

DELRec: Distilling Sequential Pattern to Enhance LLM-based Recommendation

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Abstract

Sequential recommendation (SR) tasks enhance recommendation accuracy by capturing the connection between users' past interactions and their changing preferences. Conventional models often focus solely on capturing sequential patterns within the training data, neglecting the broader context and semantic information embedded in item titles from external sources. This limits their predictive power and adaptability. Recently, large language models (LLMs) have shown promise in SR tasks due to their advanced understanding capabilities and strong generalization abilities. Researchers have attempted to enhance LLMs' recommendation performance by incorporating information from SR models. However, previous approaches have encountered problems such as 1) only influencing LLMs at the result level; 2) increased complexity of LLMs recommendation methods leading to reduced interpretability; 3) incomplete understanding and utilization of SR models information by LLMs.

To address these problems, we propose a novel framework, DELRec, which aims to extract knowledge from SR models and enable LLMs to easily comprehend and utilize this supplementary information for more effective sequential recommendations. DELRec consists of two main stages: 1) *SR Models Pattern Distilling*, focusing on extracting behavioral patterns exhibited by SR models using soft prompts through two well-designed strategies; 2) *LLMs-based Sequential Recommendation*, aiming to fine-tune LLMs to effectively use the distilled auxiliary information to perform SR tasks. Extensive experimental results conducted on three real datasets validate the effectiveness of the DELRec framework.

CCS Concepts: • Information systems → Recommender systems.

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1 INTRODUCTION

Sequential recommendation (SR) tasks aim to improve the accuracy of recommendations by understanding and modeling the relationship between users' interaction history and their evolving preferences. However, traditional SR models only capture sequential patterns within training data, often overlooking the broader context and semantic information embedded in item titles that can be obtained from external sources. These limitations restrict their predictive ability and adaptability to constantly changing scenarios.

Recently, large language models (LLMs) have shown promise in SR tasks due to their advanced comprehension abilities and powerful generalization capabilities. As LLMs are trained on vast datasets containing abundant information, including inherent item features and details, they can infer user preferences and predict future actions by leveraging LLMs' understanding of item attributes and reasoning based on world knowledge. However, using LLMs directly as sequential recommenders can pose certain problems. For instance, due to a lack of domain-specific expertise in recommendation or an incomplete understanding of the recommendation patterns in SR tasks, LLMs often exhibit poor performance when directly used as recommender.

Therefore, researchers have previously proposed providing LLMs with auxiliary information from conventional SR models. These approaches aim to assist LLMs in making more accurate recommendations when performing SR tasks. We can roughly categorize the alignment of SR models with LLMs' recommendation into three paradigms: 1) providing SR models information in textual form to LLMs; 2) combining the embeddings from SR models encodings with those from LLM encodings; 3) supplying LLMs with embeddings derived from SR models encodings. They are illustrated in Figure 1. However, previous methods have encountered certain issues.

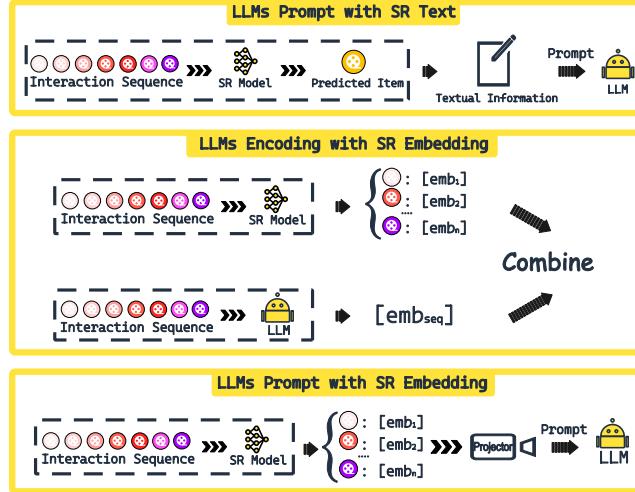


Figure 1. Demonstration of three paradigms of the alignment of SR models with LLMs’ recommendation

- **LLMs Prompt with SR Text:** This paradigm typically involves directly incorporating the recommendation results or textual information from conventional SR models into the prompt. However, this paradigm often suffers from subpar recommendation performance due to the limited information provided by the prompt. The prompt can only assist LLMs in making decisions based on the results but cannot guide LLMs from the perspective of the recommendation process. One fundamental reason is that natural language is often insufficient for accurately and comprehensively describing the specific recommendation behavior patterns of SR models.
- **LLMs Encoding with SR Embedding:** This paradigm instead of using LLMs as recommenders and utilizes their encoding and representation capabilities. It typically involves utilizing LLMs to encode a given text or sequence and simultaneously employing conventional models to obtain item or user encodings. Subsequently, these two types of embeddings are combined and processed in various ways to generate recommendation scores for items. Although this paradigm enables the integration of information from both SR models and LLMs, it also introduces challenges in comprehending and interpreting recommendations. This may potentially undermine some key advantages of using LLMs for recommendations, such as their simplicity and interpretability.
- **LLMs Prompt with SR Embedding:** This paradigm combines some advantages from the previous paradigms by typically merging embeddings from SR models with a prompt before inputting them into LLMs to generate item recommendations. This paradigm uses embeddings encoded by SR models as auxiliary information for the recommendation process provided to LLMs and often involves

a projector to align the dimensions of SR model’s embeddings with the language space of LLMs. However, due to poor projector design or changes in embedding dimensions that result in information loss, LLMs may not fully comprehend the meanings conveyed by these embeddings.

To tackle the aforementioned problems, we propose Distilling Sequential Pattern to Enhance LLM-based Recommendation (DELRec) framework, which aims to distill the behavioral patterns of SR models and empower LLMs to easily comprehend and leverage this supplementary information for more effective sequential recommendations. DELRec is roughly shown in Figure 2, and it contains:

- **SR Models Pattern Distilling:** Rather than inputting encoded information from SR models or LLMs as previous methods did, the approach of *SR Models Pattern Distilling* is inspired by knowledge distillation techniques used in LLMs. The objective is to distill the recommendation patterns and information of conventional SR models understandable to LLMs. This involves using LLMs to extract useful knowledge into soft prompts. Through two learning components, namely *SR Models Temporal Analysis* and *Recommendation Pattern Simulating*, LLMs are empowered to comprehend and simulate recommendation process employed by SR models effectively. This is a process of transforming the knowledge of SR models into a form that LLMs can understand and use.
- **LLMs-based Sequential Recommendation:** After getting the distilled SR knowledge in the first stage for SR tasks, we propose *LLMs-based Sequential Recommendation* for effectively instructing LLMs. Instead of using a projector for embedding mapping, we insert the learned soft prompts directly into the prompt, and then fine-tune the LLMs to adapt to the learning tasks that utilize auxiliary information.

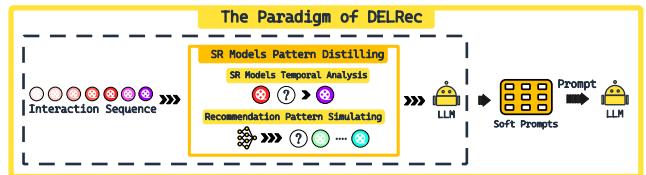


Figure 2. Demonstration of the paradigm of DELRec with proposed learning components

The main contributions of our work are summarized as follows:

- Proposing two novel components in DELRec to distill the sequential recommendation patterns of SR models in soft prompts as accurately as possible.
- Designing an ingenious method to fine-tune LLMs to enable them to use the distilled auxiliary information appropriately, thereby reducing information loss.

- Conducting extensive experiments to demonstrate the effectiveness of DELRec.

2 PRELIMINARY

2.1 Task Formulation

We consider a recommender system with a set of users U , where a user $u \in U$ has an interaction sequence that consists of a sequence of n items (I_1, I_2, \dots, I_n) in chronological order (n can be different for different users). The SR task is defined as follows: given the user interaction sequence $I_{1:n-1} = (I_1, I_2, \dots, I_{n-1})$, a sequential recommender aims to predict the target item I_n from a set of candidate items C , where candidate set that consists of m items (I_1, I_2, \dots, I_m) is typically selected from the entire item set I , where $m \ll |I|$.

Different from conventional SR models, we leverage LLMs to solve the recommendation task in an instruction following paradigm. Specifically, for each user u , we construct a history prompt including the user's interactions $I_{1:n-1} = (I_1, I_2, \dots, I_{n-1})$, a candidate item prompt including the candidate items C , and soft prompts including the recommendation patterns and information of conventional SR models. The aforementioned prompts are concatenated along with an instruction that explicitly describes the recommendation task, forming the final prompt P for LLMs. Finally, LLMs employ the prompt P to predict the target item I_n .

2.2 Prompt Tuning

Prompt tuning stands out as a sophisticated technique that refines the ability of LLMs to conform to specific linguistic tasks and patterns, through allowing soft prompts within the prompt P to adapt to the target task. Specifically, it involves constructing a dataset $D = \{(x_i, y_i)\}_{i=1, \dots, N}$, where x_i denotes the prompts and y_i the anticipated outcomes. We can instruct LLMs to update the parameters of the soft prompts while using D with an emphasis on the target learning objective:

$$\max_{\Phi} \sum_{(x,y) \in D} \sum_{t=1}^{|y|} \log(P_{\Phi_0 + \Phi}(y_t | x, y_{<t})), \quad (1)$$

where Φ represents the parameters of soft prompts, Φ_0 is the parameters of the LLMs, y_t is the t -th token of y , and $y_{<t}$ indicates the sequence of tokens preceding y_t .

2.3 Parameter Efficient Fine-Tuning

The comprehensive fine-tuning of all parameters within LLMs demands considerable time and computational resources. To mitigate this issue, the approach of Parameter-Efficient Fine-Tuning (PEFT) concentrates on adjusting a minimal subset of parameters, thereby reducing computational demands while maintaining notable performance levels. An example of a PEFT method is AdaLoRA (Adaptive LoRA), which is a method to optimize the number of trainable parameters for weight matrices and layers, unlike LoRA which evenly distributes parameters across all modules. It

allocates more parameters to important weight matrices and layers, while less important ones receive fewer parameters. The optimization goal for AdaLoRA is formulated as follows:

$$\max_{\Theta} \sum_{(x,y) \in D} \sum_{t=1}^{|y|} \log(P_{\Phi_0 + \Delta\Phi_0(\Theta)}(y_t | x, y_{<t})), \quad (2)$$

where AdaLoRA introduces the parameters Θ , which are smaller than the original LLM parameters Φ_0 .

3 METHODOLOGY

To distill the recommendation behavior patterns of conventional SR models that LLMs can understand, and to utilize them in sequential recommendation tasks based on LLMs, we propose the DELRec framework, as presented in Figure 3. Specifically, it involves two key stages. In the first stage, We do not directly use discrete hard prompts in the whole prompt as usual to add auxiliary information of SR models to LLMs or manually describe the recommendation process of SR models. Instead, we insert a series of soft prompts into the prompt and freeze the parameters of LLMs, allowing LLMs to learn the recommendation information and patterns of conventional SR models through our proposed *SR Models Pattern Distilling*.

Then, in the second stage, align the knowledge distilled from the SR models with LLM-based recommendation tasks, namely, insert the soft prompts learned in the first stage into the prompt and freeze the parameters of soft prompts. Then, fine-tune LLMs to make more accurate sequential recommendations using the auxiliary information from SR models. We now turn our attention to the specific architecture and training approach of DELRec.

3.1 Hybrid Prompt Construction

First, we will introduce the concepts of hard prompt and soft prompt involved in the DELRec framework, as well as the construction of our hybrid prompt.

Hard Prompt. In conventional LLM recommendation tasks, hard prompts are commonly used to construct the prompt or directly provide guidance information within the general prompt for LLMs, (e.g. as depicted in Figure 4).

Hard prompts also known as discrete prompts, are composed of specific vocabulary. These prompts are artificially designed and do not change during the training process of the LLMs. Explicitly, They are a set of fixed words that instruct the models how to perform in specific tasks. Denote hard prompts as hp_i , where i is the index of hard prompts in the prompt, and the general prompt P_0 is entirely constructed by hard prompts:

$$P_0 = \{hp_1, hp_2, \dots, hp_l\}, \quad (3)$$

here, l represents the number of hard prompts in the prompt. Then, after the prompt P_0 is processed by the LLM tokenizer and word embedding layer, it will become the corresponding

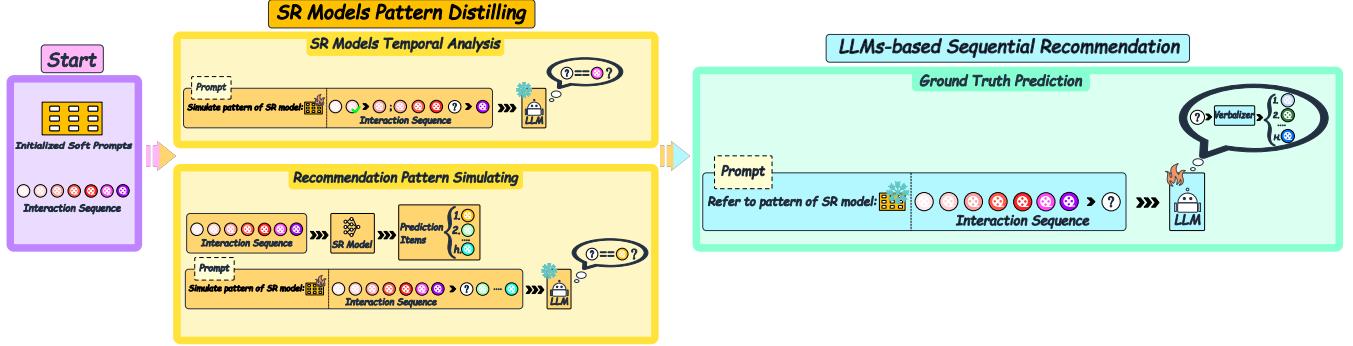


Figure 3. Illustrating the proposed DELRec that distills the recommendation behavior patterns and information of conventional SR models, with soft prompts can more easily align with LLMs and facilitate their understanding.

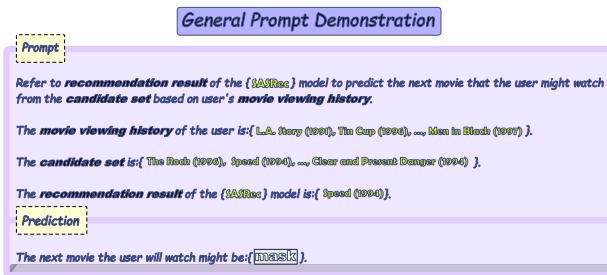


Figure 4. Demonstration of a general prompt that typically relies entirely on hard prompts to provide information for LLMs. We use movie recommendations as the background for the prompt and SASRec as the example SR model.

embeddings in the language space. We can represent this process as follows:

$$E_0 = \sum_{i=1}^l f_{tkz}(hp_i) \in \mathbb{R}^{l \times d^n}, \quad (4)$$

where E_0 is the corresponding embeddings of hard prompts in the language space of dimensionality d^n , and f_{tkz} indicates the LLM tokenizer and word embedding layer.

Soft Prompt. Although hard prompts usually correspond to natural language and are easily understood by humans, the purpose of prompt construction is to find a method that allows LLMs to effectively perform a task. Rather than being for human consumption, it is not necessary to limit the prompt to human-interpretable natural language. Therefore, unlike the general prompt P_0 , we will insert a portion of soft prompts into the construction of the hybrid prompt, as shown in Figure 5.

These soft prompts remove the constraint of hard prompts that the embedding of the prompt words can only be the embedding of natural language words. These soft prompts can be adjusted according to the training data from downstream tasks, allowing us to provide some "only LLMs understand"

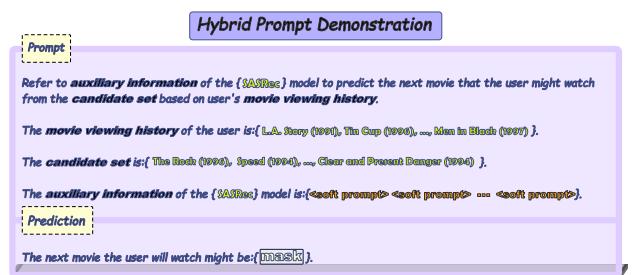


Figure 5. Demonstration of a hybrid prompt inserting a series of soft prompts when constructs the prompt, and these soft prompts are directly randomly initialized as word embeddings.

knowledge to the LLMs in the prompt, and this knowledge is difficult or impossible for us to describe in natural language. Formally, we denote soft prompts as sp_j , where j is the index of soft prompts in the prompt, and our hybrid prompt P_1 is constructed by both hard and soft prompts:

$$P_1 = \{hp_1, hp_2, \dots, sp_1, sp_2, \dots, sp_k, \dots, hp_{l-1}, hp_l\}, \quad (5)$$

where k represents the number of soft prompts in the hybrid prompt. Afterwards, similar to the general prompt P_0 constructed by pure hard prompts, Both hard prompts and soft prompts in the hybrid prompt P_1 will also become word embeddings. However, unlike hard prompts that will correspond to a fixed position in the language space, soft prompts will be processed into randomly initialized embeddings. As LLMs learn the target task, the position of the soft prompts in the language space will change:

$$E_1 = \sum_{j=1}^k f_{iniz}(sp_j) \in \mathbb{R}^{k \times d^n}, \quad (6)$$

where E_1 represents the corresponding embeddings directly initialized by the soft prompts, and f_{iniz} indicates the process of randomly initializing to the same dimension as the word embeddings in the language space of LLMs.

Prompt Design. In our prompt design, inspired by previous research, since LLMs cannot understand the semantic information of id-based item representations well, we will use pure text to represent the user’s interaction sequence and candidate item set (*e.g.*, *L.A. Story* (1991), *Tin Cup* (1996), ..., *Men in Black* (1997)). And based on the aforementioned hard prompts and soft prompts, we will design various hybrid prompts corresponding to different tasks.

Specifically, our prompt design will be different in two stages. In the *SR Models Pattern Distilling* stage, we will design different prompts for each of the two components, aiming to better distill the recommendation behavior patterns and information of SR models. In the *LLMs-based sequential recommendation* stage, the goal of our prompt design is to enable LLMs to better use the information distilled in the first stage to make accurate recommendations. The two stages described above are introduced next.

3.2 SR Models Pattern Distilling

Previous research has shown that providing LLMs with information from conventional recommendation models will enhance the performance of LLMs as recommenders. Inspired by this, we will provide LLMs with better, more understandable and usable information. To this end, we propose the *SR Models Pattern Distilling*, and use the soft prompts mentioned above to more accurately capture the recommendation behavior patterns of conventional SR models for LLMs. Specifically, the *SR Models Pattern Distilling* stage is divided into two components, namely *SR Models Temporal Analysis* and *Recommendation Pattern Simulating*. Next, we will introduce these in detail one by one.

SR Models Temporal Analysis. Since one of the focuses of SR tasks is to recommend items that are temporally closer based on the user’s interaction sequence, which exhibits strong temporal dynamics, it is crucial to perform a temporal analysis of SR models and providing similar temporal knowledge to LLMs in order to better simulate the recommendation patterns of SR models.

Most SR models (*e.g.* SASRec) achieve this by aggregating the features of items in user interaction sequence to the most recent item in the sequence. Our idea is to enable LLMs to similarly recognize and learn the importance of “the most recent item”, thereby acquiring relevant temporal knowledge. Therefore, our proposed strategy is to provide the interaction sequence and target item, and let the LLMs predict the most recent item in the sequence—a behavior we refer to as PMRI (Predicting Most Recent Item).

Specifically, our strategy will allow LLMs to perform PMRI on the sequences and we will also provide In-Context Learning (ICL) in an ingenious way to not only help LLMs enhance their learning efficiency and quality, but also increase LLMs’ awareness of temporal coherence, our strategy is as follows:

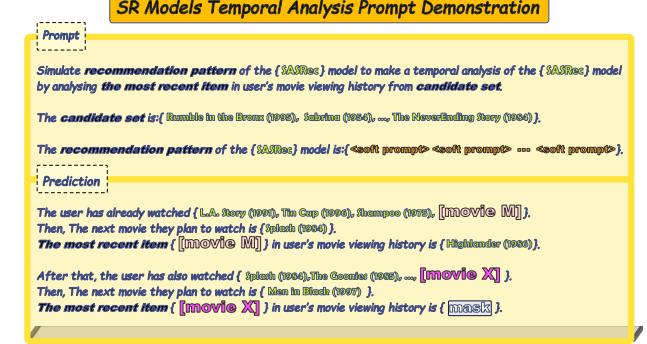


Figure 6. Demonstration of the prompt for *SR Models Temporal Analysis*. The previous part of the interaction sequence is used as ICL to provide LLMs with examples that bridge the gap between previous and subsequent parts. LLMs are then tasked with PMRI, enabling them to learn a similar process to temporal feature aggregation of SR models.

Given the user interaction sequence $I_{1:n-1} = (I_1, I_2, \dots, I_{\alpha-1}, I_\alpha, \dots, I_{n-2}, I_{n-1})$, then we inform LLMs that the α -th item will be the next interaction item for the sequence of the first k items $I_{1:\alpha-1}$, which takes the previous part of the sequence as ICL provided to the LLMs. Similarly, we take the last item I_{n-1} as the next item for sequence $I_{\alpha:n-2}$ and mask the second-to-last item I_{n-2} , allowing LLMs to predict the masked item I_{n-2} and assign it as the label y^0 for this task. During the prediction process, we will use a simple verbalizer to effectively convert the output of the LLM head (*i.e.*, the output scores of all tokens) into ranking scores for all items. In the learning process, the parameters of the LLMs Φ_0 are frozen, and only the parameters of the soft prompts Φ are updated. Afterward, the soft prompts in the prompt will contain knowledge of the SR models’ aggregation of item features and knowledge similar to the temporal information of SR models. The prompt of whole process is shown in Figure 6. Formally, the learnable parameters of soft prompts Φ are optimized by minimizing the loss function of *SR Models Temporal Analysis*:

$$L_{\text{temporal_analysis}} = \sum_{(x^0, y^0) \in D_0} -\log(P_{\Phi_0 + \Phi}(y^0 | x^0)), \quad (7)$$

where $D_0 = \{(x^0, y^0)\}_{i=1, \dots, N}$ contains the prompt and masked item in the aforementioned.

Recommendation Pattern Simulating. Besides *SR Models Temporal Analysis*, it is also essential for LLMs to be able to simulate conventional SR models in making similar recommendations, which enables the distillation from the recommendation knowledge of SR models into soft prompts.

Specifically, we will have LLMs simulate the recommendation patterns of SR models as closely as possible and let LLMs predict the recommendation results of SR models (*rather than the ground truth*) based on the user interaction sequence. This process can be described as: given the user

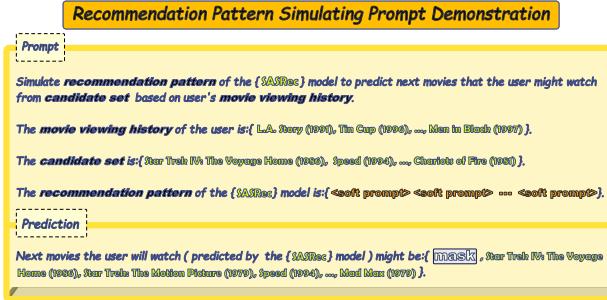


Figure 7. Demonstration of the prompt for *Recommendation Pattern Simulating*. We will use LLMs to learn from the recommendation results of SR models, thereby simulating the recommendation patterns of SR models.

interaction sequence $I_{1:n-1} = (I_1, I_2, \dots, I_{n-1})$ and providing the top h recommended items $sr_{1:h} = (sr_1, sr_2, \dots, sr_h)$ based on the SR model’s predicted probabilities for interaction sequence, we take the highest probability item sr_1 as the label y^1 for the *Recommendation Pattern Simulating* task. Then, during the prediction of y^1 , LLMs update the parameters of soft prompts, allowing LLMs to fit the results of the SR model well. The prompt of the task is shown in Figure 7. Specifically, the loss function of *Recommendation Pattern Simulating* task can be formulated as:

$$L_{pattern_simulating} = \sum_{(x^1, y^1) \in D_1} -\log(P_{\Phi_0 + \Phi}(y^1 | x^1)), \quad (8)$$

where $D_1 = \{(x_i^1, y_i^1)\}_{i=1, \dots, N}$ consists of the prompt and SR models predicted item in the aforementioned *Recommendation Pattern Simulating* step.

After obtaining the loss functions for *SR Models Temporal Analysis* and *Recommendation Pattern Simulating*, we will proceed to update the parameters of soft prompts in a multi-task learning (MTL) manner, allowing LLMs to learn from two target tasks simultaneously, thereby achieving the distillation of recommendation behavior patterns for SR models. The learning objective can be defined as:

$$\min_{\Phi} \{\lambda_1 L_{temporal_analysis} + \lambda_2 L_{pattern_simulating}\}, \quad (9)$$

where λ_1 and λ_2 represent the weights of learning objectives of the two components. We employ HydaLearn, an intelligent algorithm for task weight adjustment in MTL[HydaLearn], to dynamically adjust the values of λ_1 and λ_2 during training.

3.3 LLMs-based Sequential Recommendation

In the first stage (SR Models Pattern Distilling), we successfully distilled the recommendation patterns from the SR models. In previous research, to enable LLMs to utilize auxiliary information from conventional SR models (such as item embeddings), people often used projectors (*e.g.*, MLP, Tiny Transformers) to map the embeddings into the language space of LLMs. However, this approach often suffers

from poorly designed projectors, which may fail to fully convey the information embedded in the original embeddings to LLMs or limit their generalization capabilities, etc. Therefore, the soft prompts we distilled can achieve plug-and-play and overcome these issues. The prompt is shown in Figure 8.

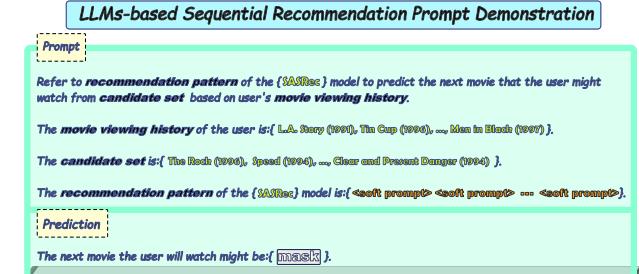


Figure 8. Demonstration of the prompt for *LLMs-based Sequential Recommendation*. We will provide LLMs with the recommendation patterns and information of SR models (*i.e.*, the soft prompts) distilled from the first phase and guide the LLMs to use this auxiliary information to predict the ground truth.

Specifically, we directly incorporate the learned soft prompts $sp_{1:k} = (sp_1, sp_2, \dots, sp_k)$ into the hybrid prompt $P1$. In other words, we use the distilled recommendation behavior patterns from the SR models as context for LLMs to predict the target I_n :

$$I_n = LLM(P1(sp_{1:k})) \quad (10)$$

where $P1(\cdot)$ represents the process of integrating soft prompts $sp_{1:k}$ into hybrid prompt $P1$, and $LLM(\cdot)$ indicates that LLMs utilize the prompt to perform SR tasks.

LLMs Fine-tuning. However, considering there may be noise or harmful information in soft prompts, which may guide LLMs to make predictions that are more inclined to SR models’ predictions than to ground truth. Therefore, we need to fine-tune the parameters of LLMs to guide them to regard soft prompts as reference more. Formally, given a user interaction sequence $I_{1:n-1} = (I_1, I_2, \dots, I_{n-1})$, where the next item I_n the user will interact with is the label \bar{y} . In the learning process, when using soft prompts as auxiliary information to guide LLMs in predicting label \bar{y} , freeze the parameters of soft prompts Φ and fine-tune the LLMs using PEFT (AdaLora). Formally, the learning objectives of the LLMs-based Sequential Recommendation can be described as follows:

$$\min_{\Theta} \{L_{recommendation} = \sum_{(\bar{x}, \bar{y}) \in \bar{D}} -\log(P_{\Phi_0 + \Delta\Phi_0(\Theta) + \Phi}(\bar{y} | \bar{x}))\}, \quad (11)$$

where $\bar{D} = \{(\bar{x}_i, \bar{y}_i)\}_{i=1, \dots, N}$ contains the prompt \bar{x} and the anticipated ground truth \bar{y} .

Table 1. Statistics of Datasets

Dataset	#sequence	#item	#interaction
MovieLens	6,040	3,416	100,000
Steam	11,938	3,581	274,726
Beauty	22,363	12,099	198,474

4 EXPERIMENTS

In this section, we assess the performance of our proposed framework, DELRec, on three real-world datasets. We compare it against various baselines, including conventional SR models and LLMs-based models.

- **RQ1:** Whether the proposed framework outperforms baseline methods, including the deep learning models and other LLM based models, for SR?
- **RQ2:** Are our proposed DELRec able to learn meaningful recommendation behavior patterns or information?
- **RQ3:** How can key components affect our proposed method. Specifically, how is the efficacy of the proposed *SR Models Temporal Analysis* and *Recommendation Pattern Simulating*?
- **RQ4:** How do hyperparameters influence DELRec?

4.1 Setup

4.1.1 Datasets. We evaluate the proposed DELRec and baseline methods on three real-world datasets in sequential recommendations, namely MovieLens-1M and Beauty, as well as Steam.

- **MovieLens-1M** is a commonly used movie recommendation dataset that includes ratings given by users to movies and the titles of those movies.
- **Beauty** is a dataset containing user feedback on beauty products from Amazon website.
- **Steam** not only contains user reviews of video games on the Steam Store, but also covers a variety of game titles.

We show the detailed statistics of the datasets in Table 1. For all datasets, we follow [SASRec] in treating users' implicit feedback as interactions between users and items, and determine the sequence order of inputs based on timestamps. Subsequently, we filter out users and items with fewer than 5 interactions. Meanwhile, we arrange them in chronological order as [LLaRA] do, and divide the data into training, validation, and test sets in an 8:1:1 ratio. This division method ensures that interactions used for training do not appear in subsequent data, thereby avoiding any potential information leakage.

4.1.2 Baselines. To demonstrate the effectiveness of our DELRec framework, we use two types of baselines.

- **Conventional SR Models:** The first type includes conventional SR models: **GRU4Rec**[16] (based on RNN), **Caser**[44]

(based on CNN) and **SASRec**[25] (based on attention), which are often used as standard comparisons.

- **LLMs-based Models:** The second type of baseline includes: (1) **Bert-Large** is a milestone LLM capable of performing Masked language modeling (MLM) tasks. (2) **FLan-T5-Large/XXL** are well-known open-source LLMs with an encoder-decoder structure. (3) **LlamaRec** uses a traditional model to recall items and construct a candidate set and a verbalizer to directly output item rankings. (4) **RecRanker** cleverly samples items and users and inputs the results of conventional recommendation models into the prompt. (5) **LLaRA** inserts the embedding of items encoded by the SR model into the prompt. For the validity of the experiment, we have replaced the backbone of LLMs-based baselines with **FLan-T5-XL**.

4.1.3 Implementation Details. For our proposed DELRec framework, we choose **FLan-T5-XL** as our backbone and we will also use **FLAN-T5-Large** to perform ablation experiments. It's worth noting that the backbone of our proposed framework can also use open-source Decoder-Only structured LLMs, such as Llama2[Llama], and is not constrained by the types of LLMs. For the training of conventional SR models, we use the Adam optimizer, with a learning rate of 1e-3 and a batch size of 128. For the first stage of DELRec (*SR Models Pattern Distilling*), for the length of user interaction sequences n , we take 10, and we take the most recent 10 interactions as the user interaction sequence in order, and pad sequences that are less than 10. For the number of user candidate items m takes 20, and we insert the correct value to be predicted and 19 random items into the item candidate set. Regarding the number of examples α in the ICL of *SR Models Temporal Analysis*, we have chosen α as 3 for MovieLens-1M and Beauty based on [Improve Temporal Awareness], and we have selected α as 5 for Steam. For the first stage of Prompt Tuning, we use the Lion optimizer, with a learning rate of 5e-3 and weight decay of 1e-5 on and run on 5 Nvidia 3090 GPUs. For the second stage (*LLMs-based Sequential Recommendation*), we use the same values of n and m as in the first stage, and also use AdaLoRA and Lion optimizer, with a learning rate of 1e-4 and weight decay of 1e-6.

4.1.4 Evaluation Metrics. For ranking evaluation, we use top- k Hit Rate (HR@ k) as measurement metric, specifically adopting HR@1, HR@5.

4.2 Performance Comparison (RQ1)

Table 2 presents the performance of our method DELRec and various baselines under three evaluation metrics. Comparing DELRec with the aforementioned baseline models, we can derive the following observations.

- DELRec outperforms all baseline models on the MovieLens-1M, Beauty, and Steam datasets. It achieves the highest

Table 2. Overall Performance

		<i>MovieLens-1M</i>		<i>Steam</i>		<i>Beauty</i>	
		HR@1	HR@5	HR@1	HR@5	HR@1	HR@5
Conventional	Caser	0.3150	0.6340	0.3767	0.6680	0.2241	0.4187
	GRU4Rec	0.3062	0.6295	0.3786	0.6835	0.2369	0.4544
	SASRec	0.3341	0.6704	0.3852	0.6977	0.2573	0.4629
LLMs-based	Bert-Large	0.0306	0.0821	0.0201	0.0424	0.0166	0.0354
	Flan-T5-Large	0.0375	0.0703	0.0240	0.0493	0.0195	0.0346
	Flan-T5-XL	0.0938	0.2441	0.0723	0.1662	0.0652	0.1071
	LlamaRec	0.2870	0.5873	0.3511	0.6478	0.2361	0.4418
	RecRanker	0.3246	0.6292	0.3724	0.6537	0.2670	0.4943
Ours	LLaRA	0.3523	0.6553	0.4035	0.6911	0.3152	0.6063
	DALRec (Caser)	0.3664	0.6804	0.4157	0.6946	0.3249	0.6175
	DALRec (GRU4Rec)	0.3635	0.6722	0.4296	0.7099	0.3413	0.6229
Ours	DALRec (SASRec)	0.3701	0.6919	0.4372	0.7285	0.3477	0.6513

HR@1, HR@5, and NDCG@5 scores compared to conventional SR models that only recommend through user interactions or LLMs that lack recommendation knowledge. The key reason behind this superior performance is that DELRec effectively combines the information from conventional SR models with the powerful reasoning capabilities and extensive world knowledge of LLMs to complete more accurate recommendations.

- When comparing with some original open-source LLMs (*e.g.*, **BERT**, **Flan-T5**), it is evident that these baseline models not only underperform DELRec in recommendation tasks but also exhibit lower metrics compared to conventional SR models and other LLMs-based recommendation methods. The reason behind this discrepancy lies in the fact that while these LLMs possess strong generalization capabilities, they lack domain-specific knowledge and understanding of recommendation patterns, which hinders their performance in recommendation tasks. Therefore, providing appropriate auxiliary information to adapt LLMs to specific recommendation tasks becomes crucial.
- When considering the other LLMs-based improvements we have chosen, the reasons for DELRec's superior performance can be analyzed from several perspectives. Firstly, while some methods enable LLMs to perform recommendation tasks (*e.g.*, **LlamaRec**), although they filter out recommended items from conventional models for LLMs, there is still room for improvement in terms of providing guidance information for LLMs' recommendations. Secondly, some methods directly provide recommendation results from conventional recommendation models to LLMs (*e.g.*, **RecRanker**), but since there is no information on users' past behavior with respect to recommendations, LLMs can only make decisions based on these results. Thirdly, methods that provide user or item encoding information through dimension transformation to LLMs (*e.g.*, **LLaRA**),

Table 3. Ablation analysis for learned soft prompts on three datasets (HR@1).

	<i>MovieLens-1M</i>	<i>Steam</i>	<i>Beauty</i>
No Soft Prompts	0.3020	0.3426	0.2965
Manual Construction	0.3106	0.3608	0.2898
Random Soft Prompts	0.2752	0.2977	0.2284
Default	0.3701	0.4372	0.3477

while containing some pattern information from SR models, suffer from loss of information due to inconsistent dimensions and may not align perfectly with the linguistic meaning of LLMs, resulting in lower performance compared to DELRec.

4.3 Ablation Studies (RQ2 & RQ3)

To address **RQ2**, we conducted an experiment on the soft prompts distilled in the initial stage of DELRec and we use **SASRec** as the backbone model. As these soft prompts do not correspond to natural language and are not easily interpretable by humans, we performed three transformations on a portion of the soft prompts to verify if they truly capture meaningful recommendation behavior patterns or information. These transformations include:

- **No Soft Prompts:** We removed the soft prompts section and the part of instruction that directs LLMs to refer to auxiliary information from the SR models.
- **Manual Construction:** Similar to the general prompt where hard prompts are used to construct auxiliary information, for constructing auxiliary information, we attempted to describe the recommendation process of SASRec model in natural language and replaced the original soft prompts with it.

- **Random Soft Prompts:** Soft prompts that have not undergone distillation in the first stage were directly initialized randomly and inserted into our prompt.

Finally, the three transformed methods are compared with the complete DELRec after fine-tuning in the second stage. Table 3 shows the measurement metrics of DELRec under four different conditions. Based on our observations, we make the following inferences.

- In methods that solely utilize pure hard prompts without soft prompts or manual construction, the Manual Construction method enhances LLMs by describing the recommendation patterns of the SR model in natural language. However, due to inaccuracies or insufficient information in these descriptions, the metrics of this method only show slight improvements compared to the No Soft Prompts method.
- Among the few baselines we selected, the Random Soft Prompts method performs poorly in terms of metrics. This can be attributed to random soft prompts being scattered throughout the semantic space with no meaningful context, resulting in strong noise and providing little assistance or potentially misleading LLMs.
- Soft prompts that have undergone our designed *SR Models Pattern Distilling* approach surpass all three methods mentioned above. This indicates that our distillation method is able to effectively extract valuable recommendation patterns and information from SR models for LLMs.

We will verify the impact of various components in DELRec on the framework through the following ablation experiments (**RQ3**). The results are shown in Table 4. We introduce the variants and analyze their effect respectively:

- **w/o SMPD (SR Models Pattern Distilling):** By eliminating the process of distilling recommendation behavior patterns from SR models in the first stage of DELRec, we observed a decline in performance. This is because LLMs lack auxiliary information from SR models, which hinders their ability to guide the recommendation process effectively.
- **w/o LSR (LLMs-based Sequential Recommendation):** After distillation in the first stage, excluding the fine-tuning process of LLMs in the second stage resulted in a decrease in metrics. This can be attributed to using information extracted directly from SR models, which introduces noise that may interfere with LLM recommendations. Additionally, LLMs are more likely to favor the items predicted by the SR model rather than the ground truth.
- **w/o SMTA (SR Models Temporal Analysis):** Removing *SR Models Temporal Analysis* during the first stage leads to distilled soft prompts lacking temporal characteristics. As a result, there is insufficient guidance for LLMs to mimic feature aggregation processes similar to those employed by SR models.
- **w/o RPS (Recommendation Pattern Simulating):** Eliminating *Recommendation Pattern Simulating* during the first stage

Table 4. Ablation analysis (HR@1) on three datasets.

	<i>MovieLens-1M</i>	<i>Steam</i>	<i>Beauty</i>
w/o SMPD	0.3020	0.3426	0.2965
w/o LSR	0.2814	0.3235	0.2666
w/o SMTA	0.3425	0.3710	0.2949
w/o RPS	0.3379	0.3555	0.3103
w Flan-T5-Large	0.2592	0.3018	0.2384
Default	0.3701	0.4372	0.3477

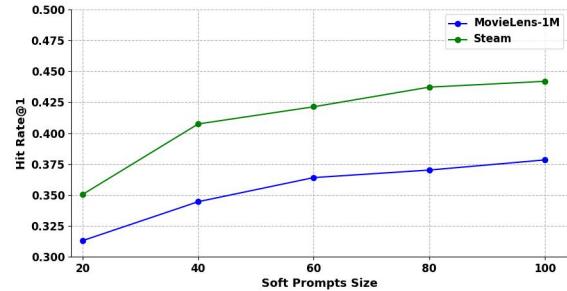


Figure 9. Performance comparison w.r.t different soft prompts size k for training DELRec on the three datasets.

disrupts alignment between prediction results of LLMs and those of SR models. Consequently, it becomes challenging for LLMs to effectively simulate overall recommendation behavior patterns exhibited by SR models.

- **w Flan-T5-Large:** In addition to conducting ablation experiments on components within DELRec framework, we also explored using **Flan-T5-Large** as a smaller-scale backbone language model within our framework. The experimental results indicated that both size and capacity of LLMs have an impact on DELRec's performance.

4.4 Hyperparameter Analysis (RQ4)

We will conduct experiments on the hyperparameters in our proposed DELRec, including soft prompts size k and top h recommended items from the SR model (e.g., SASRec).

- **Soft Prompts Size:** Regarding the size of soft prompts, we examined its impact on DELRec's performance. As depicted in Figure 9, we observed that DELRec's performance metrics initially improve with an increase in k . However, after reaching a certain value, these metrics start to level off. This can be attributed to the fact that while soft prompts enhance prompt information through LLMs' learning process, an excessive amount of soft prompts may introduce noise or potentially lead to overfitting. Consequently, after soft prompts reach a certain size, they will not significantly contribute to the improvement of overall performance.

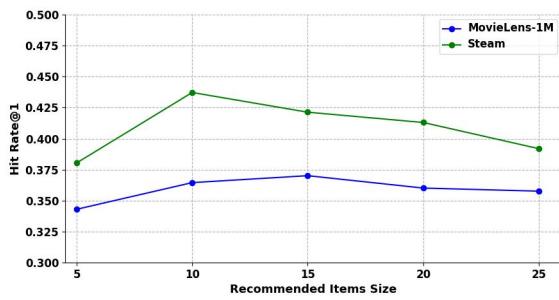


Figure 10. Performance comparison w.r.t different recommended items size h for training DELRec on the three datasets.

- **Recommended Items Size:** We investigated how the overall performance changes with varying sizes h of recommended items provided by the SR model during the *Recommendation Pattern Simulating*. Figure 10 illustrates that there is a relationship between h and overall performance. The variation observed can be explained by considering that providing SR model-recommended items helps LLMs understand recommendation patterns. However, if too large recommended items size is set, it may not only mislead LLMs but also result in excessively long prompts which could potentially impact LLMs' attention mechanism.

4.5 Case Study

In order to further investigate the effectiveness of integrating recommendation behavior patterns from SR models with the world knowledge of LLMs, we conducted a comparative case study among FLan-T5-XL, SASRec, and DELRec.

Here we choose a distinct example. For a user with a movie viewing history that includes "American Beauty (1999)", "Legends of the Fall (1994)", "Gladiator (2000)", "Out of Sight (1998)", "GoldenEye (1995)", "Mission: Impossible (1996)", "Malice (1993)", "Amistad (1997)", "Jurassic Park (1993)" and "Men in Black (1997)". We have utilized Flan-T5-XL, SASRec, and DELRec to generate recommendations for this particular user.

As shown in Figure 11, we observe that based on the knowledge contained in Flan-T5-XL, it recommended the sequel film "Men in Black II (2002)" to the user since their last watched movie was "Men in Black (1997)". On the other hand, SASRec predicted recommendations by considering the user's most recent viewing history and suggested an action/sci-fi film called "Aliens (1986)" which aligns with the theme of "Men in Black (1997)". In contrast, DELRec combined conventional recommendation patterns with rich world knowledge. It took into account the changing preferences of users from drama/classic to action/sci-fi genres and

it recommended "Back to the Future (1985)", which indeed was the next interaction by the user.



Figure 11. Case study comparison results of the effectiveness of three models in recommending movies: FLan-T5-XL, SASRec and DELRec.

5 RELATED WORK

In this section, we provide a literature review on LLMs for Sequential Recommendation and Prompt Tuning for Recommendation. Our work in this paper draws inspiration from these approaches to align SR models with LLMs-based recommendation.

5.1 LLMs for Sequential Recommendation

In the field of SR, recognizing the sequence of user interactions is crucial for predicting their next preference. Modern Sequential Recommender Systems (SRS) employ various techniques such as RNNs, CNNs, or transformers to identify sequential pattern in user interactions. For example, GRU4Rec utilizes GRU for analyzing session-based data, while Caser uses CNNs to model interactive data across multiple dimensions. SASRec incorporates an attention mechanism to assign weights automatically to different interactive items.

With the ongoing development of LLMs, researchers are exploring methods to integrate SR models with LLMs [33, 55, 51] in order to enhance the performance of SR tasks. LLM-TRSR segments a user's historical behavior into multiple blocks and summarizes them using an LLM-based summarizer before inputting them into prompts for sequential recommendation. Tempura employs three incentive strategies to increase the temporal awareness of LLMs and uses prompt learning to enable LLMs to return and integrate multiple results. LLaRA leverages multimodal mapping by inserting prompts with item embeddings encoded by SR models then fine-tunes LLMs with item interaction relationships. However, previous methods have encountered challenges such as LLMs not fully utilizing this information and excessive complexity among other issues.

5.2 Prompt Tuning for Recommendation

Prompt tuning is an effective paradigm where, specifically in the field of prompt tuning, prompts can be classified into two categories: hard and soft prompts. Hard prompts provide explicit textual information to language models for a given task prompt, while soft prompts can adapt and change based on specific tasks, thereby enhancing the performance of language models in recommendation tasks. Currently, most recommendation systems that are based on language models primarily utilize pure hard prompts to generate prompts for the language models. However, only a few methods have explored the use of prompt tuning in recommendation systems. For instance, RA-Rec[71] employs ID embeddings as soft prompts and incorporates an innovative alignment module along with an effective tuning method using a custom data structure for alignment.

Although soft prompts are widely utilized in various other tasks involving LMs, they are rarely employed in LLM-based SR tasks.

6 CONCLUSION

This work introduces a novel framework, DELRec, which aims to enhance the performance of LLMs in SR tasks. The framework achieves this by extracting behavioral patterns from conventional SR models. Through two main components, namely *SR Models Pattern Distilling* and *LLM-based Sequential Recommendation*. DELRec not only reduces information loss but also improves the recommendation effectiveness of LLMs. Extensive experiments on three real-world datasets have been conducted to validate the effectiveness of our proposed framework. Overall, DELRec offers a new perspective and approach for utilizing LLMs in complex sequential recommendation tasks, particularly in capturing semantic information and global context that traditional SR models fail to capture. The introduction of DELRec also provides valuable insights for future researchers in designing more efficient and accurate recommendation systems.

7 Citations and Bibliographies

Some examples. A paginated journal article [2], an enumerated journal article [10], a reference to an entire issue [9], a monograph (whole book) [23], a monograph/whole book in a series (see 2a in spec. document) [17], a divisible-book such as an anthology or compilation [12] followed by the same example, however we only output the series if the volume number is given [13] (so Editor00a's series should NOT be present since it has no vol. no.), a chapter in a divisible book [34], a chapter in a divisible book in a series [11], a multi-volume work as book [22], a couple of articles in a proceedings (of a conference, symposium, workshop for example) (paginated proceedings article) [3, 15], a proceedings article with all possible elements [33], an example of an enumerated proceedings article [14], an informally published

work [16], a couple of preprints [6, 7], a doctoral dissertation [8], a master's thesis: [4], an online document / world wide web resource [1, 27, 35], a video game (Case 1) [26] and (Case 2) [25] and [24] and (Case 3) a patent [32], work accepted for publication [29], 'YYYYb'-test for prolific author [30] and [31]. Other cites might contain 'duplicate' DOI and URLs (some SIAM articles) [21]. Boris / Barbara Beeton: multi-volume works as books [19] and [18]. A couple of citations with DOIs: [20, 21]. Online citations: [35–37]. Artifacts: [28] and [5].

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