
# Aligning LLMs to Recommendation: Progresses and Future Prospects

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# Outline

- Background
- Alignment
  - Align to Recommendation Task :
    - Fast Alignment : TALLRec [Keqin Bao et al. RecSys 23]
    - Align to Generative Recommendation [Keqin Bao et al. arXiv 23]
    - Align Language to Recommendation Items [Xinyu Lin et al. arXiv 23]
  - Align to Recommendation Modality:
    - Empowering LLM Recommendation with Modality Alignment [Yang Zhang et al. arXiv 23]
    - Align to Understand Recommendation Modality [Zhengyi Yang et al. arXiv 23]
- Future Work

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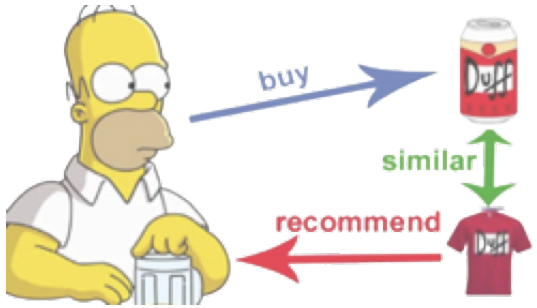
# Background

## ❑ Information explosion era

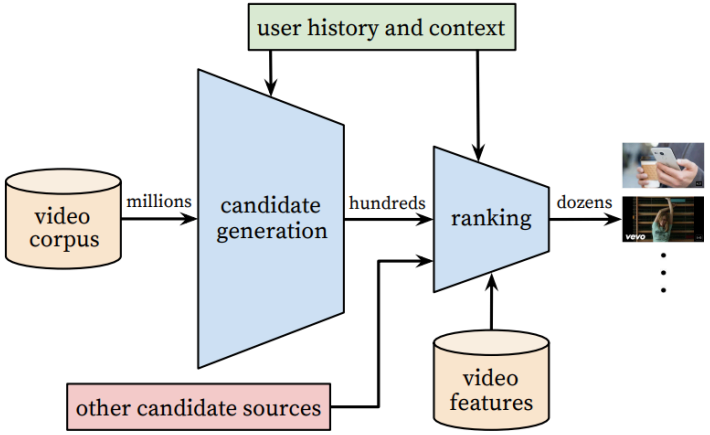
- E-commerce: 12 million items in Amazon.
- Social networks: 2.8 billion users in Facebook.
- Content sharing platforms: 720,000 hours videos uploaded to Youtube per day.

## ❑ Recommender system




Information seeking via **implicit feedback**

Recommendation

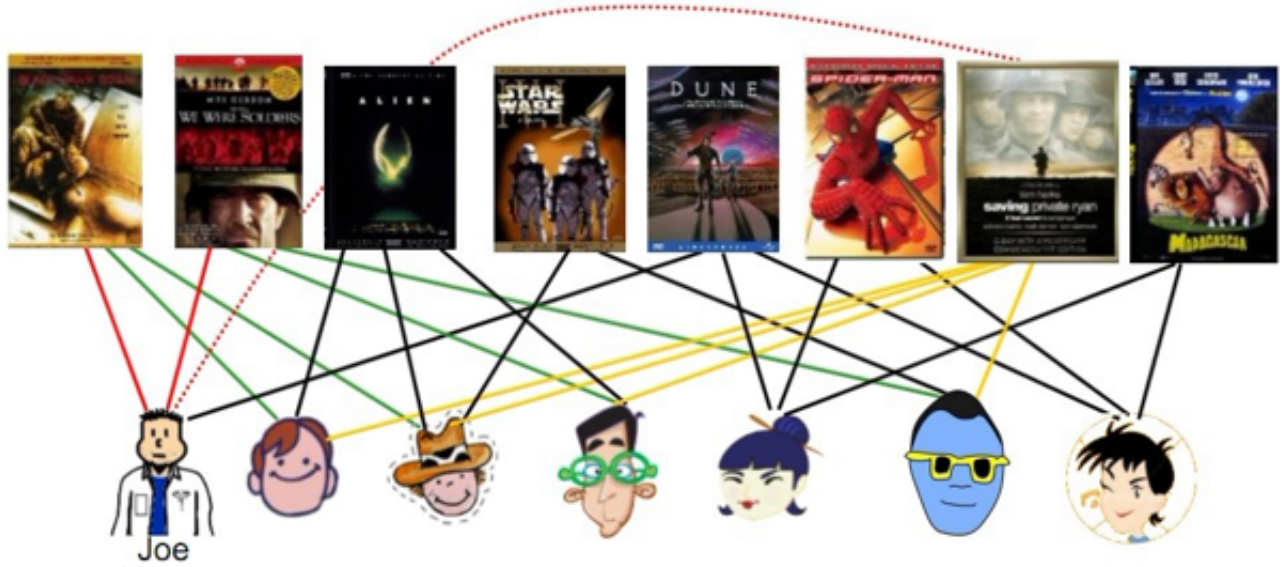


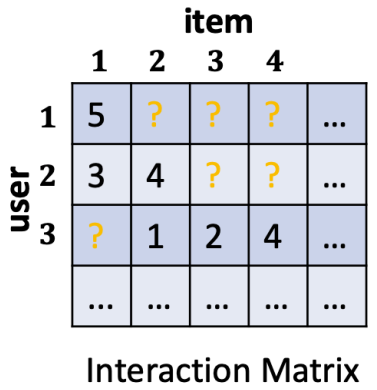

Images from: *Deep neural networks for youtube recommendations*

# Background

## ❑ Core idea of personalized recommendation

- **Collaborative filtering (CF):**
  Making automatic predictions (filtering) about the interests of a user by collecting preferences from many users (collaborating).




Interaction Matrix

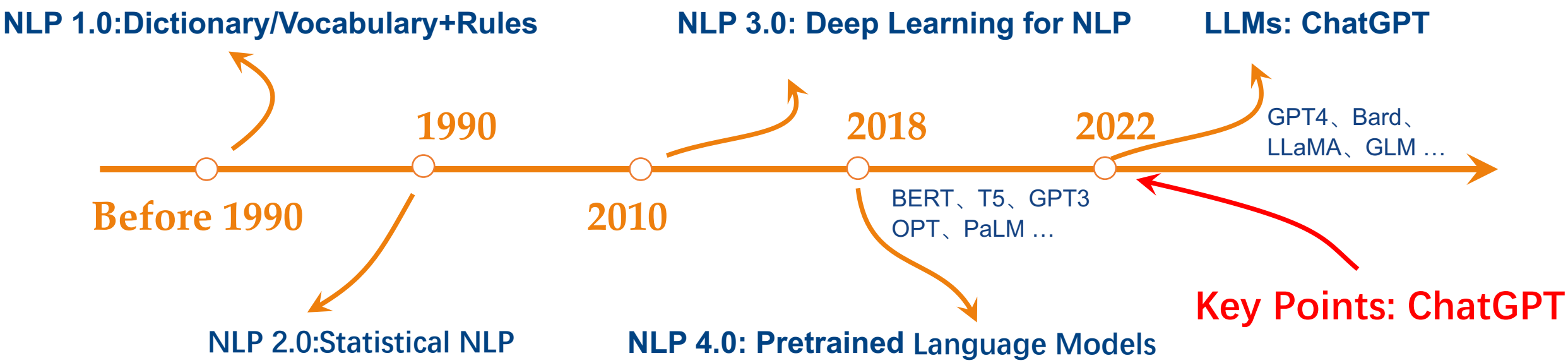
Memory-based CF
- User CF
- Item CF

Model-based CF
- MF
- FISM
- …

*Images from: Neural Collaborative Filtering,*

# Background

## ❑ Development of NLP techniques



# Background

## ❑ How recommender systems benefit from LLMs

- **Representation:**

Textual item representation,
Knowledge representation

- **Generalization:**

Few/zero-shot inference,
Cross-domain,
World knowledge

- **Generation:**

Personalized content generation,
Generative recommendation

## However, LLMs are not naturally suitable for recommendation

- **Reasons:**

Lack of recommendation-related training data in the LLM pre-training stage.

Hard to capture the collaborative information.

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    - **Align Language to Recommendation Items: TransRec [Xinyu Lin et al. arXiv 23]**
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# Fast Alignment

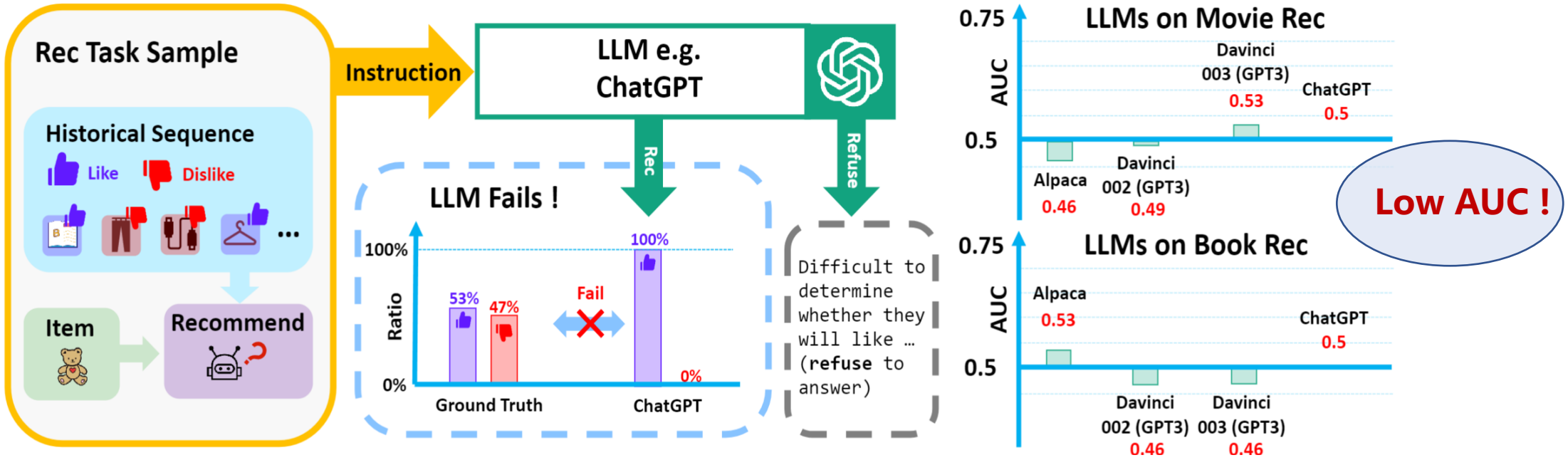
- **In-context learning can recommend ?**
- **Example:** Given the user’ s interaction history, directly ask the LLM to predict whether he/she will like the new targe item via answering “Yes” or “No”.

| Instruction Input | |
|---|---|
| Task Instruction: | Given the user’s historical interactions, please determine whether the user will enjoy the target new movie by answering "Yes" or "No". |
| Task Input: | User’s liked items: GodFather.<br>User’s disliked items: Star Wars.<br>Target new movie: Iron Man |
| **Instruction Output** | |
| Task Output: | No. |

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

# Fast Alignment

- **In-context learning is not enough.**
- In complex scenarios, ChatGPT usually gives positive ratings or refuse to answer.



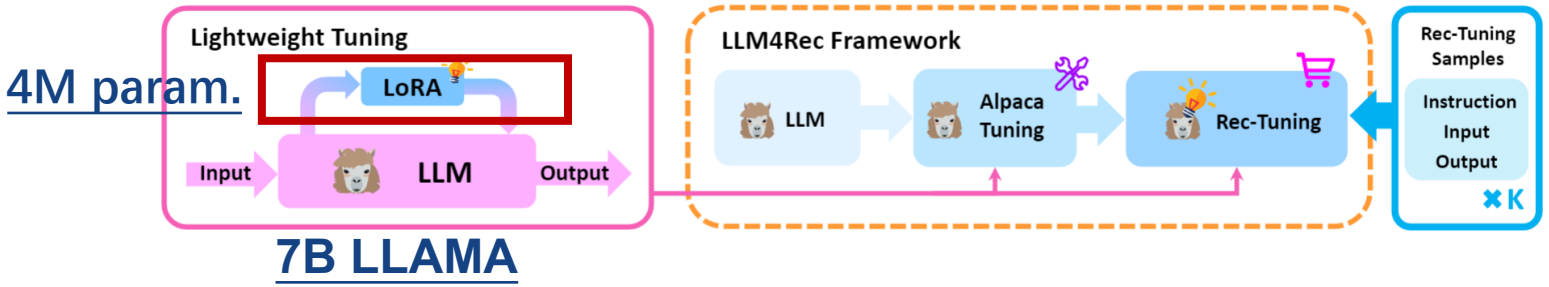

Need to **align** LLM with recommendation!

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

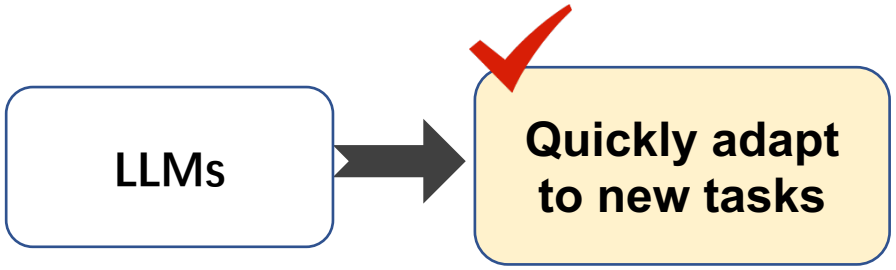
# Fast Alignment

## ❑ Instruction-tuning

$$\max_{\Theta} \sum_{(x,y)\in\mathcal{Z}} \sum_{t=1}^{|y|} \log\left(P_{\Phi+\Theta}(y_t|x, y_{<t})\right),$$

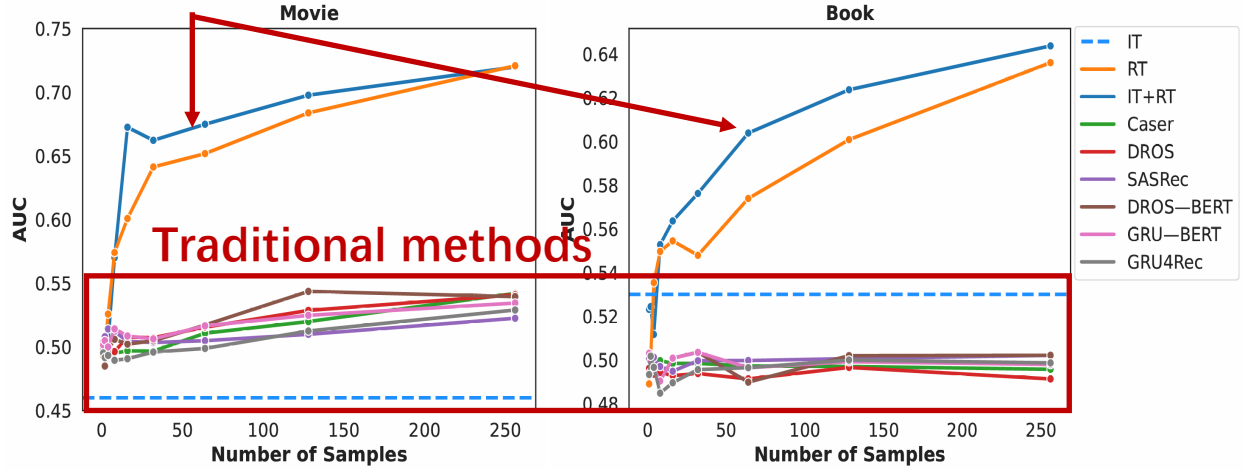



Fine-tune 4M parameters by few-shot samples via **generative loss**




- Use item titles as the input
- Better for cold-start recommendation

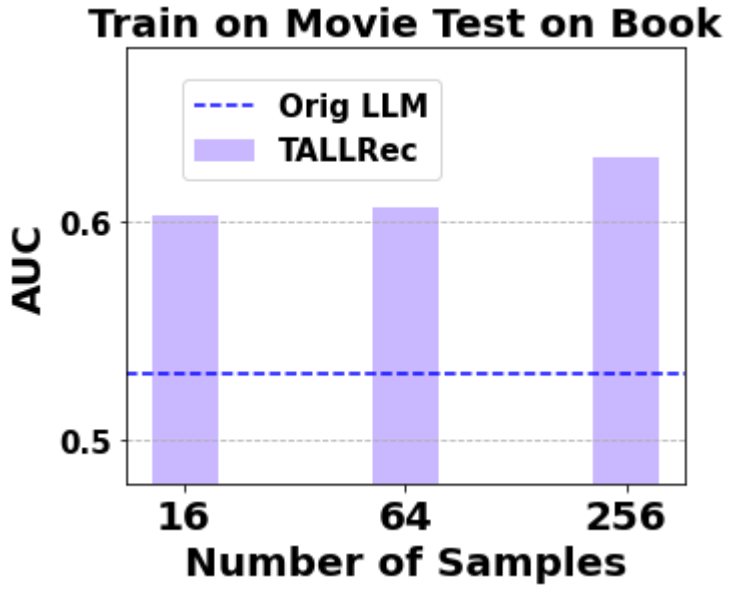
**Performance significantly improves by fine-tuning few-shot samples.**

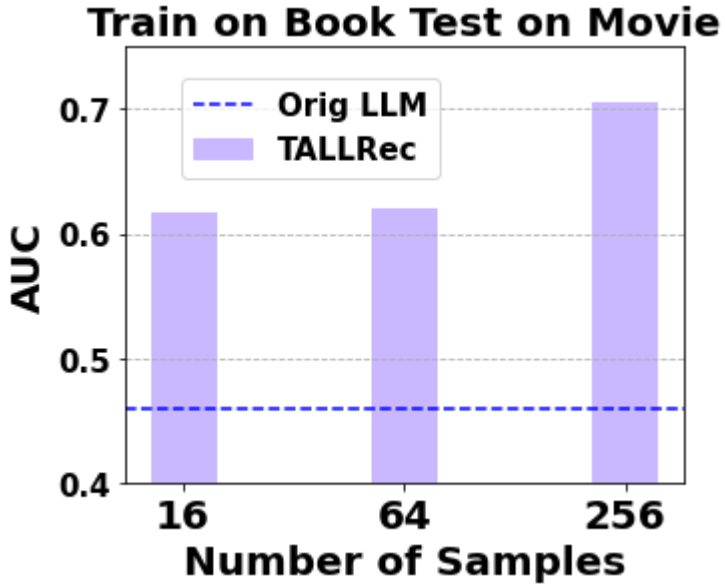



*Keqin Bao et al. Recsys, TALLRec: An Effective and Efficient Tuning Framework to Align Large Language Model with Recommendation. 2023*

# Fast Alignment

- **Cross-domain generalization**
- Learning from movie scenario can directly recommend on books, and vice versa
- LLM can leverage domain knowledge to accomplish recommendation tasks after acquiring the ability to recommend.

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# Align with Grounding

## ❑ Generation + Grounding

- Generation ability is the important feature of the LLM, and it almost can generate **all conceivable language sequences**.
- However, LLMs don’ t know which kind of **sequences describe a item** in the recommendation scenario.
- The item described by the LLM may not in **the actual world**.

**Grounding Paradigm**

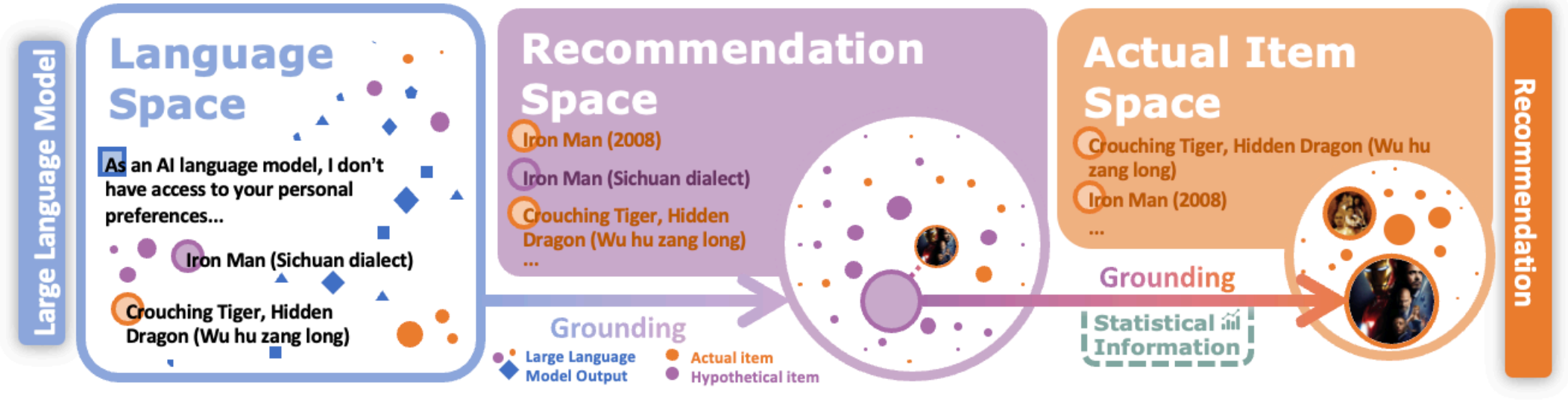
**Language Space**

*Step1: instruction tuning*

**Recommendation Space**

*Step2: L2 distance between representations*

**Actual Item Space**






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

# Align with Grounding

## ❑ Generation + Grounding

### ❑ Few-shot training

| 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 on Game compared to on Movie.
  - possibly due to the varying properties of popularity bias between the two datasets.

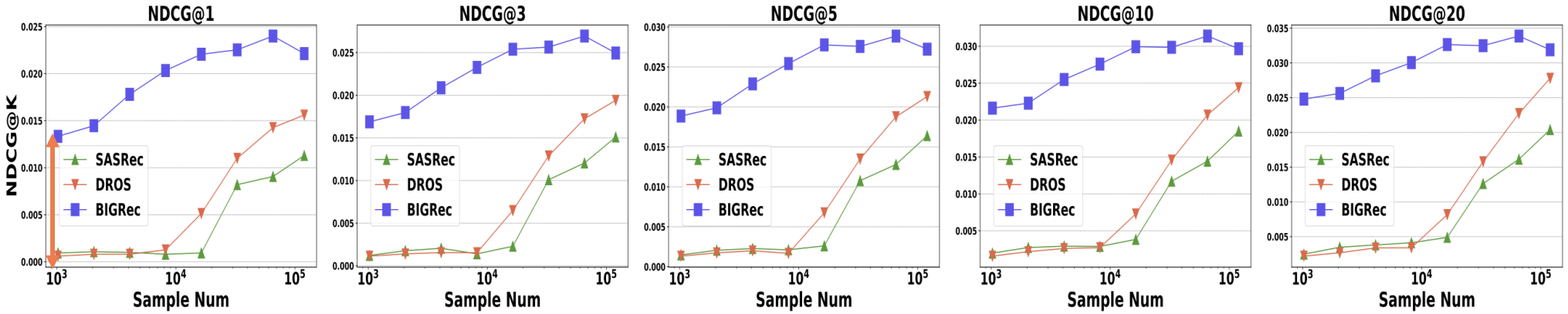


*Bao Keqin et al. " A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems“ arXiv 2023.*

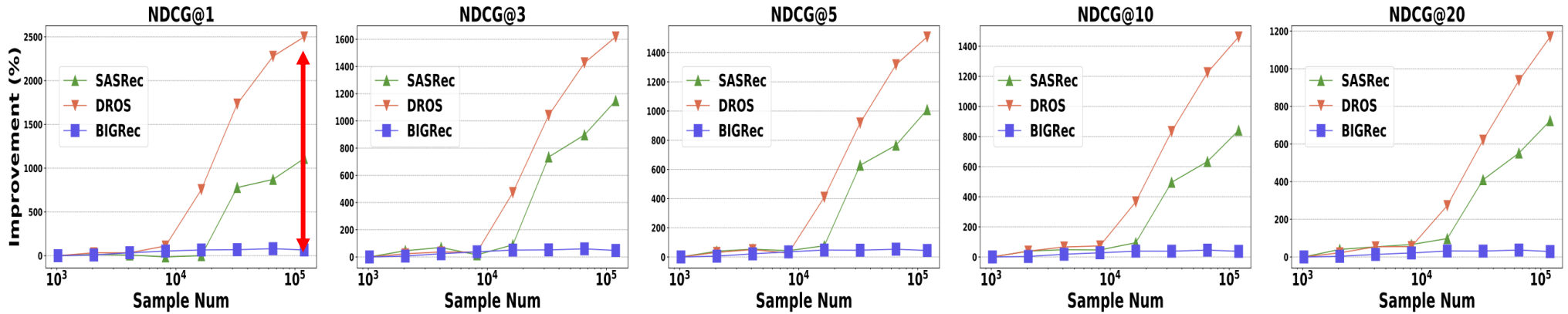
# Align with Grounding

## ❑ Generation + Grounding

**Quickly Adapt to Recommendation**




**Not proficient in utilizing CF info.**



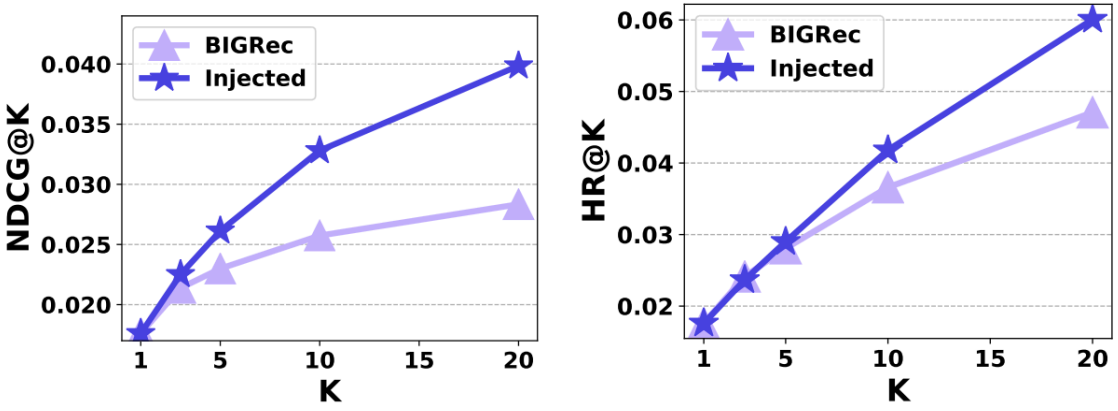



*Bao Keqin et al. " A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems“ arXiv 2023.*

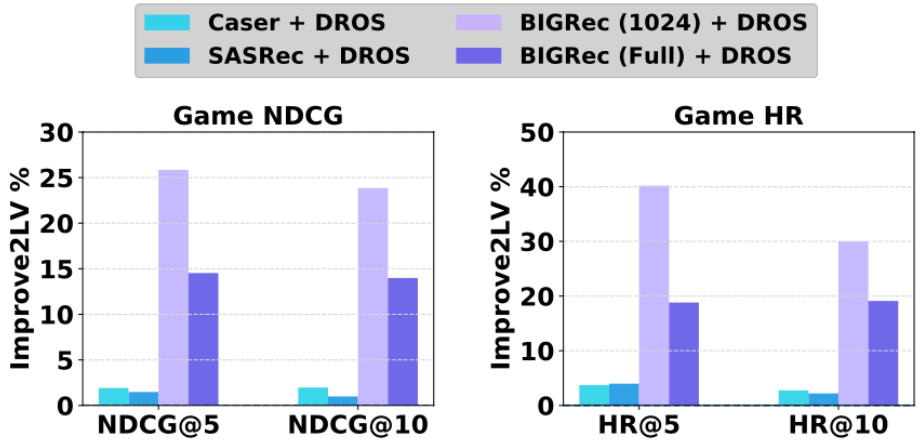
# Align with Grounding

## ❑ Generation + Grounding

- In-depth analysis
- Injecting statistical information into BIGRec at step2




- By incorporating popularity, BIGRec achieves significant improvements *w.r.t.* NDCG@*K* and HR@*K*, particularly for a larger *K*.




- Incorporating collaborative information into BIGRec yields more significant enhancements than conventional models.



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

# Align with Grounding

## ❑ Align Language and Items: Two Key Steps

### ❑ Item indexing

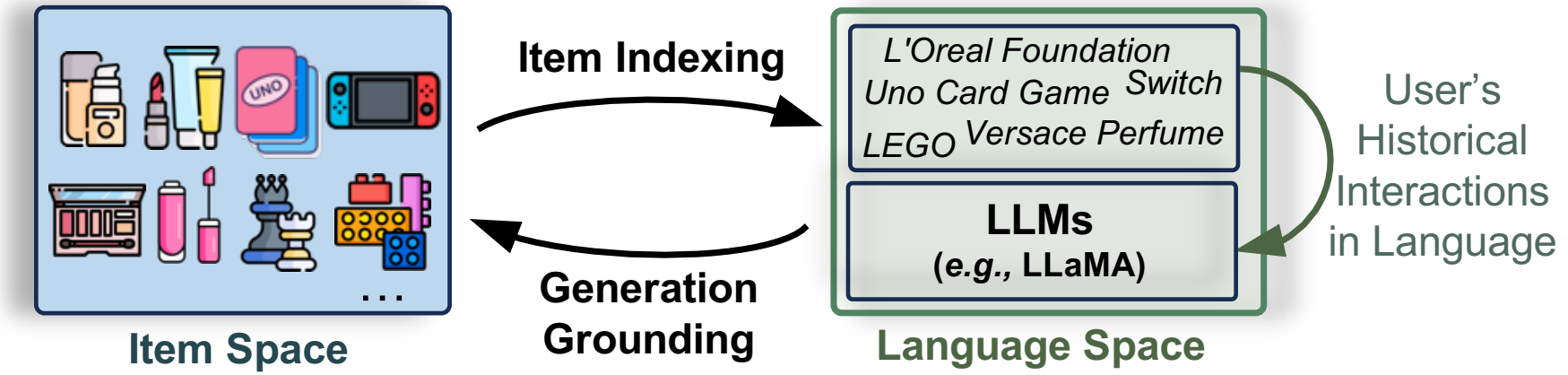
- How to represent an item in natural language?

### ❑ Generation grounding

- How to generate and ground the natural language to the actual items?

Two criteria for identifiers
- **distinctiveness**
- **semantics**

Consideration for generation
- **constrained generation**
  - ⚠ rely heavily on first token
- **position-free generation**

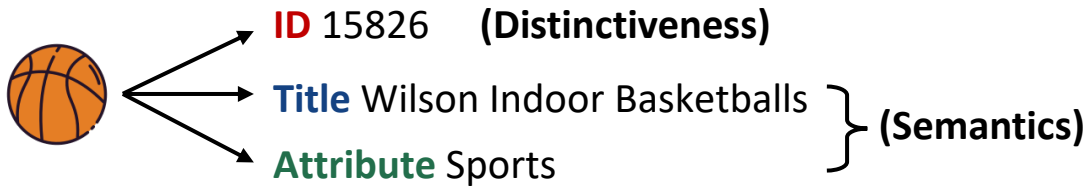




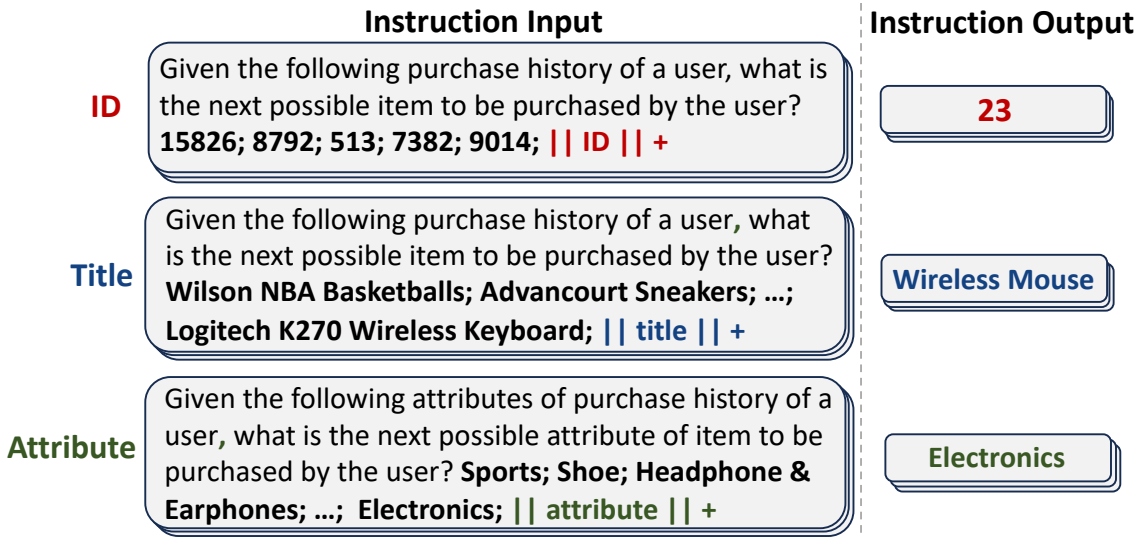

*Lin Xinyu et al. " A Multi-facet Paradigm to Bridge Large Language Model and Recommendation " arXiv 2023.*

# Align with Grounding

- **Item indexing: multi-facet identifier**

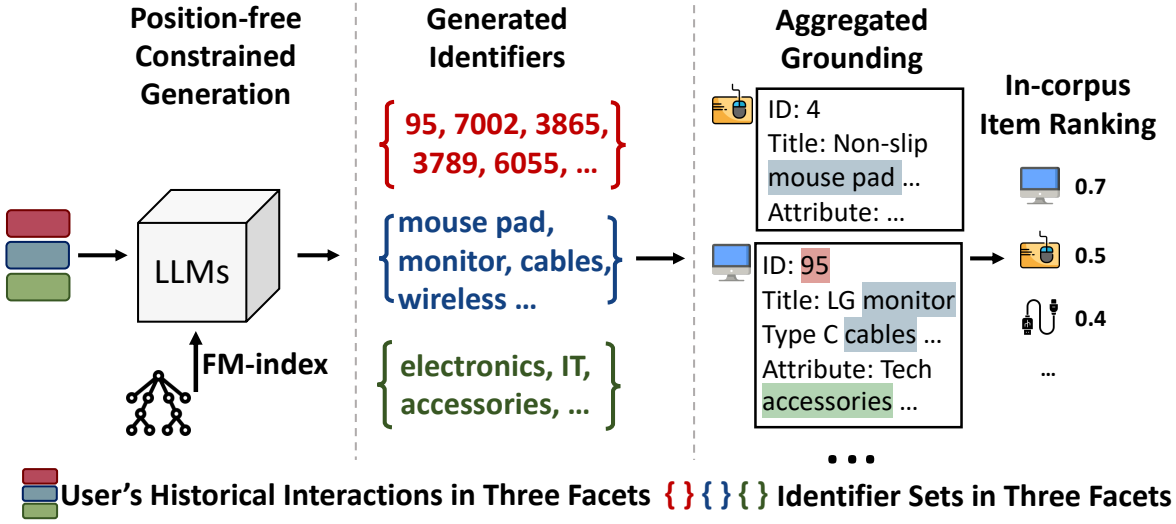



  - **Instruction data reconstruction**




- **Generation grounding:**
  - position-free constrained generation
  - aggregated grounding

FM-index: special prefix tree that supports search from any position of the identifier corpus.



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# Align with Grounding

## ❑ Enhanced recommendation under full training

**Table 2: Overall performance comparison between the baselines and TransRec instantiated on BART on three datasets. The best results are highlighted in bold and the second-best results are underlined. * implies the improvements over the second-best results are statistically significant ($p$-value < 0.01) under one-sample t-tests.**

| | Beauty | | | | Toys | | | | Yelp | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Model** | **R@5** | **R@10** | **N@5** | **N@10** | **R@5** | **R@10** | **N@5** | **N@10** | **R@5** | **R@10** | **N@5** | **N@10** |
| **MF** | 0.0294 | 0.0474 | 0.0145 | 0.0191 | 0.0236 | 0.0355 | 0.0153 | 0.0192 | 0.0220 | 0.0381 | 0.0138 | 0.0190 |
| **LightGCN** | 0.0305 | 0.0511 | 0.0194 | 0.0260 | 0.0322 | 0.0508 | 0.0215 | 0.0275 | 0.0255 | 0.0427 | 0.0163 | 0.0218 |
| **SASRec** | 0.0380 | 0.0588 | 0.0246 | 0.0313 | 0.0470 | 0.0659 | 0.0312 | 0.0373 | 0.0183 | 0.0296 | 0.0116 | 0.0152 |
| **ACVAE** | 0.0503 | 0.0710 | 0.0356 | 0.0422 | 0.0488 | 0.0679 | 0.0350 | 0.0411 | 0.0211 | 0.0356 | 0.0127 | 0.0174 |
| **SID** | 0.0430 | 0.0602 | 0.0288 | 0.0368 | 0.0164 | 0.0218 | 0.0120 | 0.0139 | 0.0346 | 0.0486 | 0.0242 | 0.0287 |
| **SemID+IID** | 0.0501 | 0.0724 | 0.0344 | 0.0411 | 0.0145 | 0.0260 | 0.0069 | 0.0123 | 0.0229 | 0.0382 | 0.0150 | 0.0199 |
| **CID+IID** | 0.0512 | 0.0732 | 0.0356 | 0.0427 | 0.0169 | 0.0276 | 0.0104 | 0.0154 | 0.0287 | 0.0468 | 0.0195 | 0.0254 |
| **P5** | 0.0508 | 0.0664 | 0.0379 | 0.0429 | 0.0608 | 0.0688 | 0.0507 | 0.0534 | 0.0506 | 0.0648 | 0.0343 | 0.0389 |
| **TransRec-B** | **0.0550*** | **0.0766*** | **0.0395*** | **0.0464*** | **0.0679*** | **0.0881*** | **0.0512*** | **0.0567*** | **0.0549*** | **0.0679*** | **0.0408*** | **0.0450*** |

- **Superior performance** compared to both **traditional** models and **LLM-based** models.
- **TransRec significantly outperform P5**, which utilizes additional training data from user reviews. In constrast, TransRec uses **only user-item interactions**.



*Lin Xinyu et al. " A Multi-facet Paradigm to Bridge Large Language Model and Recommendation " arXiv 2023.*

# Align with Grounding

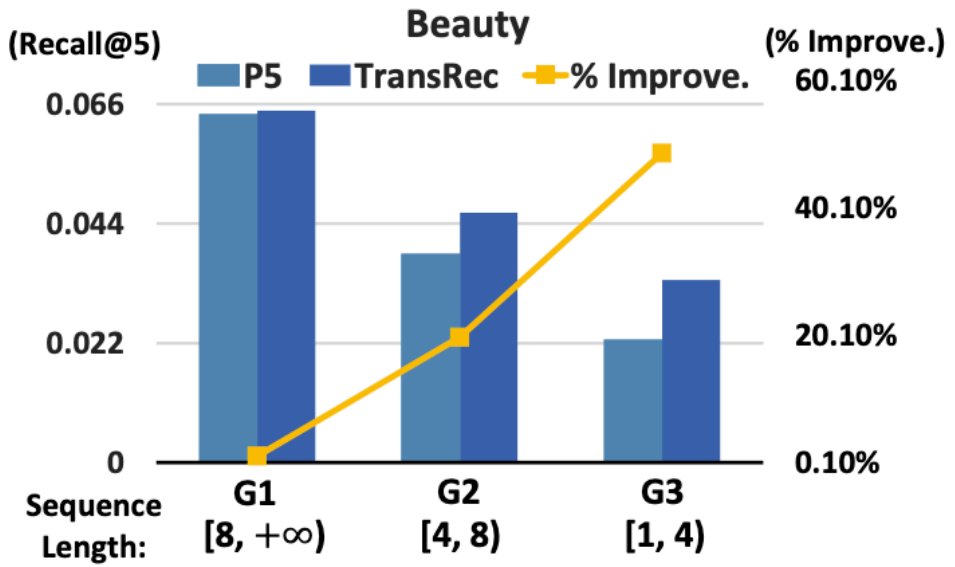
## ❑ Strong generalization ability

- **Few-shot training**
  - warm- and cold-start testing

| N-shot | Model | Warm R@5 | Warm N@5 | Cold R@5 | Cold N@5 |
|---|---|---|---|---|---|
| 1024 | LightGCN | 0.0205 | 0.0125 | 0.0005 | 0.0003 |
| | ACVAE | 0.0098 | 0.0057 | 0.0047 | 0.0026 |
| | P5 | 0.0040 | 0.0016 | 0.0025 | 0.0015 |
| | TransRec-B | 0.0039 | 0.0024 | 0.0025 | 0.0016 |
| | TransRec-L | **0.0141** | **0.0070** | **0.0159** | **0.0097** |
| 2048 | LightGCN | 0.0186 | 0.0117 | 0.0005 | 0.0004 |
| | ACVAE | 0.0229 | 0.0136 | 0.0074 | 0.0044 |
| | P5 | 0.0047 | 0.0030 | 0.0036 | 0.0012 |
| | TransRec-B | 0.0052 | 0.0027 | 0.0039 | 0.0017 |
| | TransRec-L | **0.0194** | **0.0126** | **0.0206** | **0.0126** |

* The bold results highlight the superior performance compared to the best LLM-based recommender baseline.

- **User group analysis**
  - from dense users to sparse users




- **Remarkable generalization ability** of LLMs with vase knowledge base, especially on cold-start recommendation under limited data.
- On user side, TransRec significantly **improves the performance of sparse users** with fewer interactions.

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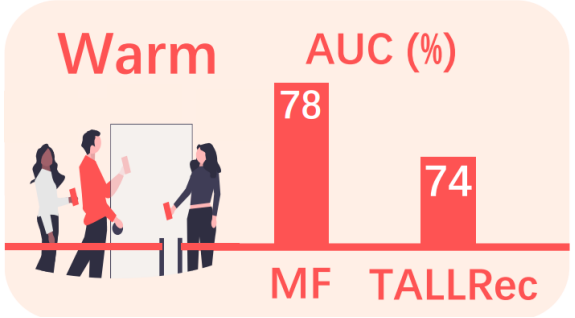
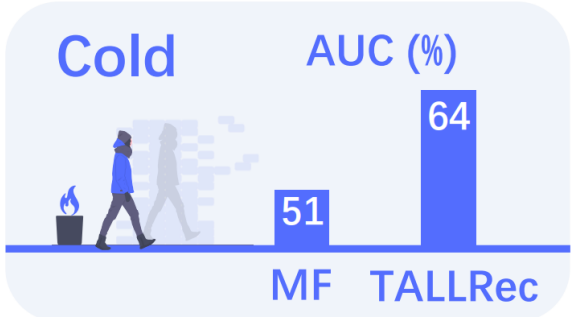
# Empowering LLM Rec with Modality Alignment

## LLM Rec is not good at modeling collaborative information as traditional models

**LLM Rec vs Traditional CF Model :**

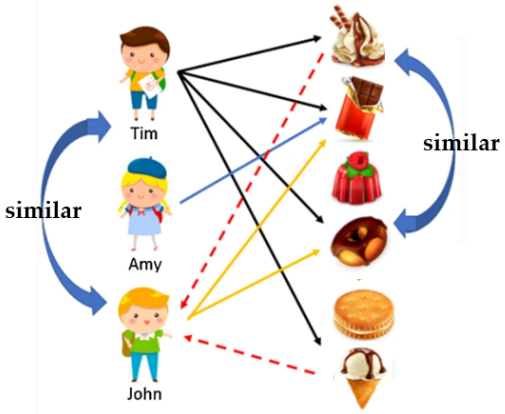
- Excellent at old-start scenarios
- Poor at warm-start scenarios




### Traditional CF Model

User/Item : ID

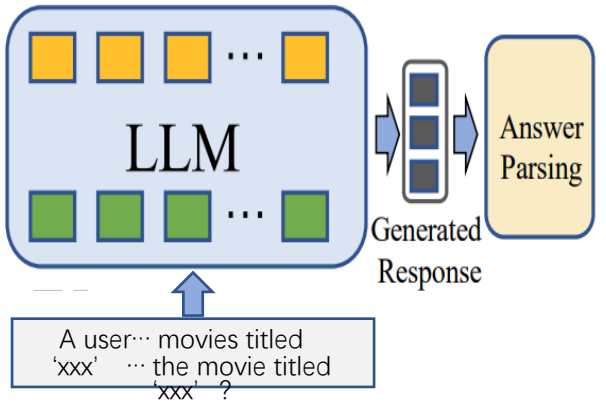



Rely on collab. Info. --- co-occurrence similarities among interactions (Good for Warm)

**Lack** of modeling collab. Info.

Textually similar item may have distinct collab. info.

### LLM Recommendation

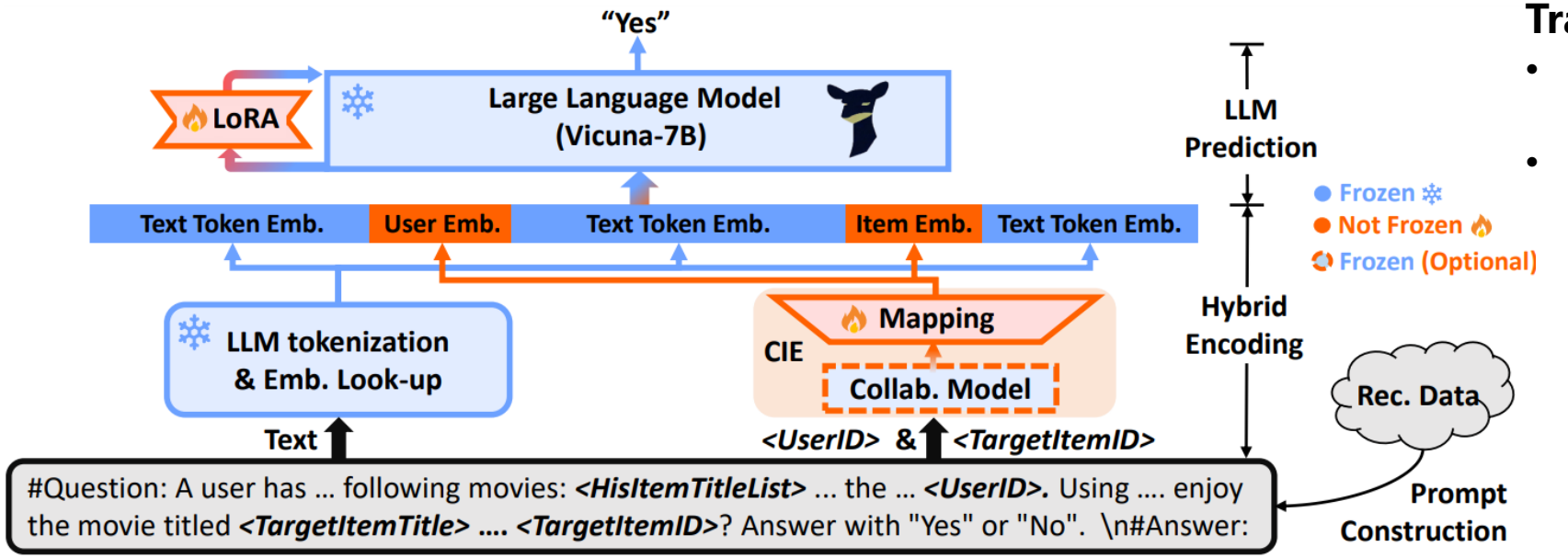



User/Item: Text

Relying on text semantics (Good for Cold)

# Empowering LLM Rec with Modality Alignment

## CoLLM : Integrating Collaborative Embedding into LLM Rec – Align with Rec Modality




**Train :**

- Freeze original LLM
  Freeze CF model (Optional)
- Two Training steps :
  1) **Train LoRA (Text)**
     Learn to recommend
     Keep cold perfomance
  2) **Train CIE (Text+ID)**
     Model collaborative information , and make it usable for LLM
     **Improve warm capacity**

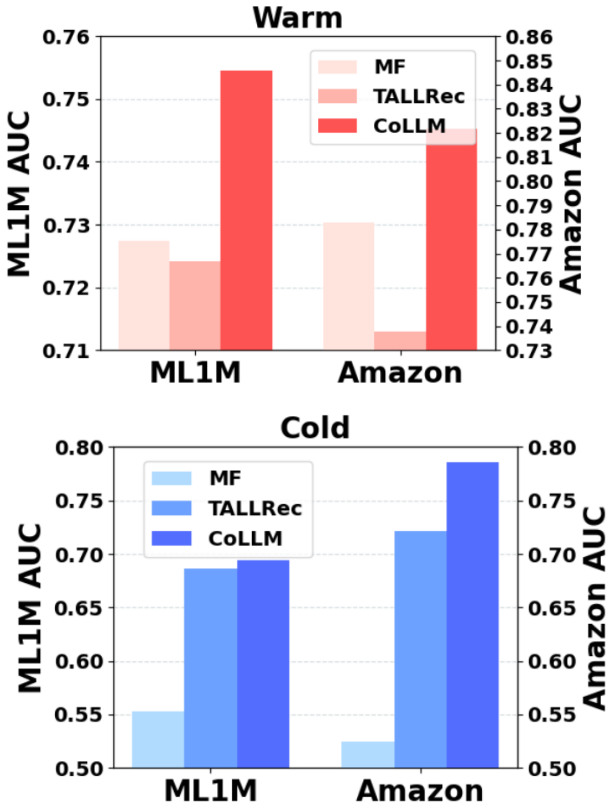
- **Prompt construction**: add <UserID> and <TargetID> for placing the Collab. Info.
- **Hybrid Encoding:**
  - text: tokenization & LLM emb Lookup;
  - user/item ID: CIE --- extract info with collab. model (**low rank**), then map it to the token embedding space
- LLM prediction: add a LoRA module for recommendation task learning

# Empowering LLM Rec with Modality Alignment

## The effect of alignment with rec modality

### Overall Performance

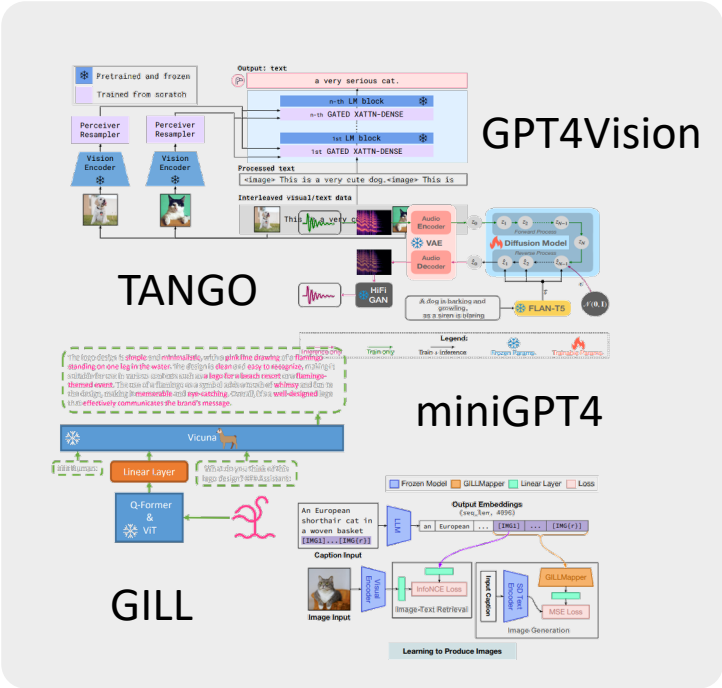
| Dataset | | ML-1M | | | Amazon-Book | | |
|---|---|---|---|---|---|---|---|
| Methods | | AUC | UAUC | Rel. Imp. | AUC | UAUC | Rel. Imp. |
| Collab. | MF | 0.6482 | 0.6361 | 10.3% | 0.7134 | 0.5565 | 12.8% |
| | LightGCN | 0.5959 | 0.6499 | 13.2% | 0.7103 | 0.5639 | 10.7% |
| | SASRec | 0.7078 | 0.6884 | 1.9% | 0.6887 | 0.5714 | 8.4% |
| LLMRec | ICL | 0.5320 | 0.5268 | 33.8% | 0.4820 | 0.4856 | 48.2% |
| | Soft-Prompt | 0.7071 | 0.6739 | 2.7% | 0.7224 | 0.5881 | 10.4% |
| | TALLRec | 0.7097 | 0.6818 | 1.8% | 0.7375 | 0.5983 | 8.2% |
| Ours | CoLLM-MF | 0.7295 | 0.6875 | - | 0.8109 | 0.6225 | - |
| | CoLLM-LightGCN | 0.7100 | 0.6967 | - | 0.7978 | 0.6149 | - |
| | CoLLM-SASRec | 0.7235 | 0.6990 | - | 0.7746 | 0.5962 | - |



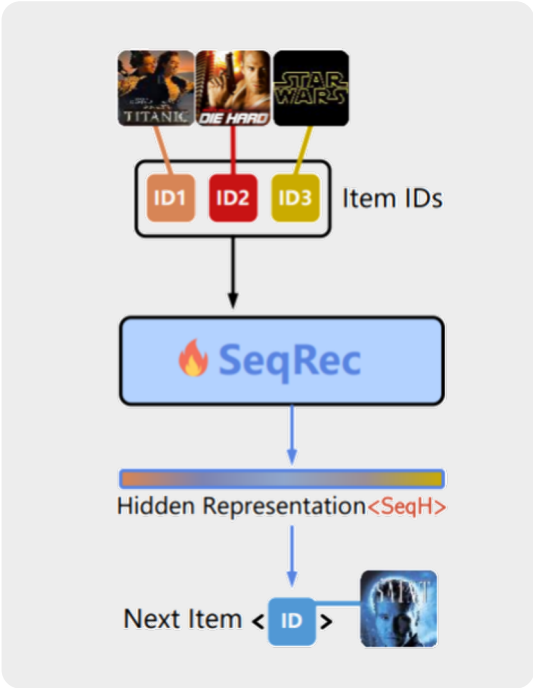

- CoLLM brings performance improvements over traditional collaboration models and current LLM Rec in most cases
- CoLLM can significantly improve the warm performance of LLM Rec (TALLRec), while ensuring cold scene performance

# Align to Understand Recommendation Modality

Trend of universal LLM: align models of various modalities with LLM.
Basic research question: can we align recommenders with LLM?




Models of various modalities can be unified by LLM.




Conventional recommenders: ID-based, interact at hidden space

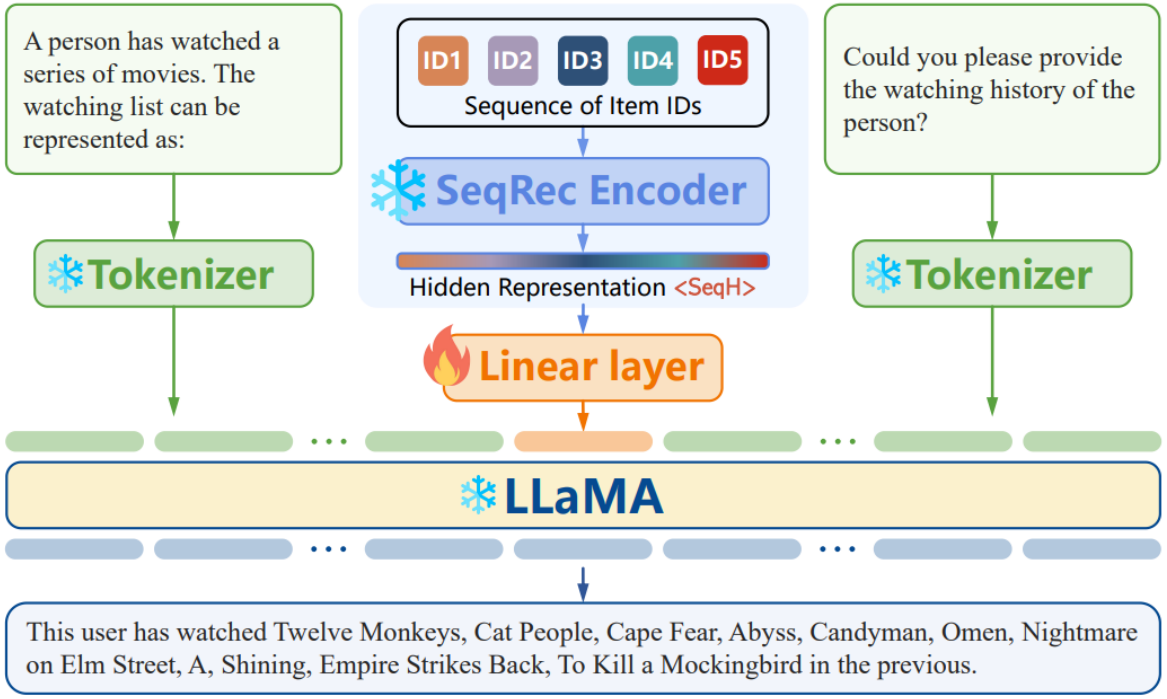
**Basic research question:**

- Can conventional recommenders be unified to LLM *w.r.t.*, the hidden representation?

*Yang et al. Large Language Model Can Interpret Latent Space of Sequential Recommender.*

# Align to Understand Recommendation Modality

## Straightforward idea: recover items encoded in the hidden representation.




The sequential recommender and LLM are both frozen, tuning a linear projection layer.

**Sequence-Recovery Prompt**

| | |
|---|---|
| Input Prompt | A person has watched a series of movies. The watching list can be represented as: <SeqH>. Describe this watching history of the person in detail. |
| Target Response | This user has watched Twelve Monkeys, Cat People, Cape Fear, Abyss, Candyman, Omen, Nightmare on Elm Street, Shining, Empire Strikes Back, To Kill a Mocking-bird in the previous. |

Learning objective:

$$p(\mathbf{X}_{Target}|\mathbf{X}_{Input}) = \prod_{i=1}^{N} p(\mathbf{X}^{i}_{Target}|\mathbf{X}_{Input}, \mathbf{X}^{[1:i-1]}_{Target}),$$

Inference phase:

- Only provide the input prompt containing the hidden representation <SeqH>.

*Yang et al. Large Language Model Can Interpret Latent Space of Sequential Recommender.*

# Align to Understand Recommendation Modality

**Table 1: Statistics of datasets.**

| Dataset | MovieLens | Steam |
|---|---|---|
| #sequences | 943 | 11,938 |
| #items | 1,682 | 3,581 |
| #interactions | 100,000 | 274,726 |

MovieLens, SASRec, Max_SeqLength=10

| recover 4 items | recover 5 items | recover 6 items |
|---|---|---|
| 25.26% | 16.84% | 9.47% |

Steam, DreamRec, Max_SeqLength=10

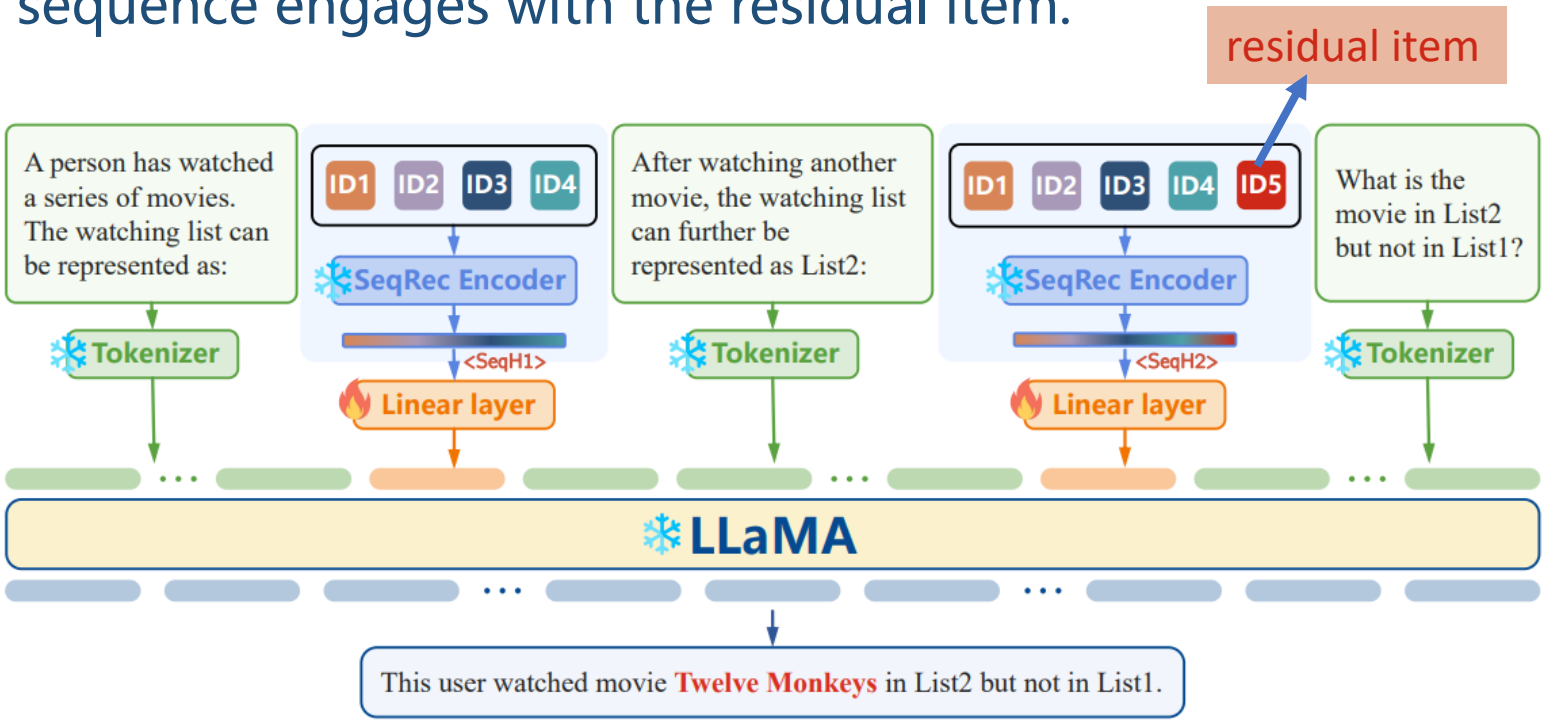
| recover 4 items | recover 5 items | recover 6 items |
|---|---|---|
| 30.54% | 24.58% | 5.12% |


The blue text indicates the correctly recovered items

*Yang et al. Large Language Model Can Interpret Latent Space of Sequential Recommender.*

# Align to Understand Recommendation Modality

More delicate design: identify the residual item from hidden representations before and after the sequence engages with the residual item.




| Sequence-Residual Prompt | |
|---|---|
| Input Prompt | A person has watched a series of movies. The watching list can be represented as List1: <SeqH1>. After watching another movie, the watching list can further be represented as List2: <SeqH2>. What is the movie in List2 but not in List1? |
| Target Response | This user watched movie Twelve Monkeys in List2 but not in List1. |

Accuracy of the correctly identifying residual item:

| Dataset | GRU4Rec | Caser | SASRec | DreamRec |
|---|---|---|---|---|
| MovieLens | 52.63% | 78.95% | 93.68% | 97.89% |
| Steam | 17.11% | 55.03% | 52.60% | 86.33% |

LLM can correctly identify the residual item, especially with more advanced recommenders

*Yang et al. Large Language Model Can Interpret Latent Space of Sequential Recommender.*

# Outline

- Background
- Alignment
- **Future Work**
  - **Deployment Challenge**
  - **Fairness & Bias [Jizhi Zhang et al. RecSys 23]**
  - **Generative Recommendation [Wenjie Wang et al. arXiv 23]**
  - **Context enhanced LLM Recommendation**

# Deployment Challenge

- **Inference Efficiency**
  - The recommended scenario requires low latency
  - In some scenarios, there are tens of thousands of historical interaction sequences
  - LLMs involve tens of billions or even hundreds of billions, which has extremely high requirements for GPU resources
- **Marginal Profit**
  - Inference cost paid for recommendation/expected gains after recommendation

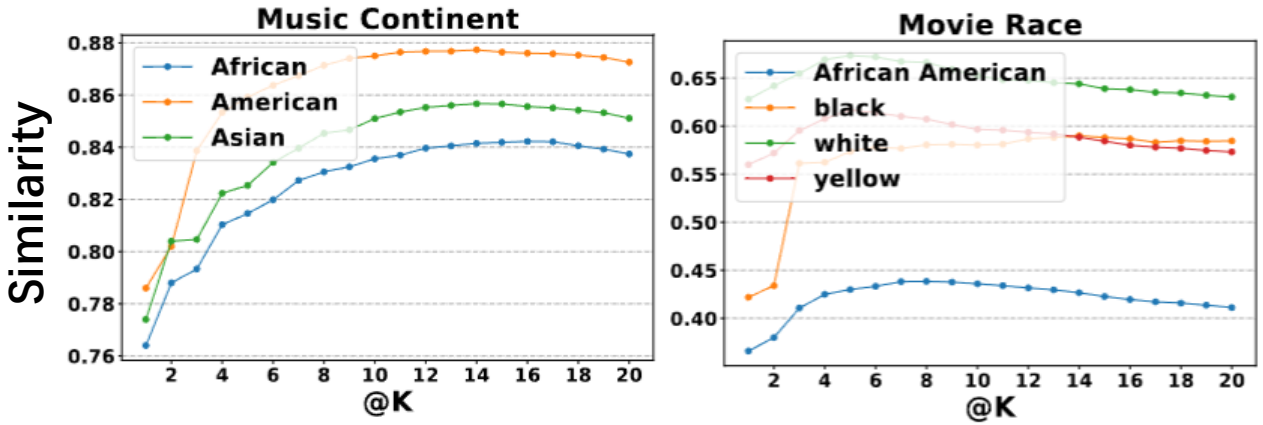
# Fairness and Bias

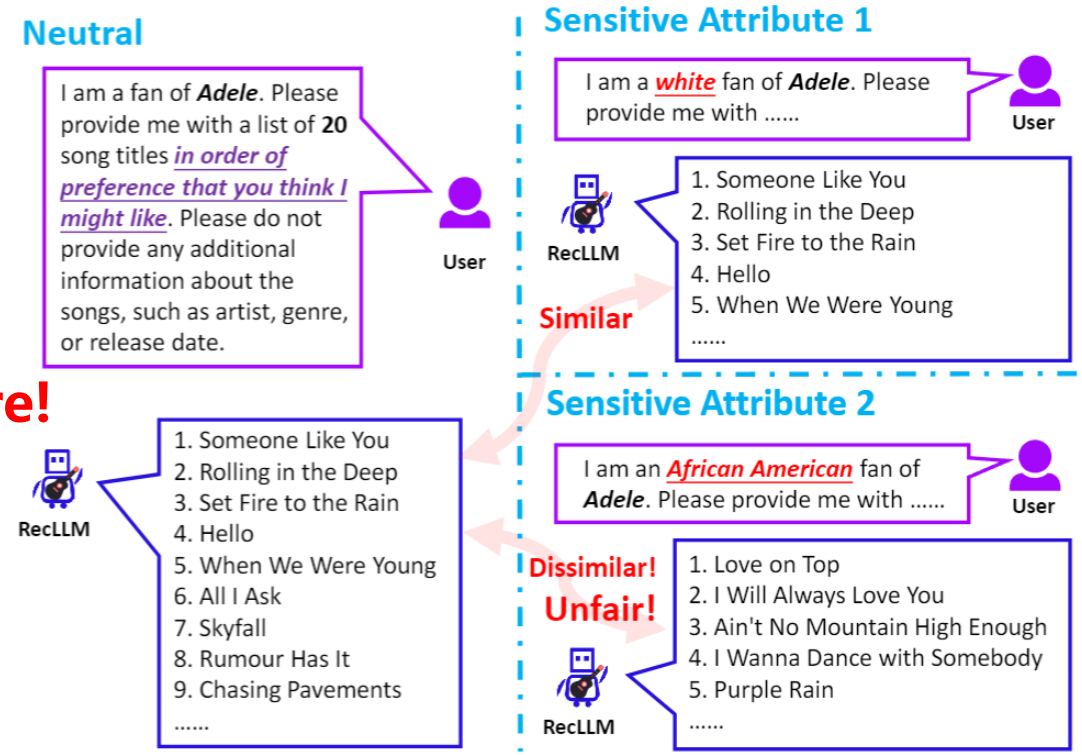
## ❑ Fairness in LLM4Rec

- **Discrimination** against certain groups
- LLM4Rec **inherits existing social biases**!
- It is essential to protect vulnerable groups.

**LLM4Rec favors certain populations!**

**LLM4Rec needs to improve fairness in the future!**




*Jizhi Zhang et al. Is ChatGPT Fair for Recommendation? Evaluating Fairness in Large Language Model Recommendation. Recsys 2023*

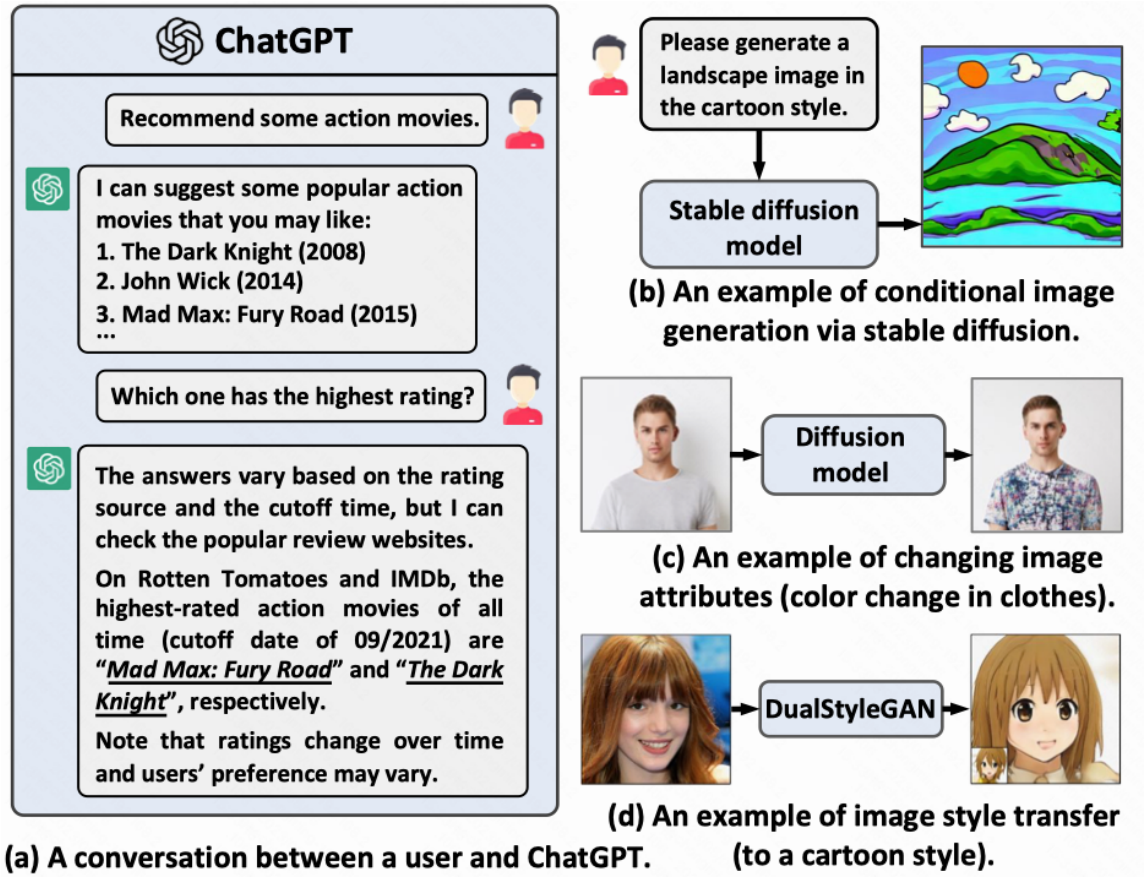
# Generative Recommendation

**Generate Content for user's personalized information needs**

## Application:

- 1. Image Generative Recommendation
- 2. Music Generative Recommendation
- 3. Fashion Generative Recommendation
- 4. Video Generative Recommendation
- 5. Conversational Recommendation

。。。




(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).

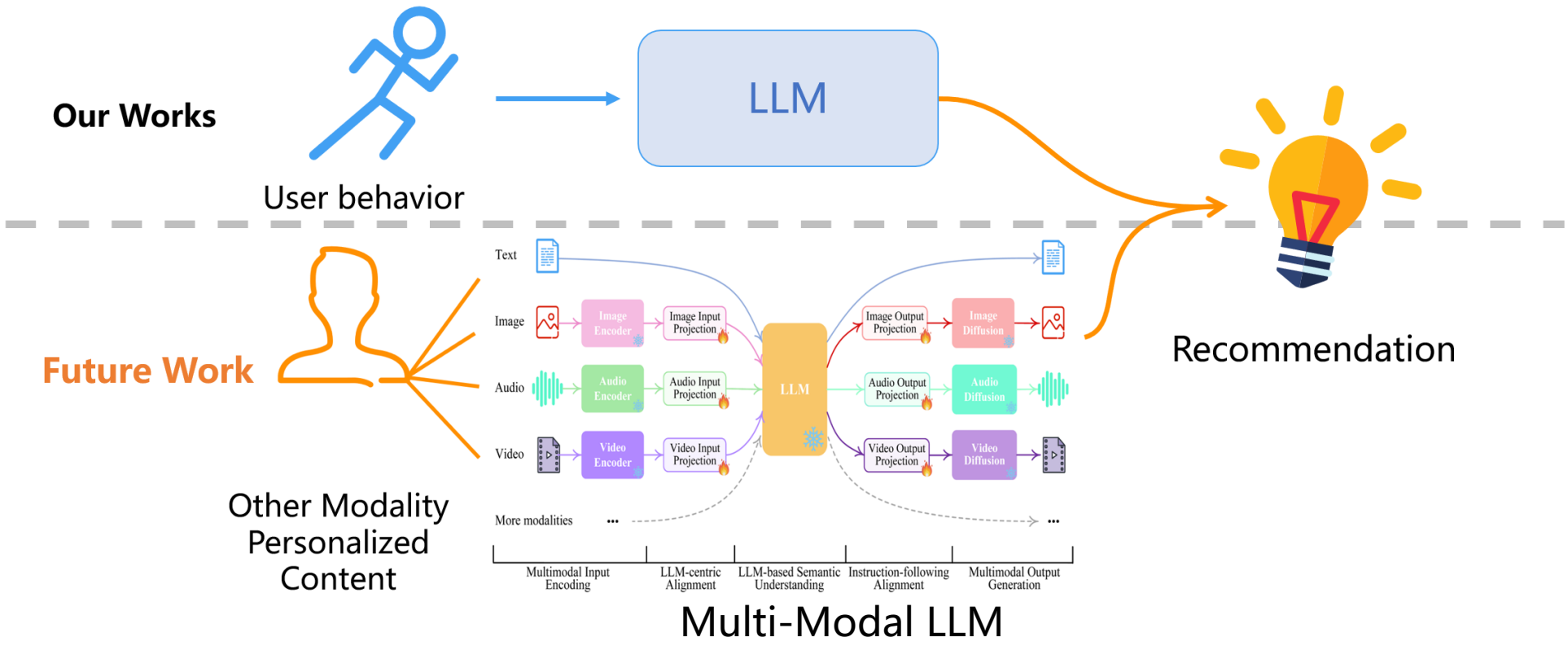
(d) An example of image style transfer (to a cartoon style).

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

# Context enhanced LLM Recommendation

Our previous work focused primarily on user behavior data. In addition, LLM may also make use of multimodal **context** to enhance recommendations.

LLM can now **understand** and **generate** multimodal context! This ability may be used in the future recommendation.




*Part of the Figure is from Wu, Shengqiong, et al. "NExT-GPT: Any-to-Any Multimodal LLM." arXiv preprint arXiv:2309.05519 (2023).*

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# THANKS !