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## **ABSTRACT** Traditional sess behavior sequer Although this s

Traditional session-based recommendation (SBR) utilizes session behavior sequences from anonymous users for recommendation. Although this strategy is highly efficient, it sacrifices the inherent semantic information of the items, making it difficult for the model to understand the true intent of the session and resulting in a lack of interpretability in the recommended results. Recently, large language models (LLMs) have flourished across various domains, offering a glimpse of hope in addressing the aforementioned challenges. Inspired by the impact of LLMs, research exploring the integration of LLMs with the Recommender system (RS) has surged like mushrooms after rain. However, constrained by high time and space costs, as well as the brief and anonymous nature of session data, the first LLM recommendation framework suitable for industrial deployment has yet to emerge in the field of SBR.

To address the aforementioned challenges, we have proposed the LLM Integration Framework for SBR (LLM4SBR). Serving as a lightweight and plug-and-play framework, LLM4SBR adopts a two-step strategy. Firstly, we transform session data into a bimodal form of text and behavior. In the first step, leveraging the inferential capabilities of LLMs, we conduct inference on session text data from different perspectives and design the component for auxiliary enhancement. In the second step, the SBR model is trained on behavior data, aligning and averaging two modal session representations from different perspectives. Finally, we fuse session representations from different perspectives and modalities as the ultimate session

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representation for recommendation. We conducted experiments on two real-world datasets, and the results demonstrate that LLM4SBR significantly improves the performance of traditional SBR models and is highly lightweight and efficient, making it suitable for industrial deployment.

#### **CCS CONCEPTS**

• Information systems → Recommender systems.

## **KEYWORDS**

Recommender System; Session-based Recommendation; Large Language Models; Data Augmentation

#### **ACM Reference Format:**

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#### **1** INTRODUCTION

The 21st century is an era of information explosion. Recently, Recommender systems (RS) [14, 27] have received widespread attention from industry and academia as a crucial tool to solve information overload. To achieve personalized and accurate recommendations, RS usually uses the user's personal information and historical behavior records to model user portraits. As both user privacy concerns and businesses' demands for accurately capturing user dynamic intent continue to escalate, research on Session-based Recommendation (SBR) [15, 41] has become a crucial aspect of RS, which only relies on the behavior sequence generated by the user within the session time to model, and does not require user profiles. Traditional SBR research [2, 15, 31, 37, 41] is based on the ID-based (behaviorbased) recommendation paradigm. After encoding the items into one-hot features, methods such as Markov chains [29], recurrent

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neural networks (RNN) [28], graph neural networks (GNN) [32], etc., are employed to model anonymous session sequences.

While traditional recommendation methods can efficiently and accurately model collaborative information, they often overlook semantic information in interaction behavior, such as item name, price, etc. Particularly in SBR, where sequence lengths are typically short and data sparsity is high, and the SBR model uses one-hot encoding of the item ID to represent the item, which results in a serious lack of correlation between items. Consequently, solely modeling sparse behavioral information is insufficient for understanding users' true intent. Semantic information, unlike interaction information, inherently possesses similarities and correlations between items. For example, if a user clicks on "iPhone 15," "running shoes," "iPhone 14," "milk," and "skirt," solely modeling behavior might mistakenly prioritize the last few clicks, such as "milk" and "skirt," in determining session intent. However, leveraging semantic information, we can analyze that the user in the current session is likely more interested in the Apple product series. Therefore, if we can appropriately infer semantic information within the session, we can better understand the true intent behind the session sequence.

With the strong debut of large language models (LLMs) [1, 3, 35, 46], it has not only shaken the entire field of natural language processing (NLP) [5], but also caused turmoil in various fields, and the RS is no exception. LLMs trained on large-scale corpora exhibit robust language comprehension abilities as well as a certain degree of logical reasoning capability. LLMs like GPT-4 are capable of handling complex tasks and engaging in dialogues, inspiring researchers in RS to envision new directions for the future development of RS. But how should RS be combined with LLM? This is the issue that RS researchers are most concerned about. Recently, there has been a proliferation of work exploring the combination of RS and LLM. Some works [6, 11] take advantage of LLM by converting tasks in RS into language understanding or language generation tasks in NLP, through pre-training, fine-tuning, etc. Some researchers [7, 13, 17] have applied LLM to different recommendation system processes to explore LLM's ability to encode features, sort, and score. The above attempts to combine RS with LLM have achieved many encouraging results, but they are not suitable for SBR. SBR combined with LLM has the following difficulties:

- LLM hallucinations are more likely to occur. The sequence length in SBR is typically short, and access to users' personal information is unavailable. When the information available to the LLM is very limited, the LLM may not be able to generate valid answers or may generate false items that exceed the item set returned.
- A "repeater" problem occurred when fine-tuning LLM. Session data is typically augmented through sequence splitting, resulting in datasets containing numerous similar sessions. Consequently, fine-tuning LLMs may lead to instances where the model excessively duplicates input text or repetitively repeats the same sentences when generating responses.
- **Training and inferring consume a lot of resources.** LLM is complex in calculation takes up a lot of GPU memory, and takes a long time to infer. The recommendation task pursues real-time performance, so LLM-based RS models are difficult to implement in industrial practice.

To address these difficulties, we propose a lightweight and effective LLM-enhanced framework framework (LLM4SBR) for SBR. The framework comprises two distinct stages, intent inference and representation enhancement. In the intent inference stage, our framework employs LLM as the inference engine. We guide LLM in inferring through carefully crafted prompts from different perspectives. The intent localization module is crafted to eliminate hallucinations and semantically enhance the reasoning results. Subsequently, these refined outcomes are encoded into an embedded form and stored in external files. Moving on to the representation enhancement stage, the traditional SBR model simultaneously loads interaction data in ID format and intention inference data in text format. On one hand, the SBR model models conversation representations from different perspectives based on interaction data, while on the other hand, it parses text data into embedded forms. Subsequently, alignment and uniformity of session embeddings and inference embeddings are performed separately for each perspective. Finally, all embeddings from all perspectives are fused as the ultimate session representation for prediction.

We summarize significant contributions as follows:

- We are the first to propose an LLM enhancement framework for SBR. We divide the LLM inference and SBR model training into two stages. The LLM inference results are saved in an external file in advance, ensuring that GPU usage and training time during training depend only on the SBR model.
- We proposed an intent localization module, which addresses hallucinations and enhances semantic aspects in the preliminary results of LLM inference. In addition, We achieve a finer-grained modal alignment by performing alignment and uniformity between embeddings from different perspectives, facilitating the effective integration of interaction ID information and textual information.
- Experiments on two real-world datasets show that our proposed framework LLM4SBR can be applied to most current SBR models and achieve substantial performance improvements.

## 2 RELATED WORK

#### 2.1 Session-based Recommendation

In the field of SBR, the available information is very limited, consisting only of interaction data within the session. Therefore, the focus of SBR research lies in how to effectively model interaction behavior and learn session preferences. Based on different modeling emphases, we can broadly categorize SBR methods into two types: traditional SBR methods and methods focusing on modeling item transition relationships.

In traditional SBR methods, S-POP [2] recommends based on the most popular items, and Item-KNN [8] calculates item similarity based on historical behavior to recommend similar items. As Markov chains exhibit advantages in modeling sequential data, FPMC [31] captures data sequence information and user preferences by combining first-order Markov chains with matrix factorization. In the SBR methods based on deep learning, inspired by the field of NLP, GRU4Rec [15] proposed for the first time to use of the recurrent neural network (RNN) to simulate user preference changes in behavioral sequence data. Based on this research, Stamp improved performance by introducing an attention mechanism to make preferences more targeted. NARM [19] uses the attention network to capture users' short-term interests and long-term dependencies.

As GNN shows its prowess in various fields, SBR researchers have found that by constructing session data into the form of graphs, they can better capture the complex transformation relationships between items and greatly improve recommendation performance. SR-GNN[41] is the first model to represent sequences in the form of session graphs, utilizing gated graph neural networks as encoders. GC-SAN [43], an upgraded version of SR-GNN, incorporates attention mechanisms to make session representations more targeted. GCE-GNN [39], HADCG [33], MSGAT [30] and KMVG[4] construct multiple graphs with different structures, simultaneously considering both local item collaborations and global session collaboration relationships. In addition, DHCN [42], HL[38], and HIDE [24] captures the complex high-order miscellaneous information of the items by building the hypergraph.

Although the aforementioned SBR methods have achieved good performance, they solely rely on modeling the interaction information of sessions, thus lacking effective utilization of semantic information embedded within the sequences.

#### 2.2 Recommender System with LLM

Generative dialogue models represented by ChatGPT have caused a stir in research in various fields. According to how LLM participates in the recommendation system, we simply divide it into LLM as Recommender and LLM-enhanced Recommender.

2.2.1 *LLM as Recommender.* The model of LLM as Recommender realizes the transformation from the ID paradigm to the modal paradigm by converting the recommendation task into a task in natural language processing.

The M6-Rec [6] model extends the pre-trained language model M6 [25] by transforming recommendation tasks into either language understanding or language generation tasks. It establishes a unified foundational recommendation model to reduce downstream tasks' dependence on data. Shijie Geng et al. [11] proposed the P5 paradigm, which enables predictions in a zero-shot or few-shot manner by providing adaptive personalized prompts tailored to different users. This approach reduces the need for fine-tuning. Wang-cheng Kang et al. [17] evaluated the performance of LLMs of different sizes (250M - 540B parameters) in zero-shot, few-shot, and fine-tuning scenarios to explore the extent to which LLM understands user preferences based on the user's previous behavior. Sunhao Dai et al. [7] enhance the recommendation capabilities of ChatGPT by combining ChatGPT with traditional information retrieval (IR) ranking functions. GPT4Rec [20] first generates queries based on a language model, and then optimizes product retrieval separately through a search engine, addressing optimization from two aspects. VIP5 [12] explores a multi-modal base model of the P5 recommendation paradigm that considers both visual and textual modalities. Zhu Sun et al. [34] proposed the PO4ISR model of SBR, which promotes LLM to continuously reflect and update the results from the perspective of real-time optimization prompts to improve the accuracy of recommendations. Agent4Rec [47] utilizes a generative agent empowered by LLM to simulate and infer personalized user preferences and behavioral patterns. The core of

the above method is to enhance recommendation performance by improving LLM's adaptability to recommended data and reasoning capabilities.

Although these methods have made breakthrough progress in zero-shot, few-shot, and interpretability aspects, they suffer from drawbacks such as high fine-tuning costs and difficulty in capturing specific fine-grained behavioral patterns. Consequently, they face challenges in being deployed in industrial applications.

2.2.2 LLM-enhanced Recommender. LLM-enhanced RS treats LLM as a tool to enhance the performance of recommendation models. The large-model recommendation framework proposed by Weiwei et al. [40] leverages graph-enhanced strategies based on LLM to enhance RS, addressing challenges posed by data sparsity and low-quality side information in RS. Chat-Rec [10] integrates traditional RS with conversational AI like ChatGPT, eliminating the need for training to gain a deep understanding of user preferences through LLM's comprehension of dialogue context. CTRL [22] regards the original table data and the corresponding text data as two different modalities, and uses the collaborative CTR model and the pre-trained language model respectively for feature extraction, and adjusts the knowledge of the two modalities through comparative learning. LlamaRec retrieves candidates based on user interaction history through a sequence recommendation model. Candidates and historical records are designed as textual prompts, with the output of LLM transformed into a ranked probability distribution. E4SRec [23] is a solution that combines sequence recommendation with LLMs. It takes only ID sequences as input and ensures efficient controllable generation by predicting all candidate sequences at each forward pass. The above method has made us realize the potential of integrating LLM with RS and how a two-stage framework can better balance efficiency and performance compared to an endto-end framework. Jesse Harte et al. [13] devised three strategies for leveraging LLM, and found that using embeddings initialized with LLM significantly enhances the performance of sequence recommendation models. This inspires us about the importance of textual semantics.

The above methods explore the effectiveness of LLM in RS from different perspectives. Compared to the "LLM as Recommender" approach, they have greatly improved performance and efficiency. However, these methods do not fully leverage and integrate textual and interaction information, and they are not applicable to SBR scenarios with short sequences and no user information.

Considering aspects such as performance, efficiency, and hallucinations of LLMs, effectively integrating LLM with traditional RS models remains a challenging issue. In comparison, our framework is the first plug-and-play LLM framework designed for SBR. It effectively addresses several aspects mentioned above and better meets real-world industrial demands.

## **3 METHODOLOGY**

The overall architecture of LLM4SBR is depicted in Figure 1. This section will introduce the problem definition and the specific implementation details of each module in turn.

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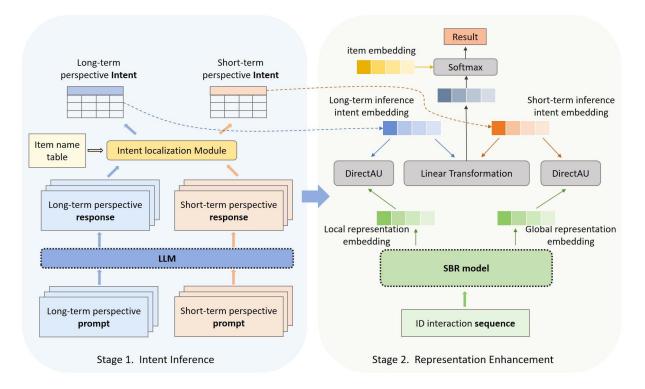


Figure 1: LLM4SBR framework diagram. LLM4SBR is a two-stage framework. In the first stage—the Intent Inference Stage, LLM makes initial inferences based on prompts from different perspectives (long-term and short-term). Subsequently, the intent localization module is utilized to eliminate hallucinations and enhance semantics in the inference results, with the embeddings of the results stored in an external file as text data. Then, in the second stage—Representation Enhancement Stage—interaction data and text data are synchronously loaded into the model. Traditional SBR models are used to model the interaction data to obtain local and global session representations. Meanwhile, we parse the inference embeddings stored in text format for each perspective and restore them to tensor form for subsequent computations. After aligning and uniforming session representations and inference representations of the same perspective, all representations are fused into the final session representation for prediction.

## 3.1 **Problem Formulation**

The objective of SBR is to predict the next interaction item expected to occur in the current session history of an anonymous user. Here, we provide the problem definition in mathematical terms. Each data entry in the dataset represents a session sequence. Let the collection of all sessions be denoted as  $S = \{s_1, s_2, \dots, s_m\}$ , where *m* is the total number of sessions. The item set is the summary of items that have appeared in all sessions, which we define as  $I = \{i_1, i_2, \dots, i_n\}$ , where *n* is the total number of items in the set. We represent the t-th session  $s_t$  in the dataset as  $s_t = \{i_{t,1}, i_{t,2}, \dots, i_{t,k}, \dots, i_{t,|s_t|}\}$ , where  $|s_t|$  is the length of the current session, and  $i_{t,k} \in I$  represents the *k*-th clicked item in the current the modeling goal of session  $s_t$  as predicting the click of the  $|s_t|$ +1th item based on the historical behavior records of  $s_t$ .

#### 3.2 Intent Inference Stage

*3.2.1 Prompt Design.* At the current stage, the logical reasoning ability of LLM is limited. To achieve more accurate inference, we introduce perspective-limiting qualifiers as auxiliary, enabling LLM

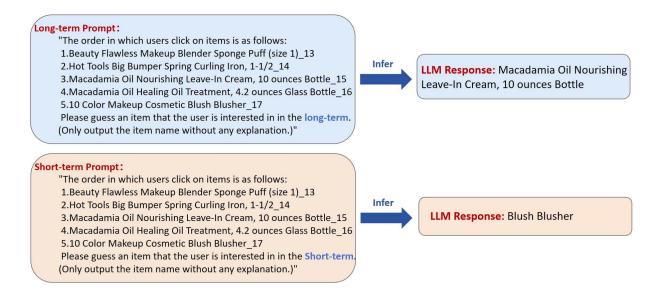
to speculate on existing items in a sequence from a specific perspective rather than directly predicting using LLM.

Specifically, in our prompt design, we utilize the perspectivelimiting qualifiers based on commonly used behavioral modeling perspectives in SBR (long-term and short-term). By artificially setting them, we decompose the text inference task into finer-grained perspective inference subtasks, thereby maximizing the utilization of LLM's reasoning capabilities. It is worth noting that the perspective settings are not fixed and can be freely added or removed, endowing the framework with scalability.

The specific prompt design is illustrated in Figure 2, where we denote perspective-limiting qualifiers with blue color. A prompt consists of three parts: [background prompt, item name sequence, and task prompt]. Some studies [16, 21] suggest that ID information helps LLM distinguish between different items more accurately. Inspired by this, we incorporate corresponding ID information after the item names in the prompt design. Therefore, we present the prompt template as follows:

"The order in which users click on items is as follows:

1. ItemName\_ItemID



#### Figure 2: Illustration of the design of prompts.

N. ItemName ItemID

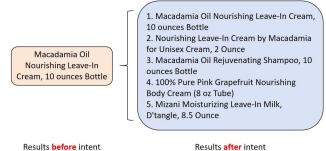
Please guess an item that the user is interested in in the (perspectivelimiting qualifiers). (Only output the item name without any explanation.)"

*3.2.2 LLM Inference.* To enhance the effective utilization of semantic information and understand the genuine intent of sessions, we leverage the contextual understanding and logical reasoning capabilities of LLMs to achieve intent inference from different perspectives.

In the aspect of selecting large models, we have chosen the Qwen-7B <sup>1</sup> model as the inference model after comprehensive consideration of LLM's inference capability, adaptability to both Chinese and English languages, and model parameter count. It is worth noting that here, the LLM is interchangeable. LLMs with more parameters and stronger reasoning capabilities can produce more accurate inference results. We adopt the form of question and answer, input different perspective prompts as questions to the LLM, and then the LLM returns its inferring results according to the prompts. In addition, to standardize the answers of the LLM, we specially mark "(Only output the item name without any explanation.)" in the prompts.

3.2.3 Intent Localization. To assist LLM in eliminating hallucinations and achieving and achieving semantic enhancement, we designed the intent localization module. Although in most cases, the LLM inference result is an accurate item name, sometimes it may be just a vague item category or key project term. In rare cases, a reasonable inference result may not be obtained. The red portion in Figure 3 illustrates the initial inference results of LLM.

Inspired by the RAG retrieval model [18], addressing hallucinations in LLM requires providing relevant external knowledge to LLM. The text retrieval scheme of the RAG model is usually based



localization

localization

Figure 3: The result of intent localization module.

on the similarity of text embeddings, so we first encode all inference results and the text of the item set into embedding forms using a pre-trained BERT model  $[9]^2$ .

$$E_{infer} = Bert(Text_{infer}), \tag{1}$$

$$E_{\text{item}} = \text{Bert}(\text{Text}_{\text{item}}),$$
 (2)

where  $e_{infer}, e_{item} \in \mathbb{R}^{d_{text}}$ .

Then, we compute the cosine similarity scores between each inference result and all item embeddings. Utilizing text embedding similarity, we select the Top-f most similar actual items from the item set, where f is a hyperparameter that controls the number of semantically similar items to be filtered. We multiply the embeddings of selected items by their corresponding similarity scores and then sum them up to obtain the inference result of the LLM. Figure 3 illustrates the comparison of inference results before and after using the intent localization module. Finally, the inference results from each perspective undergo hallucinations removal and semantic enhancement through this module. To reduce unnecessary

<sup>&</sup>lt;sup>1</sup>https://github.com/QwenLM/Qwen

<sup>&</sup>lt;sup>2</sup>https://huggingface.co/bert-base-uncased

computation time in the next stage, we store the adjusted results' embeddings in an external file.

$$Similarity = \frac{e_{\text{infer}}^{i} T e_{\text{item}}^{j}}{\|e_{\text{infer}}^{i}\|\|e_{\text{item}}^{j}\|},$$
(3)

$$h_{\text{infer}} = \sum_{j=1}^{f} \frac{\exp(Similarity)}{\sum_{j=1}^{f} \exp(Similarity)} e_{\text{item}}^{j}, \tag{4}$$

where  $e_{infer}^i \in E_{infer}$  is the text embedding of the inference result and  $e_{item}^i \in E_{item}$  is the text embedding of the item name.

## 3.3 Representation Enhancement Stage

After the intent inference stage, we move into the representation enhancement phase. In this stage, the SBR model processes behavioral modeling data and parsed inference data. Subsequently, the alignment and uniformity of session embeddings and inference embeddings are conducted separately for each perspective. Ultimately, all perspective inference embeddings are fused with session embeddings to form the final session representation used for prediction.

Most of the state-of-the-art (SOTA) models in RS are currently based on the item-ID paradigm. Although this paradigm may sacrifice semantic information, its performance and efficiency are undeniably superior. There is still a long way to go to subvert the ID paradigm. [45] Therefore, we opt to model user behavior based on the item-ID paradigm while simultaneously injecting multimodal information for supplementary enhancement. The SBR model in the framework is interchangeable. In the subsequent experimental section, we also test the performance after replacing SR-GNN with other SBR models.

*3.3.1 SBR Modeling.* In this section, we use the SBR model to model interactive information in conversation sequences and learn user behavior preferences. The SBR model here can be replaced arbitrarily. Given that SR-GNN [41] stands as one of the classic models in SBR, and the state-of-the-art (STOA) models in SBR predominantly rely on GNN, this model holds significant importance. Therefore, we primarily select it as the prototype SBR model within the framework for the experimental segment. Specifically, SR-GNN constructs session data into a session graph, where each node in the graph represents a unique item in the session. It utilizes GGNN to learn node features, then takes the last clicked item in the session as the local embedding of the session. It aggregates all node information and utilizes a soft attention mechanism to represent global preferences.

$$H_t^l, H_t^g = \mathbf{SBR} \cdot \mathbf{Model}(\mathcal{I}_t), \tag{5}$$

where  $I_t \subseteq I$  represents the set of items interacted with in session at time t.  $H_t^l$ , and  $H_t^g$  represent the local embedding and global embedding of session t respectively.

*3.3.2 Text Embeddings Parsing.* In the intent inference stage, we save the inference results' embeddings in an external file. Therefore, we need to read out the embeddings of the inference, then parse and restore them into tensor form, followed by performing dimension alignment.

$$H_{\text{infer}} = W_1(\text{Parse}(H_{\text{infer}}^{\text{str}})) + b_1$$
(6)

,

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Here,  $w_1 \in \mathbb{R}^{d \times d_{text}}$  is the weight matrix, and  $b_1 \in \mathbb{R}^d$  is the bias term.  $H_{infer}^{str}$  represents the inference embeddings stored as strings, and Parse denotes the conversion between strings and embeddings using the "*ast.literal\_eval*" function.

3.3.3 *Representation Alignment and Fusion.* The SBR model models interaction information within sessions, while LLM employs its knowledge to infer the textual content corresponding to sessions. Although both have the same goal, they are not in a unified embedding space. To better integrate embeddings and enhance session representation quality, we incorporate DirectAU [36] for alignment and uniformity of representation.

$$\mathcal{L}_a = \mathbb{E}_{(infer,t)\sim sess} ||h_{infer}^p - h_t^p||^2 \tag{7}$$

$$h_{e} = \log e^{-2||h_{\text{infer}}^{\tilde{p}} - h_{\text{infer}'}^{\tilde{p}}||^{2}}/2 + \log e^{-2||h_{t}^{\tilde{p}} - h_{t'}^{\tilde{p}}||^{2}}/2 \qquad (8)$$

where  $\mathcal{L}_a$  denotes alignment loss function and  $\mathcal{L}_u$  denotes uniformity loss function. For each perspective (long-term, short-term), we separately compute the alignment loss between the inference representation and session representation under that perspective, as well as the uniform loss within each inference representation and each session representation.  $h_{infer}^p$  and  $h_t^p$  represent the inference representation and session representation, respectively, corresponding to the session *t* under the same perspective.

 $\mathcal{L}_{u}$ 

Then, we fuse the session representations from different perspectives and modalities into the final session representation.

$$H_{sess} = W_2[H_t^l; H_t^g; H_{infer}^{lt}; H_{infer}^{st}], \qquad (9)$$

where  $W_2 \in \mathbb{R}^{d \times 4d}$  is a weight matrix.  $H_t^l$  is the local preference representation obtained in the SBR model, where the local preference embedding is simply defined as the last clicked item.  $H_t^g$  is the global embedding obtained by the SBR model, which is obtained by the soft attention mechanism. For details, please see SR-GNN [41]. Additionally,  $H_{infer}^{st}$  and  $H_{infer}^{lt}$  represent the short-term and long-term perspective text embeddings of LLM inference, respectively. From this, the four embeddings are compressed into the same embedding space through a linear layer.

*3.3.4 Prediction and Optimization.* By taking the item of the session representation and the item representation, scores for each candidate item are obtained. Then, the softmax function is applied to obtain the model's predicted values *Y*.

$$\hat{y}_i = softmax(h_{sess}^I v_i), \tag{10}$$

where  $\hat{y}_i$  represents the probability that each item in the itemset becomes the next item in the current session. The loss function for SBR tasks is defined as the cross-entropy between the predicted values and the ground truth, as shown below:

$$\mathcal{L}_r = -\sum_{i=1}^n y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i),$$
(11)

where y is the one-hot encoding vector of the ground truth item.

Ultimately, the joint learning loss function is composed of both the recommendation loss function and the auxiliary task (alignment and uniformity) loss function.

$$\mathcal{L} = \mathcal{L}_r + \tau \left( L_a + L_u \right) \tag{12}$$

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## Table 1: Statistics of the utilized datasets.

Datasets	Train	Test	Clicks	Items	Avg.len.
Beauty	158,139	18,000	198,502	12,101	8.66
ML-1M	47,808	5,313	987,610	3,416	17.59

where  $\tau$  controls the proportion of auxiliary tasks.

## **4 EXPERIMENTS**

## 4.1 Experimental Settings

4.1.1 Datasets. We initially hoped to validate the performance using commonly used datasets in SBR, as they are more representative. Unfortunately, we couldn't find any session datasets that provide both interaction ID sequences and item name information. Taking this into consideration, we opted for Beauty<sup>3</sup> and MovieLens-1M (ML-1M)<sup>4</sup> datasets, which are the closest in format. The details of these two datasets are shown in Table 1. For both datasets, we adhere [19, 41] to removing sessions with a length of 1 and items that appear fewer than 5 times across all sessions.

- Beauty dataset comprises evaluations and ratings from users on various beauty products. We treat all ratings sequences from a single user as a session sequence. We enhance the dataset using the commonly employed sequence segmentation method [19, 26, 41] in SBR. For instance, consider an original session s = [*i*<sub>t,1</sub>, *i*<sub>t,2</sub>, ..., *i*<sub>t,n</sub>]. After segmentation by sequence, we obtain ([*i*<sub>t,1</sub>], *i*<sub>t,2</sub>), ([*i*<sub>t,1</sub>, *i*<sub>t,2</sub>], *i*<sub>t,3</sub>), ..., ([*i*<sub>t,1</sub>, *i*<sub>t,2</sub>, ..., *i*<sub>t,n-1</sub>], *i*<sub>t,n</sub>).
- ML-1M dataset consists of over 1 million ratings from more than 6,000 users on over 4,000 movies. Considering our research question, we partition the movie rating data of the same user in this dataset into multiple session sequences using a 10-minute interval as the splitting point.

4.1.2 Evaluation metrics. In terms of the evaluation indicators used in the experiment, We chose the most commonly used ones in SBR tasks: Precision (P) @K and Mean reciprocal rank (MRR) @K. After referring to the classic work [39, 42] in recent years, we set the length of the candidate set @K to 5, 10, and 20, which is the most meaningful for comparison.

4.1.3 Parameter Settings. All experiments were conducted on NVIDIA A100 GPUs. For fairness in performance comparison, the optimizer used throughout the experiments was unified as Adam with a learning rate of 0.001, decayed by 0.1 every three epochs, and an L2 penalty set to  $10^{-5}$ . For the SBR model involved in the experiments, the batch size is 100 and the dimension size is 100.  $\tau$  is set to 0.1. We initially set the hyperparameter f in the intent localization module to 5, and subsequent hyperparameter experiments 4.4 will discuss the optimal value. We followed the optimal parameter settings as published in their paper for the remaining parameters.

#### 4.2 Performance Experiment and Analysis

In this section, we mainly compare the performance of the SBR model and the corresponding SBR model applying the LLM framework under different Top-*K*.

*4.2.1 Backbone.* To validate the effectiveness of the framework, we selected four classic models from SBR to replace the SBR model in the framework and compared the performance between each pair. The introduction of the SBR models is as follows:

- **SR-GNN** [41] is the first model to construct data into session graphs, utilizing GGNN to capture complex transition relationships among items.
- **TAGNN** [44] adds a target-sensitive attention mechanism based on SR-GNN.
- GCE-GNN [39] constructs session graphs and global graphs respectively, and learns relevant information from the item level and session level.
- *S*<sup>2</sup>-**DHCN** [42] uses hypergraph convolution to learn high-order relationships in item sequences, and uses self-supervised learning to alleviate the data sparse problem of hypergraphs.

The comparison results of the overall performance experiments are shown in Table 2. We record the performance with K set to 5, 10, 20. It is worth noting that in the evaluation system of RS, smaller K values are more significant. From the results displayed in Table 2, we draw the following observations:

- LLM4SBR significantly improves backbone performance. In the models enhanced through the LLM framework, all demonstrate performance improvement. This confirms that the text representations derived from LLM inference contain rich and valuable information, which can greatly help the SBR model understand the potential intention of the conversation data.
- LLM4SBR has a greater improvement for smaller *K* values. For example, LLM4SBR (TAGNN) improved the P@5 index of the two data sets by 27.28% and 107.5% respectively. We believe this is due to the semantic enhancement achieved by LLM4SBR during the intent localization stage, where it utilizes f similar semantic items. Consequently, it results in more accurate predictions for the top few items in the predicted candidate set. We also observe slight decreases in performance for  $S^2$ -DHCN and GCE-GNN on a few metrics (P@20 and MRR@20) after integrating with the framework. We posit that when the original SBR model already effectively models the data, enhancing the inference information through the intent localization module may introduce noise. Compared to the improvement magnitude, the decrease is very slight. Moreover, since noise issues can be effectively controlled by adjusting the hyperparameter f in the intent localization module, the negative impact can be almost negligible.
- LLM4SBR can compensate for poor modeling caused by a lack of interactive information. GCE-GNN captures effective information at both the item and session levels by constructing global graphs and session graphs simultaneously, due to the model's complex computations, in scenarios with limited data volume, it becomes challenging for this model to learn effective session representations. LLM4SBR (GCE-GNN) showed the greatest improvement, especially on the ML-1M dataset, P@5, P@10, and P@20 increased by 37.59%, 96.2%, and 128.54% respectively. We attribute this to the effective text information obtained from LLM inference, which compensates for the information scarcity in GCE-GNN's session modeling, allowing it to achieve better performance. In addition, The architectures of SR-GNN

<sup>&</sup>lt;sup>3</sup>https://jmcauley.ucsd.edu/data/amazon/links.html

<sup>&</sup>lt;sup>4</sup>https://grouplens.org/datasets/movielens/

Dataset				Beauty					1	ML-1M		
Model	P@5	P@10	P@20	MRR@5	MRR@10	MRR@20	P@5	P@10	P@20	MRR@5	MRR@10	MRR@20
SR-GNN	6.30	10.02	14.86	3.18	3.70	3.99	4.29	8.64	13.01	2.16	3.09	3.19
LLM4SBR(SR-GNN)	7.58	11.29	16.30	4.34	4.62	5.00	7.38	11.52	17.54	4.06	4.55	5.26
SR-GNN Improv.	20.31%	12.67%	9.69%	36.47%	24.86%	25.31%	72.02%	33.33%	34.82%	87.96%	47.25%	64.89%
TAGNN	6.12	10.06	15.23	3.10	3.63	3.97	3.60	6.19	10.28	1.77	2.15	2.23
LLM4SBR(TAGNN)	7.79	11.79	16.76	4.39	4.78	5.05	7.47	12.33	18.60	4.03	4.79	4.87
TAGNN Improv.	27.28%	17.19%	10.04%	41.61%	31.68%	27.20%	107.5%	99.19%	80.93%	127.68%	122.79%	118.38%
GCE-GNN	6.39	8.93	12.38	3.97	4.30	4.54	5.16	6.85	9.67	3.18	3.41	3.60
LLM4SBR(GCE-GNN)	7.75	12.48	18.08	3.91	4.41	4.80	7.10	13.44	22.10	3.14	3.63	4.21
GCE-GNN Improv.	21.28%	39.75%	46.04%	-1.51%	2.56%	5.73%	37.59%	96.20%	128.54%	-1.25%	6.45%	16.94%
S <sup>2</sup> -DHCN	7.14	11.97	17.54	2.97	3.61	3.99	8.35	14.55	23.38	3.66	4.51	5.09
LLM4SBR(S <sup>2</sup> -DHCN)	7.77	11.85	17.48	4.26	4.79	5.15	9.54	15.31	22.67	5.13	5.91	6.40
S <sup>2</sup> -DHCN Improv.	8.82%	-1.00%	-0.34%	43.43%	32.68%	29.07%	14.25%	5.22%	-3.03%	40.16%	31.04%	25.73%

Table 2: Performance comparison experimental results (%).

\* We highlight the best performance values for each metric in bold and underscore the best values within the backbones.

and TAGNN are based on directed session graphs, utilizing GNN to capture complex transition relationships between items. However, limited by the number of layers in GNNs, both of these models struggle to effectively capture useful information from long-term items. After adding LLM4SBR, both of the above two models have achieved substantial performance improvements. Inference information from a long-term perspective solves the problem of insufficient capture of long-term dependencies in the model.

In conclusion, the effectiveness of the LLM4SBR framework is undeniable. As a plug-and-play framework, it significantly enhances the prediction accuracy of traditional SBR models.

#### 4.3 Ablation Experiment and Analysis

To examine the necessity and relative importance of the long-term and short-term inference perspectives, we designed two variants: LLM4SBR w/o Long and LLM4SBR w/o Short. LLM4SBR w/o Long indicates inference without considering the long-term perspective, retaining only the short-term perspective. Conversely, LLM4SBR w/o Short retains only the long-term perspective and removes the short-term perspective during inference. We compared the performance of these two variants with the whole performance and visualized the comparison as a bar chart to clearly illustrate the differences between them.

Through observation and analysis of Figure 4, we summarized the following conclusions:

- Both long-term and short-term perspectives are necessary. Because the whole framework represented by the blue column in the figure shows the best performance on both datasets. This demonstrates the need to leverage LLM for separate perspective inference, removing any perspective will result in a performance loss.
- The contribution of long-term and short-term perspective inference varies across the two datasets. In Beauty, the framework relies more on the information provided by the shortterm perspective, as discarding the inference results of the shortterm perspective would lead to a greater performance drop. Conversely, in Ml-1M, it's the opposite; the framework relies more on the inference results of the long-term perspective. Through

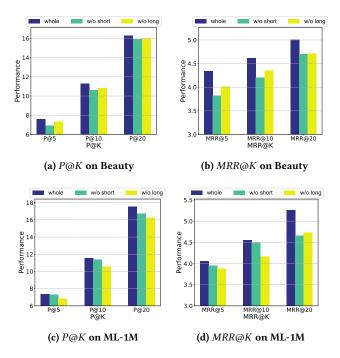


Figure 4: Inference perspective ablation experiment results

discussion and analysis, we attribute this performance difference to the length of the dataset sessions. Session intent in short sequences is usually relatively stable, and the intent is mainly reflected in the last few clicks. This underscores the increased importance of accurately modeling short-term interests in shortsession scenarios. However, as the session length increases, the session intent is influenced by various factors, thereby increasing the importance of long-term dependency relationships within the session. Finally, we believe that considering the inference results of multiple perspectives simultaneously can enhance the stability of the framework's performance, making it adaptable to datasets with varying session lengths.

Model	Occupies video memory (M)			
Dataset	Beauty	ML-1M		
SR-GNN	1,314	1,224		
LLM4SBR(SR-GNN)	1,330	1,304		

Table 3: The result of space occupation experiment

## 4.4 Hyperparameter Experiment and Analysis

In this section, we discuss the hyperparameter f set within the intent localization module. This hyperparameter is designed to eliminate hallucination and enhance semantics in the preliminary inference results of LLM, using a candidate set of items with similar semantics. The hyperparameter f is configured to control the range of selecting items with similar semantics. The value of f is set to 0, 1, 3, and 5, and we discuss four scenarios accordingly: (1) directly utilizing the inference results of LLM, (2) eliminating hallucination using the most similar item, (3) eliminating hallucination and enhancing semantics using the Top-3 most similar items, and (4) eliminating hallucination and enhancing semantics using the Top-5 most similar items.

The experimental results are shown in Figure 5. Firstly, across all three plots, although the optimal hyperparameter values differ for each plot, we can see that the performance is consistently the worst when f = 0. We believe this is logical and demonstrates the necessity of the intent localization module in the framework. If the results of LLM inference are not processed, hallucinations occurring in some session data may lead to a decrease in the overall framework performance. Taking a closer look at the local details, in Figures 5a and 5b, the performance peaks when f = 1, with P@5and P@10 being 7.69 and 11.48 respectively. However, in Figure 5c, a notable peak is observed when f = 3, achieving the best performance with P@20 is 18.56. When the value of K is relatively small (K = 5, K = 10), the performance is best when f = 1. We believe this is because utilizing multiple similar items for semantic enhancement of intent may introduce noise, thereby leading to a slight performance decrease. As the value of K increases, the performance of the f = 3 and f = 5 becomes similar, both surpass f = 1. This suggests that introducing multiple similarly named items appropriately can increase the diversity of candidate items while enhancing performance.

In summary, values of f ranging from 1 to 5 are all effective. Depending on the requirements for different values of K, selecting different values of f can better leverage the module's effectiveness.

## 4.5 Space Occupation Experiment and Analysis

Recommendation models based on LLM often require a large amount of video memory. To explore the spatial effectiveness of the LLM4SBR framework, we recorded the memory usage of SR-GNN and LLM4SBR (SR-GNN).

The results are shown in Table 3, the memory usage rates of the two are very close. Through the two-stage strategy, LLM inference is performed only once in the first stage, and then the inference results are stored in an external file. During the second stage of SBR model training, the memory consumption is limited to the original SBR model, the ID sequence data, and the pre-stored inference embeddings, significantly reducing memory usage. Additionally, since the second stage only requires parsing the stored inference embeddings into tensors, its increased time complexity is O(1), the model's time complexity mainly depends on the original SBR model. Taking into account time and space factors, the LLM4SBR framework we proposed can be implemented in industrial environments.

## **5 CONCLUSIONS AND FUTURE WORK**

In this paper, we explore the feasibility of combining LLM with SBR models while considering both effectiveness and efficiency. In short sequence data, LLM can infer preferences directly leveraging its language understanding capability without fine-tuning. This approach is more efficient in utilizing information compared to encoding text data into embeddings for training, and it allows us to place LLM and SBR in separate stages, greatly reducing training costs. Regarding the LLM hallucination, we found that it can be corrected through the similarity of text embeddings, and enhancement with similar samples can improve the diversity of inference results to a certain extent.

In addition, we propose a scalable two-stage LLM enhancement framework (LLM4SBR) tailored for SBR. Specifically, in the semantic reasoning phase, we utilize LLM as the inference engine, designing prompt-guided inference processes from different perspectives and leveraging an intent localization module to eliminate LLM hallucinations and achieve semantic enhancement. In the representation enhancement stage, we perform fine-grained alignment and uniformity of text embeddings and session embeddings from different perspectives. This effectively facilitates the fusion of representations from different modalities, thereby enhancing the final session representation. Extensive experiments have demonstrated the effectiveness of the LLM4SBR framework, which significantly enhances most SBR models while also improving model interpretability and enhancing the diversity of candidate selection.

For future work, we will continue exploring whether adding additional LLM inference perspectives can yield greater benefits, as well as assessing the effectiveness of utilizing LLM Agent for logical reasoning. In addition, we also want to explore the application of other downstream tasks combined with LLM. Finally, we hope for this work to open up new avenues in SBR research, accelerating deeper exploration into the integration of LLM with RS.

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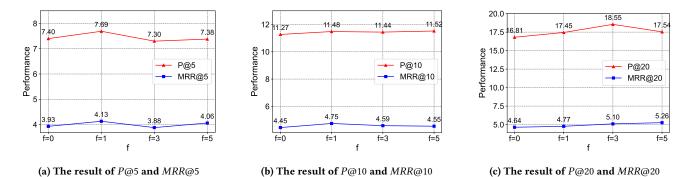


Figure 5: Hyperparameter experimental results of different f settings of the Intent positioning module on ML-1M

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