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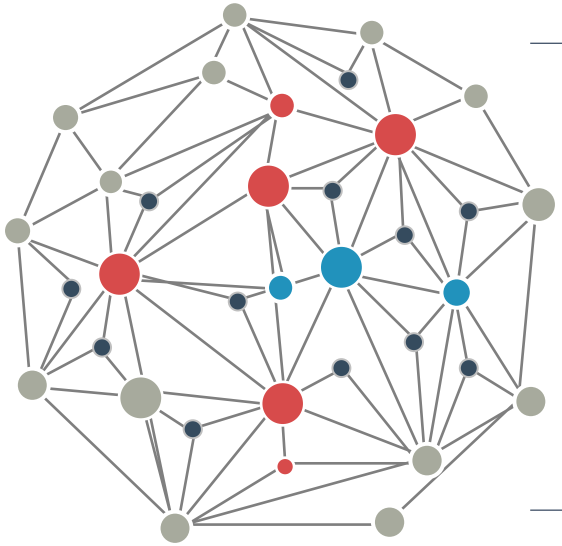


通向推荐大模型的可能性

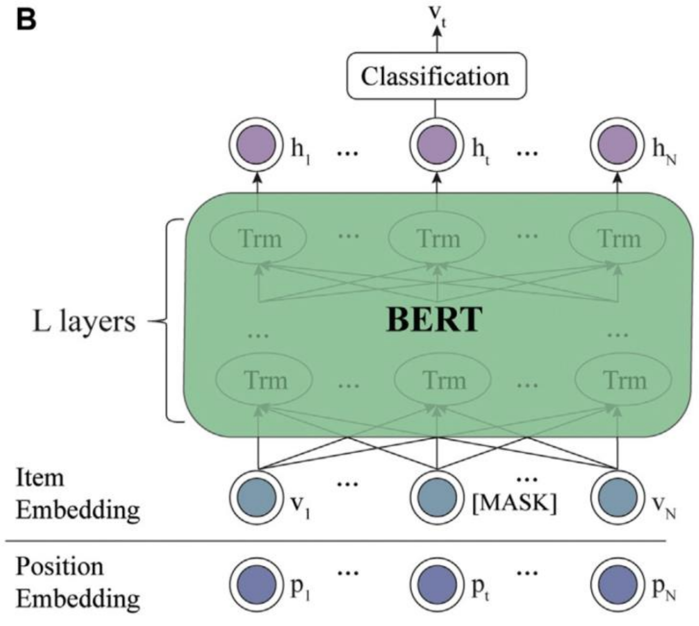
腾讯微信 谢若冰

基础：推荐系统和语言模型的相似性

语言文本序列　威廉·莎士比亚是英国文学史上最杰出的戏剧家，也是西方文艺史上杰出的作家之一…

推荐行为序列



BERT architecture for masked item prediction.

共同的核心任务：下一个token（字词/物品）生成

思考：预训练语言模型正统治NLP的诸多任务，那推荐系统领域是否也能构建**推荐大模型**呢？

挑战：推荐系统和语言模型的差异性

WeChat

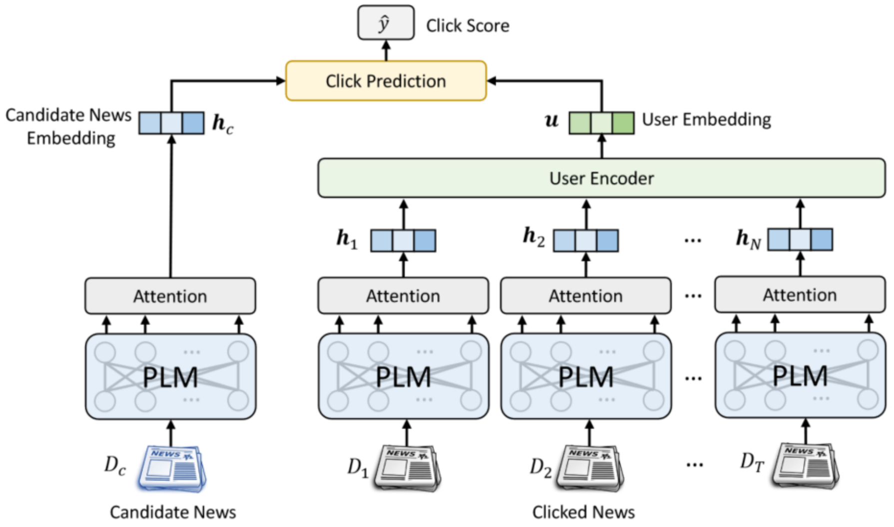
语言序列： 威廉 · 莎士比亚是英国文学史上最杰出的戏剧家，也是西方文艺史上杰出的作家之一…

物品序列：

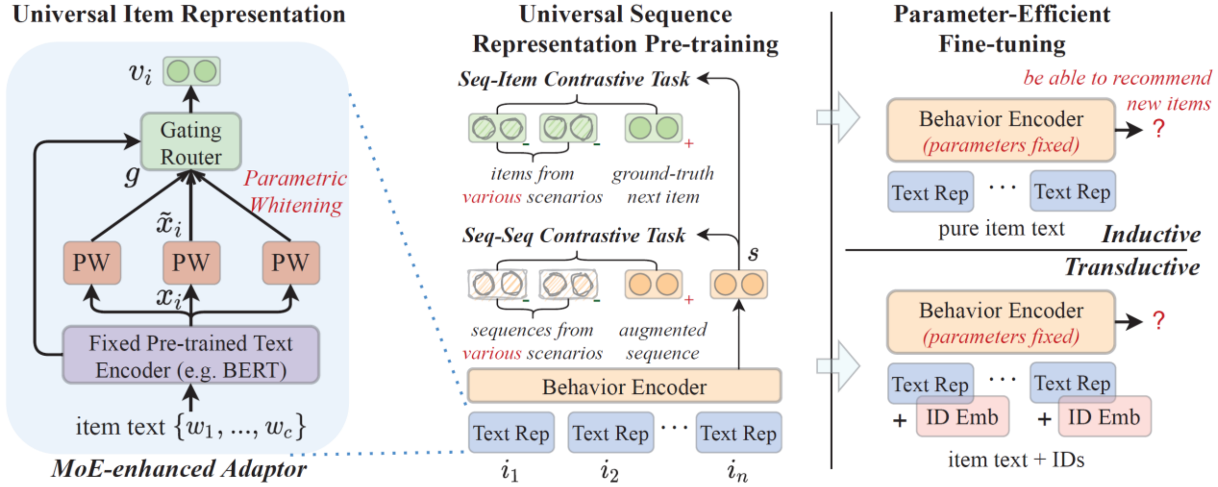
	语言模型	推荐系统
个性化	较通用的语言模型	用户行为偏好千人千面
序列token	字词（万级别，语义明晰）	物品（亿级别，包含多模态信息，语义模糊）
下游任务	多种多样（分类、问答、生成、序列标注等等）	更加集中（关注推荐核心任务——不同场景下的下一个物品推荐）
稀疏性	训练数据相对较充分	由于个性化，用户-物品交互信息极其稀疏，长尾效应明显

可能性一：预训练语言模型+传统推荐行为模型

- 预训练语言模型建模物品的文本信息，推荐行为模型建模行为序列
  - 文本序列和行为序列分开建模，直观且实用的预训练模型使用方法
  - 使用预训练语言模型加强对物品文本信息的理解



Wu C, et al. Empowering news recommendation with pre-trained language models. SIGIR'21.



Hou Y, et al. Towards Universal Sequence Representation Learning for Recommender Systems. KDD'22.

可能性二：直接使用原始预训练语言模型建模行为序列

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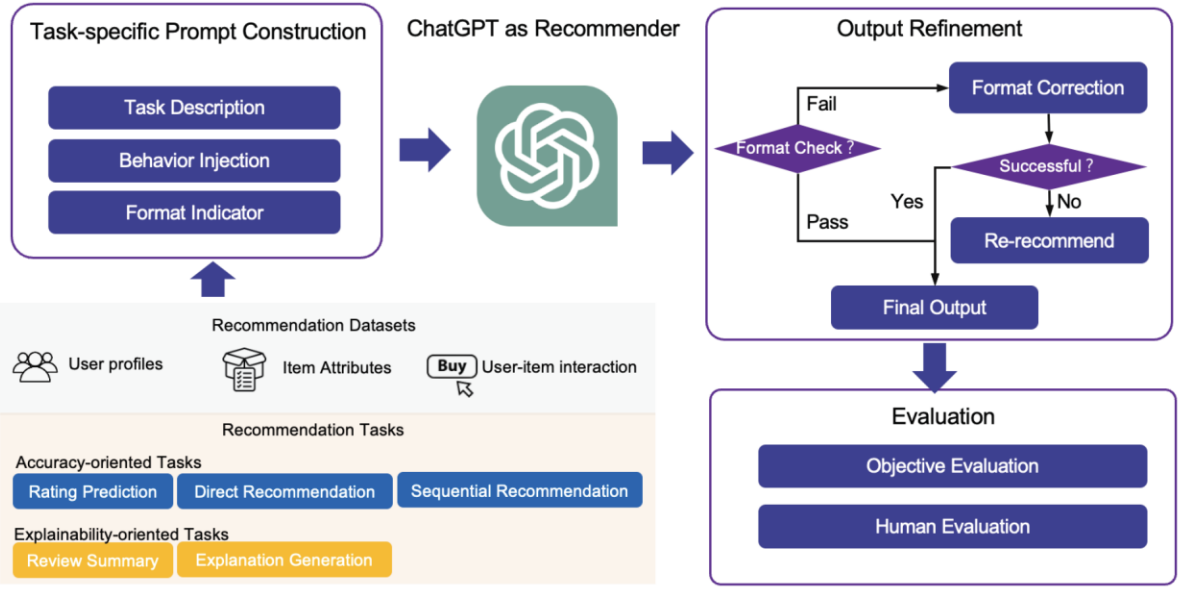
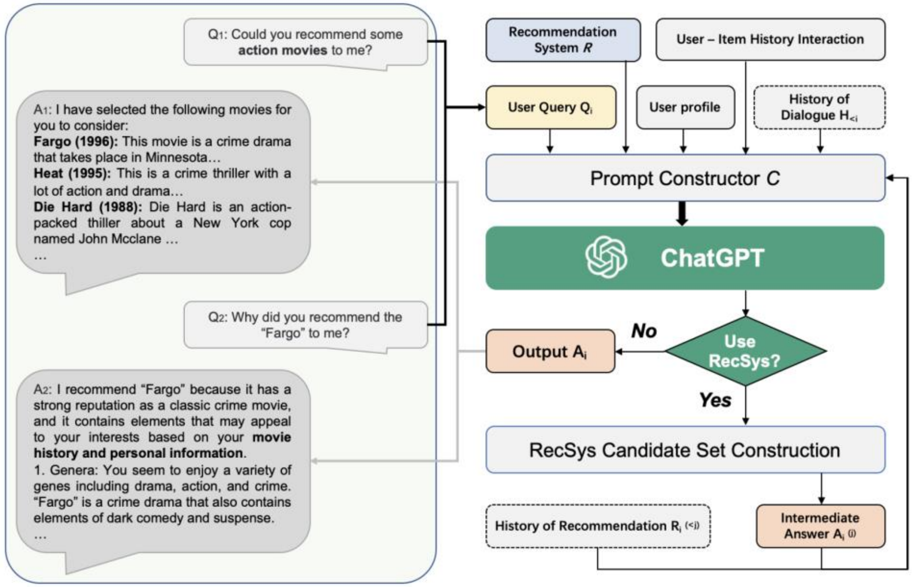
- 将用户行为序列转换为文本序列，直接使用预训练语言模型进行推荐任务
  - 直接基于PLM进行下游推荐任务，zero-shot设定下展示出一定潜力
  - 文本和行为序列存在较大gap，直接使用PLM效果欠佳



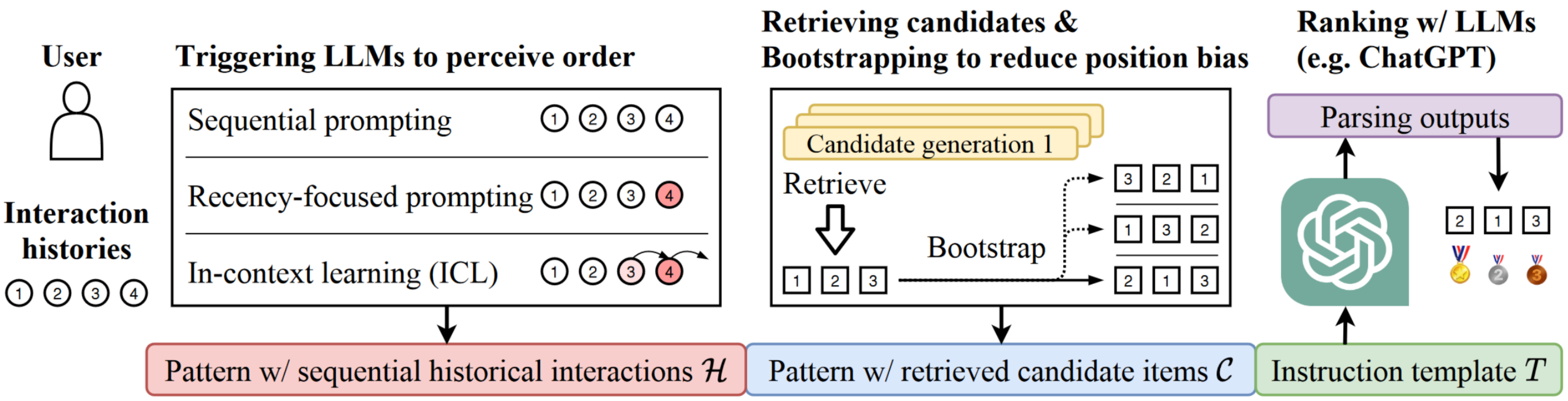
Liu J, et al. Is ChatGPT a Good Recommender? A Preliminary Study. arXiv'23.



Gao Y, et al. Chat-REC: Towards Interactive and Explainable LLMs-Augmented Recommender System. arXiv'23.

可能性二：直接使用原始预训练语言模型建模行为序列

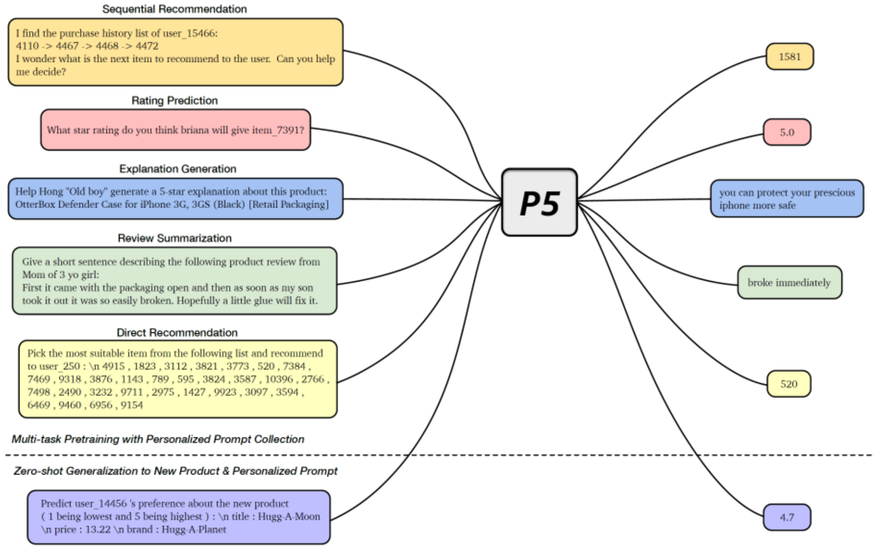
- 深入探索预训练语言模型直接用于推荐的insight
  - PLM对于用户行为序列的顺序关系理解不够
  - 可以通过设置合理的prompt进行弥补
  - …



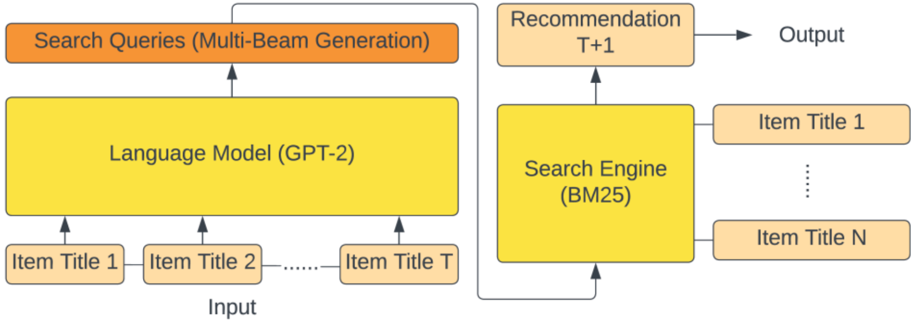
Hou Y, et al. Large Language Models are Zero-Shot Rankers for Recommender Systems. arXiv'23.

可能性三：基于行为序列微调预训练语言模型

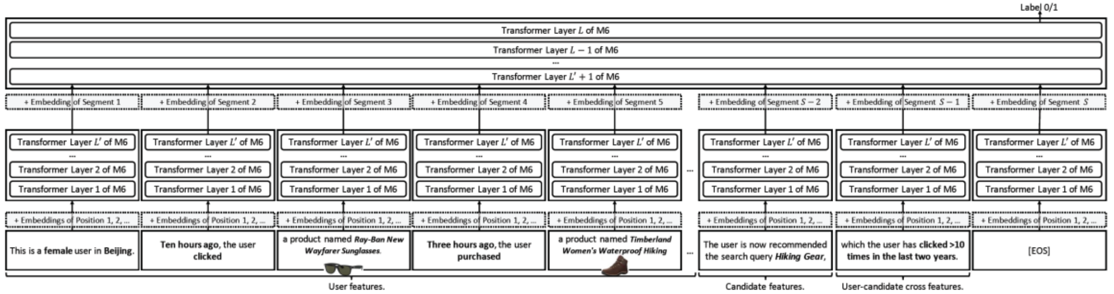
- 将用户行为序列转换为文本序列，基于行为序列微调预训练语言模型
  - 基于行为微调后，推荐任务上相对zero-shot大幅提升
  - 仍然有较大提升空间——用户行为信息起到了统治性的作用



Geng S et al. Recommendation as language processing (rlp): A unified pretrain, personalized prompt & predict paradigm (p5) RecSys’22.



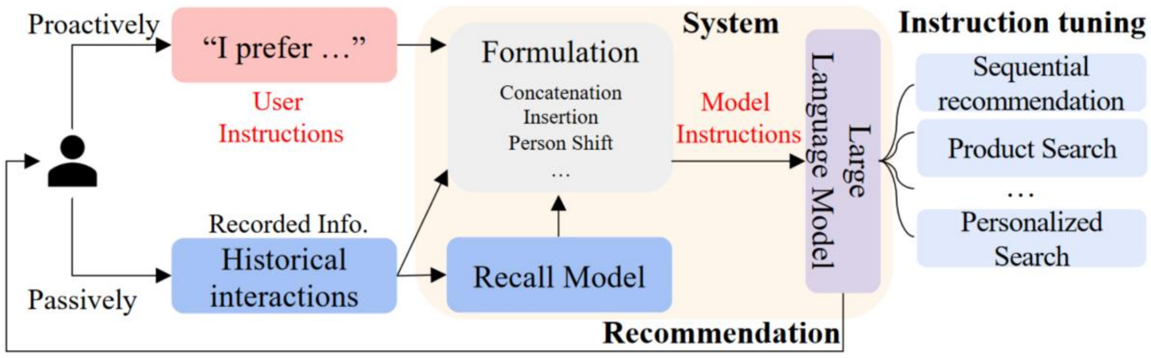
Li J, et al. GPT4Rec: A Generative Framework for Personalized Recommendation and User Interests Interpretation. arXiv’23.



Cui Z, et al. M6-Rec: Generative Pretrained Language Models are Open-Ended Recommender Systems. arXiv’22.

可能性三：基于行为序列微调预训练语言模型

- 指令微调：基于自然语言，满足用户多种交互形式/偏好/意图下的推荐需求



Preference	Intention	Task Form
None (Cold-start users)	None (Exploratory interaction)	Pointwise (Discriminate a candidate)
Implicit (User's context info.)	Vague (Ambiguous idea of target)	Pairwise (Compare a item pair)
Explicit (Explicit expression)	Specific (Clear idea of target)	Matching & Reranking (Retrieving the candidates, refining the ranking)

Instantiation	Model Instructions
$\langle P_1, I_0, T_0 \rangle$	The user has purchased these items: <historical interactions> . Based on this information, is it likely that the user will interact with <target item> next?
$\langle P_2, I_0, T_3 \rangle$	You are a search engine and you meet a user's query: <explicit preference> . Please respond to this user by selecting items from the candidates: <candidate items>.
$\langle P_0, I_1, T_2 \rangle$	As a recommender system, your task is to recommend an item that is related to the user's <vague intention> . Please provide your recommendation.
$\langle P_0, I_2, T_2 \rangle$	Suppose you are a search engine, now the user search that <specific Intention> , can you generate the item to respond to user's query?
$\langle P_1, P_2, T_2 \rangle$	Here is the historical interactions of a user: <historical interactions> . His preferences are as follows: <explicit preference> . Please provide recommendations .
$\langle P_1, I_1, T_2 \rangle$	The user has interacted with the following <historical interactions> . Now the user search for <vague intention> , please generate products that match his intent.
$\langle P_1, I_2, T_2 \rangle$	The user has recently purchased the following <historical items>. The user has expressed a desire for <specific intention>. Please provide recommendations.

Zhang J, et al. Recommendation as Instruction Following: A Large Language Model Empowered Recommendation Approach. arXiv'23.

可能性四：预训练行为模型建模全量用户行为序列

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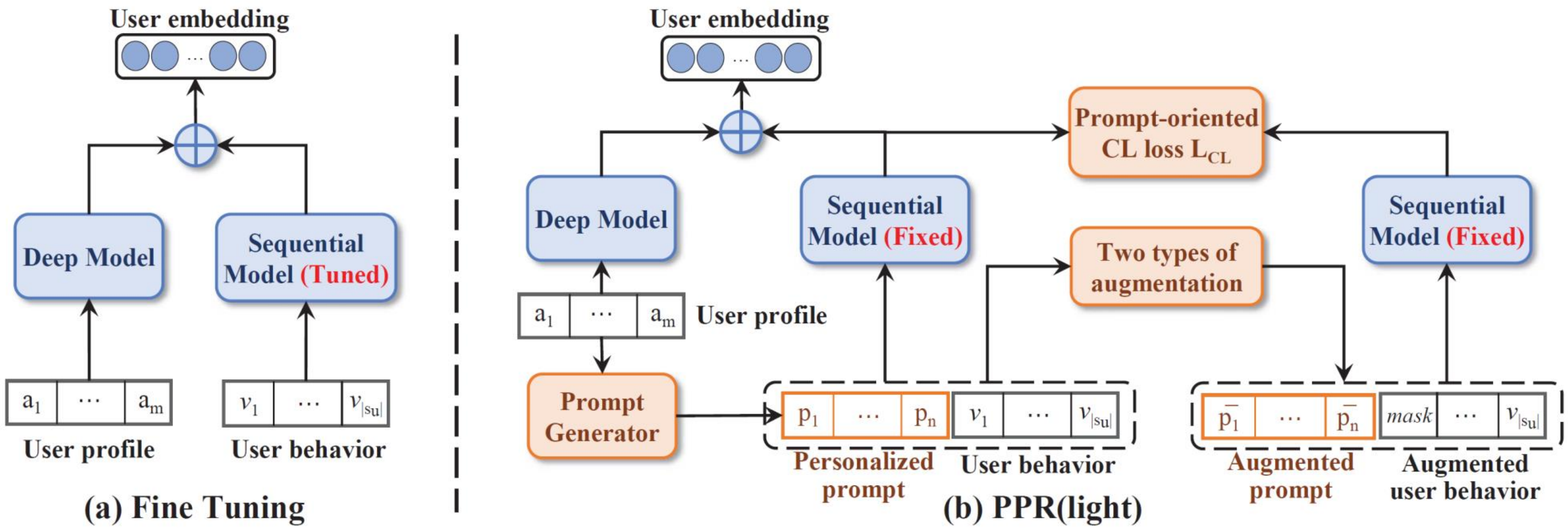
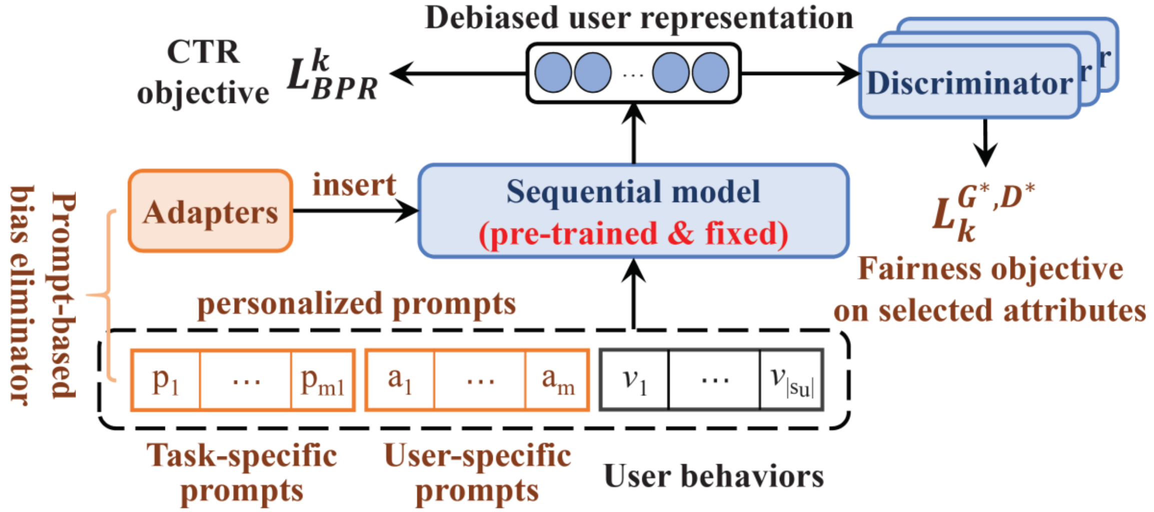
- 直接基于用户全量行为序列信息，构建推荐预训练行为模型
  - 预训练行为模型+个性化prompt能服务多种下游推荐任务
  - 目前缺少和PLM的联动，未能充分利用大语言模型的红利



Wu Y, et al. Personalized Prompts for Sequential Recommendation. arXiv'22.

Warning: 构建可信的预训练推荐模型

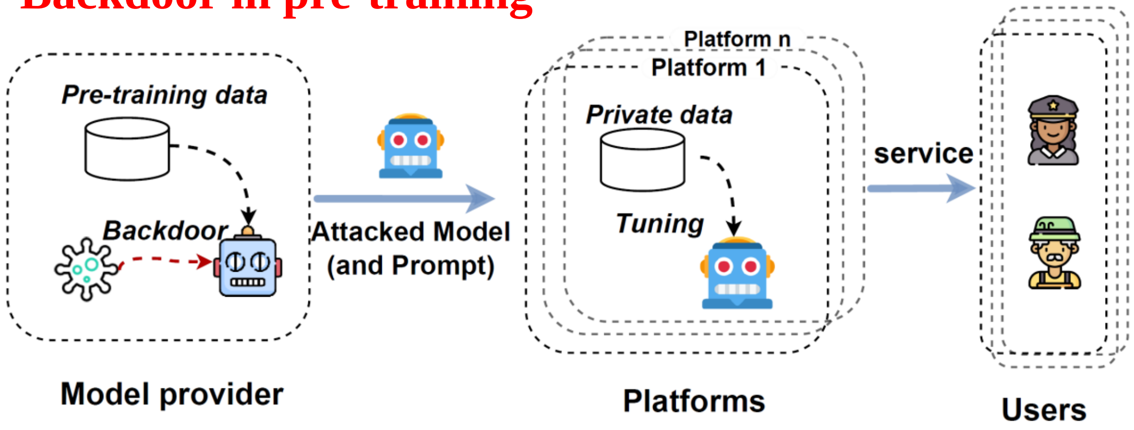
- 基于推荐预训练模型的**用户可选择的公平性**



Wu Y, et al. Selective fairness in recommendation via prompts. SIGIR'22

- 基于推荐预训练模型的**安全性问题**——大模型下新的攻防范式

Backdoor in pre-training



Wu Y, et al. Attacking pre-trained recommendation. SIGIR'23

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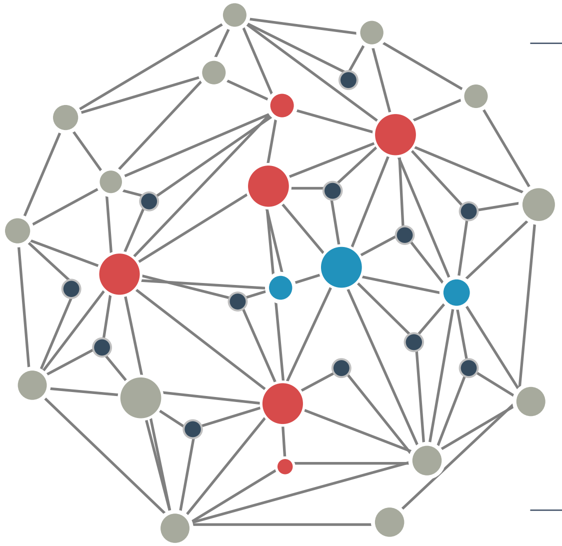

感谢聆听！

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