Point-of-interest Re-ranking by Modeling Session Context and Geography-semantics Interaction

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ABSTRACT

Point-of-interest (POI) search plays a crucial role in location-based services, such as online navigation and ride-hailing platforms. The primary objective of POI search is to identify the most relevant destinations from a large number of POI candidates based on a given query text. Generally, users engage in a series of search interactions by issuing several reformulated queries and examining the returned list of POIs until they locate the target POI. These search behaviors collectively form a POI search session. This paper specifically focuses on re-ranking the POI candidates in such POI search sessions. We begin by highlighting a limitation of existing POI re-rank models in capturing the implicit feedback and the geography-semantics context within the POI search session. To address this limitation, we propose a POI session search model that utilizes a pre-trained model to jointly model multi-granularity context and relevance within the POI search session. Extensive experiments conducted on real-world datasets collected from the Didichuxing application demonstrate that the proposed framework outperforms existing POI re-rank methods in terms of re-ranking performance.

KEYWORDS

POI Search, Pre-training Model, Geographical Context

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1 INTRODUCTION

In recent years, Point-of-Interest (POI) search has become a crucial component in online navigation applications like Google Maps and Baidu Maps, as well as ride-hailing platforms like Uber and DidiChuxing. When using the POI search, the user types textual queries into the input box of the POI search system. In response, the system generates ranked POIs retrieved from an extensive collection of POIs. In general, the user will continuously modify the query and examine the real-time retrieved list of POIs from the search system, until they can locate and click the target POI, thus providing positive feedback. The search behaviors that transpire within a short period are defined as a POI search session.

Enhancing the Point of Interest (POI) search system can significantly improve users' experiences, thereby benefiting location-based services. Traditional Point of Interest re-rank models commonly depends on term matching [15]. However, with the advancement of deep learning techniques, numerous neural POI search models have been proposed, incorporating recurrent neural networks (RNNs) [10, 13] and convolutional neural networks (CNNs) [7, 8, 17] to obtain semantic representations for textual information in POI searches, including queries and POI names. In the last few years, researchers have suggested leveraging spatial-temporal contexts [8, 9, 21] in POI searches to enhance the representations of queries and POIs.

Despite being adopted in many real-world applications, existing POI search models typically approach the query-POI matching problem as a standalone ad-hoc re-ranking task, neglecting the potential insights derived from the complicated context within a POI search session. Neglecting the rich contextual information may limit the model's ability to comprehend users' query intent effectively. For example, as shown in Figure 1, a user seeks help related to oral health, and adopts a series of search behaviors to form a POI search session. For a POI session search system, it models the non-click signals on "Peking University Stomatological Hospital" and other unrelevant hospitals within the POI search session, and thus re-rank the target POI at a high position. Therefore, it is important to design a re-ranking model that can effectively leverage the implicit feedback and the geography-semantics context within the POI search session. Such a model can enhance the understanding of users' query intent, thereby improving the re-ranking performance for POI search.

To address this problem, this paper introduces a POI session search model to improve the POI re-ranking performance. The proposed model can capture fine-grained interactions at three distinct levels of granularity within the POI search session, leveraging the architecture of pre-trained models. These levels encompass the

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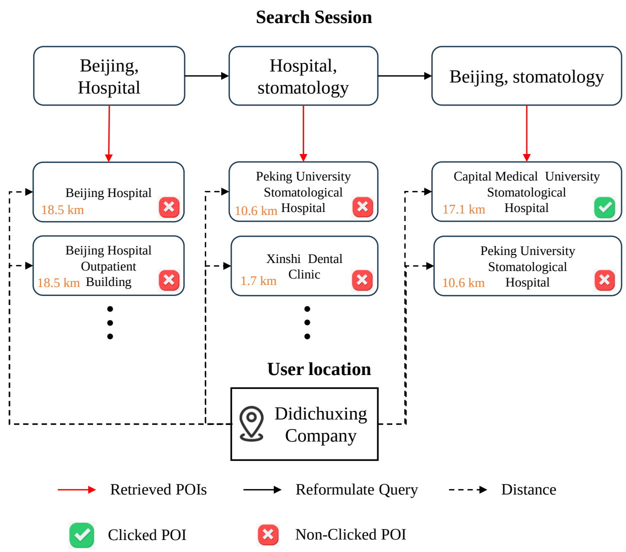

Figure 1: The overview of the ad-hoc POI search system and POI session search system.

query-POI level, list level, and session level. At the query-POI level, the model captures the matching signal between the geography-semantics context of the query-POI pair. At the list level, based on intermediate-iteration queries, it evaluates the contribution of implicit feedback among query-POI pairs from the corresponding ranking POI list provided by the search system. Lastly, at the session level, the model incorporates the overall context of the entire POI search session. Through the utilization of multi-granularity interactions, our proposed POI session search model effectively captures the implicit feedback and geography-semantics context in the POI search sessions.

To demonstrate the effectiveness of our POI re-rank model, experiments are conducted on the real-world data collected from Didichuxing. We observe that our models can achieve better performance over existing POI search models in re-ranking performances.

2 RELATED WORK

In this section, we provide a concise overview of relevant literature in the domains of POI search, spatial keyword queries, and session search methods.

2.1 POI Search

Point-of-Interest (POI) search holds a crucial role in online navigation and ride-hailing platforms. In general, to balance both effectiveness and efficiency in POI search, a widely adopted approach is to introduce a retrieve-and-then-rerank pipeline. This paper concentrates on existing works associated with the POI re-rank stage within this pipeline.

Second-stage POI re-rank aims to generate a prioritized list of POIs based on the candidate results recalled by the first stage, and re-ranking the target POI to a higher position in the list. With the development of deep learning, researchers are increasingly employing neural networks to autonomously learn representations for the textual information of POIs. Models from the DSSM-family [10, 13, 17] utilize neural networks to encode POI text to vector embedding in a semantic space. Chen [7], Fan et al. [8] use LSTM and convolutional neural network to acquire textual features. More recently, researchers have recognized the importance of contextual features in enhancing the retrieval performance, due to the spatial-temporal sensitivity in the POI search task. Huang et al. [9] builds connections between user profiles and POIs. Fan et al. [8] propose a time- and geography-aware POI matching model that takes spatial-temporal contexts into account, such as the timestamp and geographical coordinates. Zhao et al. [23] incorporate geographical information of query-POI pairs, and utilize convolutional networks and self-attention methods to capture the correlations between queries and POIs. Graph neural network-based methods are proposed to better model the structural information between queries and POIs. Yuan et al. [22] employ Graph Attention Networks (GAT) [19] to address the query-POI matching problem. They use two graph attention networks to capture the global query-POI interaction and the time-evolving user preferences, respectively.

However, there is a challenge that has not been fully addressed in previous works. Existing POI search models tend to treat the query-POI matching problem as an ad-hoc re-rank task, overlooking the implicit context derived from the POI search session.

2.2 Session Search

Some conventional methodologies have been proposed to exploit session context for inferring underlying search intent [3, 4, 16, 18, 20]. Based on the statistical language models, Shen et al. [16] utilizes both the session context and the latest query to enhance ranking effectiveness. These studies have consistently demonstrated the superiority of modeling search sessions over simplistic term-weighting methods.

With the advancement of deep learning, researchers have increasingly focused on developing neural ranking models that integrate contextual information [1, 2, 5, 6, 14, 24, 25]. Specifically, Ahmad et al. [2] used recurrent neural networks (RNNs) and attention mechanisms to learn the representations of queries and documents by optimizing both ranking and query suggestion tasks. Utilizing a BERT encoder with a hierarchical behavior-aware attention module, Qu et al. [14] modeled concatenated current session sequences to obtain context features for ranking. Meanwhile, Zuo et al. [25] adopted a Transformer-based encoder to capture historical query changes with different granularities. Considering session interaction encoding, Chen et al. [5, 6] employed a pre-training model with an encoder-decoder architecture, incorporating three generative training objectives. Zhu et al. [24] adopted data augmentation and contrastive learning methods to pre-train a BERT encoder to enhance its capability to model session sequences. Although most existing models use an encoder to capture contextual information within search session sequences for evaluating ranking scores, a common assumption is the presence of one or more positive feedback instances at each timestamp of the search session. These session search models are specifically tailored to address such data patterns.

3 THE PROPOSED METHOD

In this section, we begin by presenting the problem formulation for the POI re-rank task. Following that, we introduce the POI session search model, designed to utilize multi-granularity interactions within the POI search session. Lastly, we present the formula for the training objective.

3.1 Problem Formulation

In a POI search session denoted as S, a user issues T reformulated queries $\{q_1, q_2, ..., q_T\}$, and evaluates the returned list of POIs to identify the target POI p_S^+. At the timestamp t within the POI search session S, the user submits a request query q_t to the system, and the system will return a ranked list of n POIs $Rec(q_t) = \{p_1^t, ..., p_n^t\}$ from the entire POI set P. The representation of the POI search session S encompasses $\{\langle q_1, Rec(q_1)\rangle, ..., \langle q_{T-1}, Rec(q_{T-1})\rangle, \langle q_T, Rec(q_T), p_S^+\rangle\}$. It is crucial to emphasize that positive feedback is attributed only to the last timestamp T in the POI search session S, where the user interacts by clicking on the target POI p_S^+. A single query request q_t comprises a timestamp t, a input query prefix x_{q_t}, and a location l_{q_t}. Each POI p in the POI set P is characterized by a name n_p, an address a_p, and a location l_p.

Regarding the POI as a retrieval-and-rerank pipeline, the objective of the POI retrieval is to recall candidate POIs in set P within an acceptable latency. Subsequently, a POI re-rank model is utilized to generate a prioritized list of POIs based on the results obtained from the POI retrieval stage.

Query logs are used to evaluate ranking metrics of the POI re-rank model. For ranking evaluation, we will use the final query within each query log session, evaluating the ranking performance based on the POI re-rank model and the POIs recalled in the retrieval stage.

3.2 POI Session Encoder

In this section, we first present the Geohash Coding methodology employed in location-based tasks. Utilizing the shared pre-trained models with the Transformer architecture, we formulate a POI session encoder. This encoder captures the three tiers of granularity, namely, the query-POI level, list level, and session level, facilitating interaction within the POI search session. The representation of the POI session encoder is illustrated in Figure 2.

3.2.1 ***Geohash Code for Location.*** The location l_p of a POI p are articulated as the geographical coordinates $\langle x_l, y_l\rangle$, constituting a numerical pair denoting longitude and latitude. Nevertheless, it may be inadequate to directly embrace this as the spatial characteristic, for the reason that this simple numerical pair fails to capture the geographical hierarchy inherent in the POI. In order to address this problem, we instead employ the Geohash algorithm [12] for encoding the location into a string of fixed length.

$$g_l = Geohash(\langle x_l, y_l\rangle) \tag{1}$$

The distinct positions of the Geohash code correspond to regions of varying granularity. In our task, the Geohash code spans 12 characters, each derived from a set comprising 10 Arabic numerals and 26 English alphabets.

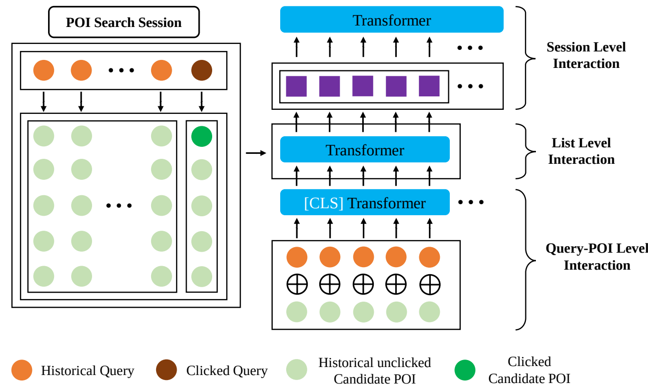

Figure 2: The overview of the POI session encoder.

3.2.2 ***Query-POI Level Interaction.*** At each timestamp t within the POI search session S, to model the comprehensive interaction of geographical-semantic context between the query request q_t and each POI $p_i^t \in Rec(q_t)$, we concatenate the geohash of the query g_{q_t}, the textual query x_{q_t}, the geohash of the POI $g_{p_i^t}$, the name of the POI $n_{p_i^t}$, and the address of the POI $a_{p_i^t}$ into an input sequence for the transformer. Subsequently, we designate the embedding of the $[CLS]$ token, denoted as $h_{qp}^{[CLS]}(q_t, p_i^t) \in \mathbb{R}^{1\times d}$, as the feature representing the Query-POI level interaction.

$$\begin{aligned} h_{qp}^{[CLS]}(q_t, p_i^t) = Transformer\big([CLS] \oplus \\ g_{q_t} \oplus [SEP] \oplus x_{q_t} \oplus [SEP] \oplus \\ g_{p_i^t} \oplus [SEP] \oplus n_{p_i^t} \oplus [SEP] \oplus a_{p_i^t} \oplus [SEP]\big) \end{aligned} \tag{2}$$

3.2.3 ***List Level Interaction.*** At time t within the POI search session denoted as S, to assess the contribution of implicit feedback among query-POI pairs, which involves the query request r_t and the corresponding ranking list of POIs $Rec(q_t) = \{p_1^t, ..., p_n^t\}$ generated by the search system. We construct the interaction sequence at the Query-POI level, using query-POI pairs as the input for the transformer. The hidden states obtained at the output of the final layer of the model serve as features $h_l(q_t, Rec(q_t)) \in \mathbb{R}^{n\times d}$ for List-level interaction.

$$\begin{aligned} h_l(q_t, Rec(q_t)) = \{h_l(q_t, p_1^t), ..., h_l(q_t, p_n^t)\} = \\ Transformer\left(\left\{h_{qp}^{[CLS]}(q_t, p_1^t), ..., h_{qp}^{[CLS]}(q_t, p_n^t)\right\}\right) \end{aligned} \tag{3}$$

3.2.4 ***Session Level Interaction.*** To incorporate the global context of the entire POI search session, we formulate the interaction sequences at the List level for all timestamps. These sequences serve as the input to the transformer. The resulting hidden states at the output of the last layer of the model represent the features, denoted as $h_{T-1}^s \in \mathbb{R}^{n(T-1)\times d}$, characterizing the session-level interaction.

$$\begin{aligned} h_{T-1}^s = \{h_s(q_t, p_1^t), ..., h_s(q_t, p_n^t)\}_{t=1,...,T-1} = \\ Transformer\left(\{h_l(q_t, Rec(q_t))\}_{t=1,...,T-1}\right) \end{aligned} \tag{4}$$

3.2.5 ***Modeling relevance.*** To compute the relevance between the POI search session S and the candiate POIs, we concatenate the

the historical session-level interaction h^s_{T-1}, the context $\langle g_{q_T}, x_{q_T} \rangle$ of the current query q_T, and the context $\langle g_p, n_p, a_p \rangle$ of candidate POI p as the input to the transformer. Then, we select the embedding of [CLS] token to calculate the matching score between the search session S and candidate POI p by applying an MLP function as:

$$\begin{aligned} h^{[CLS]} = Transformer\,([CLS] \oplus h^s_{T-1} \oplus \\ g_{q_T} \oplus [SEP] \oplus x_{q_T} \oplus [SEP] \oplus \\ g_p \oplus [SEP] \oplus n_p \oplus [SEP] \oplus a_p \oplus [SEP]) \end{aligned} \quad (5)$$

$$f(S,p) = Sigmoid\left(MLP\left(h^{[CLS]}\right)\right) \quad (6)$$

3.2.6 ***Training Objective.*** We train the re-ranking task using the cross-entropy loss and negative samples Φ, which consists of four randomly chosen non-click POIs retrieved with the search system and four negative POIs randomly sampled from the whole POI set.

$$L = \sum_S \left(-\log\left[f\left(S, p_S^+\right)\right] - \sum_{p_S^- \in \Phi_S} \log\left[1 - f\left(S, p_S^-\right)\right] \right) \quad (7)$$

4 EXPERIMENTS

We conduct experiments on real-world datasets collected from the Didichuxing application. We validate the performance of our proposed framework in the POI re-ranking task.

4.1 Problem Definition

To assess our methodology, we employ a substantial real-world dataset, extracted from the Didichuxing application's data in August 2022. This dataset comprises 16,717,537 click logs (i.e., search session), 1,713,280 POIs, and 1,530,964 distinct queries. The mean duration of a POI search session stands at 1.62. We refine the click logs by filtering for session lengths within the range of $[1, 10]$, query reformulation lengths within $[1, 10]$, and a time gap for query reformulation exceeding 1 second but less than 10 seconds, resulting in the retention of 1,457,291 click logs. For each query, the search system will retrieve the top 50 candidate POIs.

For assessing the ranking performance, based on the last query within each query search session, and the candidate POIs, we report the MRR@K and NDCG@K metrics, $(K \in \{1, 3, 5, 10\})$.

4.2 Baselines

We evaluate the proposed framework by comparing it with six ad-hoc ranking models and three context-aware ranking models. The ad-hoc ranking models solely leverage the data from the query and the POI to obtain the ranking score. In contrast, the context-aware ranking models incorporate session context modeling to produce the prediction.

4.2.1 ***Ad-hoc Ranking Models.***

- **LSTM-DSSM** [10] employs a long short-term memory neural network for acquiring semantic embeddings of query prefixes and POIs texts.
- **PALM** [23] introduces a spatial-temporal dual attention network to effectively capture the preferences in query-POI matching.
- **ST-PAC** [8] utilizes both LSTM and convolutional neural networks to encode textual features from query prefixes and POI texts, respectively. These features are then combined with time- and geography-aware features.
- **Meta ST-PAC** [8] adopt meta-learning mechanism to train LSTM and convolutional neural models. The time-, geography-, and text-aware features are extracted to address the challenge of data sparsity.
- **DrW** [11] introduces a deep relevance with weight learning model to further enhance the effectiveness of retrieval ranking.
- **Ad-hoc Bert Re-ranker** concatenates geohash codes, textual information from the query request at the last stamp, and candidate POI to serve as the input sequence for the BERT-based cross-encoder, predicting the matching score through an MLP function.

4.2.2 ***Context-aware Ranking Models.***

- **HQCN (Geo)** [25] models multi-granularity historical query change, and introduces the query change classification task to improve the ranking performance. Specially, we add the geohash code to the token embeddings.
- **ASE (Geo)** [6] employs an encoder-decoder structure, and designs three generative tasks specifically for session search to assist the encoder in inferring the search intent. Specially, we add the geohash code to the token embeddings.
- **Session Query Bert Re-ranker** concatenates the geohash codes and textual information of the query requests in the whole search session and candidate POI, as the input sequence to the BERT-based cross-encoder, and predicts the matching score by an MLP function.

4.3 Implementation Details

For training our model, we employ the BERT-base model supplied by Hugging Face [2] to initialize the parameters of our methods. The optimization is facilitated through the AdamW optimizer with a learning rate set at 5e-5. Furthermore, the batch size is configured to be 16.

For more details refer to our code[3].

4.4 Results and Analysis

In this section, we represent our experimental results, and provide the corresponding analysis.

4.4.1 ***Re-ranking Performance.*** The experimental results of the POI re-ranking models based on click logs are presented in Table 1. Regarding the overall performance, our framework exhibits a notable enhancement across all baseline models, verifying the effectiveness of incorporating session context and user effort into the modeling process. Specifically, for the effectiveness of the **geographical context**, we note that all geography-aware models surpass the LSTM-DSSM, demonstrating the pivotal role of geographical context in the POI search task. For the effectiveness of the **POI session context**, we observe the following: 1) Leveraging the pre-training model, our framework, Session Query Bert Re-ranker,

[2]https://huggingface.co/bert-base-chinese
[3]https://anonymous.4open.science/r/poi-rerank-D324/

Table 1: The re-ranking metrics of all models on the test dataset. We use paired t-test with p-value threshold of 0.05. ∗ indicates significant difference over best baselines. The metrics of the best baselines are underlined and highlighted.

Models	NDCG MRR@1	MRR @3	MRR @5	MRR @10	NDCG @3	NDCG @5	NDCG @10
Ad-hoc							
LSTM-DSSM	0.2252	0.3189	0.3435	0.3636	0.3583	0.4128	0.4726
PALM	0.2425	0.3377	0.3629	0.3832	0.3779	0.4323	0.4921
ST-PAC	0.2803	0.3835	0.4072	0.4258	0.4229	0.4771	0.5363
Meta ST-PAC	0.2967	0.3988	0.4226	0.4407	0.4372	0.4916	0.5503
DrW	0.3457	0.4513	0.4778	0.4902	0.4920	0.5488	0.5979
Ad-hoc Bert Re-ranker	0.4473	0.5569	0.5805	0.5941	0.6026	0.6554	0.6966
Context-aware							
HQCN (Geo)	0.3917	0.5084	0.5335	0.5470	0.5538	0.6076	0.6498
ASE (Geo)	0.4680	0.5816	0.6036	0.6164	0.6287	0.6792	0.7183
Session Query Bert Re-ranker	0.4512	0.5651	0.5881	0.6010	0.6125	0.6644	0.7032
Our Model							
Our	**0.4808**∗	**0.5929**∗	**0.6154**∗	**0.6277**∗	**0.6395**∗	**0.6900**∗	**0.7268**∗

and ASE (Geo) outperform the Ad-hoc Bert Re-ranker. 2) Enhanced by the session context, HQCN (Geo) achieves superior performance compared to LSTM-DSSM, PALM, ST-PAC, and Meta ST-PAC. These findings emphasize the significance of session context in elevating ranking performance. For the effectiveness of the **pre-training model**, we find that: 1) The Ad-hoc Bert Re-ranker attains superior re-ranking metrics compared to other ad-hoc re-ranking models. 2) Our framework, Session Query Bert Re-ranker, and ASE (Geo) exhibit superior ranking performance over HQCN (Geo). These distinctions arise from the integration of the pre-training model, endowing a larger model capacity for capturing geographical and semantic knowledge.

5 CONCLUSION & FUTURE WORK

In this paper, we focus on the re-ranking stage of the POI search. We initially identify the limitation present in current POI re-rank models in capturing implicit feedback and the geographical-semantics context within the POI search session. To address the limitation, based on the architecture of pre-trained models, we propose a POI session search model to improve the POI re-ranking performance, which models interactions at three levels of granularity, namely, the query-POI level, list level, and session level within the POI search session. We conduct extensive experiments on real-world datasets obtained from the Didichuxing application, and demonstrate that the proposed framework attains superior re-ranking performance compared to existing POI re-rank methods. As part of future work, we identify another limitation in existing POI re-rank models, specifically in their inability to directly minimize cumulative user effort throughout the POI search session. The goal of the POI search system should not merely be to assist users in finding their target POIs through a one-time query-POI matching process. It should extend to the broader objective of minimizing cumulative user effort throughout the entire POI search session. This is crucial, as the level of user effort fundamentally shapes their overall experience with the search system.

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