中国科学技术大学
University of Science and Technology of China

数据空间研究院

大模型推荐技术及展望

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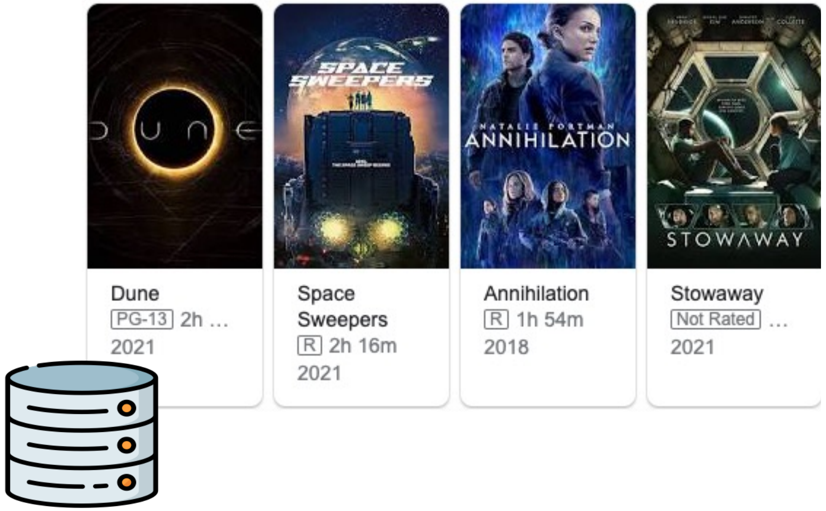
2023/8

1. 推荐及LLM简介
2. LLM赋能推荐系统
3. 大模型推荐展望

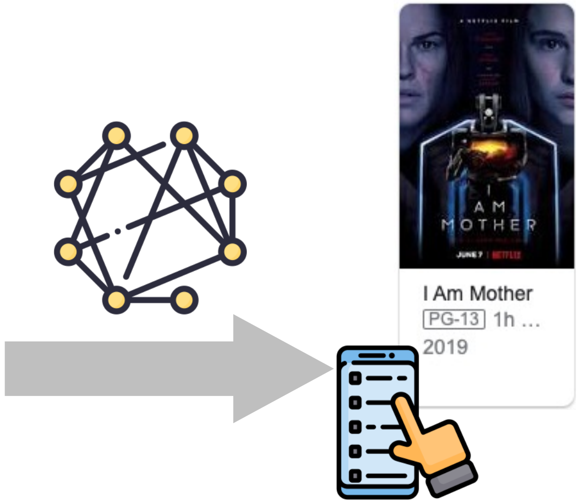
推荐方法的本质

❑ 本质：拟合历史用户行为数据，预测未来用户行为

阶段1：在历史数据里学



阶段2：预测用户下一个喜欢的物品

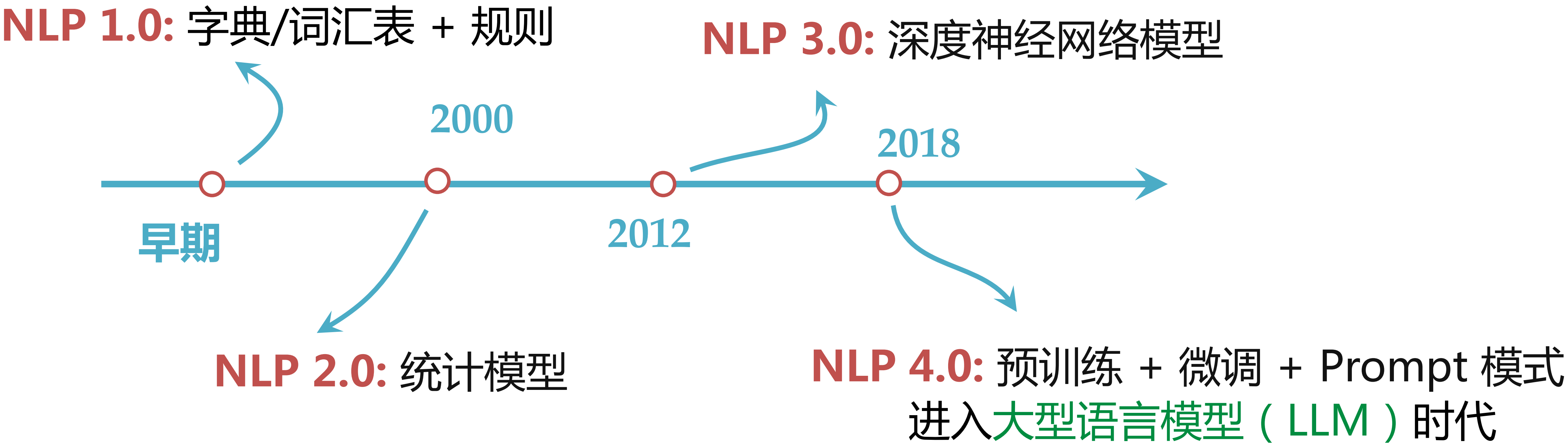


- User：行为多样、模式复杂，受众多外界因素影响
- Item：item间众多低频关联，不断出现新item

理解不到位，泛化能力差，推荐不满意

大模型新范式

❑ 自然语言处理（NLP）领域的发展：



智能涌现

用简明的语句概括一下新闻的大概内容：“新华社电…”

答案是：这篇新闻大概讲述了“阿根廷夺得世界杯冠军的历程”

学会了！

泛化能力

学会举一反三

帮我概括一下NCF文章的主要内容

好的，NCF利用神经网络对协同过滤信息建模…

英文中的“Good Morning”是中文的早上好

学会了！“Good Morning”翻译成早上好

规划能力

切分简化任务

帮我用英文概括一下面这个中文博客“大语言模型…”

规划：**先用中文概括，再翻译成英文**—”This blog is about the LLM…”

知识模型

Foundation LLM

葡萄糖的化学分子式是$C_6H_{12}O_6$

《战狼》讲述的是小人物成长为拯救国家和民族命运的孤胆英雄的传奇故事

爱因斯坦提出的质能方程是$E=mc^2$

勾股定理是直角三角形两个直角边的平方和等于斜边的平方

人类的血液中含有红细胞、白细胞、血小板等不同种类细胞

在位时间最长的皇帝——(清)爱新觉罗.玄烨

推荐系统“馋”大模型啥？

- User：行为多样、模式复杂，受众多外界因素影响
- Item：在物理世界中存在千丝万缕的关联，很多关联都很低频

理解不到位，泛化能力差，推荐不满意

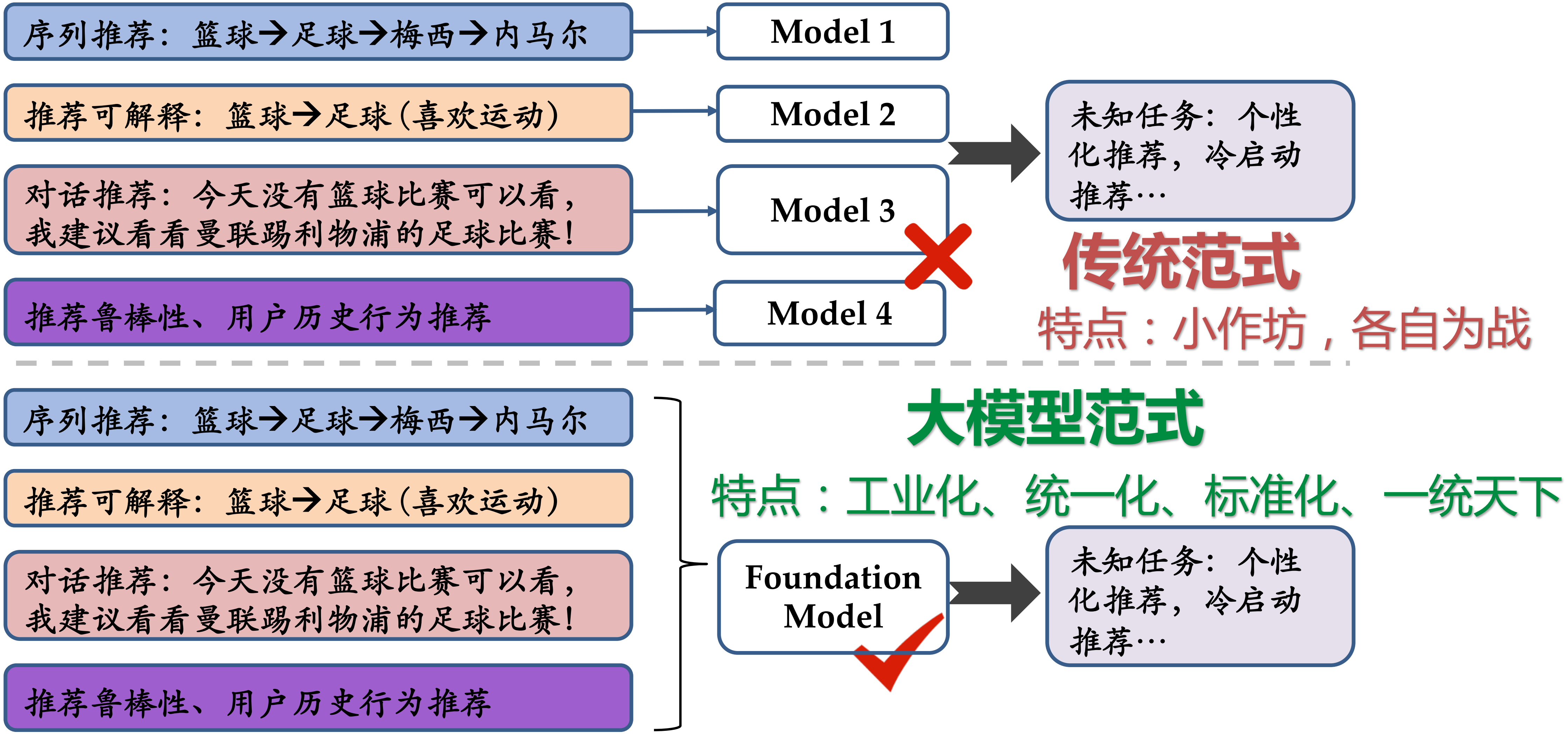
- **Learning**：Pretrain-finetune, prompt learning, instruction-tun.
- **Model**：Well-trained models with extraordinary abilities

Representation：Textual feature, text is all you need	**Chat**	**Generalization & Generation**：Few/zero-shot, cross-domain, knowledge, personalized gen.

- **Architecture**：Transformer, self-attention

推荐系统“馋”大模型啥？

❑ Open-ended Domains and Tasks



推荐系统“馋”大模型啥？

Open-ended domains & tasks

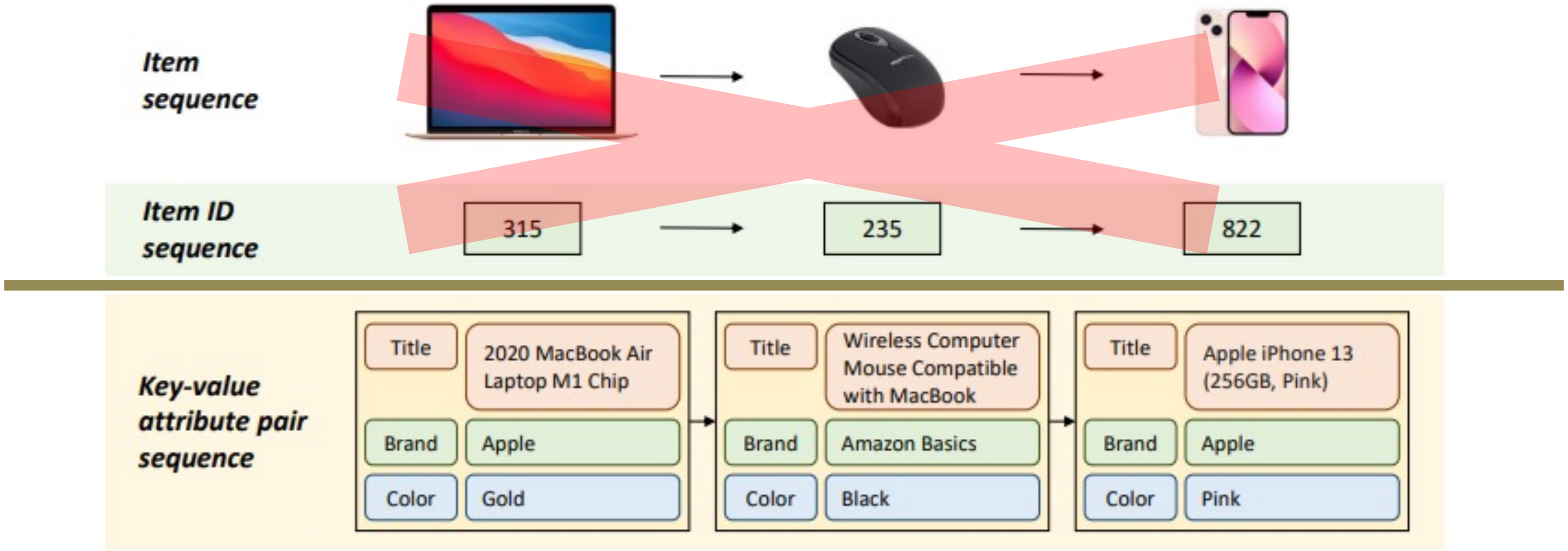
❑ 用文本统一表示，用prompt统一task，用LLM跨域

- **Learning：** Prompt learning/instruction-tuning [1,2,3,5,6,9,12]
- **Representation：** Text is all you need [4,5,6,7,8,9,12]
- **Generalization：** Few-shot, cross-domain [5,6,7,8], know. [10,11]

[1] *Zhang Yuhui, et al.* ”Language Models as Recommender Systems: Evaluations and Limitations“ *NeurIPS Workshop 2021.*
[2] *Zhang Zihuo and Wang Bang.* ”Prompt Learning for News Recommendation“ *SIGIR 2023.*
[3] *Geng Shijie et al.* ”Recommendation as Language Processing (RLP): A Unified Pretrain, Personalized Prompt & Predict Paradigm (P5)“ *RecSys 2022.*
[4] *Li Jiacheng et al.* ”Text Is All You Need: Learning Language Representations for Sequential Recommendation“ *KDD 2023.*
[5] *Cui Zeyu et al.* ”M6-Rec: Generative Pretrained Language Models are Open-Ended Recommender Systems“ *arXiv 2022.*
[6] *Zhang Junjie et al.* “Recommendation as Instruction Following: A Large Language Model Empowered Recommendation Approach“ *arXiv 2023.*
[7] *Gao, et al.* “Chat-REC: LLMs-Augmented Recommender System” *2023.*
[8] *Liu, et al.* “Is ChatGPT a good recommender? A preliminary Study” *2023.*
[9] *Bao Keqin et al.* “LLM4Rec: Large Language Models for Recommendation via A Lightweight Tuning Framework” *RecSys 2023.*
[10] *Xi Yunjia et al.* ”Towards Open-World Recommendation with Knowledge Augmentation from Large Language Models“ *arXiv 2023.*
[11] *Li Jinming et al.* “GPT4Rec: A Generative Framework for Personalized Recommendation and User Interests Interpretation” *arXiv 2023.*
[12] *Hou Yupeng et al.* “Large Language Models are Zero-Shot Rankers for Recommender Systems” *arXiv 2023.*
[13] *Bao Keqin et al.* ” A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems“ *arXiv 2023.*

LLM赋能推荐---Representation

❑ Text is all you need (NO item ID)



Use nature language to do recommendation

-> Low resource, cold start …

Li Jiacheng et al. "Text Is All You Need: Learning Language Representations for Sequential Recommendation" *KDD 2023.*

LLM赋能推荐---Representation

❑ Text is all you need (NO item ID)

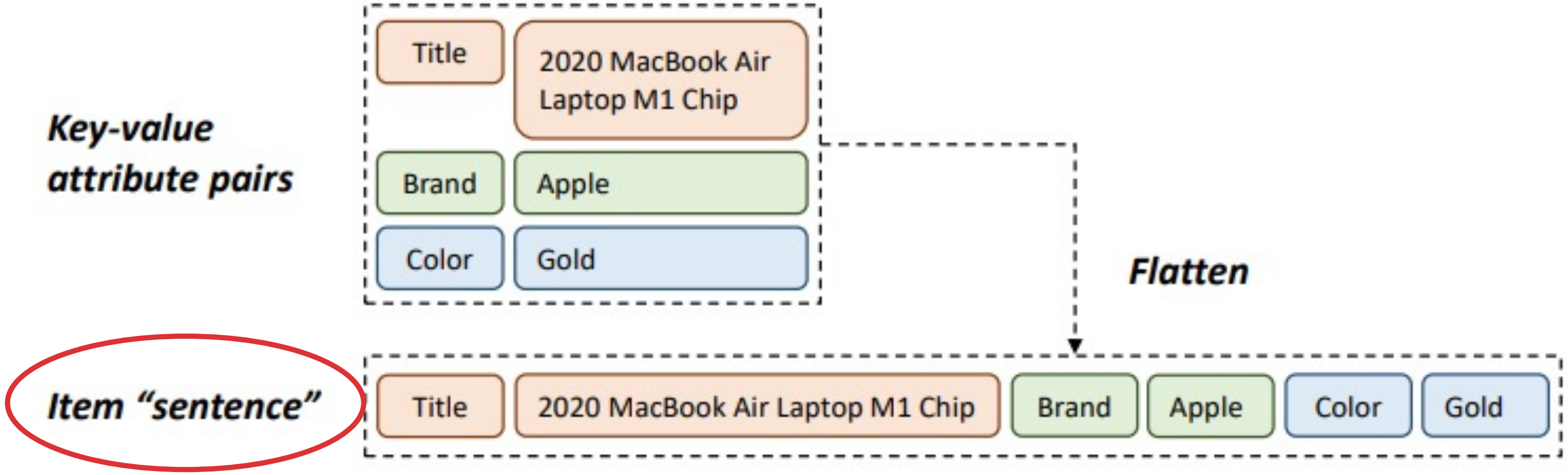


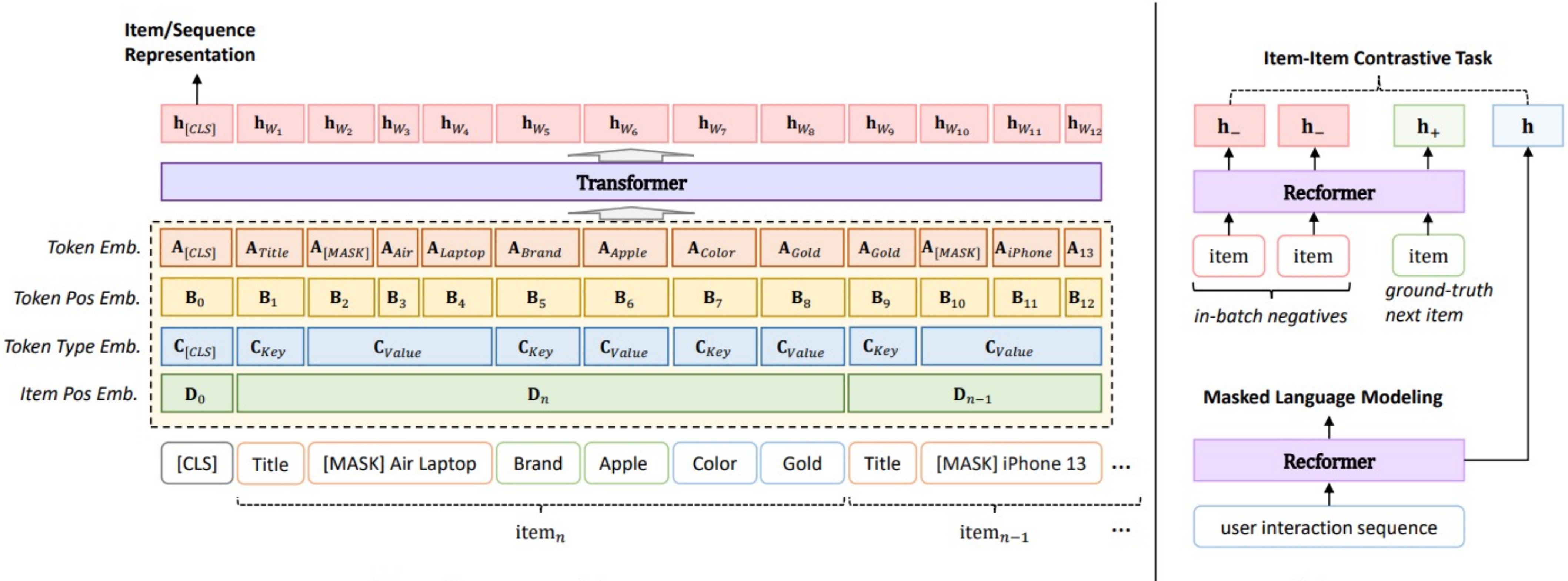
Figure 2: Model input construction. Flatten key-value attribute pairs into an item "sentence".

Item → Sentence
Item sequence → Long sentence

Li Jiacheng et al. "Text Is All You Need: Learning Language Representations for Sequential Recommendation" *KDD 2023.*

LLM赋能推荐---Representation

❑ Text is all you need (NO item ID)



(a) Recformer Model Structure

(b) Pretraining

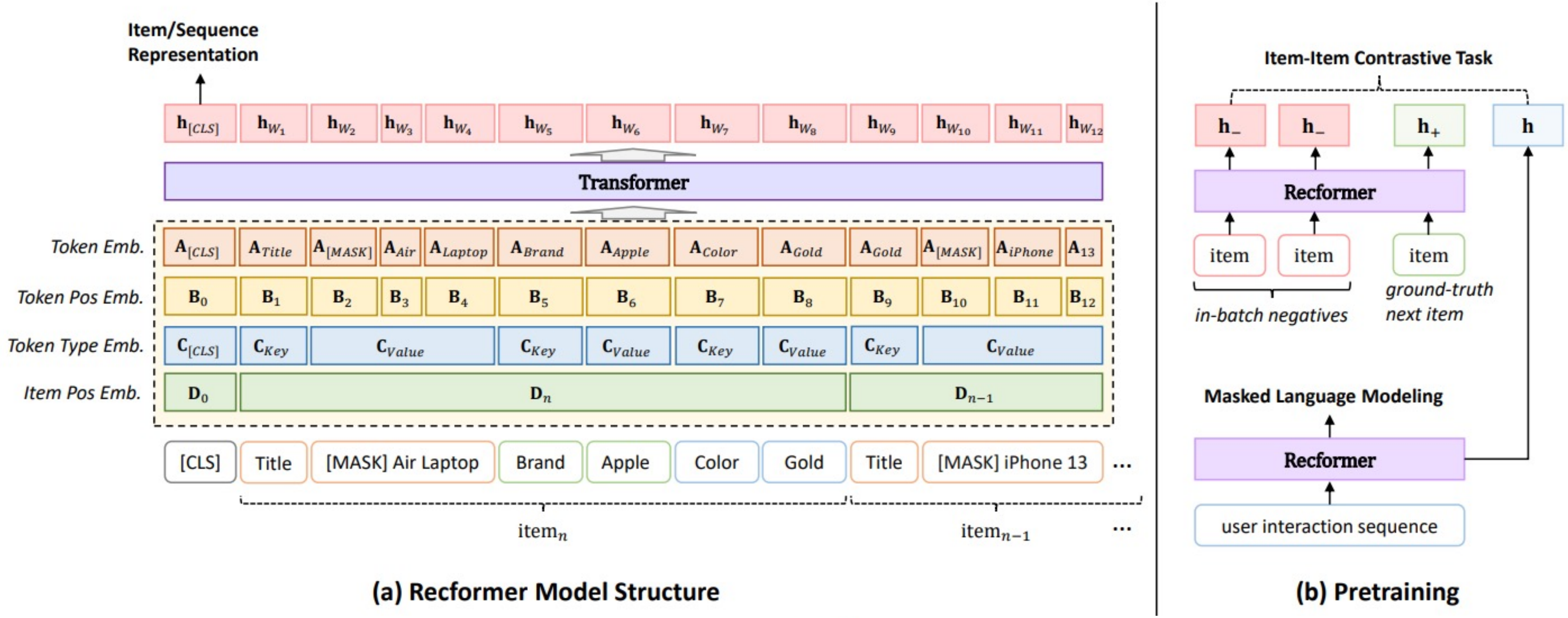
$$\mathbf{E}_w = \mathrm{LayerNorm}(\mathbf{A}_w + \mathbf{B}_w + \mathbf{C}_w + \mathbf{D}_w)$$

$$[\mathbf{h}_{[\mathrm{CLS}]}, \mathbf{h}_{w_1}, \ldots, \mathbf{h}_{w_l}] = \mathrm{Longformer}([\mathbf{E}_{[\mathrm{CLS}]}, \mathbf{E}_{w_1}, \ldots, \mathbf{E}_{w_l}])$$

Li Jiacheng et al. ”Text Is All You Need: Learning Language Representations for Sequential Recommendation“ *KDD 2023.*

LLM赋能推荐---Representation

❑ Text is all you need (NO item ID)



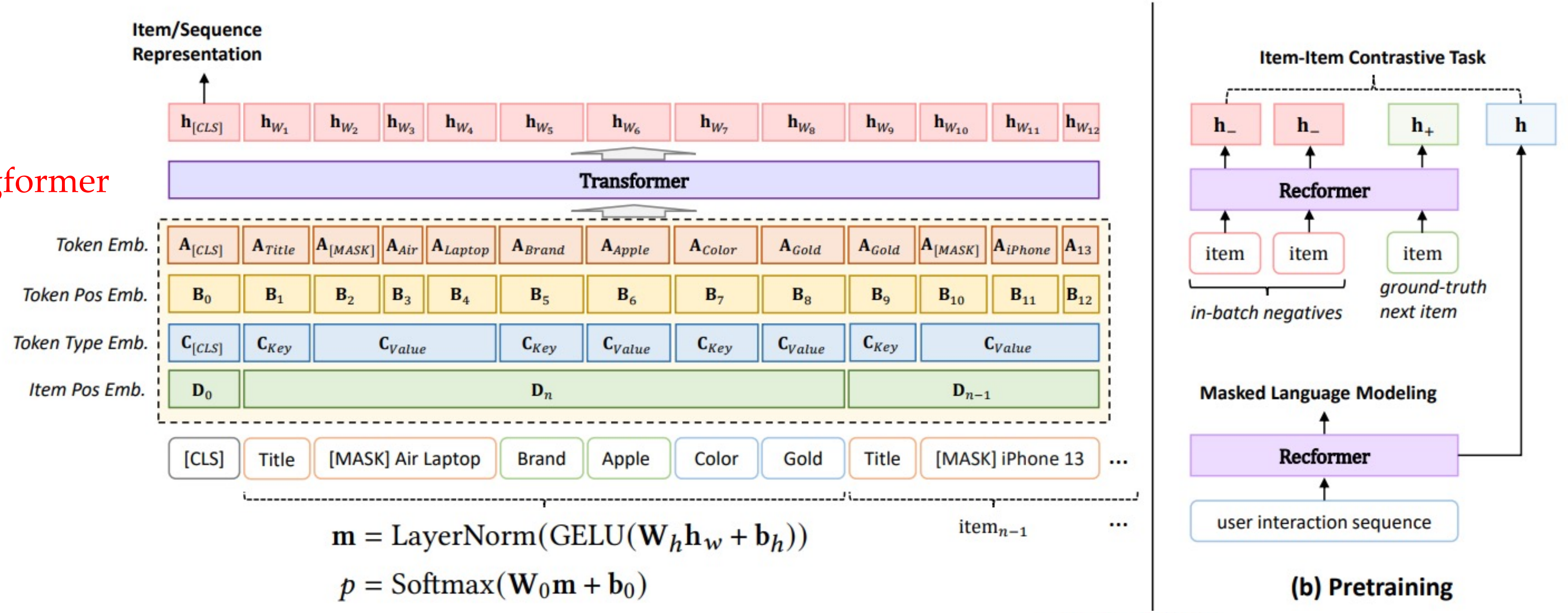
Prediction: $r_{i,s} = \dfrac{\mathbf{h}_i^\top \mathbf{h}_s}{\|\mathbf{h}_i\| \cdot \|\mathbf{h}_s\|}$

Li Jiacheng et al. "Text Is All You Need: Learning Language Representations for Sequential Recommendation" *KDD 2023.*

LLM赋能推荐---Representation

❑ Text is all you need (NO item ID)

Longformer



$$\mathbf{m} = \mathrm{LayerNorm}(\mathrm{GELU}(\mathbf{W}_h \mathbf{h}_w + \mathbf{b}_h))$$

$$p = \mathrm{Softmax}(\mathbf{W}_0 \mathbf{m} + \mathbf{b}_0)$$

Pre-train:

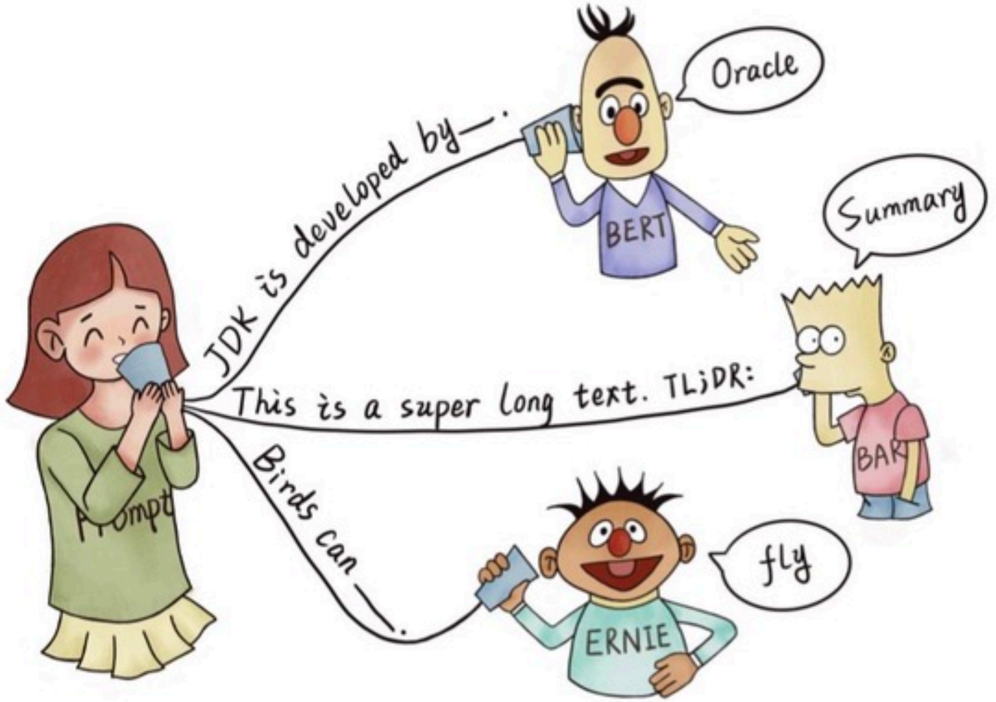
$$\mathcal{L}_{\mathrm{MLM}} = -\sum_{i=0}^{|\mathcal{V}|} y_i \log(p_i) \qquad \mathcal{L}_{\mathrm{IIC}} = -\log \frac{e^{\mathrm{sim}(\mathbf{h}_s, \mathbf{h}_i^+)/\tau}}{\sum_{i \in \mathcal{B}} e^{\mathrm{sim}(\mathbf{h}_s, \mathbf{h}_i)/\tau}} \qquad \mathcal{L}_{\mathrm{PT}} = \mathcal{L}_{\mathrm{IIC}} + \lambda \cdot \mathcal{L}_{\mathrm{MLM}}$$

Li Jiacheng et al. "Text Is All You Need: Learning Language Representations for Sequential Recommendation" *KDD 2023.*

LLM赋能推荐---Learning Paradigm

❑ Prompt learning

每个task被一个prompt描述
Sentiment analysis：
Input：I love this movie.
Prompt: This is [z].

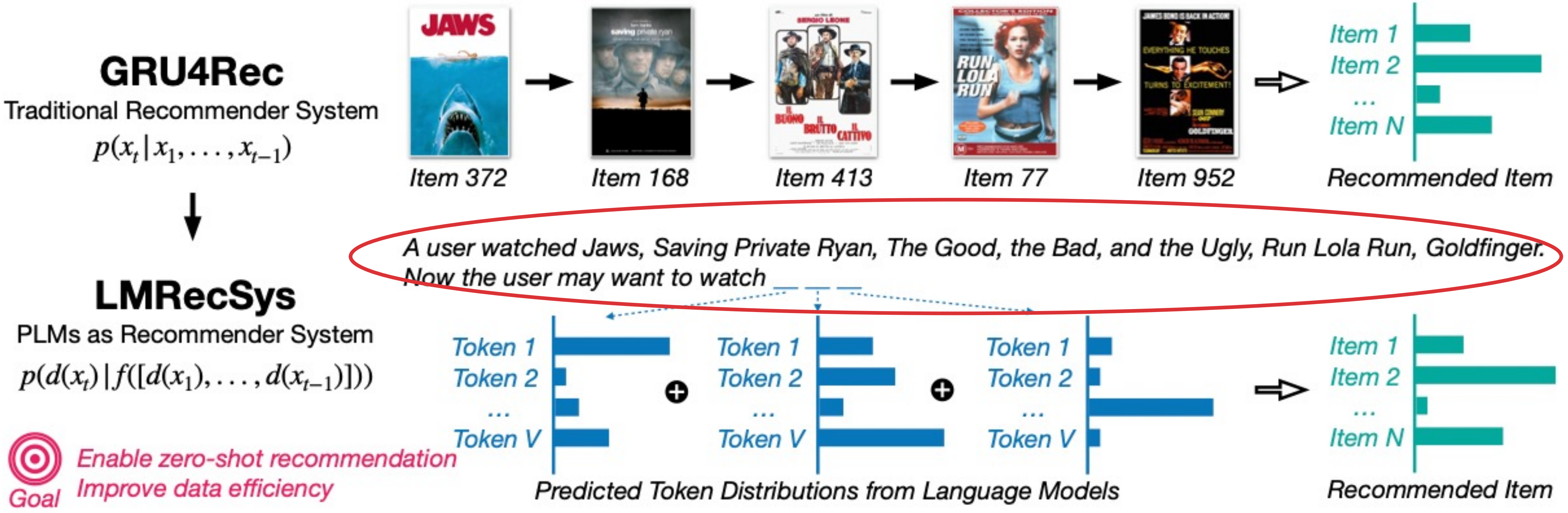


Sample-level learning f(y|x) → **Task**-level learning f(y|x,p)

Liu Pengfei, et al. "Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing" arXiv 2021.

LLM赋能推荐---Learning Paradigm

❑ Prompt learning



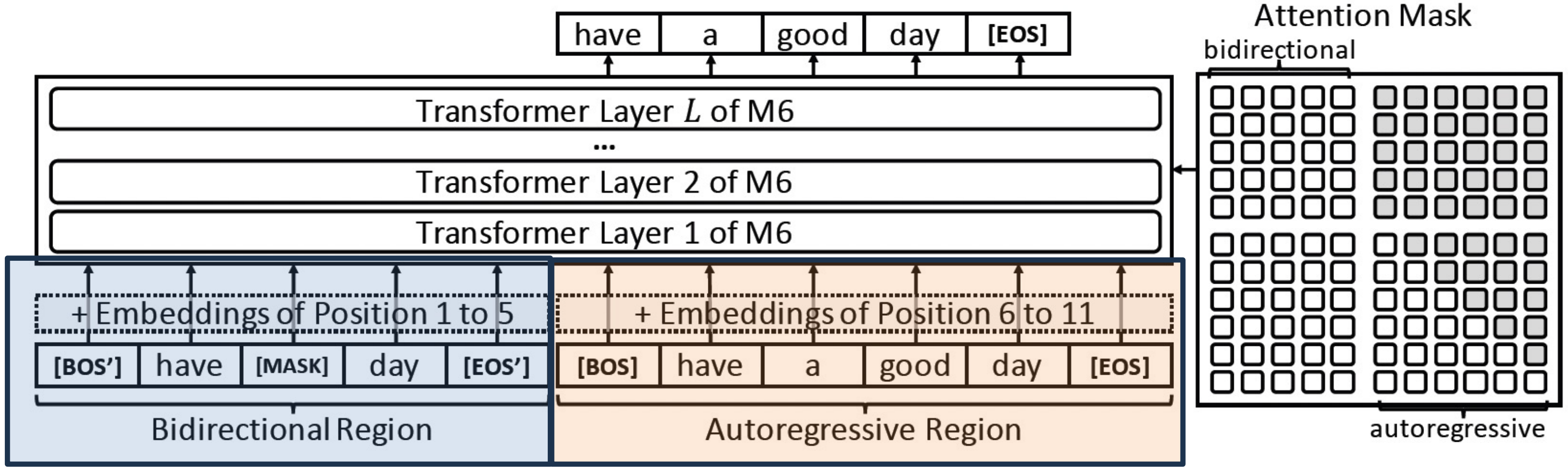
BERT/GPT2

Zhang Yuhui, et al. "Language Models as Recommender Systems: Evaluations and Limitations" NeurIPS Workshop 2021.

LLM赋能推荐---Generalization

❑ Open-ended domains and tasks

M6



Understanding

Generation

Figure 1: The text infilling objective used by the pretraining procedure of M6. [MASK] represents an undetermined number of unknown tokens. [BOS] and [EOS] mean the beginning and the end of a sentence, respectively. The autoregressive language modeling loss is imposed on the outputs of the autoregressive region, and not on the bidirectional re-

Cui Zeyu et al. "M6-Rec: Generative Pretrained Language Models are Open-Ended Recommender Systems" *arXiv 2022.*

LLM赋能推荐---Generalization

❑ Open-ended domains and tasks

Scoring tasks (e.g., CTR)

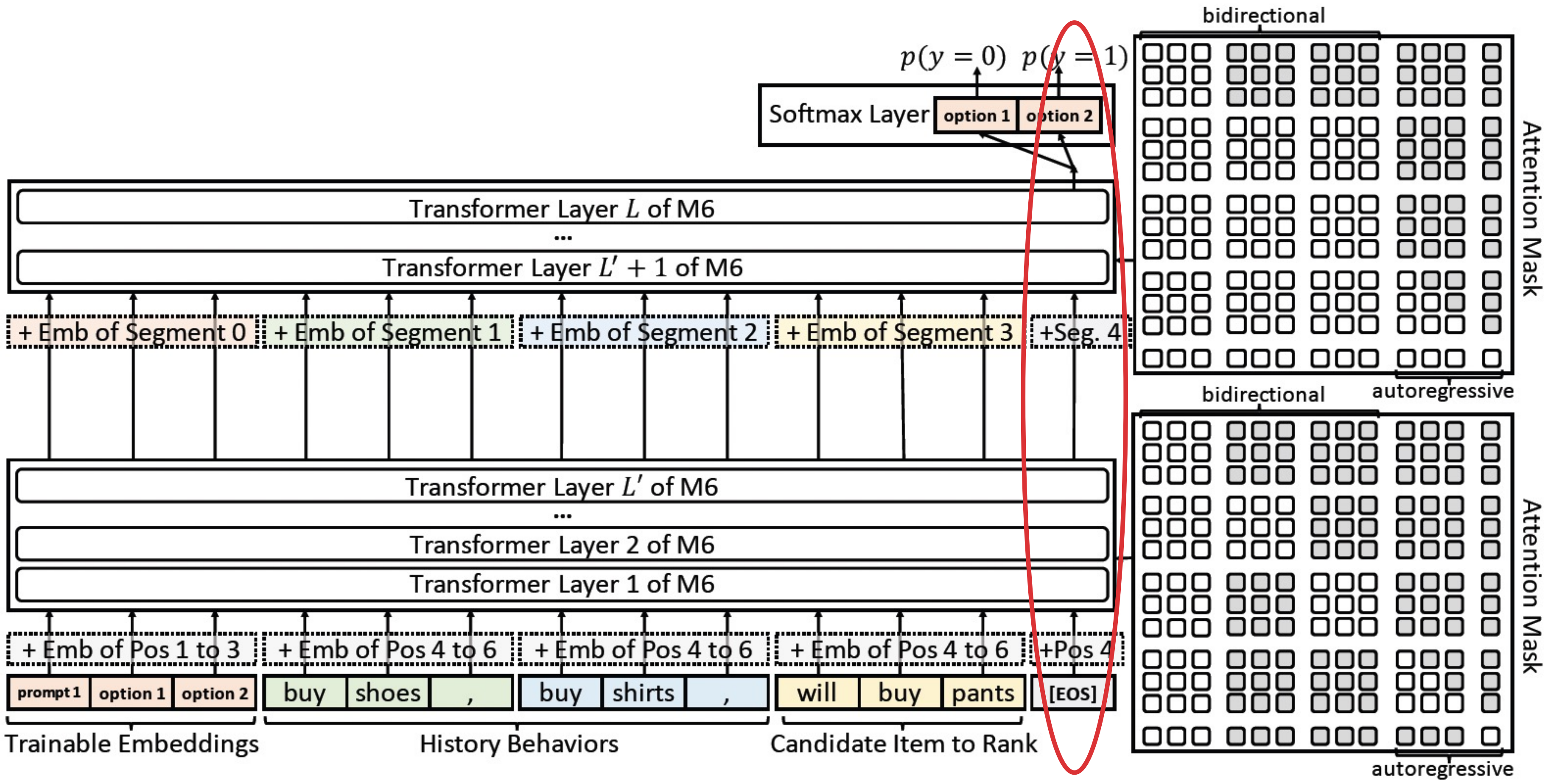
[BOS′] December. Beijing, China. Cold weather. A male user in early twenties, searched "winter stuff" 23 minutes ago, clicked a product of category "jacket" named "men's lightweight warm winter hooded jacket" 19 minutes ago, clicked a product of category "sweat-shirt" named "men's plus size sweatshirt stretchy pullover hoodies" 13 minutes ago, clicked … [EOS′]

[BOS] The user is now recommended a product of category "boots" named "waterproof hiking shoes mens outdoor". The product has a high population-level CTR in the past 14 days, among the top 5%. The user clicked the category 4 times in the last 2 years. [EOS]

Cui Zeyu et al. "M6-Rec: Generative Pretrained Language Models are Open-Ended Recommender Systems" *arXiv 2022.*

LLM赋能推荐---Generalization

❑ Open-ended domains and tasks



Cui Zeyu et al. "M6-Rec: Generative Pretrained Language Models are Open-Ended Recommender Systems" *arXiv 2022.*

LLM赋能推荐---Generalization

❑ Open-ended domains and tasks

Generation tasks. Content generation has become an important topic in modern recommender systems. M6-Rec uses the following plain text format to support both personalized product design [18] and explainable recommendation [61]:

[BOS′] … [EOS′] [BOS] The user now purchases a product of category "…" named "…". Product details: … The user likes it because … [EOS]

Different prompts

Generation task: conversational recommendation. M6-Rec supports this task by marking the speaker of each sentence:

[BOS′] … [EOS′] [BOS] USER: Hi! SYSTEM: What kind of movie do you like? USER: I like horror movies. SYSTEM: How about *The Shining (1980)*? … [EOS]

Cui Zeyu et al. "M6-Rec: Generative Pretrained Language Models are Open-Ended Recommender Systems" *arXiv 2022.*

LLM赋能推荐

- ❑ Not really “LARGE” Language Model
  BERT, GPT2, Longformer, T5, M6, Flan-T5
- ❑ Require tons of training data
- ❑ Weak ability (<LLM)

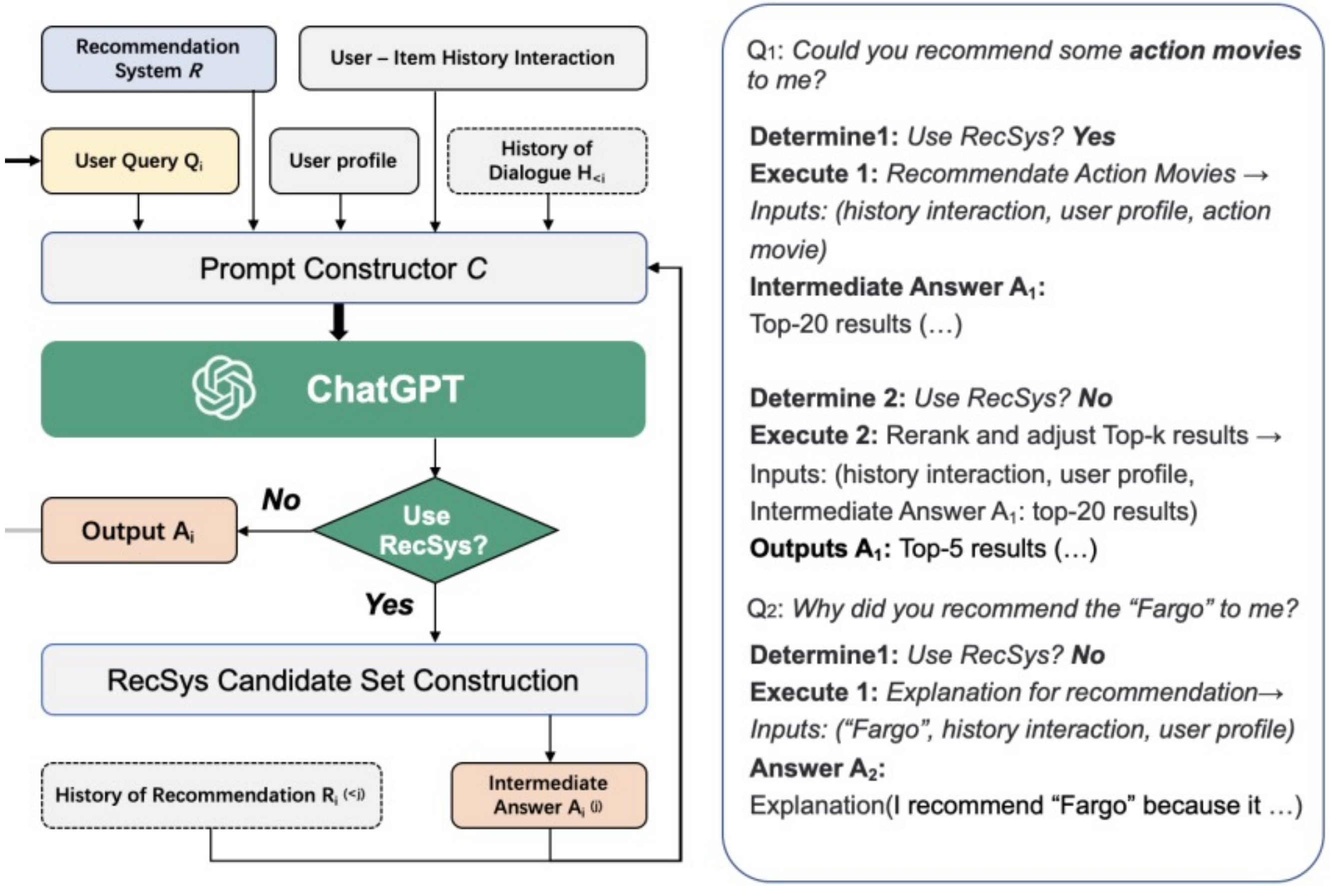
- **Learning：** Pretrain-finetune, Prompt learning, Instruction-tun.
- **Model：** Well-trained models with extraordinary abilities

Representation：	Chat	Generalization & Generation：
Textual feature, text is all you need		Few/zero-shot, cross-domain, knowledge, personalized gen.

- **Architecture：** Transformer, self-attention

LLM赋能推荐---Generalization

❑ In-context learning



Recommend through ChatGPT

Gao, et al. Chat-REC: LLMs-Augmented Recommender System. 2023.

LLM赋能推荐---Generalization

❑ In-context learning + recommendation model

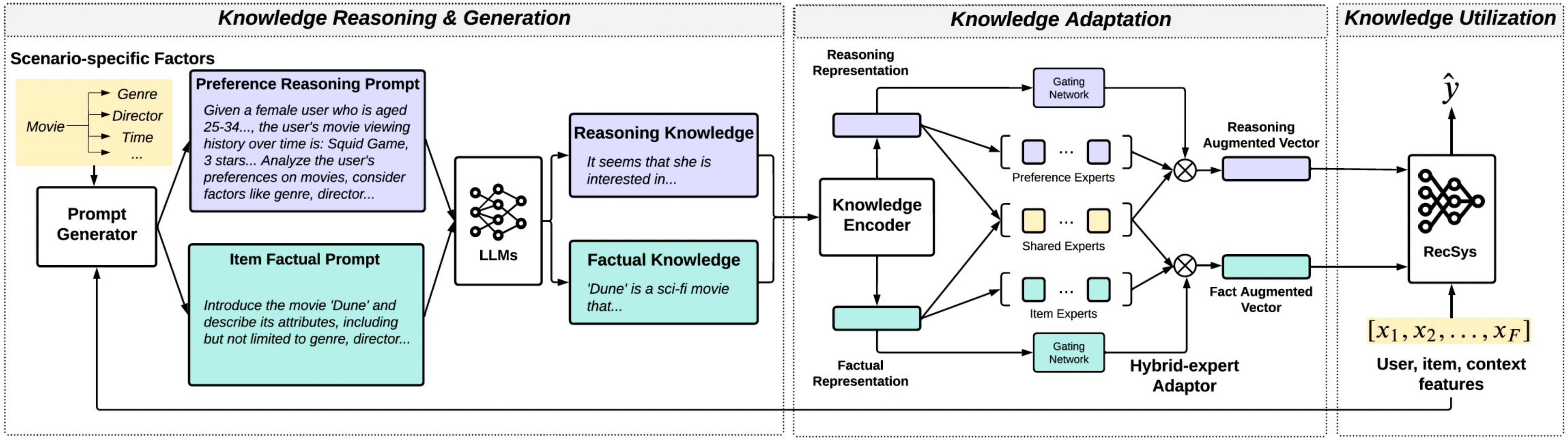


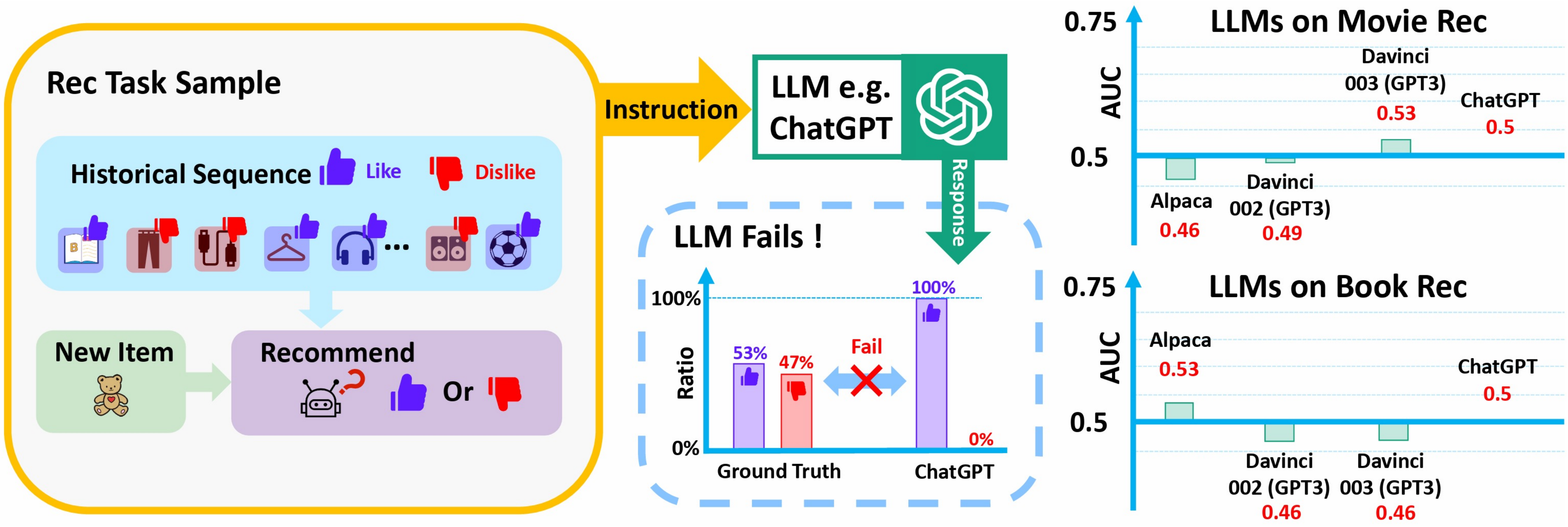
Figure 2: The overall framework of KAR, which consists of three stages: (1) Knowledge reasoning and generation; (2) Knowledge adaption; and (3) Knowledge utilization.

GPT → Open-world knowledge
Recommender model → Recommendation task

Xi Yunjia et al. "Towards Open-World Recommendation with Knowledge Augmentation from Large Language Models" *arXiv 2023.*

LLM赋能推荐---Generalization

❑ GPT不是天然做推荐的



在此推荐任务中，大模型一贯提供单一统一的答案或拒绝回答。

解决方案: 打造面向推荐场景优化的大模型

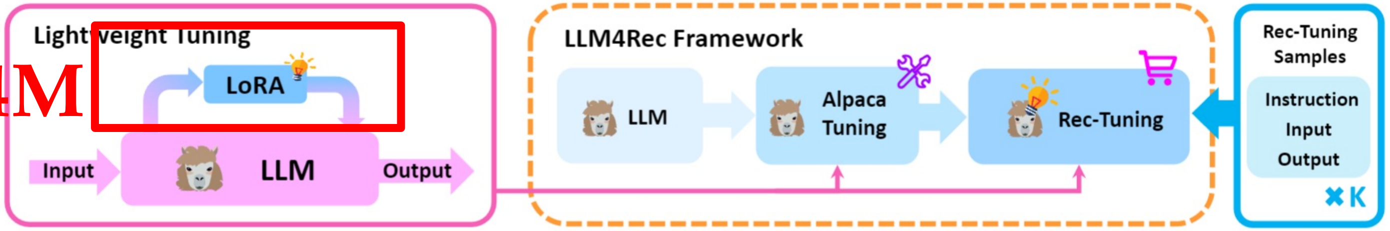
Keqin Bao et al. "LLM4Rec: Large Language Models for Recommendation via A Lightweight Tuning Framework" *Recsys 2023*

LLM赋能推荐---Generalization

❑ Tuning is necessary, but is also painful

- **Tuning LLM is heavy**

微调 4M



完整的LLAMA 7B 参数量级

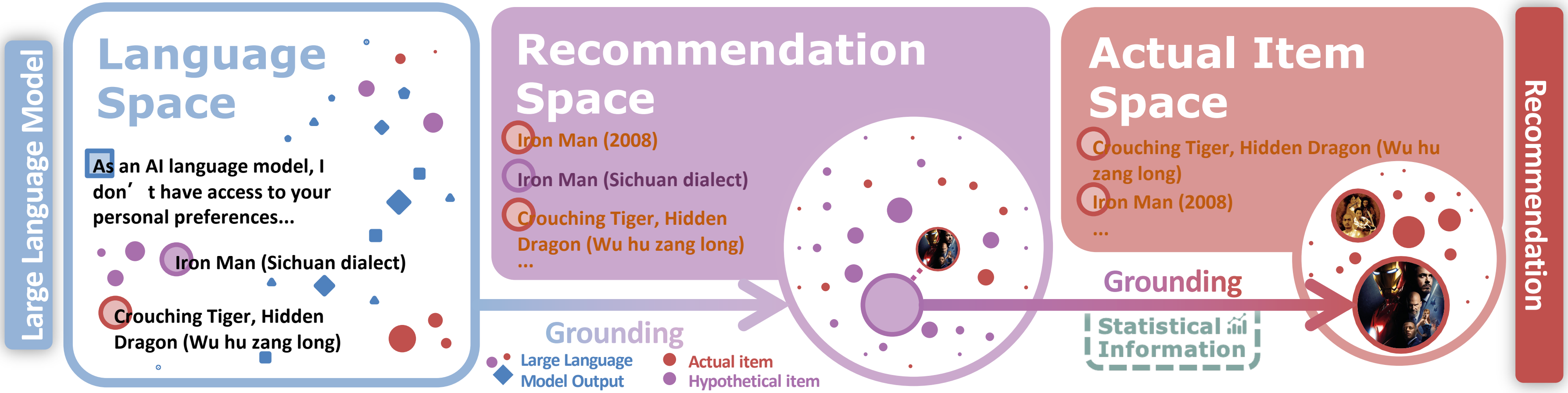
- LLAMA模型，7B参数
- 微调4M参数，不到原来模型参数的0.1%，推荐效果显著提升

- **Inference is heavy**
  - **Pair-wise (n*m times of inference)**
  - **List generation (very long beam-search)**
- **Generation ability is narrowly restricted**

Keqin Bao et al. "LLM4Rec: Large Language Models for Recommendation via A Lightweight Tuning Framework" *Recsys 2023*

LLM赋能推荐---Generalization

❑ Instruction-tuning + grounding

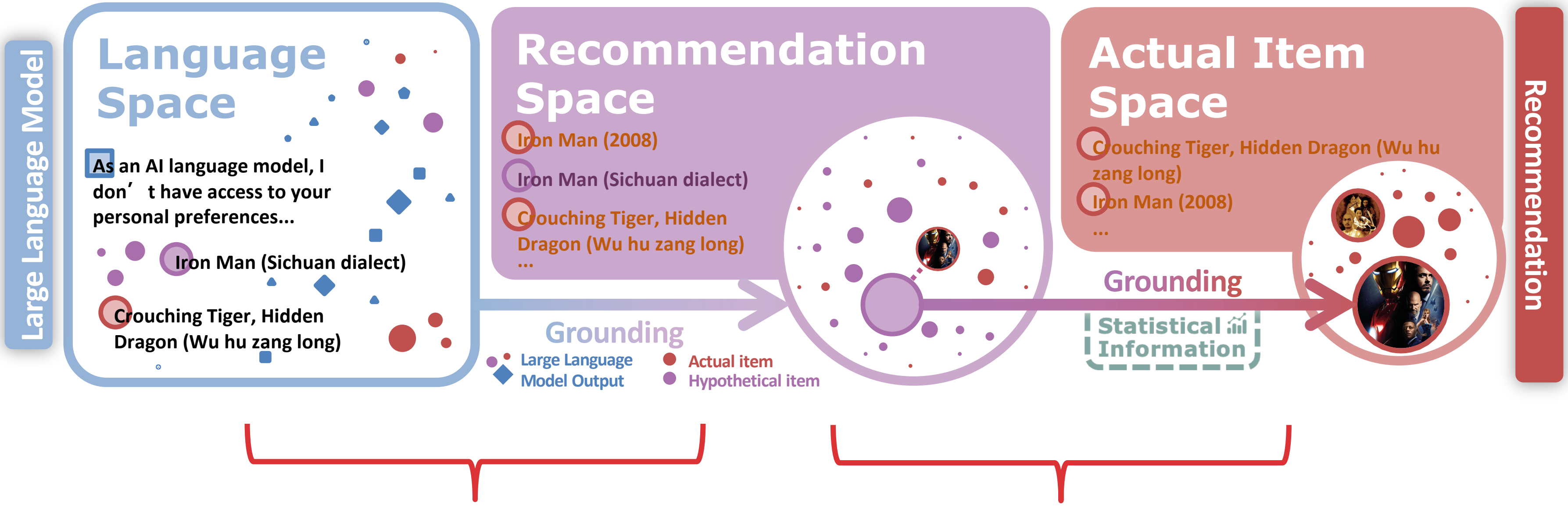


- **Language Space**: all conceivable language sequences that LLM could generate
- **Recommendation Space**: a sub-space within the language space that includes a wide range of entities that fulfill the user's preferences
- **Actual Item Space**: only the actual items in the recommendation space

Bao Keqin et al. " A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems" *arXiv 2023.*

LLM赋能推荐---Generalization

❑ Instruction-tuning + grounding



Closer to generation (TALLRec)
Closer to recommendation (KAR)

Fast all-ranking (TALLRec)
Flexible for plugin (KAR)

Bao Keqin et al. " A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems" *arXiv 2023.*

LLM赋能推荐---Generalization

❑ Instruction-tuning + grounding

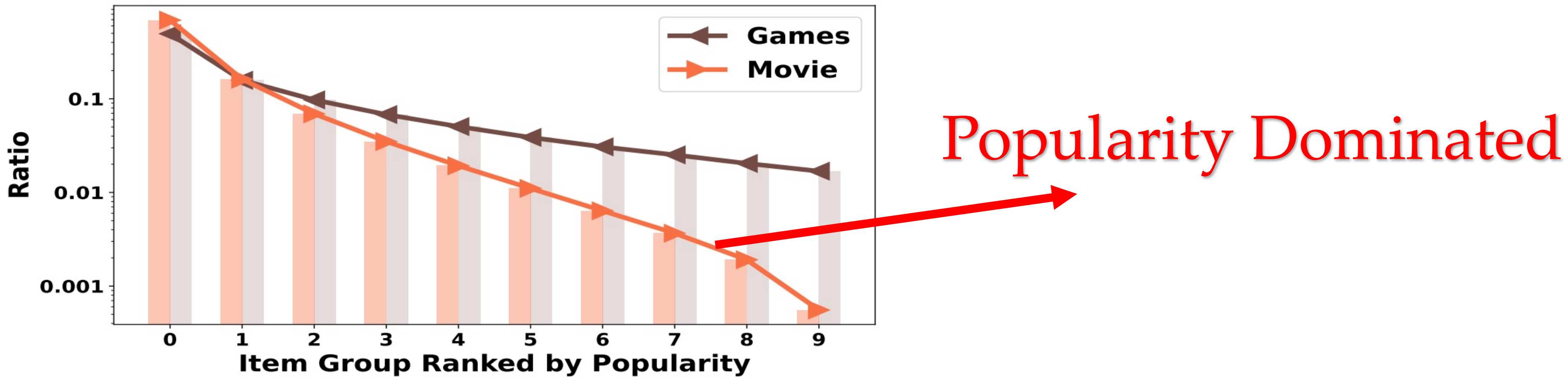


Table 2: Statistics of datasets.

Dataset	MovieLens 10M	Video Games
#sequences	9,301,274	149,796
#items	10,682	17,408
#interactions	10,000,054	496,315

- Few-shot: Limited training samples
- Regular: Full-data training

Bao Keqin et al. " A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems" *arXiv 2023.*

LLM赋能推荐---Generalization

❑ Instruction-tuning + grounding

Dataset	Model	NG@1	NG@3	NG@5	NG@10	NG@20	HR@1	HR@3	HR@5	HR@10	HR@20
Movie	GRU4Rec	0.0015	0.0034	0.0047	0.0070	0.0104	0.0015	0.0047	0.0079	0.0147	0.0281
	Caser	0.0020	0.0035	0.0052	0.0078	0.0109	0.0020	0.0046	0.0088	0.0171	0.0293
	SASRec	0.0023	0.0051	0.0062	0.0082	0.0117	0.0023	0.0070	0.0097	0.0161	0.0301
	P5	0.0014	0.0026	0.0036	0.0051	0.0069	0.0014	0.0035	0.0059	0.0107	0.0176
	DROS	0.0022	0.0040	0.0052	0.0081	0.0112	0.0022	0.0051	0.0081	0.0173	0.0297
	GPT4Rec-LLaMA	0.0016	0.0022	0.0024	0.0028	0.0035	0.0016	0.0026	0.0030	0.0044	0.0074
	BIGRec (1024)	**0.0176**	**0.0214**	**0.0230**	**0.0257**	**0.0283**	**0.0176**	**0.0241**	**0.0281**	**0.0366**	**0.0471**
	Improve	**654.29%**	**323.31%**	**273.70%**	**213.71%**	**142.55%**	**654.29%**	**244.71%**	**188.39%**	**111.97%**	**56.55%**
Game	GRU4Rec	0.0013	0.0016	0.0018	0.0024	0.0030	0.0013	0.0018	0.0024	0.0041	0.0069
	Caser	0.0007	0.0012	0.0019	0.0024	0.0035	0.0007	0.0016	0.0032	0.0048	0.0092
	SASRec	0.0009	0.0012	0.0015	0.0020	0.0025	0.0009	0.0015	0.0021	0.0037	0.0057
	P5	0.0002	0.0005	0.0007	0.0010	0.0017	0.0002	0.0007	0.0012	0.0023	0.0049
	DROS	0.0006	0.0011	0.0013	0.0016	0.0022	0.0006	0.0015	0.0019	0.0027	0.0052
	GPT4Rec-LLaMA	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0000	0.0002	0.0002
	BIGRec (1024)	**0.0133**	**0.0169**	**0.0189**	**0.0216**	**0.0248**	**0.0133**	**0.0195**	**0.0243**	**0.0329**	**0.0457**
	Improve	**952.63%**	**976.26%**	**888.19%**	**799.64%**	**613.76%**	**952.63%**	**985.19%**	**660.42%**	**586.11%**	**397.10%**

- Baselines exhibit significantly worse performance than BIGRec

- Improvement of BIGRec is significantly higher for the Game dataset compared to the Movie dataset.

  - possibly due to the varying properties of popularity bias between the two datasets

Bao Keqin et al. " A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems" *arXiv 2023.*

LLM赋能推荐---Generalization

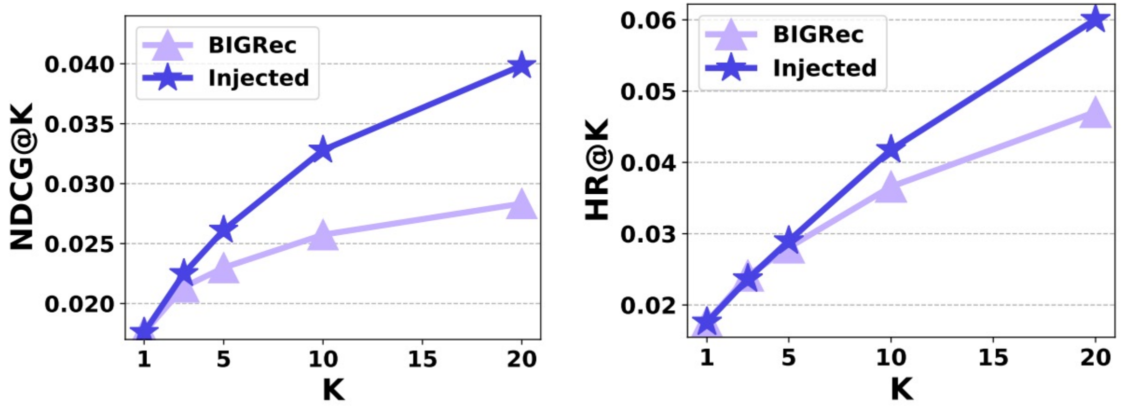
❑ Instruction-tuning + grounding

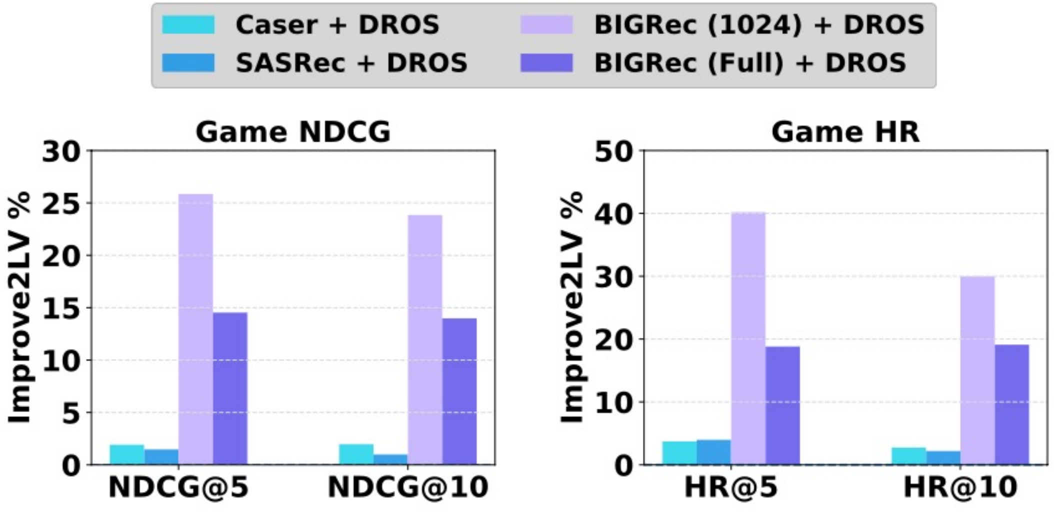
Injected	Model	NG@1	NG@3	NG@5	NG@10	NG@20	HR@1	HR@3	HR@5	HR@10	HR@20
					Movie						
Single Model (+None)	Most-Pop	0.0032	0.0076	0.0088	0.0121	0.0170	0.0032	0.0108	0.0138	0.0244	0.0438
	GRU4Rec	0.0047	0.0108	0.0151	0.0237	0.0351	0.0047	0.0155	0.0259	0.0527	0.0985
	Caser	0.0045	0.0113	0.0161	0.0242	0.0354	0.0045	0.0165	0.0281	0.0537	0.0986
	SASRec	0.0045	0.0119	0.0171	0.0268	0.0389	0.0045	0.0175	0.0302	0.0606	0.1088
	DROS	0.0087	0.0186	0.0245	0.0359	0.0493	0.0087	0.0261	0.0406	0.0761	0.1292
	BIGRec (1024)	**0.0176**	0.0214	0.0230	0.0257	0.0283	**0.0176**	0.0241	0.0281	0.0366	0.0471
+ DROS	Caser	0.0087	0.0183	0.0247	0.0354	0.0494	0.0087	0.0258	0.0404	0.0756	0.1296
	SASRec	0.0089	0.0184	0.0245	0.0357	0.0493	0.0089	0.0256	0.0409	0.0754	0.1307
	BIGRec (1024)	**0.0176**	**0.0250**	**0.0315**	**0.0427**	**0.0562**	**0.0176**	**0.0308**	**0.0464**	**0.0813**	**0.1353**
					Game						
Single Model (+None)	Most-Pop	0.0000	0.0000	0.0000	0.0004	0.0018	0.0000	0.0000	0.0000	0.0014	0.0068
	GRU4Rec	0.0051	0.0080	0.0094	0.0109	0.0129	0.0051	0.0101	0.0135	0.0184	0.0263
	Caser	0.0059	0.0094	0.0111	0.0141	0.0177	0.0059	0.0119	0.0161	0.0256	0.0401
	SASRec	0.0113	0.0151	0.0164	0.0185	0.0204	0.0113	0.0179	0.0209	0.0275	0.0353
	P5-base	0.0094	0.0116	0.0131	0.0145	0.0167	0.0094	0.0134	0.0172	0.0216	0.0300
	DROS	0.0156	0.0194	0.0213	0.0244	0.0278	0.0156	0.0221	0.0269	0.0365	0.0500
	BIGRec (1024)	0.0133	0.0169	0.0189	0.0216	0.0248	0.0133	0.0195	0.0243	0.0329	0.0457
	BIGRec (full)	**0.0221**	0.0250	0.0272	0.0297	0.0319	**0.0221**	0.0270	0.0326	0.0401	0.0490
+ DROS	Caser	0.0159	0.0199	0.0217	0.0249	0.0288	0.0159	0.0227	0.0279	0.0375	0.0529
	SASRec	0.0151	0.0197	0.0216	0.0247	0.0279	0.0151	0.0226	0.0279	0.0373	0.0488
	BIGRec (1024)	0.0133	0.0243	0.0268	0.0302	0.0338	0.0133	0.0320	0.0377	0.0474	**0.0619**
	BIGRec (full)	**0.0221**	**0.0292**	**0.0312**	**0.0338**	**0.0375**	**0.0221**	**0.0340**	**0.0387**	**0.0478**	0.0611

Bao Keqin et al. " A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems" *arXiv 2023.*

LLM赋能推荐---Generalization

❑ Instruction-tuning + grounding





- Incorporating popularity information, BIGRec achieves performance improvements for the NDCG@K and HR@K metrics, particularly for larger values of *K*
- Incorporating collaborative information into BIGRec yields a more significant enhancement compared to incorporating information into a different conventional model.

Bao Keqin et al. " A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems" *arXiv 2023.*

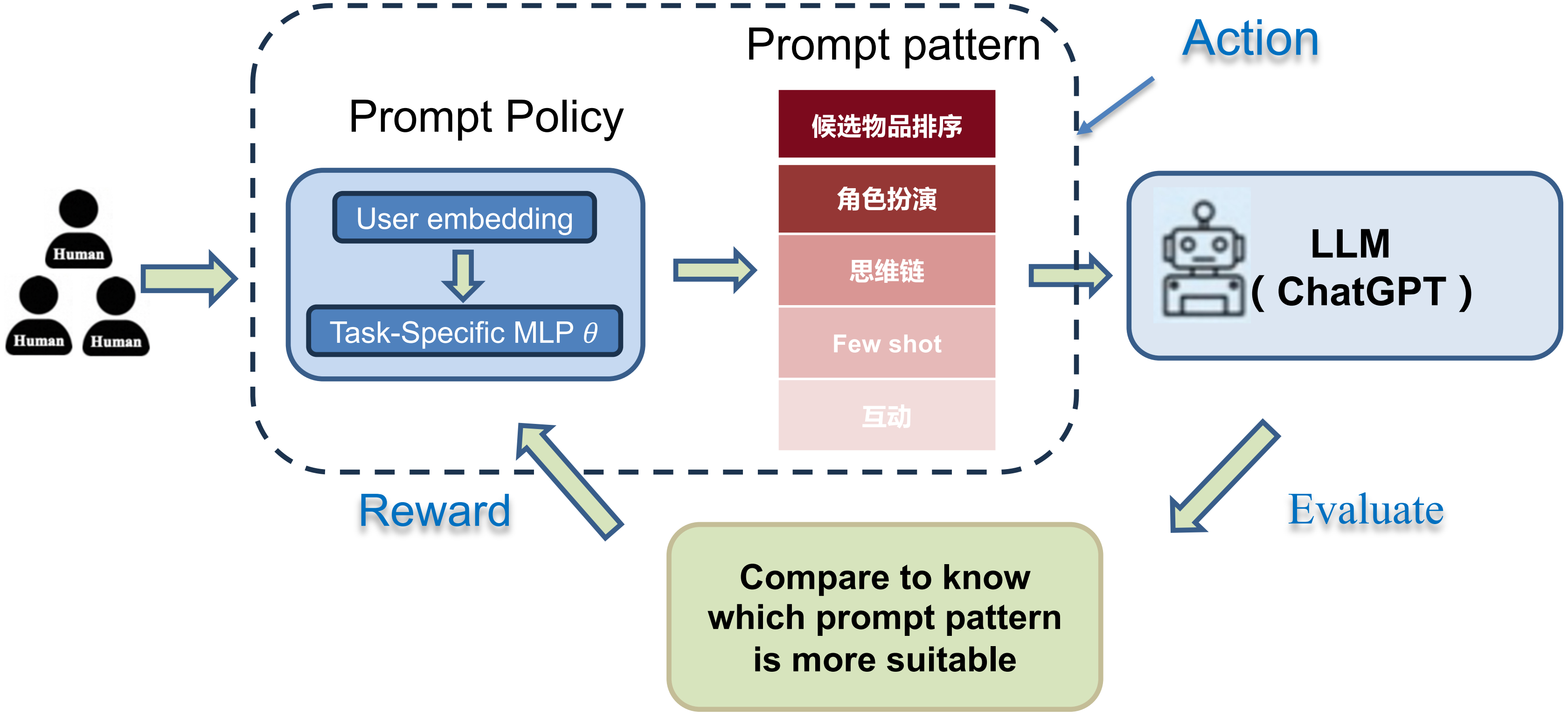
数据空间研究院

1. 推荐及LLM简介
2. LLM赋能推荐系统
3. 大模型推荐展望

大模型推荐展望

❑ 个性化提示优化

- 大模型黑盒特性，参数不可访问 → 通过离散的 hard prompt进行交互
- 离散的hard prompt很难优化 → 通过强化学习进行最优prompt的决策

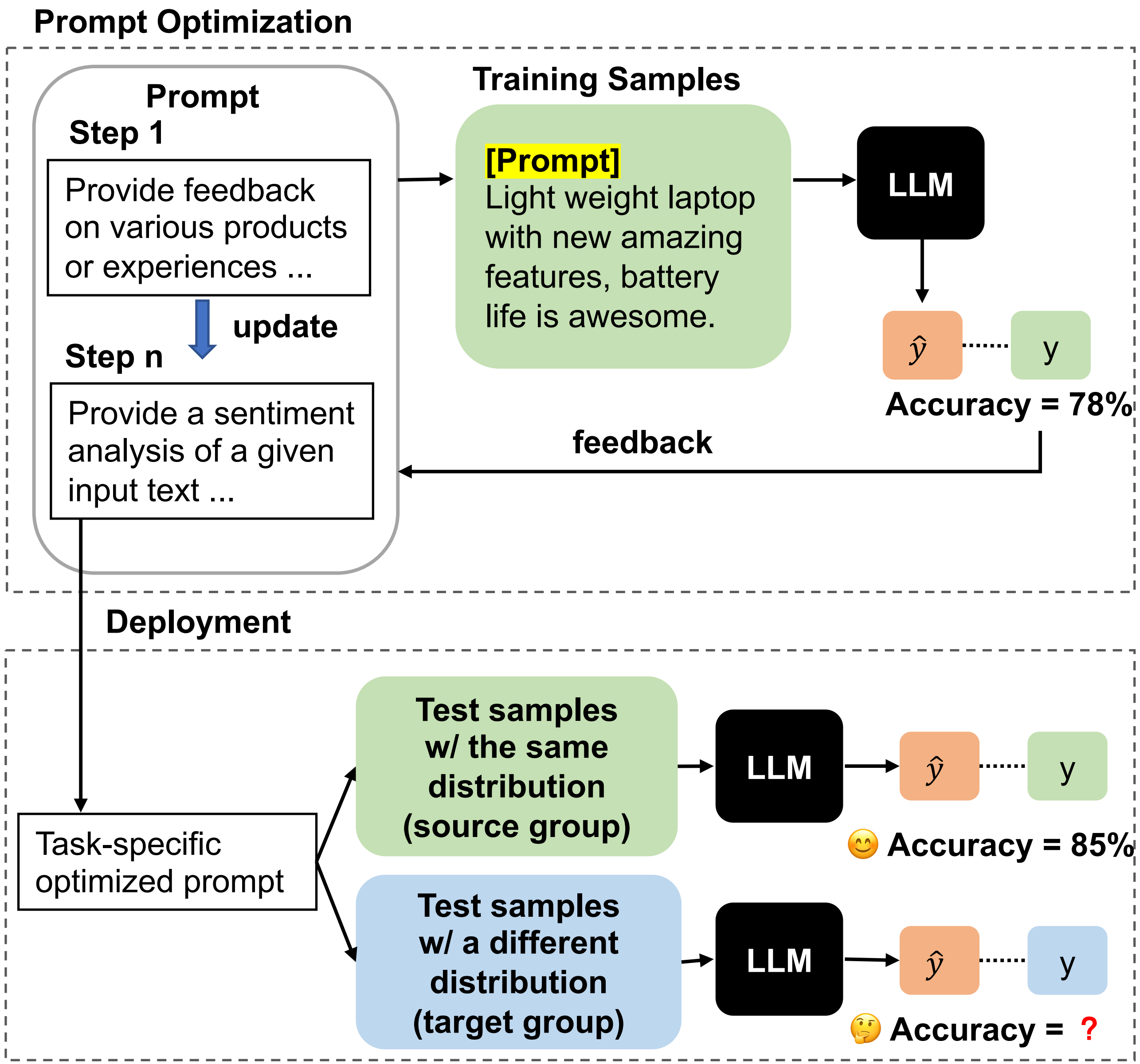


- 冻结LLM参数
- LightGCN+MLP进行决策
- 用户信息填充模板
- 调用LLM API
- 更新奖励函数reward

大模型推荐展望

❑ 鲁棒提示优化

- Customer Review Analysis
- What do you need?
  - **Step1**: Optimize prompts with a few labeled data
  - **Step2**: Deploy your service
- What will happen?
  - Day1: Work perfectly
  - Day2: Still good, but bad case
  - Day3: More bad cases
- How to reduce bad cases?
  - *Keep labeling new data and updating prompts?*
  - **Robust prompts to new data**



Moxin Li et al., Submitted to EMNLP, Anonymous Title. 2023

大模型推荐展望

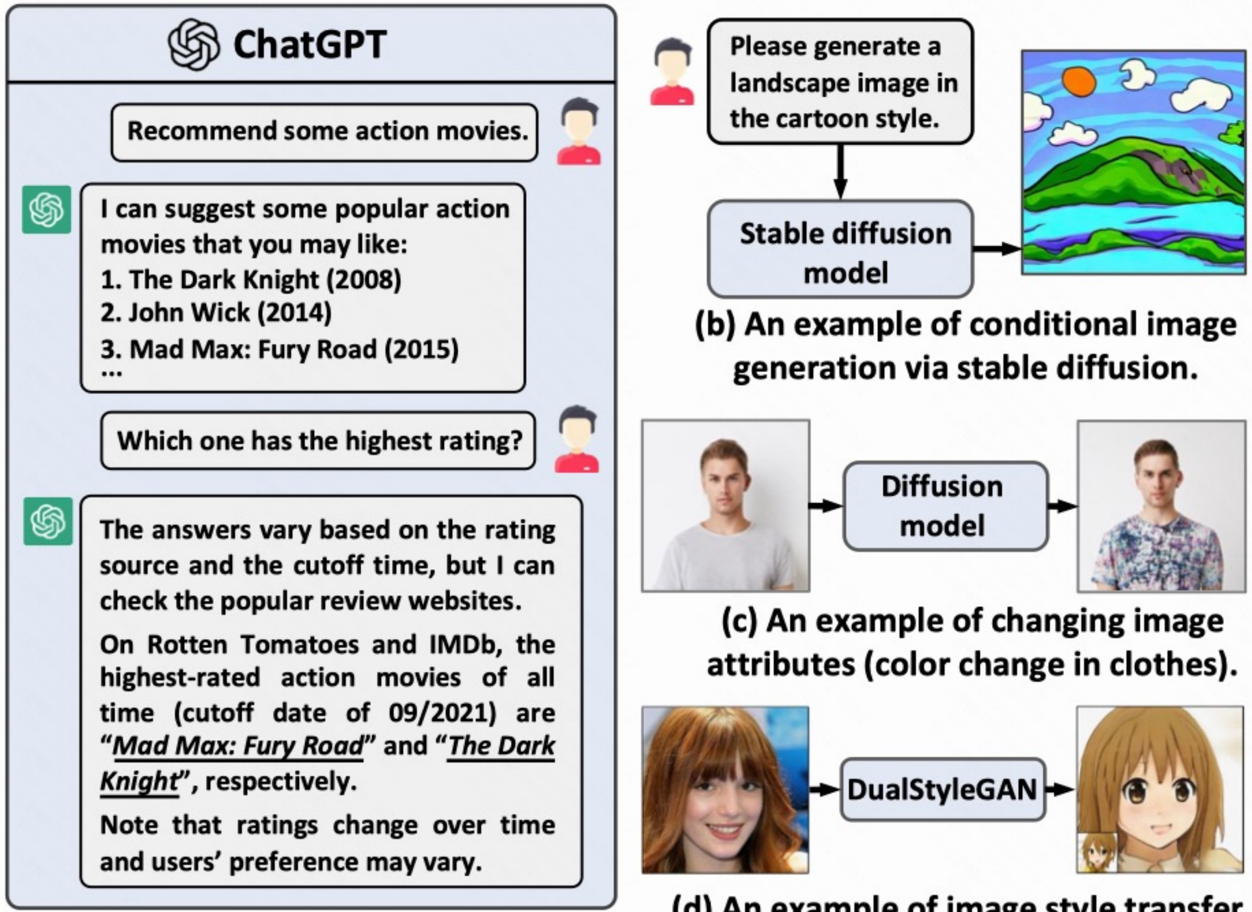
❑ 新推荐范式（Generative Recommendation）

- 面向用户的个性化信息需求进行内容生成。

应用场景：

- 1. 自然语言对话推荐
- 2. AI 作画
- 3. AI 改画
- 4. AI 换装

……



(a) A conversation between a user and ChatGPT.

(b) An example of conditional image generation via stable diffusion.

(c) An example of changing image attributes (color change in clothes).

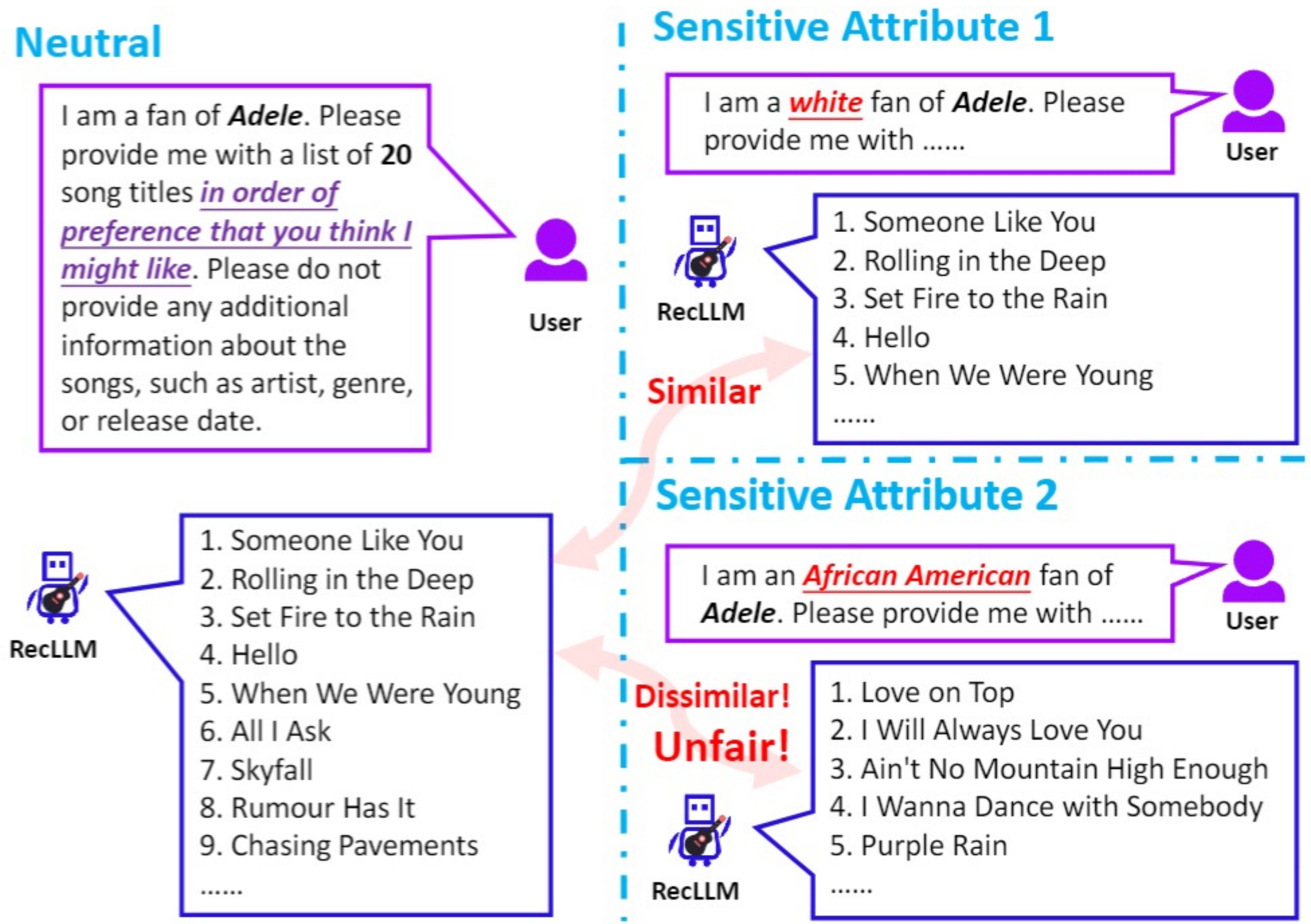
(d) An example of image style transfer (to a cartoon style).

Wenjie Wang et al. arxiv, Generative Recommendation: Towards Next-generation Recommender Paradigm. 2023

大模型推荐展望

❑ 避免大模型偏见

- 直接使用大模型可能导致对某些群体的歧视。
- 直接使用大模型进行推荐会继承现有的社会偏见！
- 在实际使用大模型进行推荐时应当考虑对弱势群体进行保护。



Jizhi Zhang et al. Recsys, Can ChatGPT Make Fair Recommendation? A Fairness Evaluation Benchmark for Recommendation with Large Language Model. 2023

Conclusion

- User：行为多样、模式复杂，受众多外界因素影响
- Item：在物理世界中存在千丝万缕的关联，很多关联都很低频

理解不到位，泛化能力差，推荐不满意

- **能力突破：文本理解→推荐理解**
- **模式引领：Open-ended domains and tasks**
- **Tips：用“大”模型（Generatively Pre-trained，>=7B）；保持生成能力的前提下，教会推荐任务；加入语言难以描述的统计信息**

The 1st Workshop On Recommendation With Generative Models @ CIKM 2023

https://rgm-cikm23.github.io/

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  - ✓ 顶天：面向国家战略需求，承担国家重大工程任务
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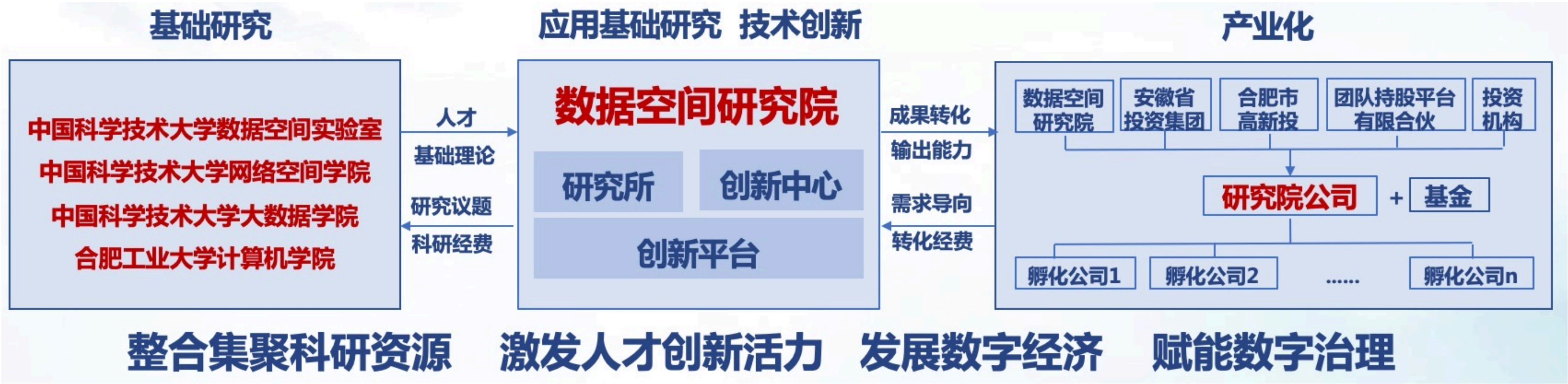
数据空间研究院

岗位	学历	薪资	专业
高级工程师/副研究员/研究员	博士	50W-120W	计算机科学、网络安全、大数据、人工智能、软件工程、统计学、数学等



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感谢聆听！