Title - Personalized Prompt for Sequential Recommendation

T5-prompt has been widely explored and verified for tuning after pre-training in NLP . but it is challenging to bring prompt-tuning from NLP to recommendation . tokens of recommendation (i.e., items) are million-level and do not have concrete explainable semantics . Personalized prompt-based recommendation (PPR) framework for cold-start recommendation is effective, parameter-efficient, and universal in various tasks . in both few-shot and zero-shot recommendation tasks, PPR models achieve significant improvements over baseline ..

BART- Personalized Prompt for Sequential Recommendation. Pre-training models have shown their power in sequential recommendation. Prompt has been widely explored and verified for tuning after pre-training in NLP. We propose a novel Personalized prompt-based recommendation (PPR) framework for cold-start recommendation. We build personalized soft prompt via a prompt generator based on user profiles, and enable a sufficient training on prompts via a new prompt-oriented contrastive learning. PPR is effective, parameter-efficient, and universal in various tasks. In both few-shot and zero-shot recommendation tasks, PPR models achieve significant improvements over baselines in three large-scale datasets. We also verify PPR’s universality in adopting different recommendation models as the backbone. Finally, we explore and confirm the capability of PPR on other tasks such as cross-domain recommendation and user profile prediction, shedding lights on the promising future directions of better using large- scale pre-trained recommendation models.

GEMINI-Personalized Prompt-based Recommendation (PPR) is a framework that leverages prompt tuning on pre-trained recommendation models. It addresses the challenges of large-scale item tokens and the need for personalized sequence modeling. PPR proposes a personalized soft prompt generator and utilizes prompt-oriented contrastive learning for training. It demonstrates effectiveness, parameter efficiency, and universality in various tasks, including cold-start recommendation, cross-domain recommendation, and user profile prediction.

GPT-4 In recent years, the growing field of sequential recommendation has witnessed significant advancements through the integration of pre-training models. These models have demonstrated their effectiveness in enhancing recommendation systems, particularly in addressing the challenges of cold-start scenarios. Previous research highlights significant advances in Natural Language Processing (NLP), where the concept of prompt-tuning has been extensively explored and validated. This technique facilitates the efficient and effective extraction of knowledge from pre-trained models for downstream tasks, utilizing fewer parameters.

Numerous studies have addressed this topic with varying approaches, yet the application of prompt-tuning to recommendation systems presents unique challenges. Unlike NLP, where tokens have clear, explainable semantics, the tokens in recommendation systems—namely, items—are often at the million-level and lack straightforward semantic interpretations. Additionally, the sequence modeling required for recommendations needs to be personalized, further complicating the application of NLP techniques to this field.

Addressing these challenges, this work introduces a novel framework called Personalized Prompt-based Recommendation (PPR). The PPR framework innovatively applies prompt-tuning to recommendation systems by generating personalized soft prompts. These prompts are tailored based on user profiles through a specially designed prompt generator. Furthermore, the framework enhances the training of these prompts through a new prompt-oriented contrastive learning method, ensuring effective and efficient learning.

The PPR framework has proven to be effective and parameter-efficient across various tasks. It demonstrates significant improvements over baseline models in both few-shot and zero-shot recommendation scenarios, as evidenced by testing on three large-scale datasets. The versatility of PPR is also confirmed through its compatibility with different backbone recommendation models. Beyond typical recommendation tasks, PPR's applicability extends to cross-domain recommendation and user profile prediction, highlighting its potential to leverage large-scale pre-trained models for a broader range of applications. This exploration opens promising avenues for future research in enhancing the utility of pre-trained recommendation models.

GPT-3 In the realm of sequential recommendation, leveraging pre-training models has proven to be powerful. While prompt-tuning has been successful in NLP for refining pre-trained models, transitioning this technique to recommendation systems poses challenges due to the vast number of items with abstract semantics and the need for personalized sequence modeling. Addressing this gap, a novel framework called Personalized prompt-based recommendation (PPR) is introduced in this study. PPR generates personalized soft prompts based on user profiles and employs prompt-oriented contrastive learning for effective training. The framework demonstrates effectiveness, parameter efficiency, and versatility across various tasks, outperforming baselines in both few-shot and zero-shot recommendation scenarios across large-scale datasets. Furthermore, PPR's adaptability to different recommendation models as backbones is confirmed, showcasing its universal applicability. The study also explores PPR's potential in cross-domain recommendation and user profile prediction tasks, hinting at promising future directions for maximizing the utility of large-scale pre-trained recommendation models. Overall, the PPR framework offers a robust solution for cold-start recommendation scenarios, emphasizing the importance of personalized prompts in enhancing the performance and efficiency of recommendation systems.

**ELitsumm** - This study introduces a novel Personalized Prompt-based Recommendation (PPR) framework that integrates prompt-tuning from Natural Language Processing (NLP) with recommendation systems to address cold-start scenarios. PPR shows significant improvements in few-shot and zero-shot scenarios and is adaptable to different models and tasks, including cross-domain recommendation and user profile prediction. Previous research has focused on improving recommendation accuracy with bidirectional self-attention, text classification and inference using cloze-style prompts, and enhancing few-shot learning. Other proposed frameworks include BERT4Rec, PET, PPT, P-Tuning, ASReP, Transformers, S3-Rec, GeoSAN, PFRec, M6-Rec, ShopperBERT, UAF, SASRec, Transformer, LM-BFF, P-Tuning v2, and a unified text-to-text paradigm for recommendation tasks. These frameworks aim to enhance the efficiency and effectiveness of sequential recommendation systems, improve user profile prediction, and enhance the transferability of recommendations.

**Litllm -**

The Pretrain, Personalized Prompt, and Predict Paradigm (P5) is a novel framework for recommendation systems that uses natural language sequences to capture deep semantics for personalization and recommendation. It shares similarities with BERT4Rec, which uses deep bidirectional self-attention to model user behavior sequences. P5 advances from deep models to large models, enabling instruction-based recommendation based on prompts and reducing the need for extensive fine-tuning. It correlates with the Pattern-Exploiting Training (PET) method, converting data to a common language format for better semantics. P5 also offers adaptive personalized prompts for different users, allowing for zero-shot or few-shot predictions. It deviates from the Self-Supervised learning for Sequential Recommendation (S3-Rec) model, employing a language modeling objective during pretraining. P5 tackles data sparsity by presenting a unified text-to-text paradigm, leveraging the power of natural language for personalization and recommendation. By incorporating the strengths of related works, P5 offers a promising solution to existing recommendation approaches and could revolutionize recommender systems.