077	0.3253	0.1918	6.63%	4.28%
w/o RE	0.0853	0.0519	0.1294	0.0883	0.1376	0.1141	0.1413	0.1104	0.3312	0.1958	1.72%	1.74%
SEAR	**0.0863**	**0.0525**	**0.1335**	**0.0901**	**0.1393**	**0.1169**	**0.1447**	**0.1124**	**0.3338**	**0.1985**	-	-

Table 5: Ablation studies on PCA. The best results are in boldface.

	Beauty		Games		Supplies		Scientific		ML-1M		Average Drop	
	H@10	N@10	H@10	N@10	H@10	N@10	H@10	N@10	H@10	N@10	H@10	N@10
w/o PCA_{IE} & PCA_{CE}	0.0770	0.0484	0.1303	0.0889	0.1364	0.1158	0.1358	0.1103	0.3225	0.1936	4.96%	2.88%
w/o PCA_{IE}	0.0837	0.0515	0.1325	0.0894	0.1391	0.1168	0.1428	0.1117	0.3275	0.1941	1.42%	1.12%
w/o PCA_{CE}	0.0815	0.0503	0.1331	0.0896	0.1387	0.1162	0.1442	0.1121	0.3329	0.1979	1.38%	1.18%
SEAR	**0.0863**	**0.0525**	**0.1335**	**0.0901**	**0.1393**	**0.1169**	**0.1447**	**0.1124**	**0.3338**	**0.1985**	-	-

In contrast, traditional collaborative SR methods and soft label enhanced SR methods that treat items merely as categorical IDs tend to underperform. This is mainly because they rely solely on the statistical co-occurrence patterns within the dataset, failing to exploit the rich semantic information embedded in the items. Semantic information is often more generalizable and enables the model to better understand and capture user preferences. Moreover, these methods typically ignore the valuable insights provided by users' explicit ratings.

Efficiency Comparison. We evaluate the efficiency of SEAR by comparing its training and testing time with that of other baseline methods. The results, summarized in Table 3, yield several key insights. First, BERT-based methods such as BERT4Rec and LLM2Bert4Rec typically incur the highest time consumption, primarily due to the computational complexity of the BERT architecture. Compared to other Mamba-based methods such as Mamba4Rec and SIGMA, SEAR achieves superior performance but incurs a higher computational cost. This is due to its integration of three types of information, resulting in a more complex model architecture, whereas Mamba4Rec and SIGMA rely solely on collaborative signals. Notably, for LLM-involved methods such as LLM2Bert4Rec, LLM-ESR, and SEAR, the LLM is only used to generate item embeddings prior to training. During training and inference, the LLM is not involved, so the overall time cost does not increase significantly. By comparison, SEAR achieves the best performance while maintaining acceptable training and testing time.

4.3 Ablation Studies

Ablation Studies on Three Types of Embeddings (RQ2). We investigate how each type of embedding affects SEAR's performance, with the results presented in Table 4. Removing semantic embeddings (SE) is equivalent to excluding the LLM component from our deep model, thereby discarding rich semantic information derived from item attributes. As expected, removing any type of embedding leads to a performance drop. Relying solely on rating embeddings (RE) results in unacceptable performance. These findings highlight the distinct roles of the three types of embeddings and emphasize the importance of their combination. Collaborative embeddings (CE), derived from historical interactions, capture implicit user preferences and behavioral patterns, while semantic embeddings provide external knowledge that helps disambiguate item meaning and improve generalization, especially for long-tail or cold-start items. Rating embeddings act as a complementary component, helping refine the model's understanding of user preferences by explicitly modeling users' sentiment or satisfaction levels with respect to items.

Ablation Studies on PCA-based initialization (RQ3). The item embeddings and collaborative embedding layers are initialized by reducing LLM embeddings using PCA. We investigate the effectiveness of this PCA-based initialization strategy, with the results presented in Table 5. The results show that initializing either the item embeddings (IE) or the collaborative embedding (CE) layer using PCA leads to improved performance. Furthermore, initializing both of them with PCA yields the best overall performance. This is due to the fact that the semantic knowledge encoded in LLM embeddings, when appropriately compressed, provides a strong prior for user-item interaction modeling.

4.4 Hyperparameter Analysis (RQ4)

We present the performance trends corresponding to variations in the hyperparameters λ and k in Fig. 4. λ controls the distribution of

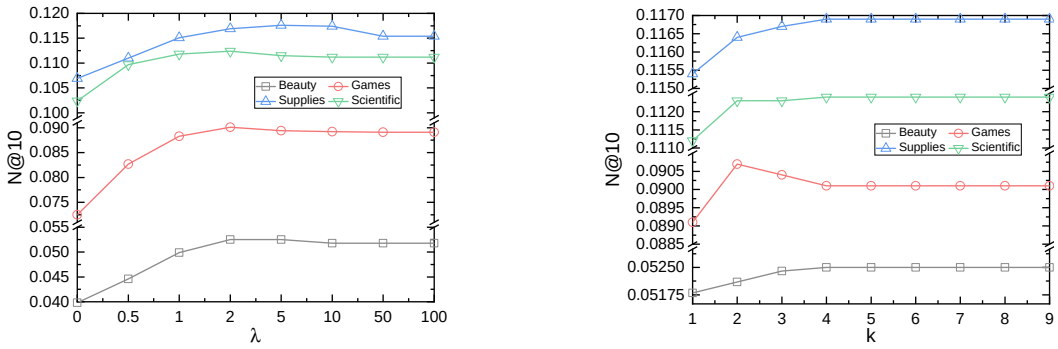
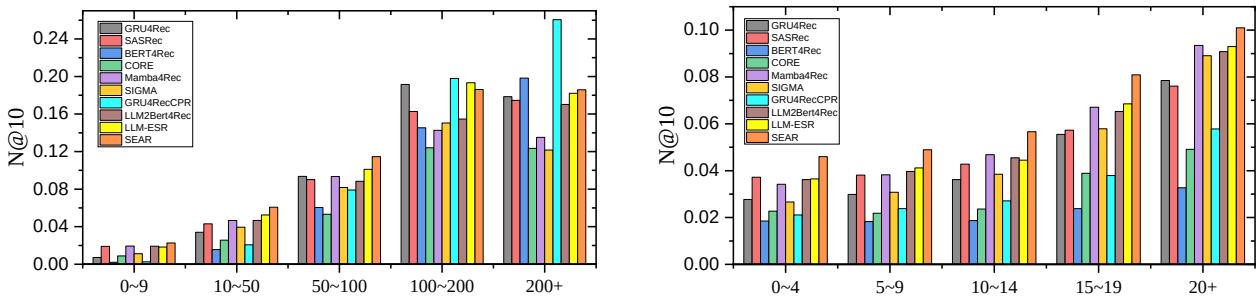


Figure 4: Effect of hyperparameters λ and k across four datasets.



(a) Item Group. (b) User Group.

Figure 5: Performance of methods on sub-test sets of the Beauty dataset, categorized by distinct user and item groups.

preference-weighted soft labels: a higher λ results in lower probabilities for items further away in the sequence. As λ increases from 0 to 100, the N@10 score first increases and then decreases. This trend occurs because a lower value of λ encourages the model to focus more on distant future items, which may not align with the user's current preferences, while a higher value of λ shifts the focus toward the immediate next item. k determines the number of future interactions considered when constructing the preference-weighted soft label. Setting $k = 1$ corresponds to training with hard labels and can be regarded as an ablation study of our soft label approach. As expected, training with preference-weighted soft labels outperforms training with hard labels, demonstrating the effectiveness of our soft label approach. Increasing k initially improves the N@10 score, indicating enhanced model performance. However, for the Games dataset, the N@10 score decreases when k exceeds 2. This may be due to the intrinsic characteristics of the dataset—items beyond the second future interaction may not accurately reflect the user's current preferences. Across all datasets, when k is larger than 5, the N@10 stabilizes. This is likely because, with λ set to 2 and without considering the rating score, the probabilities assigned to items beyond the fifth position are negligible, contributing little to the training process.

4.5 Group Analysis (RQ5)

For a more detailed analysis, we divided the Beauty dataset's test set into five subsets. For item grouping, we categorized items based on their frequency of appearance in the training dataset and split the test dataset according to the target item. For user grouping, we divided the test dataset based on the number of interactions within each user's interaction sequence. The results are presented in Fig. 5. Regarding item groups, SEAR achieves better and more balanced performance across different groups, and notably avoids a strong bias toward recommending popular items (i.e., 200+ item group). Furthermore, in user groups, SEAR consistently achieves the best performance across all groups. This indicates that even for users with few interactions, SEAR can effectively capture their preferences and recommend items of genuine interest.

5 Conclusion

In this paper, we propose SEAR, a novel framework that integrates collaborative, semantic, and rating information to enhance SR. The proposed deep model consists of an embedding layer and a sequence encoder. The embedding layer maps user-item interactions into collaborative, semantic, and rating embeddings. The sequence encoder then fuses these three types of embeddings and captures sequential patterns to model user representations. To better utilize item semantics, we incorporate an LLM. To enable the model to learn more fine-grained user behavior patterns, we construct a preference-weighted soft label based on the next k interactions. Extensive experiments demonstrate the effectiveness of SEAR.

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