Personalized Prompts for Sequential Recommendation

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ABSTRACT
Pre-training models have shown their power in sequential recommendation. Recently, prompt has been widely explored and verified for tuning in NLP pre-training, which could help to more effectively and efficiently extract useful knowledge from pre-training models for downstream tasks, especially in cold-start scenarios. However, it is challenging to bring prompt-tuning from NLP to recommendation, since the tokens in recommendation (i.e., items) do not have explicit explainable semantics, and the sequence modeling should be personalized. In this work, we first introduce prompts to recommendation and propose a novel Personalized prompt-based recommendation (PPR) framework for cold-start recommendation. Specifically, we build the personalized soft prefix prompt via a prompt generator based on user profiles and enable a sufficient training of prompts via a prompt-oriented contrastive learning with both prompt- and behavior-based augmentations. We conduct extensive evaluations on various tasks. In both few-shot and zero-shot recommendation, PPR models achieve significant improvements over baselines on various metrics in three large-scale open datasets. We also conduct ablation tests and sparsity analysis for a better understanding of PPR. Moreover, We further verify PPR’s universality on different pre-training models, and conduct explorations on PPR’s other promising downstream tasks including cross-domain recommendation and user profile prediction.

CCS CONCEPTS
• Information systems → Recommender systems.

KEYWORDS
recommendation, pre-training, prompt, contrastive learning

1 INTRODUCTION

Personalized recommendation aims to provide appropriate items for users according to their preferences, where user historical behavior sequence is an informative source for user understanding. Sequential recommendation, which takes users’ historical behavior sequences as inputs and outputs next predicted items, is widely studied and deployed in practice [9, 20, 23]. With the thriving of pre-training in NLP [2], there are lots of efforts that bring pre-training into sequential recommendation [25]. These pre-trained recommendation models usually consider user behavior sequences as token sequences in NLP, using pre-training techniques to improve the sequence modeling ability, which can alleviate the sparsity issues in real-world recommendation systems [21, 22].

Recently, in the overwhelming trend of pre-training, how to effectively and efficiently extract useful information from pre-trained models becomes a promising direction. Prompt-tuning [1, 10] is a representative and powerful method that has remarkable superiority over the generic fine-tuning paradigm especially in few-shot scenarios. It usually inserts hard text templates [1, 3] or soft continuous embeddings [11, 15] as prompts, and transforms the downstream tasks into similar well-trained pre-training tasks. The advantages of prompt-tuning locate in two aspects: (1) it bridges the gap between pre-training and downstream objectives, which could better utilize the knowledge in pre-training models. This advantage will be multiplied in cold-start scenarios. (2) Prompt-tuning only needs to tune a small set of parameters for the prompts and labels, which is more efficient. Looking back to the sequential recommendation task, the cold-start user issues (including zero-shot and few-shot scenarios) are crucial challenges due to the sparsity of interactions in real-world systems. We attempt to adopt the powerful pre-training with prompt-tuning to address the cold-start recommendation.

However, introducing prompts to recommendation is non-trivial due to the following challenges: (1) How to transfer the prompt-tuning of NLP into recommendation? Differing from words in NLP, the behaviors (items) in recommendation are hard to be directly used to build hard explainable prompts and labels. Moreover, it is also challenging to design an appropriate framework to make full use of pre-training knowledge in personalized recommendation. (2) How to build appropriate prompts for personalized recommendation? Compared with NLP, recommendation further values personalization. Therefore, the proposed prompts should better be personalized so as to more pertinently extract user-related knowledge from the huge pre-training model.
To address these challenges, we propose a novel personalized prompt-based recommendation (PPR) framework, which first adopts prompt-tuning in sequential recommendation. Specifically, PPR designs the personalized soft prefix prompt learned in the proposed prompt generator based on user profiles, which could better extract user-related knowledge from pre-training models for various downstream tasks in few-shot and zero-shot scenarios within a universal framework. We also propose a prompt-oriented contrastive learning (CL) via both prompt-based and behavior-based data augmentations to further enhance the training of prompts. Compared with the generic fine-tuning, our PPR has the following advantages: (1) PPR enables the prompt-tuning in recommendation, making full use of pre-trained models for more effective and efficient tuning via personalized prompts. (2) PPR designs a set of prompt-oriented contrastive learning losses on prompt-enhanced behavior sequences, which enables a more sufficient training for prompts. (3) PPR is effective, universal, and easy-to-deploy, which could be conveniently adopted for other downstream tasks such as cross-domain recommendation and user profile prediction.

In experiments, we conduct extensive evaluations to verify the effectiveness and universality of our personalized prompt-based recommendation. We conduct CTR prediction evaluations on three large-scale practical datasets in both few-shot and zero-shot scenarios, which confirms that PPR can achieve significant improvements on both scenarios. Ablation study and sparsity analysis are also conducted. Moreover, we also verify PPR’s universality on other pre-training models and other challenging downstream tasks (e.g., cross-domain recommendation and user profile prediction), shedding light on the promising applications of personalized prompts in practice. The contributions of this work are concluded as follows:

- We propose a novel personalized prompt-based recommendation to better extract useful knowledge from pre-training models. To the best of our knowledge, we are the first attempt to bring prompt-tuning in sequential recommendation.
- We design an universal prompt-based framework with the help of prompt-oriented contrastive learning considering prompt- and behavior-based augmentations, which further improves the model performances.
- We have verified the effectiveness and universality of PPR on different pre-trained models and downstream tasks, including few-shot recommendation, zero-shot recommendation, cross-domain recommendation, and user profile prediction.

## 2 RELATED WORKS

### Sequential Recommendation

Sequential recommendation models mainly leverage users’ chronological behavior sequences to learn user preferences. Recently, various deep neural networks have been employed for sequence-based recommendation. GRU4Rec [6] proposes to use Gated Recurrent Units in the session-based recommendation. Inspired by the success of Transformer and BERT [2], SASRec [9] and Bert4Rec [20] adopt self-attention mechanisms to model user behavior sequence. The cold-start problem on sequential recommendation also attracts wide attention of researchers. Zheng et al. [26] utilizes a meta-learning mechanism to alleviate the cold-start item problem in sequential recommendation. Liu et al. [14] augments short behavior sequence by reversely predicted items.

### Pre-training in Recommendation

Recently, pre-training models have achieved great successes in NLP [2, 13] and CV [5]. It aims to learn prior knowledge from general large-scale datasets to help the specific downstream tasks. After pre-training, models are further fine-tuned on downstream supervised signals to fit the specific task. This *pre-training and fine-tuning* paradigm is widely applied to various tasks [2]. With the thriving of pre-training, many pre-training models have been proposed in recommendation. BERT4Rec [20] adopts masked item prediction in sequential recommendation. S^2Rec [27] pre-trains the sequential encoder considering the correlations among item’s attribute, item, subsequence, and sequence. CL4Rec [22] applies CL via item crop, mask, and reorder on sequence modeling. PeterRec [24] pre-trains a CNN-based model and transfers it to solve cross-domain recommendation problem by adapter technology. UPRec [21] further highlights user profiles and social relations in pre-training. Inspired by the successes of pre-training, we propose PPR, which aims to (a) narrow the gap between pre-training models and downstream tasks, and (b) better extract useful knowledge from pre-trained models by replacing fine-tuning with personalized prompt-tuning. We have deploy PPR on different tasks and pre-training models to verify its effectiveness.

### Prompt Tuning

Prompt-tuning is first proposed in NLP, and is widely explored and dominating especially in few-shot scenarios) [1, 16]. Schick and Schütze [18] and Brown et al. [1] adopt hard prompts that consist of discrete real words. Considering that manually designing the hard prompt is both time-consuming and trivial, other works [3, 8, 19] focus on automatically searching for hard prompts. In contrast, soft prompt is composed of several continuous learnable embeddings randomly initialized. Prefix-tuning [11] optimizes continuous prompts for generation tasks in NLP. P-tuning [12] designs prompts to GPT for natural language understanding. PPT [4] conducts pre-tuning on the prompts to better initialize the soft prompts. In this work, we first introduce prompts into recommendation. Different from prompts in NLP, we design a personalized prompt for each user.

## 3 METHODOLOGY

### 3.1 Preliminaries

#### 3.1.1 Prompt in NLP

In NLP pre-training, prompt is often a piece of text inserted into the input text sequence. For example, in sentiment analysis, a prompt “it is [mask]” is inserted after the review “a real joy” as a natural sentence: “a real joy, it is [mask]”. In prompt-tuning, the predicted tokens of “[mask]” (e.g., great) will be mapped
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Figure 2: Overall architecture of (a) conventional fine-tuning, and (b) our Personalized prompt-based recommendation.

to the sentiment labels (e.g., positive) via a verbalizer. In this case, the original task (e.g., sentiment classification) can be formulated as a masked language model task, which has been fully optimized in pre-training and thus has better performances [1, 16, 19]. The advantages of prompt-tuning are as follows: (1) it can better extract useful knowledge in pre-trained models via similar modeling and objectives fully learned in pre-training based on prompts, especially for few-shot scenarios compared to fine-tuning [4], and (2) it is more efficient compared to fine-tuning, for most prompt-tuning does not fully update all parameters in pre-trained models.

3.1.2 Tasks of PPR. In this work, we propose Personalized prompt-based recommendation to provide a more effective and efficient tuning for cold-start downstream tasks based on pre-trained models in sequential recommendation. The pre-training and fine-tuning is a classical widely-used training paradigm, which first trains a pre-trained model on large-scale general dataset, and then fine-tunes the whole pre-trained model on the few-shot supervised information of downstream tasks. Recently, the pre-training and prompt-tuning paradigm has been widely verified in NLP as introduced in Sec. 2, where the prompts and verbalizer are mainly updated. PPR aims to better extract useful personalized information from pre-trained models via prompt-tuning rather than fine-tuning. Precisely, the main task that our PPR focuses on is cold-start recommendation (since prompt-tuning functions well especially in few-shot learning), which consists of both few-shot recommendation and zero-shot recommendation. Moreover, we also deploy PPR for other downstream tasks such as cross-domain recommendation and user profile prediction in Sec. 4.9 for universality.

3.1.3 Notions of PPR. The key notions used in PPR are defined as follows. We denote user and item as \( u \in U \) and \( v \in V \), where \( U \) and \( V \) are the overall user set and item set. Each user \( u \) has a historical behavior sequence \( s_u = \{v_{u1}^1, v_{u2}^1, \ldots, v_{un}^1\} \) (of length \( |s_u| \)) ordered by time. Each user has \( m \) basic attributes \( A_u = \{a_{u1}^1, a_{u2}^1, \ldots, a_{um}^1\} \) (i.e., user profiles). In cold-start recommendation, we split users into a warm user set \( U^W \) (for pre-training) and a cold user set \( U^C \) (for tuning) by their behavior sequence length. Then, we pre-train a sequential model \( f_{seq}(\{v_{u1}^1, v_{u2}^1, \ldots, v_{un}^1\}; \Theta) \) to learn user representations by warm users’ historical behaviors, where \( f_{seq}(.) \) is the sequential model, \( \Theta \) is the pre-trained model’s parameters. After that, we fine-tune the pre-trained model on cold users’ historical behaviors and get the fine-tuned model \( f_{seq}(\{v_{u1}^1, v_{u2}^1, \ldots, v_{un}^1\}; \hat{\Theta}) \), where \( \hat{\Theta} \) is the fine-tuned model’s parameters. Different from fine-tuning, our PPR inserts personalized prompts (i.e., prefix tokens) before cold users’ behaviors, noted as \( f_{seq}(\{p_{u1}^1; v_{u1}^1, p_{u2}^1; v_{u2}^1, \ldots, p_{un}^1; v_{un}^1\}; \Theta, \hat{\Theta}) \), where \( \{p_{u1}^1, p_{u2}^1, \ldots, p_{un}^1\} \) is the personalized prompt built from user profiles, and \( \hat{\Theta} \) is the parameters of the prompt generator.

3.2 Overall Framework

The overall framework of PPR is illustrated in Fig. 2. For each user, we first build the personalized prompts according to user profiles (user static attributes such as age, gender) via the prompt generator, and insert them into the beginning of the user behavior sequence. The new sequence is then fed into the pre-trained sequential model to get users’ behavioral preferences. The user profiles are further added into another network to generate users’ attribute preferences, which is an essential supplement for cold-start users widely used in industry. Finally, the user’s behavioral and attribute preferences are combined to get the final user representation. In PPR(light), the pre-training model is fixed during prompt-tuning. To enable a more sufficient training for personalized prompts, we further design a set of contrastive learning losses in PPR, adopting data augmentations on both the prompt generator and sequence modeling parts. PPR has been deployed and verified on various downstream tasks.

3.3 Pre-training of PPR

We first introduce the pre-training part of PPR. There are various self-attention based sequential models [9, 20, 22] verified to be effective as pre-training models. Following Xie et al. [22], we also use the classical SASRec [9] as PPR’s pre-training model. Specifically, SASRec stacks Transformer(\( \theta \)) blocks to encode the historical behavior sequence. For the input behavior sequence \( s_u \), we define its \( l \)-layer’s behavior matrix as \( H_u^{l} = \{h_{u1}^{l}, h_{u2}^{l}, \ldots, h_{u|s_u|}^{l}\} \), where \( h_{ui}^{l} \) is the \( i \)-th behavior’s representation of \( u \) at the \( l \)-th layer. The \((l+1)\)-layer’s behavior matrix \( H_u^{l+1} \) is then learned as follows:

\[
H_u^{l+1} = \text{Transformer}^l(H_u^l), \quad u_o = f_{seq}(s_u; \Theta) = h_{u|s_u|}^l. \quad (1)
\]
where $\mathbf{a}$ is the final user representation of $u$ learned in pre-training to predict user’s next items, which is generated as the last behavior’s representation at the L-th layer (i.e., $h^T_{\mathbf{u},[s_n]}$). Here, $L$ is the number of Transformer layers.

Following classical ranking models [9, 17, 22], the pre-training model is optimized under the objective $L_o$ as follows:

$$L_o = - \sum_{(u,v) \in S^+} \sum_{(u,v) \in S^-} \log \sigma(u^+_v - u^-_v), \quad u \in U^w,$$

(2)

where $(u,v) \in S^+$ indicates the positive set where $u$ has clicked $v$, and $(u,v) \in S^-$ indicates the negative set where $v$ is randomly sampled negative items. $\sigma(\cdot)$ is the sigmoid function. We optimize the parameters $\Theta$ of the pre-training model via $L_o$ on pre-training dataset of $u \in U^w$ for downstream tasks. Differing from classical prompt-tuning in NLP that usually adopts the masked language model (MLM) pre-training task [2], PPR mainly concentrates on the next-item prediction task in pre-training. It is because that the next-item prediction task perfectly fits our downstream tasks (cold-start recommendation and user profile prediction) with PPR, which can stimulate the maximum potential of prompt. Note that our PPR can be flexibly adopted on different pre-training models. To verify the universality of PPR, we further deploy PPR on CL4Rec [22], which also achieves consistent improvements (in Sec. 4.7).

### 3.4 Personalized Prompt-tuning

After pre-training, PPR conducts a personalized prompt-tuning instead of fine-tuning to better learn from pre-trained models.

#### 3.4.1 Personalized Prompt Generator

The key of our PPR is generating an effective prompt that helps to narrow the gap between pre-trained models and downstream tasks. However, it is challenging to find appropriate prompts in recommendation, since (1) it is difficult to build hard prompts and labels (i.e., some real tokens) in PPR. Unlike words in NLP, the tokens (i.e., items) in recommendation do not explicit meaningful semantics. (2) Moreover, unlike NLP, recommendation should be personalized, thus the prompts should also be customized for different users. In a sense, each user’s recommendation can be viewed as a task, while there are millions of users in a real-world system. It is impossible to manually design personalized prompts for all users.

In PPR, to automatically build personalized prompts for all users, we rely on the essential and informative user profiles. User profiles can be learned from all types of user information, such as user static attributes (e.g., age, gender, location), user cumulative interests, and user behaviors in other domains. In the task of cold-start recommendation, we mainly consider the user attributes $A_u$. Specifically, we concatenate $m$ user profile embeddings as $x_u = [a_{1u}^T|a_{2u}^T|\cdots|a_{m_u}^T]$, where $a_{iu}^T$ is the $i$-th user profile embedding. We conduct a Multi-layer perceptron (MLP) to learn the personalized prompt representation $p_u^T = (p_{1u}^T, \cdots, p_{nu}^T)$ containing $n$ tokens as follows:

$$p_u^T = \text{PPG}(x_u|\theta) = W_2\sigma(W_1x_u + b_1) + b_2,$$

(3)

where $W_1 \in \mathbb{R}^{d_u \times d'}, W_2 \in \mathbb{R}^{d' \times k}, b_1 \in \mathbb{R}^d$ and $b_2 \in \mathbb{R}^{d'}$ are trainable parameters in $\theta$, $d_u$, $d'$, and $d'$ are the embedding sizes of concatenated user profile $x_u$, hidden layer, and output prompts respectively. $n$ is the number of prompt tokens.

Inspired by the success of prefix-tuning [11], we adopt the prompt tokens as a prefix and connect them with user behavior sequence as: $\hat{s}_u = \{p_1^u, p_2^u, \cdots, p_n^u, v_1^u, v_2^u, \cdots, v_{[s_n]}^u\}$. This prompt-enhanced sequence contains both task-specific and user-specific information. For example, if $A_u = \{20-year-old, female\}$, the prompt-enhanced sequence $\hat{s}_u$ can be translated as “in cold-start recommendation, a user is a 20-year-old female, she likes $v_1, v_2, \cdots, v_{[s_n]}$”, which provides a more personalized context of user behavior sequences. Through these personalized prompts, the information of various user profiles is naturally fused into user behavioral information and jointly optimized. Hence, the power of pre-trained models (e.g., sequential modeling) can be fully reused to capture user diverse preferences from different sources, which is essential in cold-start scenarios.

#### 3.4.2 Tuning of PPR

After generating the personalized prompts, we need to construct the final user representation for recommendation. Precisely, we first input the prompt-enhanced sequence $\hat{s}_u$ to the pre-trained sequential model in Eq. (1) to get the user behavioral preference $u_t$. Next, we directly learn from user profiles via an MLP to get the user attribute preference $u_a$. Finally, both $u_t$ and $u_a$ are combined to get the final user representation $u_p$. We have:

$$u_p = u_a + u_t, \quad u_a = \text{MLP}_a(x_a|\phi), \quad u_t = f_{seq}(\hat{s}_u|\Theta, \phi).$$

(4)

$\Theta, \phi, \text{and } \phi$ are parameters of the sequential model, the prompt generator, and the user profile learner for $u_a$, respectively. To tune these parameters, we propose two prompt tuning strategies, PPR(light) and PPR(full), to balance effectiveness and efficiency in the scene of sequential recommendation.

In PPR(light), we merely update the newly-introduced parameters, i.e., $\theta$ of the prompt generator in Eq. (3) and $\phi$ of the user profile learner in Eq. (4), with other parameters fixed. It is similar to the typical prompt-tuning manner in NLP [11]. This is a straightforward and efficient prompt-tuning manner, which completely relies on the pre-trained models in sequence modeling and item representation learning. The tuned parameters of PPR(light) are greatly reduced compared to fine-tuning (note that even the item embeddings are also fixed for efficiency). The tuned personalized prompts works as an inducer, which smartly extracts useful knowledge related to the current user from large-scale pre-trained model.

However, due to the huge gaps between NLP and recommendation tasks, the widely-verified “light” prompt-tuning does not always perform satisfactory enough in downstream tasks. It is because that in plenty of NLP downstream tasks such as sentiment analysis, text classification, and sequence labeling, the numbers of predicted labels are limited. On the contrary, the predicted items in recommendation (i.e., labels of verbalizer) are often million-level in practice, which should also be trained sufficiently in tuning. Hence, we propose another PPR(full) manner for a wider range of tuning, which further tunes the parameters of $\Theta$ (including parameters of item embeddings and sequential model) besides $\theta$ and $\phi$.

We follow the pre-training objective in Eq. (2) to build the optimization objective $L_p$ of our prompt-tuning as follows:

$$L_p = - \sum_{(u,v) \in S^+} \sum_{(u,v) \in S^-} \log \sigma(u^+_p v - u^-_p v), \quad u \in U^c.$$  

(5)

$S^+_p$ and $S^-_p$ are similar positive and negative sample sets in tuning.
3.5 Prompt-oriented Contrastive Learning
The main challenge of cold-start recommendation is the lack of sufficient tuning instances. Recently, contrastive learning (CL) has shown its power in recommendation [22, 27]. These CL-based models usually conduct self-supervised learning (SSL) as supplements to supervised information via certain data augmentations, which could obtain more effective and robust user representations and alleviate the data sparsity issue. Inspired by those methods, we also adopt CL as auxiliary losses via two types of data augmentations based on elements of our prompt-tuning.

3.5.1 Prompt-based Augmentation. In real-world systems, the user basic attributes are usually noisy or even missing, while they are the main source of our personalized prompts, which are essential especially in zero-shot scenarios. Therefore, we design a prompt-based data augmentation to improve the effectiveness and robustness of the prompt generator. Specifically, we conduct a random element-level masking on the feature elements of user profile embeddings $x_u$ to obtain $\bar{x}_u$ with a certain mask ratio $\gamma_1$. Formally, the augmented prompt-enhanced behavior sequence is noted as $\tilde{s}_u^1 = \{\tilde{p}_1^u, \tilde{p}_2^u, ..., \tilde{p}_{\ell_u}^u, \tilde{v}_1^u, ..., \tilde{v}_{\ell_u}^u\}$, where $\tilde{p}_i^u = PPG(\bar{x}_u)[\theta]$. This augmentation can also avoid the possible overfitting of our prompt generator on some abnormal profiles.

3.5.2 Behavior-based Augmentation. Besides the prompt generator, we also conduct data augmentations on the original user historical behaviors for SSL on prompt-enhanced sequence modeling. Following previous CL-based models [22, 27], we randomly zero-mask proportional items in user behavior sequence with the mask ratio $\gamma_2$. Intuitively, the augmented prompt-enhanced behavior sequence is noted as $\tilde{s}_u^2 = \{p_1^u, p_2^u, ..., p_{\ell_u}^u, \tilde{v}_1^u, ..., \tilde{v}_{\ell_u}^u\}$, which strengthens the sequence modeling ability from another aspect.

3.5.3 Contrastive Learning. In prompt-oriented contrastive learning, we hope PPR can distinguish whether two user representations learned from (augmented) prompt-enhanced behavior sequences derive from the same user. To achieve this goal, we need to minimize the differences between the original and augmented sequences of the same users while maximize the gaps between different users’ representations. Specifically, for a batch $B$ with size $N$, we apply the above two augmentations to each user $u$, and get the augmented sequences $\tilde{s}_u^1$ and $\tilde{s}_u^2$. We regard the original and the corresponding augmented user behavioral representations of $u$ as the positive pair $(u, \tilde{u})$. The rest augmented user representations $\tilde{u}'_u$ of other users $u'$ in the batch form the negative set $S_n^B$ of $u$. We use the cosine similarity $\text{sim}(\cdot, \cdot)$ to measure the similarity. Formally, the loss function of contrastive learning $L_{CL}$ is formulated as:

$$L_{CL} = - \sum_{u \in U^*} \log \frac{\exp(\text{sim}(u, \tilde{u})/\tau)}{\exp(\text{sim}(u, \tilde{u}) + \sum_{u' \in S_n^B} \exp(\text{sim}(u, \tilde{u}'_u))}. $$

(6)

Here, the augmented user representation $\tilde{u}$ equals $f_{seq}(\tilde{s}_u^1[\Theta, \theta])$ or $f_{seq}(\tilde{s}_u^2[\Theta, \theta])$. $\tau$ is the temperature hyper-parameter. The prompt-oriented contrastive learning loss is used as an auxiliary task of $L_p$ in prompt-tuning to fully train the personalized prompts. The overall loss $L_{all}$ is defined with the loss weight $\lambda$ as follows:

$$L_{all} = L_p + \lambda L_{CL}.$$  

(7)

4 EXPERIMENTS
In this section, we conduct extensive experiments to answer the following six research questions: (RQ1): How does PPR perform in few-shot scenarios (Sec. 4.4)? (RQ2): Can PPR work well in zero-shot recommendation (Sec. 4.5)? (RQ3): What are the effects of different components in PPR (Sec. 4.6)? (RQ4): Can PPR also work on different pre-training models (Sec. 4.7)? (RQ5): Can PPR achieve improvements under different sparsity (Sec. 4.8)? (RQ6): Is PPR still effective on other downstream recommendation tasks (Sec. 4.9)?

4.1 Datasets
We evaluate PPR on three real-world open datasets, namely CIKM, QQBrowser, and AliEC & AliAD. In all datasets, the users are split into warm users and cold-start users according to a threshold of interacted items (users having less than 10 clicks are regarded as cold-start users). The click instances of warm users are used as the pre-train set, while those of cold-start users are used as the tuning set for downstream tasks. For cold-start recommendation, we randomly split the cold-start users into train (80%) and test (20%) sets in tuning. More details are in Table 1.

CIKM. The CIKM dataset is an E-commerce recommendation dataset released by Alibaba. It has 60 thousand warm users with 2.1 million click instances in the pre-train set. Other 21 thousand cold users with 143 thousand instances are used for tuning and testing. Each user has 3 attributes: gender, age, consumption level.

QQBrowser. It is collected from QQ Browser [24] on news/videos. This dataset has 107 thousand warm users and 28 thousand cold users. Each user has 3 attributes: gender, age, life status.

AliEC & AliAD. This dataset contains two sub-datasets: AliEC for E-commerce and AliAD for advertising. AliAD is much sparser than AliEC. For cold-start recommendation and user profile prediction tasks, we evaluate on AliEC. It has nearly 99 thousand warm users and 6.4 thousand cold users. AliAD is used for cross-domain recommendation. This dataset has 8 user attributes for each user.

| Dataset    | # user   | # item   | # pre-training instance | # tuning instance |
|------------|----------|----------|-------------------------|------------------|
| CIKM       | 80,964   | 87,894   | 2,103,610               | 143,726          |
| QQBrowser  | 134,931  | 97,904   | 15,359,880              | 263,572          |
| AliEC      | 104,984  | 109,938  | 8,768,915               | 39,292           |

4.2 Competitors
In this work, we adopt the representative SASRec [9] as our base pre-training model, while it is also convenient to deploy our PPR on other pre-training models (e.g., CL4Rec [22], see Sec. 4.7). In few-shot recommendation, we compare our PPR with several competitive sequential models as follows: (1) BERT4Rec [20], which is a classical pre-training recommendation model based on BERT. It uses masked item prediction as its pre-training task. (2) CL4Rec
Table 2: Results on few-shot recommendation. All improvements are significant over baselines (t-test with p<0.05).

| Dataset | Model       | AUC    | HIT@5   | NDCG@5  | HIT@10  | NDCG@10 | HIT@20  | NDCG@20 | HIT@50  | NDCG@50 |
|---------|-------------|--------|---------|---------|---------|---------|---------|---------|---------|---------|
| CIKM    | BERT4Rec   | 0.8482 | 0.5191  | 0.4279  | 0.6255  | 0.4616  | 0.7367  | 0.4902  | 0.8965  | 0.5220  |
|         | CL4Rec     | 0.8590 | 0.5865  | 0.4942  | 0.6699  | 0.5252  | 0.7612  | 0.5481  | 0.8960  | 0.5750  |
|         | pre-train  | 0.8630 | 0.5779  | 0.4906  | 0.6695  | 0.5203  | 0.7660  | 0.5446  | 0.9039  | 0.5721  |
|         | fine-tuning | 0.8731 | 0.5886  | 0.4948  | 0.6856  | 0.5255  | 0.7837  | 0.5508  | 0.9159  | 0.5772  |
|         | PPR(light)  | 0.8774 | 0.5918  | 0.4976  | 0.6889  | 0.5290  | 0.7903  | 0.5547  | 0.9230  | 0.5795  |
|         | PPR(full)   | 0.9520 | 0.8169  | 0.6680  | 0.9031  | 0.6960  | 0.9589  | 0.7104  | 0.9926  | 0.7066  |

| QQBrowser | BERT4Rec   | 0.9546 | 0.7782  | 0.6295  | 0.8734  | 0.6606  | 0.9386  | 0.6772  | 0.9858  | 0.6867  |
|           | CL4Rec     | 0.9554 | 0.7817  | 0.6304  | 0.8779  | 0.6618  | 0.9426  | 0.6783  | 0.9863  | 0.6872  |
|           | pre-train  | 0.9572 | 0.7842  | 0.6338  | 0.8818  | 0.6657  | 0.9448  | 0.6817  | 0.9873  | 0.6904  |
|           | fine-tuning | 0.9645 | 0.8142  | 0.6659  | 0.9017  | 0.6944  | 0.9578  | 0.7087  | 0.9919  | 0.7156  |
|           | PPR(light)  | 0.9640 | 0.8068  | 0.6545  | 0.8982  | 0.6843  | 0.9575  | 0.6994  | 0.9926  | 0.7066  |
|           | PPR(full)   | 0.9632 | 0.8169  | 0.6680  | 0.9031  | 0.6960  | 0.9589  | 0.7104  | 0.9920  | 0.7171  |

| AliEC    | BERT4Rec   | 0.8758 | 0.5543  | 0.4370  | 0.6738  | 0.4757  | 0.7898  | 0.505   | 0.9266  | 0.5324  |
|          | CL4Rec     | 0.8787 | 0.5878  | 0.4696  | 0.6977  | 0.5052  | 0.8021  | 0.5316  | 0.9248  | 0.5562  |
|          | pre-train  | 0.8838 | 0.5880  | 0.4710  | 0.7006  | 0.5073  | 0.8110  | 0.5351  | 0.9308  | 0.5592  |
|          | fine-tuning | 0.8907 | 0.6058  | 0.4851  | 0.7189  | 0.5217  | 0.8212  | 0.5475  | 0.9371  | 0.5708  |
|          | PPR(light)  | 0.8975 | 0.6123  | 0.4873  | 0.7275  | 0.5246  | 0.8363  | 0.5521  | 0.9422  | 0.5734  |
|          | PPR(full)   | 0.8941 | 0.6126  | 0.4896  | 0.7241  | 0.5256  | 0.8284  | 0.5322  | 0.9374  | 0.5739  |

We mainly focus on the few-shot and zero-shot recommendation tasks of cold-start users. For all cold-start users in test set, their first clicked items are used for zero-shot recommendation (since there is no historical behavior at this time), while the rest click behaviors are used for few-shot recommendation. We use the classical AUC, top-N hit rate (HIT@N), and Normalized Discounted Cumulative Gain (NDCG@N) as our evaluation metrics. For HIT@N and NDCG@N, we report top 5, 10, 20 and 50. For each ground truth, we randomly sample 99 items that the user did not click as negative samples as [20, 27].

### 4.3 Experimental Settings
We mainly focus on the few-shot and zero-shot recommendation tasks of cold-start users. For all cold-start users in test set, their first clicked items are used for zero-shot recommendation (since there is no historical behavior at this time), while the rest click behaviors are used for few-shot recommendation. We use the classical AUC, top-N hit rate (HIT@N), and Normalized Discounted Cumulative Gain (NDCG@N) as our evaluation metrics. For HIT@N and NDCG@N, we report top 5, 10, 20 and 50. For each ground truth, we randomly sample 99 items that the user did not click as negative samples as [20, 27].

### 4.4 Few-shot Recommendation (RQ1)
We first evaluate models on the few-shot recommendation. Table 2 shows the results on three datasets. We can find that:

1. Our personalized prompt-based model outperforms all baselines on all metrics in three datasets (the significance level is p<0.05 obtained via t-test). It indicates that our personalized prompts can extract useful information related to the current user from the huge knowledgeable pre-training models, which is beneficial especially for cold-start scenarios. Through the PPR, the powerful sequence modeling ability of the pre-trained model could be smoothly transferred into the few-shot recommendation task.

2. Comparing among different PPR settings, we observe that PPR(full) generally achieves better performances in few-shot scenarios. Different from tasks in NLP (e.g., sentiment analysis with several labels), the label set of cold-start recommendation is the whole item set (often million-level). It is natural that the tuned item representations of PPR(full) can further improve the performances.

3. PPR(light) still achieves some SOTA results on HIT@N in AliEC dataset, and generally outperforms fine-tuning in two datasets. It is challenging since PPR(light) only tunes the personalized prompt part with all pre-trained parameters unchanged. Compared to fine-tuning and PPR(full), PPR(light) is more efficient in tuning stage. We can select between the full and light PPR versions according to the priority of effectiveness and efficiency. PPR models also outperform other classical baselines such as BERT4Rec and CL4Rec.

### 4.5 Zero-shot Recommendation (RQ2)
The data sparsity issue is extremely serious in practical systems, where zero-shot users widely exist. Conventional sequential recommendation models cannot handle the zero-shot scenarios, since...
there is no historical behavior. We attempt to jointly address the zero-shot recommendation with the same PPR framework. For PPR, we directly input user profiles into the prompt generator as the few-shot recommendation without behavioral inputs. For fine-tuning, only the user profile learner (i.e., the MLP in Eq. (4)) is activated to learn from user profiles. From Table 3 we can observe that:

1) Our PPR models still achieve the best performances on most metrics of three datasets, which confirms the effectiveness of PPR in zero-shot user understanding via fully reusing pre-training knowledge. We should highlight that getting improvements in zero-shot scenarios is challenging, since all models share the same sparse user profiles and training instances in tuning. Compared with fine-tuning, PPR can better transfer the sequence modeling ability via prompt, which is the main reason of our improvements.

2) Currently, the user profiles for prompt construction are not that sufficient in the open datasets, which may limit the modeling ability of prompt-tuning. It can be expected that the improvements will be more significant if enhanced with more user features (e.g., full user profiles or user embeddings learned from other domains). We have also tested the effectiveness of PPR in cross-domain recommendation and user profile prediction tasks in Sec. 4.9.

**Joint Few-shot and Zero-shot Recommendation.** Table 2 and 3 demonstrate the effectiveness of our PPR in both few-shot and zero-shot recommendation. Considering the storage efficiency and maintenance cost in online deployment, we further conduct a challenging evaluation, using one set of model parameters to jointly address two cold-start recommendation tasks. Table 4 shows the results of joint cold-start recommendation. We can find that: PPR models significantly outperform fine-tuning by a larger margin in the joint scenarios. It indicates that the powerful personalized prompts could help to understand few-shot and zero-shot users jointly in practice, which cannot be accomplished well by most sequential models particularly relying on user behaviors.
Table 5: Results of PPR on few-shot recommendation based on CL4Rec. Improvements are significant (t-test with p<0.05).

| Dataset  | Model     | AUC   | HIT@5 | NDCG@5 | HIT@10 | NDCG@10 | HIT@20 | NDCG@20 | HIT@50 | NDCG@50 |
|----------|-----------|-------|-------|--------|--------|---------|--------|---------|--------|---------|
| CIKM     | pre-train | 0.8590| 0.5865| 0.4942 | 0.6699 | 0.5252  | 0.7612 | 0.5481  | 0.8960 | 0.5750  |
|          | fine-tuning | 0.8660| 0.5948| 0.5035 | 0.6797 | 0.5309  | 0.7719 | 0.5542  | 0.9034 | 0.5804  |
|          | PPR(light) | 0.8723| 0.6013| 0.5053 | 0.6891 | 0.5338  | 0.7851 | 0.5580  | 0.9106 | 0.5830  |
|          | PPR(full)  | 0.8769| 0.6066| 0.5093 | 0.6982 | 0.5390  | 0.7928 | 0.5628  | 0.9157 | 0.5873  |
| QQBrowser| pre-train | 0.9554| 0.7817| 0.6304 | 0.8779 | 0.6618  | 0.9426 | 0.6783  | 0.9863 | 0.6872  |
|          | fine-tuning | 0.9623| 0.8083| 0.6593 | 0.8971 | 0.6883  | 0.9548 | 0.7030  | 0.9896 | 0.7101  |
|          | PPR(light) | 0.9641| 0.8077| 0.6566 | 0.8989 | 0.6863  | 0.9583 | 0.7015  | 0.9919 | 0.7084  |
|          | PPR(full)  | 0.9642| 0.8138| 0.6652 | 0.9008 | 0.6936  | 0.9580 | 0.7082  | 0.9911 | 0.7150  |
| AliEC    | pre-train | 0.8787| 0.5878| 0.4696 | 0.6977 | 0.5052  | 0.8021 | 0.5316  | 0.9248 | 0.5562  |
|          | fine-tuning | 0.8912| 0.6057| 0.4857 | 0.7226 | 0.5234  | 0.8242 | 0.5491  | 0.9365 | 0.5716  |
|          | PPR(light) | 0.8992| 0.6114| 0.4857 | 0.7328 | 0.5250  | 0.8386 | 0.5518  | 0.9441 | 0.5729  |
|          | PPR(full)  | 0.8934| 0.6140| 0.4918 | 0.7277 | 0.5284  | 0.8290 | 0.5542  | 0.9362 | 0.5757  |

Figure 4: Improvements of PPR models on fine-tuning with different degrees of data sparsity in CIKM dataset.

4.6 Ablation Study (RQ3)

In this section, we aim to confirm that the prompt-oriented contrastive learning is essential for PPR. Fig. 3 shows the results of different ablation versions of PPR(light) and PPR(full) on the few-shot recommendation task with multiple datasets. We can find that: (1) Generally, the prompt-oriented CL brings consistent improvements on almost all metrics on both datasets, except AUC on PPR(light). It reconfirms the effectiveness of prompt-based SSL in cold-start recommendation. (2) PPR still outperforms fine-tuning on most metrics even without the prompt-oriented CL. It verifies that our personalized prompt-tuning is truly superior to fine-tuning in different ablation versions of PPR. We can flexibly choose different implementations of PPR considering the practical demand on efficiency.

4.7 Universality of PPR (RQ4)

PPR is an effective and universal tuning framework, which can be easily deployed on different pre-training models. In this section, we further adopt PPR with CL4Rec [22] used as the pre-training model. The results of PPR on few-shot recommendation based on CL4Rec are given in Table 5, from which we can find that: (1) PPR models still achieve the state-of-the-art performances on all metrics in three datasets, which proves the universality of PPR. Our personalized prompts could consistently improve cold-start recommendation with different pre-training models.

(2) Generally, PPR(full) consistently outperforms PPR(light) on most metrics. It indicates that fine-tuning item embeddings (i.e., the labels to be predicted) is essential in cold-start recommendation, which differs from the prompt-tuning in NLP. Nevertheless, PPR(light) still performs better than fine-tuning on most metrics.

4.8 Model Analyses on Sparsity (RQ5)

We further explore the influence of data sparsity on PPR to show its robustness. Specifically, we crop all user behavior sequences of both train and test sets in tuning to represent different degrees of sparsity. We define the k-shot setting where all user behavior sequences are cropped and no longer than \( k \) cropped, with \( k = 1, 5, 7 \). Fig. 4 shows the relative improvements of PPR(light) and PPR(full) on fine-tuning on AUC, HIT, and NDCG in CIKM. We find that: (1) Both PPR(light) and PPR(full) consistently outperform fine-tuning with different sparsity, which verifies the robustness of PPR on different cold-start scenarios. (2) The improvements of PPR models increase with the maximum user behavior sequence length decreasing. It indicates that our PPR can perform better on more sparse scenarios compared to fine-tuning.
to fine-tuning. It is intuitive since the personalized prompts are more dominating when the behavioral information is sparser.

4.9 Explorations on Other Tasks (RQ6)

Besides the main few-shot and zero-shot recommendation tasks, we further explore other promising usages of personalized prompts on more diversified and challenging downstream tasks, including cross-domain recommendation and user profile prediction.

4.9.1 Cross-domain Recommendation. Cross-domain recommendation (CDR) aims to transfer useful knowledge from the source domain to help the target domain [7]. We focus on the CDR scenario with overlapping users. In this work, the source domain (pre-train set) is AliEC and the target domain (tuning set) is AliAD. We directly use the user embeddings trained on the source domain as our personalized prompts. Similarly, these source-domain user embeddings are also applied as side information for fine-tuning and PPR. We also implement SASRec(target), which is only trained on the target domain without source information. Since there is no overlapping items, we do not report the result of PPR(light).

The results are shown in Table 7. We can find that PPR significantly outperforms all baselines on all metrics. The only difference between PPR and fine-tuning is the personalized prompt, which brings in impressive improvements. It implies the promising application of adopting PPR on pre-training based CDR models.

4.9.2 User Profile Prediction. User profile prediction task aims to predict users’ profiles via their behavior sequences. We conduct an exploration of PPR on this task by predicting users’ graduate state in AliEC, which is a binary classification task. Precisely in PPR, the personalized prompts are generated by users’ all profiles except the one to be predicted. For classification, we add a profile classifier on the final user representation, and so as the fine-tuning.

The results are shown in Table 6. We can find that PPR significantly outperforms fine-tuning on ACC, precision, and F1. It is be because that PPR can well prompt the pre-trained sequential model to better extract user-related knowledge for downstream tasks. We also evaluate PPR on other user profile predictions such as gender and age, where PPR(light) performs comparable with fine-tuning involving less parameter tuning. In the future, we will design customized personalized prompts specially for different downstream tasks to further improve the performance of user profile prediction.

Table 6: Results of user profile prediction on AliEC.

| Dataset   | Model     | ACC | Precision | Recall | F1  |
|-----------|-----------|-----|-----------|--------|-----|
| AliEC     | fine-tuning | 0.89 | 0.33      | 0.82   | 0.47|
|           | PPR(light) | 0.92 | 0.42      | 0.74   | 0.54|

5 CONCLUSION AND FUTURE WORK

In this work, we propose a personalized prompt-based recommendation to improve the tuning in pre-training recommendation. We conduct extensive experiments to verify the effectiveness, robustness, and universality of our PPR on cold-start recommendation tasks, and also explore the potential extensions of PPR on various downstream tasks. In the future, we attempt to verify our PPR on more recommendation tasks with customized prompt-tuning manners or pre-training tasks. We will also explore the effectiveness of PPR on industrial extremely large-scale recommendation datasets.

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Table 7: Results of cross-domain recommendation on AliEC->AliAD. All improvements are significant (t-test with p<0.01).

| Dataset | Model          | AUC | HIT@5 | NDCG@5 | HIT@10 | NDCG@10 | HIT@20 | NDCG@20 | HIT@50 | NDCG@50 |
|---------|----------------|-----|-------|--------|--------|---------|--------|---------|--------|---------|
| AliEC   | SASRec(target) | 0.6423 | 0.2752 | 0.2106 | 0.3590 | 0.2375 | 0.4594 | 0.2628 | 0.6568 | 0.3017 |
|         | fine-tuning     | 0.7165 | 0.3362 | 0.2494 | 0.4357 | 0.2813 | 0.5552 | 0.3115 | 0.7323 | 0.3465 |
| AliAD   | PPR(full)       | 0.7343 | 0.3632 | 0.2799 | 0.4595 | 0.3109 | 0.5761 | 0.3402 | 0.7631 | 0.3772 |