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Large Language Models for Generative Recommendation

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Recommender Systems are Everywhere

- Influence our daily life by providing personalized services

E-commerce

Social Networks

News Feeding

Search Engine

Navigation

Travel Planning

Professional Networks

Healthcare

Online Education

Technical Advancement of Recommender Systems

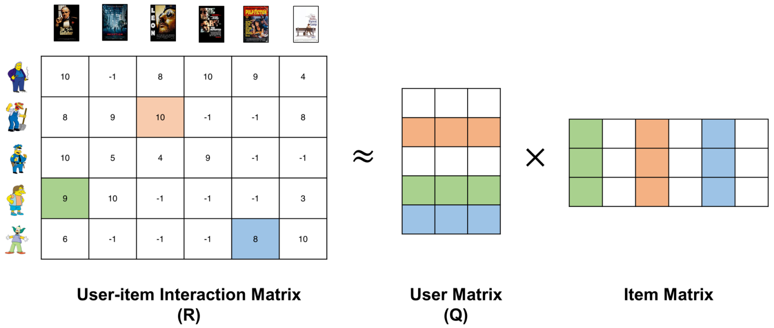
- From Shallow Model, to Deep Model, and to Large Model

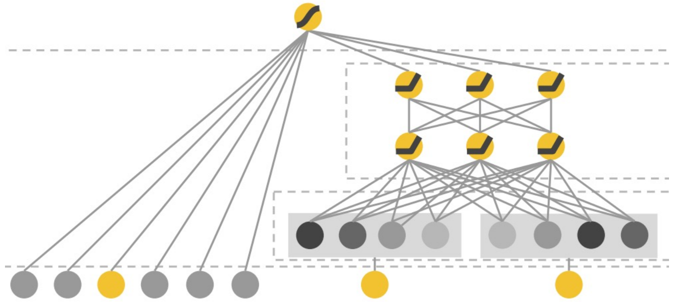
Shallow Models → Deep Models → Large Models

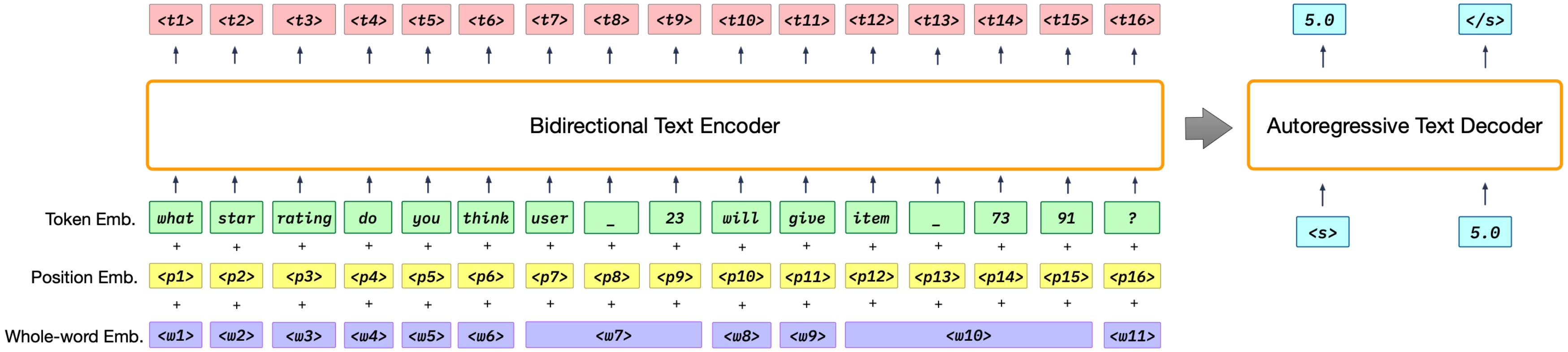
e.g. Matrix Factorization [1]

e.g. Deep & Wide NN [2]

e.g. P5 [3]



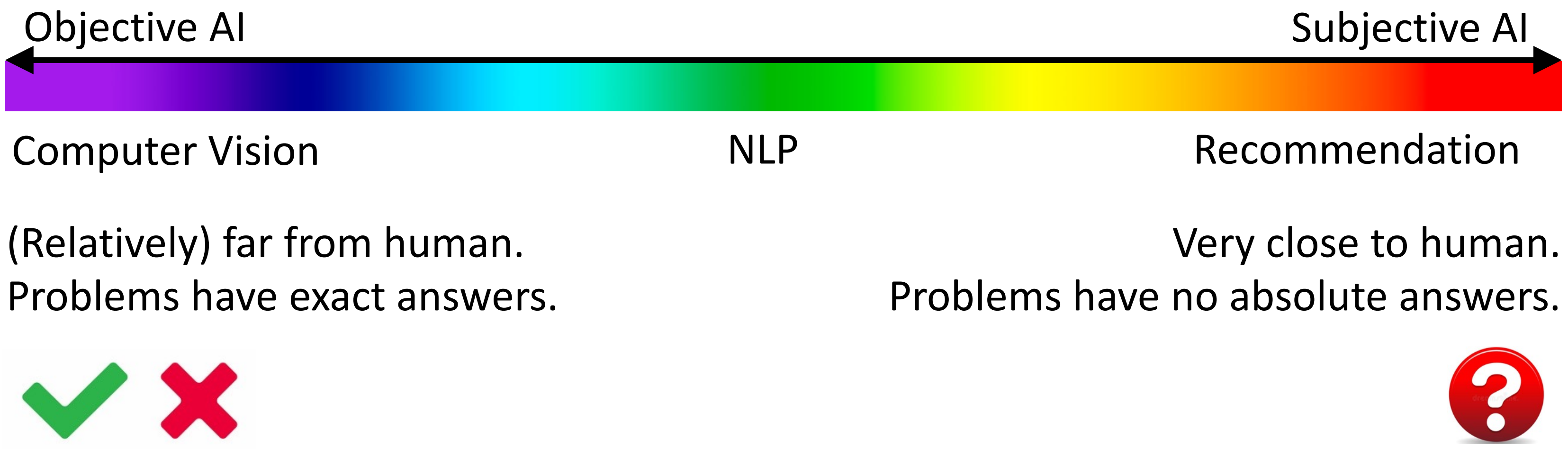




[1] Koren, Yehuda, Robert Bell, and Chris Volinsky. "Matrix factorization techniques for recommender systems." Computer 42, no. 8 (2009): 30-37.
[2] Cheng, Heng-Tze, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson et al. "Wide & deep learning for recommender systems." DLRS 2016.
[3] Geng, Shijie, Shuchang Liu, Zuohui Fu, Yingqiang Ge, and Yongfeng Zhang. "Recommendation as Language Processing (RLP): A Unified Pretrain, Personalized Prompt & Predict Paradigm (P5)." RecSys 2022.

Objective AI vs. Subjective AI

- Recommendation is unique in the AI family
  - Recommendation is most close to human among all AI tasks
  - Recommendation is a very representative Subjective AI
  - Thus, leads to many unique challenges in recommendation research



Computer Vision: (mostly) Objective AI Tasks

Objective AI

Subjective AI

Computer Vision

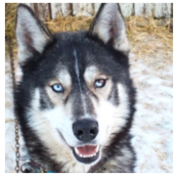
NLP

Recommendation

Image Classification

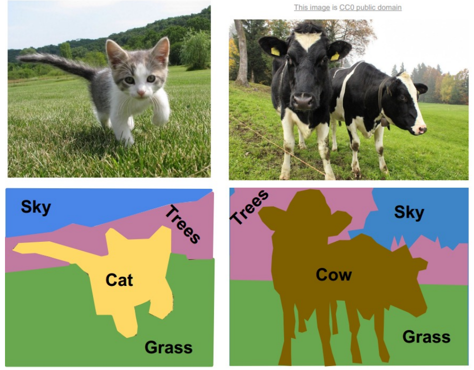
cat

dog

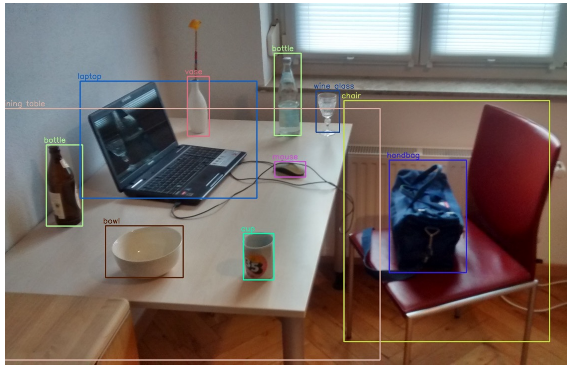


Husky like a wolf

Image Segmentation



Object Detection



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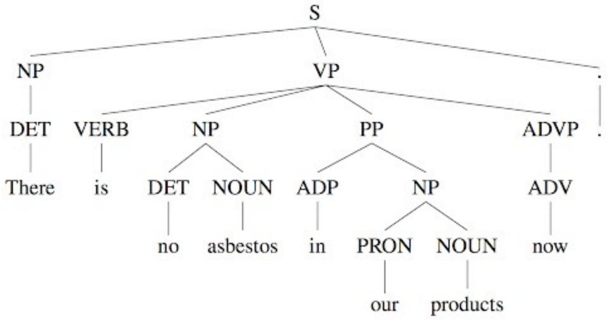
NLP: partly Objective, partly Subjective

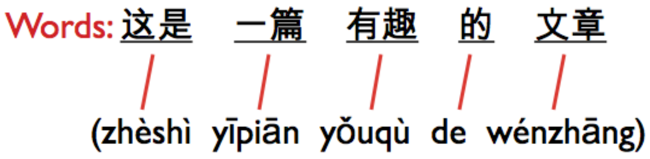
Objective AI — Subjective AI

Computer Vision | NLP | Recommendation

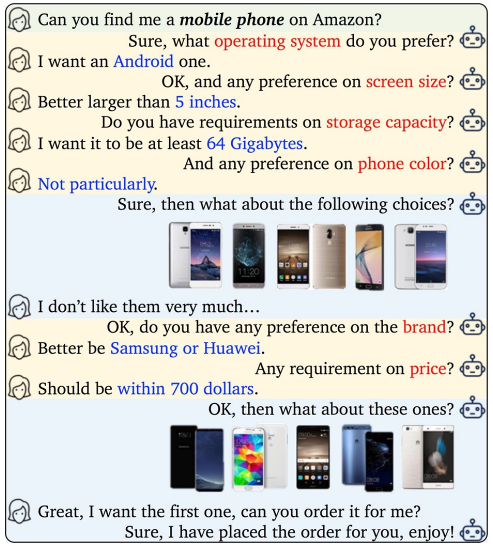
Syntactic Analysis



Word Segmentation



Dialog Systems



Recommendation: mostly Subjective AI Tasks

Objective AI — Subjective AI

Computer Vision — NLP — Recommendation

Movie Recommendation

Product Recommendation

Recommendation is not only about Item Ranking

- A diverse set of recommendation tasks
  - Rating Prediction
  - Item Ranking
  - Sequential Recommendation
  - User Profile Construction
  - Review Summarization
  - Explanation Generation
  - ……

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Subjective AI needs Explainability

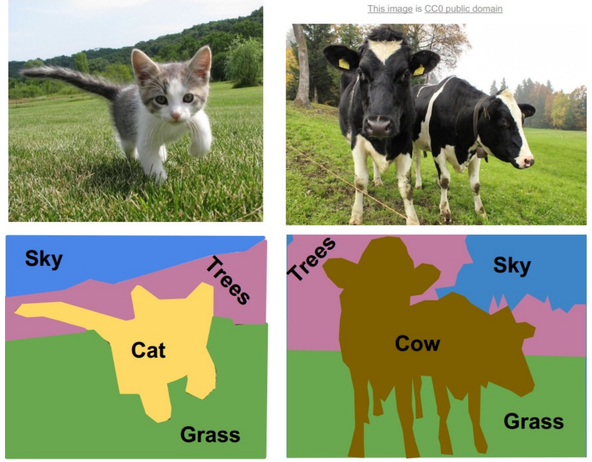
- Objective vs. Subjective AI on Explainability

Objective AI

Human can directly identify if the AI-produced result is right or wrong

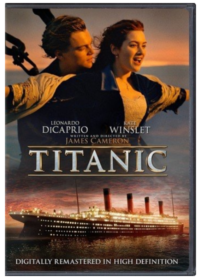

cat

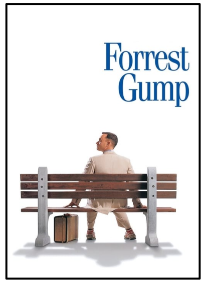

dog

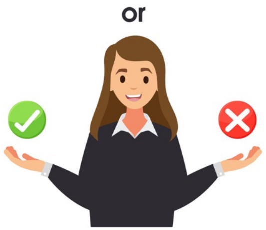


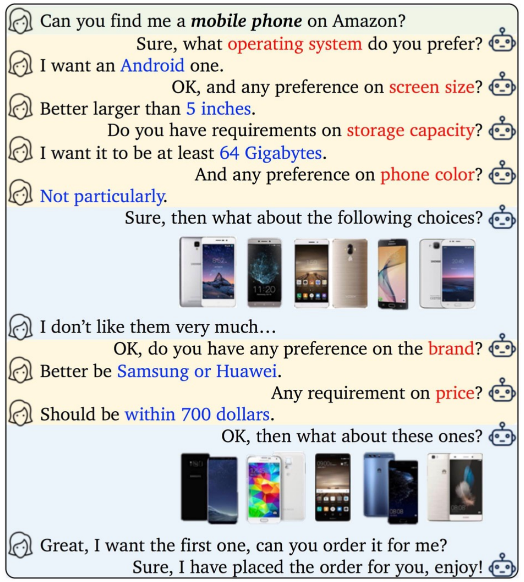
Subjective AI

Human can hardly identify if the AI-produced result is right or wrong. Users are very vulnerable, could be manipulated, utilized or even cheated by the system









Nothing is definitely right or wrong.

Highly subjective, and usually personalized.

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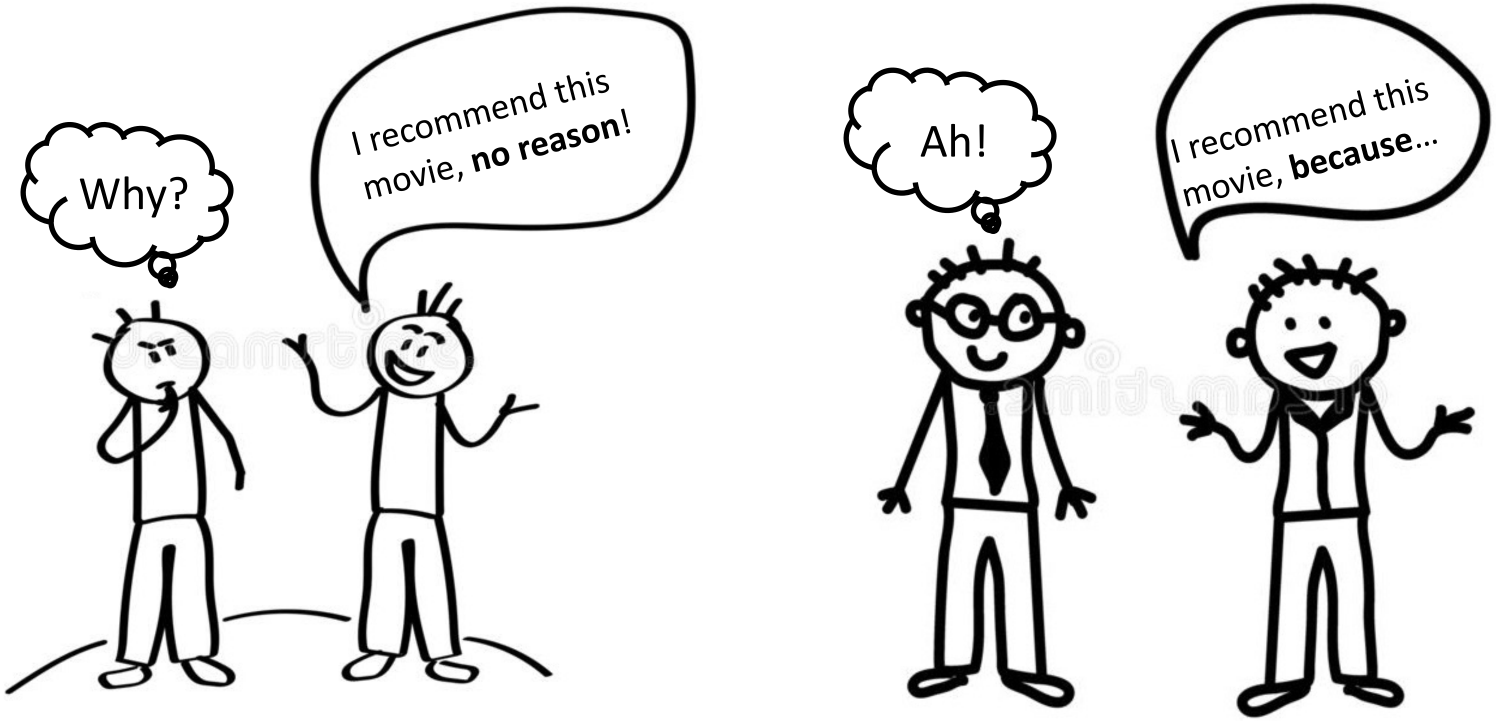
Subjective AI needs Explainability

- In many cases, it doesn't matter what you recommend, but how you explain your recommendation
- How do humans make recommendation?



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Can we Handle all RecSys tasks Together?

- A diverse set of recommendation tasks
  - Rating Prediction
  - Item Ranking
  - Sequential Recommendation
  - User Profile Construction
  - Review Summarization
  - Explanation Generation
  - Fairness Consideration
  - …
- Do we really need to design thousands of recommendation models?
  - Difficult to integrate so many models in industry production environment

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A Bird's View of Existing RecSys

- The Multi-Stage Filtering RecSys Pipeline

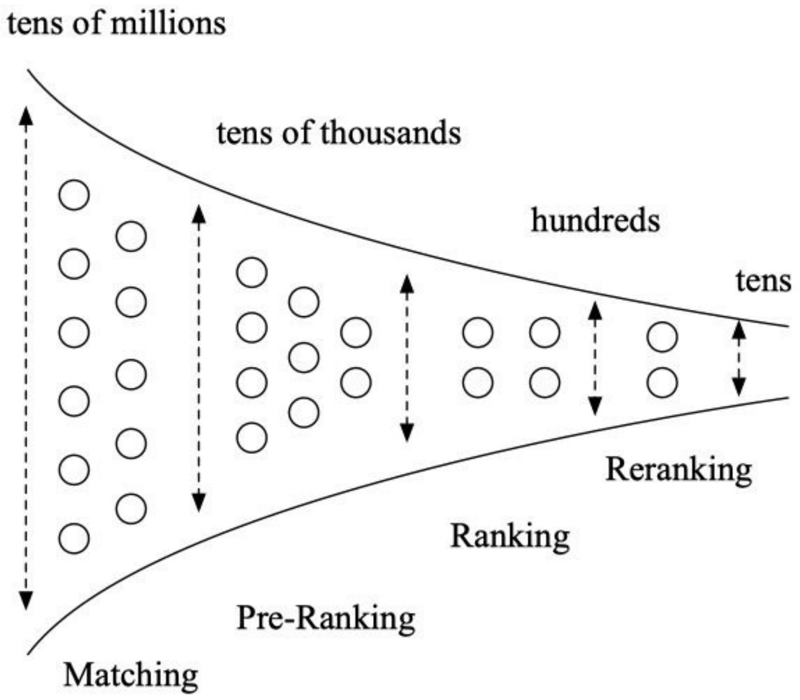
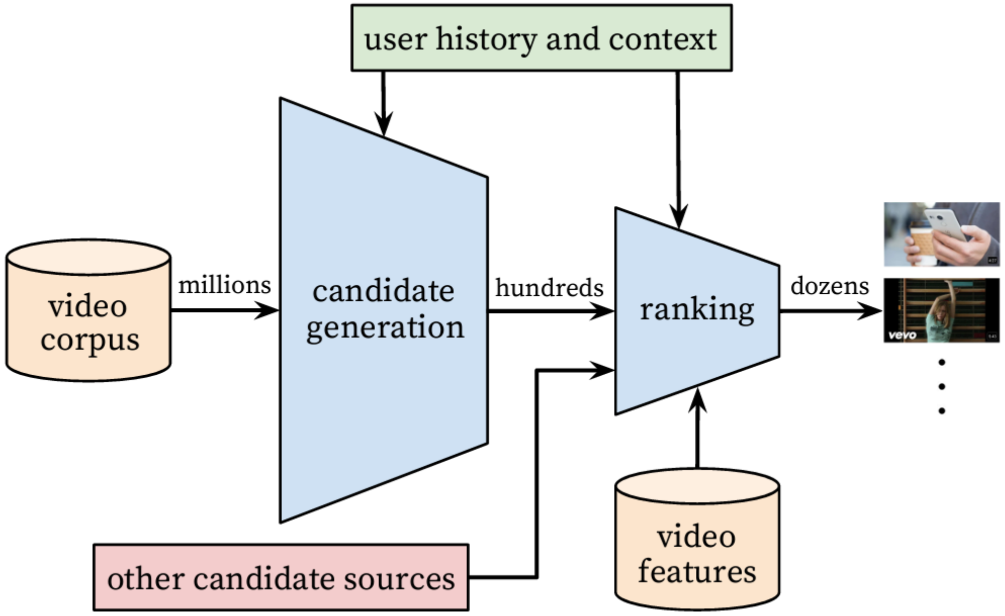


Image credit to [1]



Youtube recommendation engine

Image credit to [2]

[1] Jiang, Biye, Pengye Zhang, Rihan Chen, Xinchen Luo, Yin Yang, Guan Wang, Guorui Zhou, Xiaoqiang Zhu, and Kun Gai. "DCAF: A Dynamic Computation Allocation Framework for Online Serving System." DLP-KDD 2020.
[2] Covington, Paul, Jay Adams, and Emre Sargin. "Deep neural networks for youtube recommendations." In *Proceedings of the 10th ACM conference on recommender systems*, pp. 191-198. 2016.

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Discriminative Ranking

- User-item matching based on embeddings

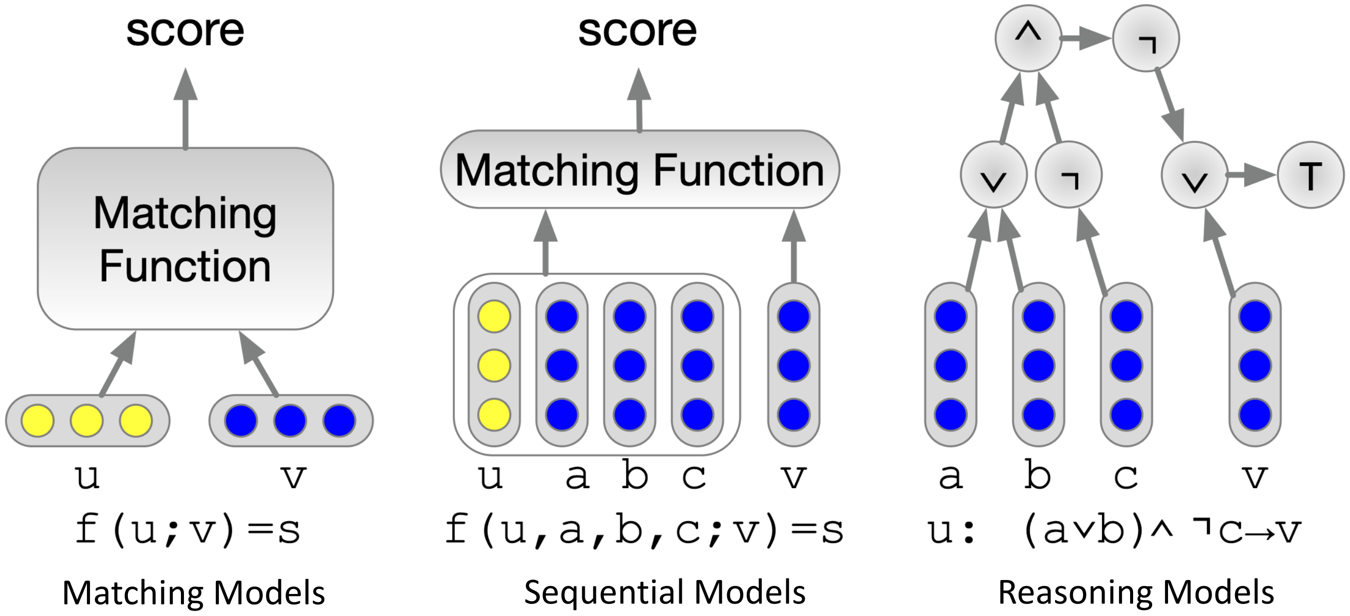

Image credit to [1]

- Discriminative ranking loss function
  - e.g., Bayesian Personalized Ranking (BPR) loss

$$maximize \sum_{(u,i,j)\in D_S} \ln \sigma(\hat{x}_{uij}) - \lambda_\Theta ||\Theta||^2 \qquad where: \hat{x}_{uij} = p_u q_i^T - p_u q_j^T$$

[1] Chen, Hanxiong, Shaoyun Shi, Yunqi Li, and Yongfeng Zhang. "Neural collaborative reasoning." In Proceedings of the Web Conference 2021, pp. 1516-1527. 2021.

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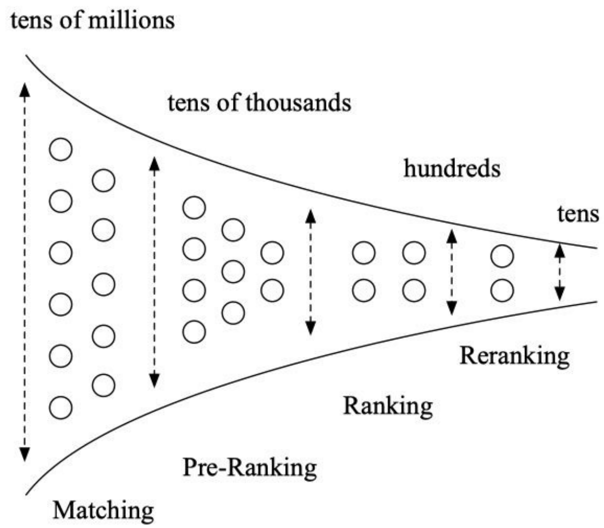
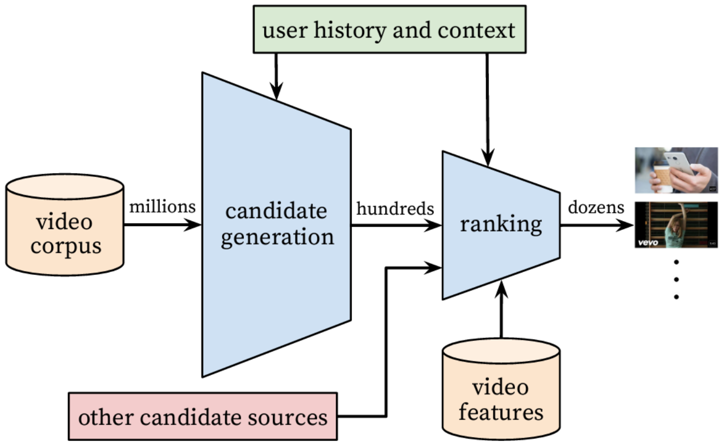
Problem with Discriminative Ranking

- Huge numbers of users and items
  - Amazon: 300 million customers, 350 million products*
  - YouTube: 2.6+ billion monthly active users, 5+ billion videos**
  - We have to use multi-stage filtering (compromise: simple rules at early stages)





- Too many candidate items, difficult for evaluation
  - Many research papers use sampled evaluation: 1-in-100, 1-in-1000, etc.

*https://sell.amazon.com/blog/amazon-stats, and https://www.bigcommerce.com/blog/amazon-statistics/
**https://www.globalmediainsight.com/blog/youtube-users-statistics/

Large Language Models (LLMs)

- Auto-regressive decoding for generative prediction

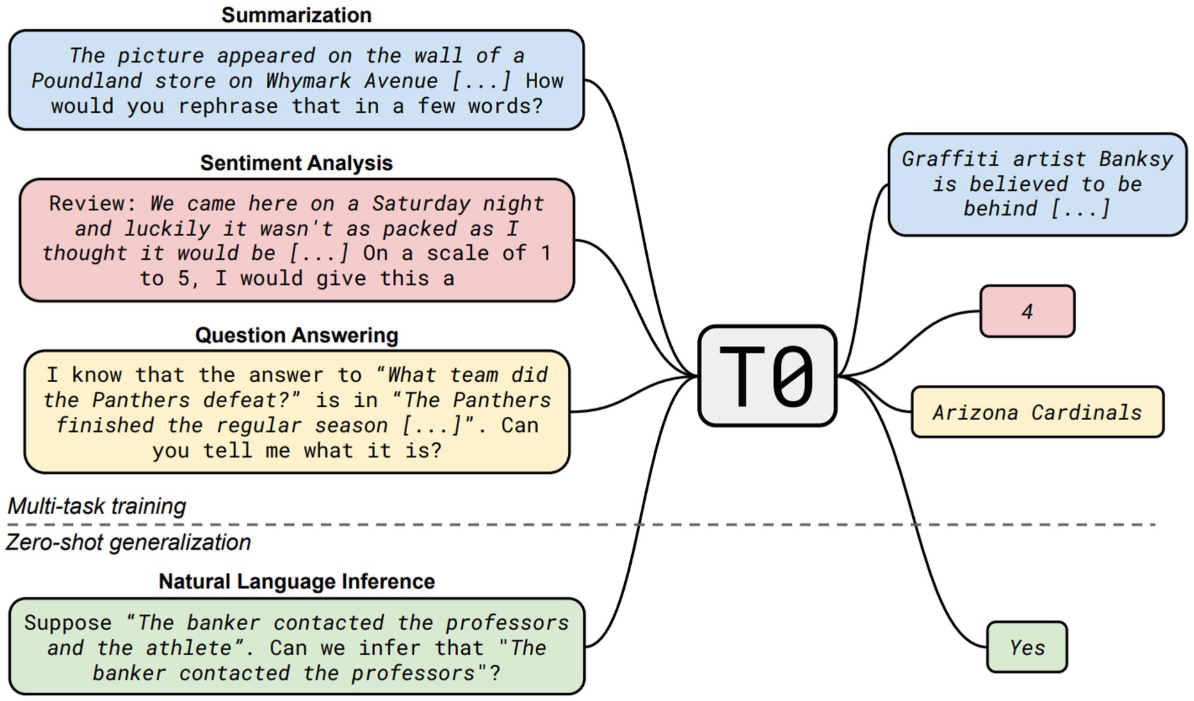


Image credit to [1]

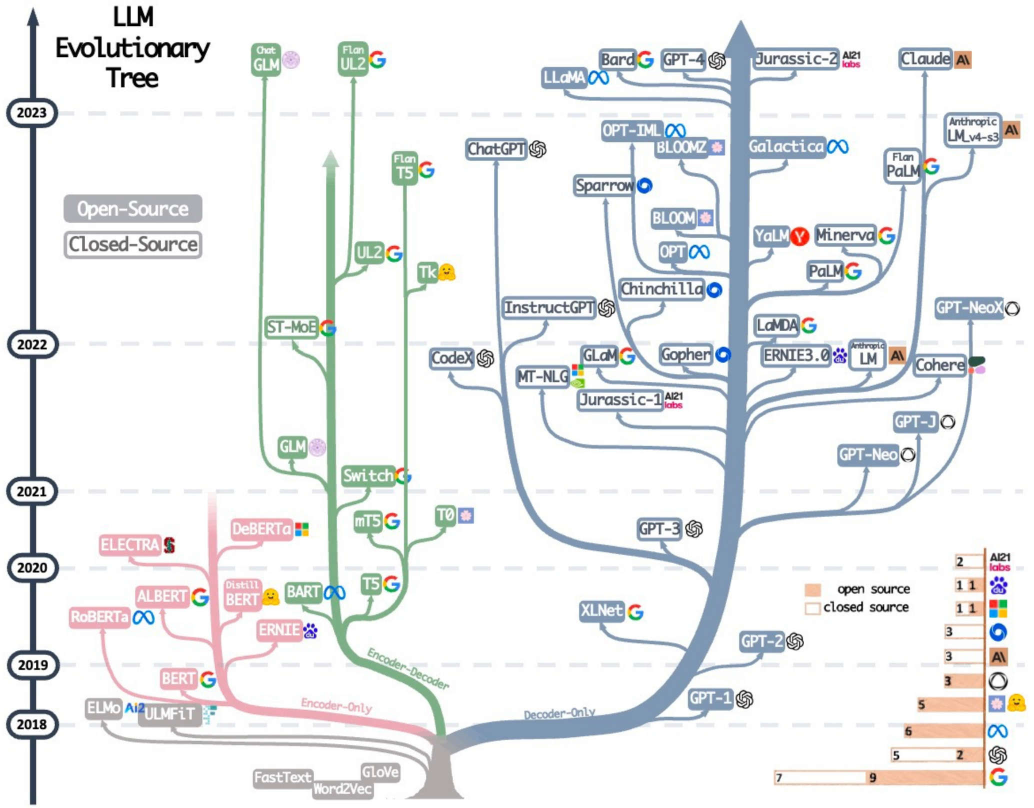


Image credit to [2]

[1] Sanh, Victor, Albert Webson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin et al. "Multitask prompted training enables zero-shot task generalization." ICLR 2022.
[2] Yang, Jingfeng, Hongye Jin, Ruixiang Tang, Xiaotian Han, Qizhang Feng, Haoming Jiang, Bing Yin, and Xia Hu. "Harnessing the Power of LLMs in Practice: A Survey on ChatGPT and Beyond." arXiv preprint arXiv:2304.13712 (2023).

Generative Pre-training and Prediction

- Generative Pre-training
  - Generative Loss Function
    - Use the previous tokens to predict next token

$$L_1(\mathcal{U}) = \sum_i \log P(u_i | u_{i-k}, \ldots, u_{i-1}; \Theta)$$

- Generative Prediction
  - Beam Search
    - Using finite tokens to represent infinite items
      - 100 vocabulary tokens, ID size 10 -> #items = 10^100
    - # of candidate tokens at each beam is fixed
    - No longer need one-by-one candidate score calculation as in discriminative ranking
    - Directly generate the item ID to recommend

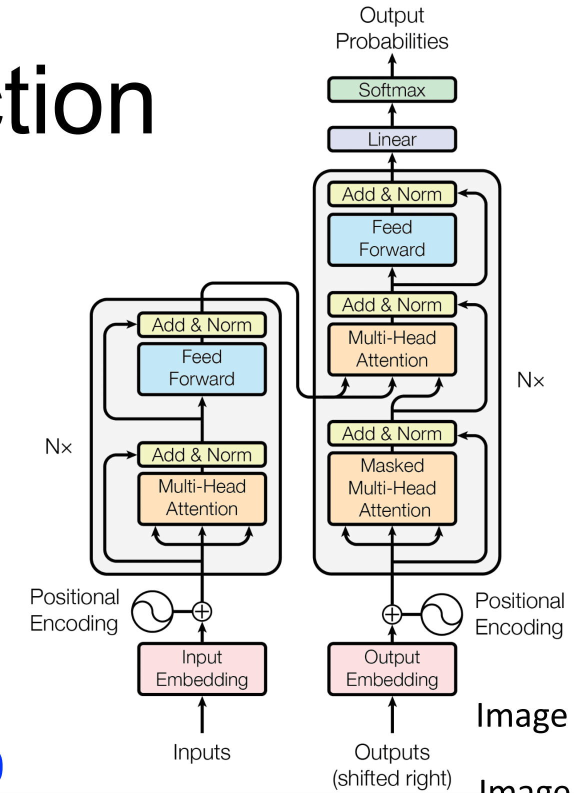
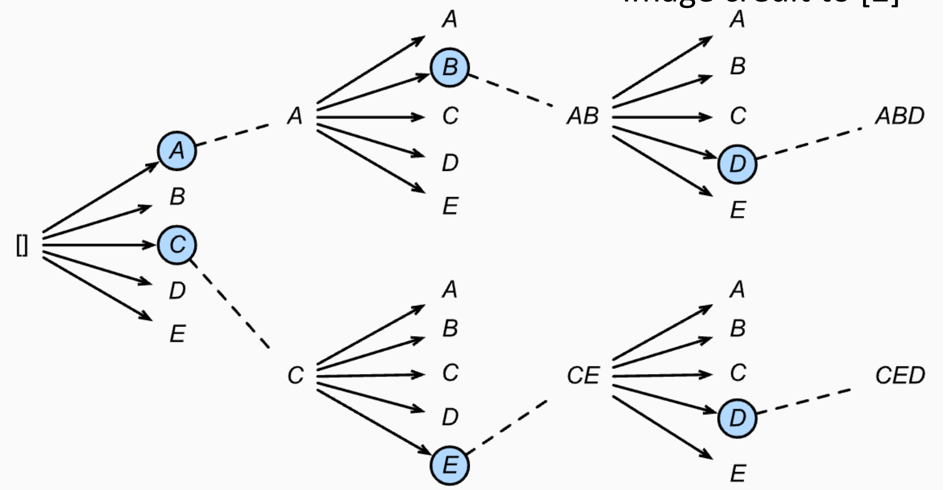


Image credit to [1]

Image credit to [2]



[1] Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." Advances in neural information processing systems 30 (2017).
[2] https://d2l.ai/chapter_recurrent-modern/beam-search.html

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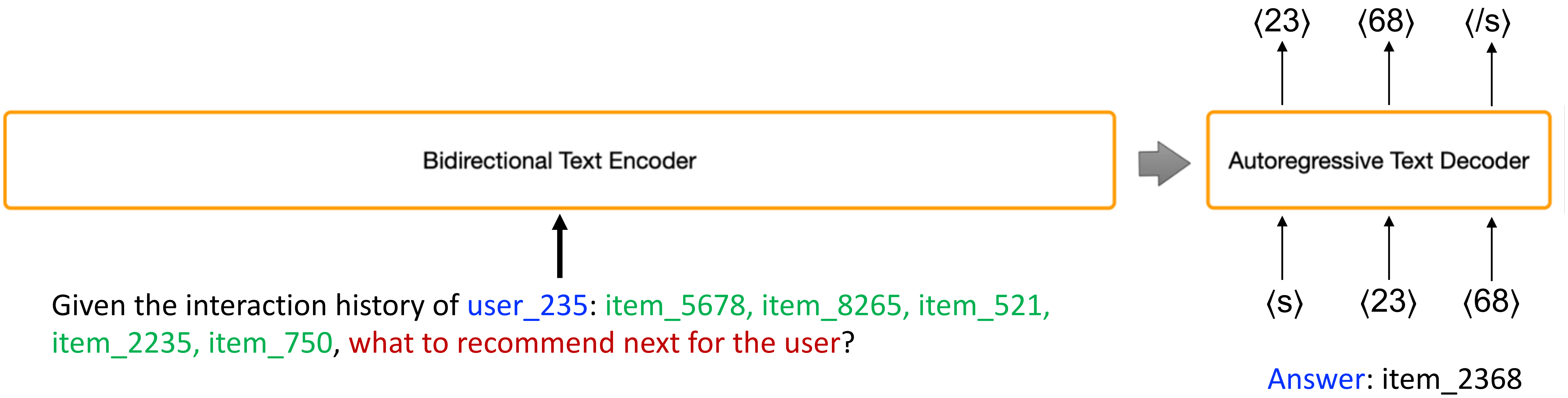
Generative Ranking

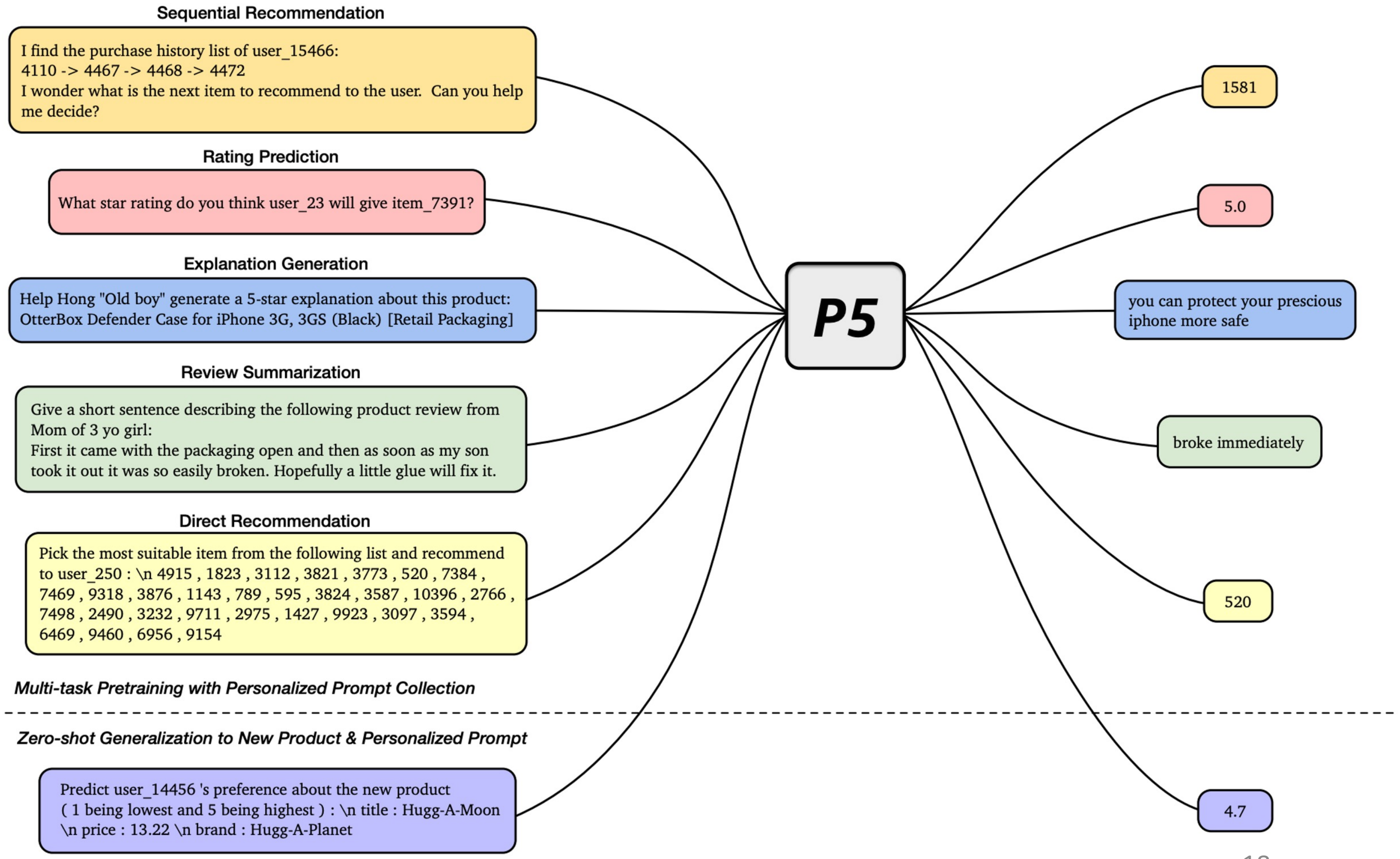
- From Multi-stage ranking to Single-stage ranking
  - The model automatically considers all items as the candidate pool
  - Fixed-size item decoding
    - e.g., using 100 tokens ⟨00⟩⟨01⟩…⟨99⟩ for item ID representation



The P5 Generative Recommendation Paradigm

- P5: Pretrain, Personalized Prompt & Predict Paradigm [1]

- Learns multiple recommendation tasks together through a unified sequence-to-sequence framework
- Formulates different recommendation problems as prompt-based natural language tasks
- User-item information and corresponding features are integrated with personalized prompts as model inputs



[1] Geng, Shijie, Shuchang Liu, Zuohui Fu, Yingqiang Ge, and Yongfeng Zhang. "Recommendation as Language Processing (RLP): A Unified Pretrain, Personalized Prompt & Predict Paradigm (P5)." RecSys 2022.

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Five Key Questions in P5 Design

- 1. What tasks are covered by P5?
- 2. How to represent user preferences and item features in P5?
- 3. How to design personalized prompts for different recommendation tasks?
- 4. What foundation model architecture as backbone for P5?
- 5. How to conduct training and inference of P5?

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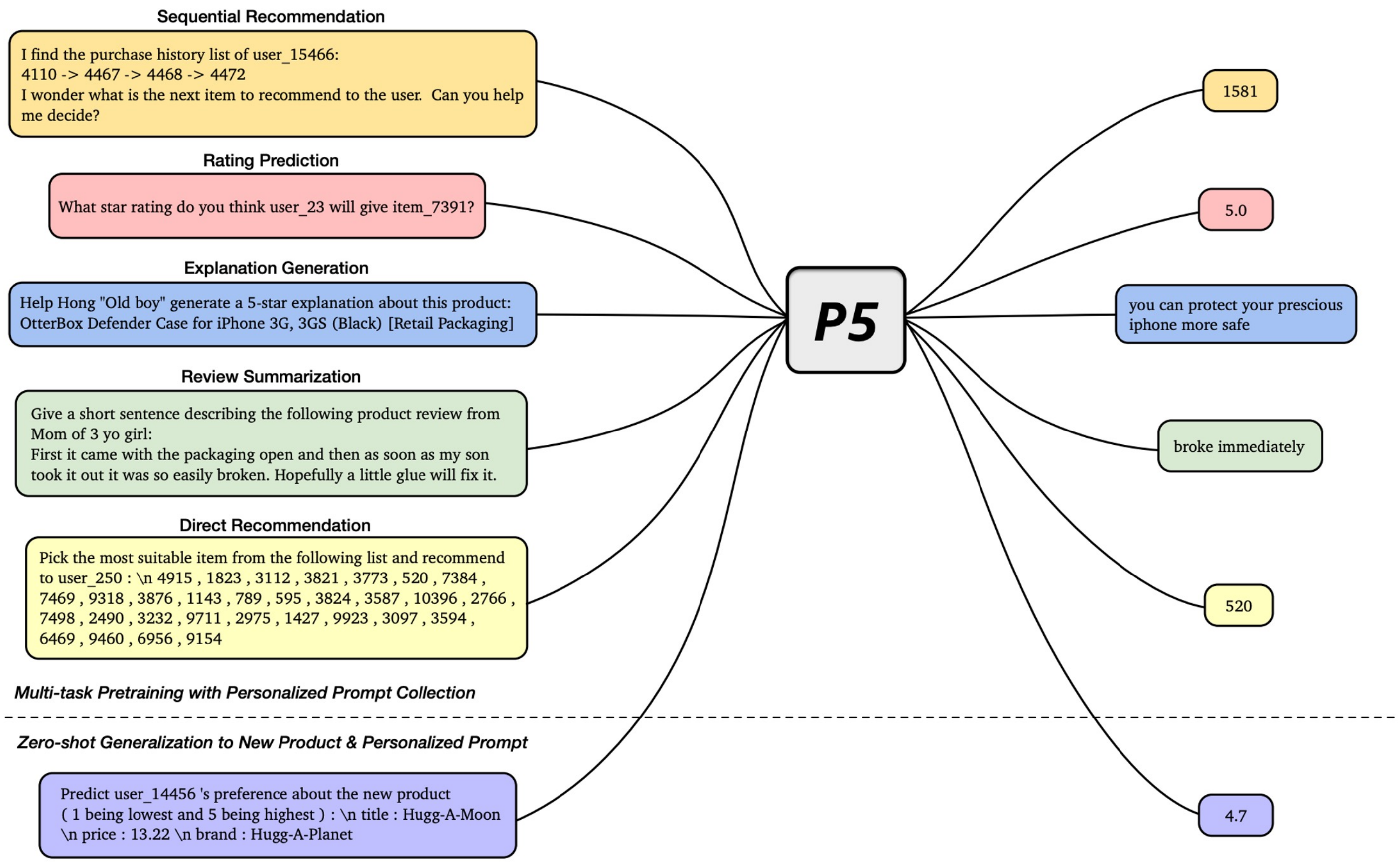
P5 Recommendation Tasks

- P5 covers **5** different **task families**
  - ***rating prediction***
  - ***sequential recommendation***
  - ***explanation generation***
  - ***review summarization***
  - ***direct recommendation***

- But is not limited these five task families, can be easily and flexibility extended with new personalized prompts



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Enable Personalization in Prompts

- Definition of **personalized prompts**
  - A prompt that includes personalized fields for different users and items

- User's preference can be indicated through
  - A **user ID** (e.g., "user_23")
  - Content **description of the user** such as location, preferred movie genres, etc.

- Item field can be represented by
  - An **item ID** (e.g., "item_7391")
  - Item **content metadata** that contains **detailed descriptions** of the item, e.g., item category

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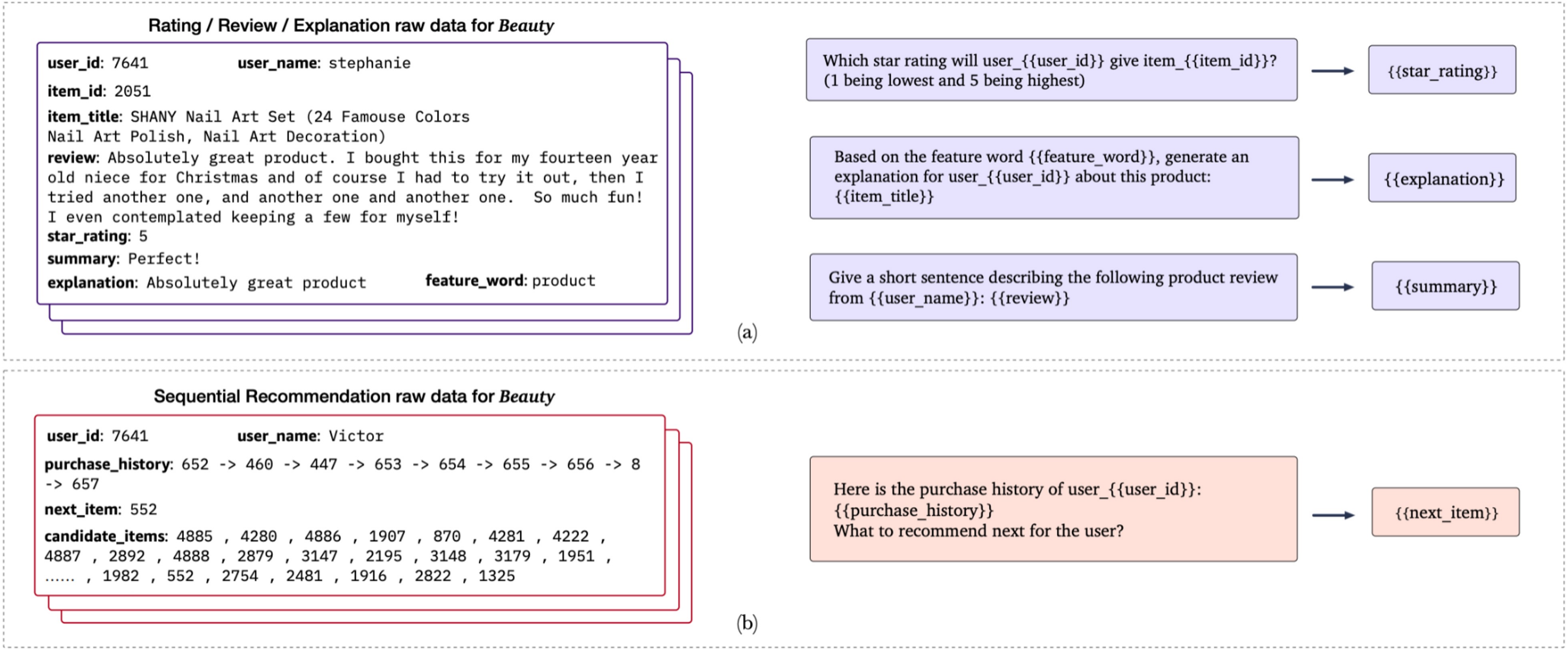
Personalized Prompt Design



Design Multiple Prompts for Each Task

- To enhance variation in language style (e.g., sequential recommendation)

Prompt ID: 2-1

```
Input template: Given the following purchase history of
user_{{user_id}}:
{{purchase_history}}
predict next possible item to be purchased by the user?

Target template: {{next_item}}
```

Prompt ID: 2-2

```
Input template: I find the purchase history list of user_{{user_id}}:
{{purchase_history}}
I wonder which is the next item to recommend to the user. Can you
help me decide?

Target template: {{next_item}}
```

Prompt ID: 2-3

```
Input template: Here is the purchase history list of
user_{{user_id}}:
{{purchase_history}}
try to recommend next item to the user

Target template: {{next_item}}
```

Prompt ID: 2-4

```
Input template: Given the following purchase history of
{{user_desc}}:
{{purchase_history}}
predict next possible item for the user

Target template: {{next_item}}
```

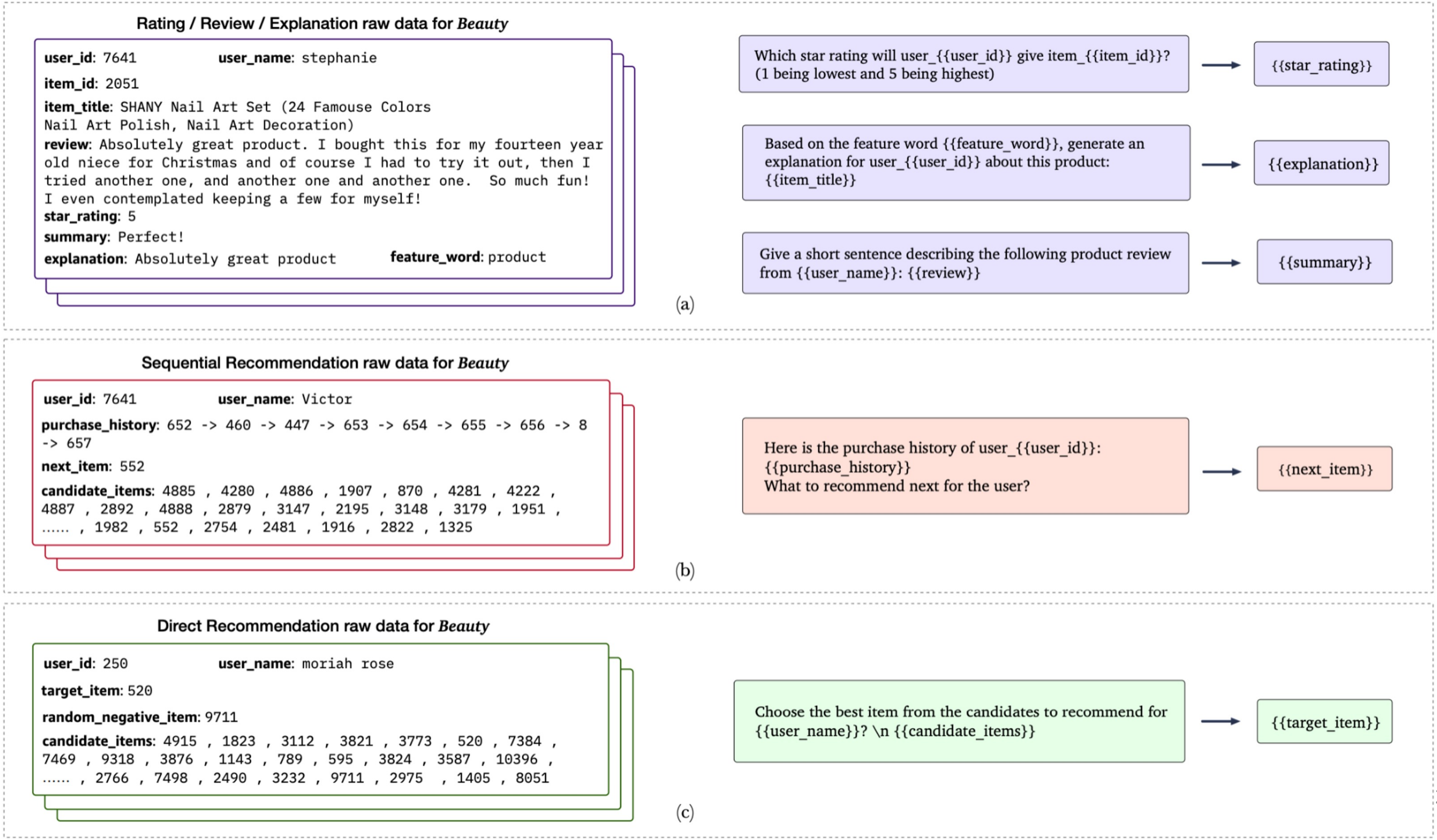
Prompt ID: 2-5

```
Input template: Based on the purchase history of {{user_desc}}:
{{purchase_history}}
Can you decide the next item likely to be purchased by the user?

Target template: {{next_item}}
```

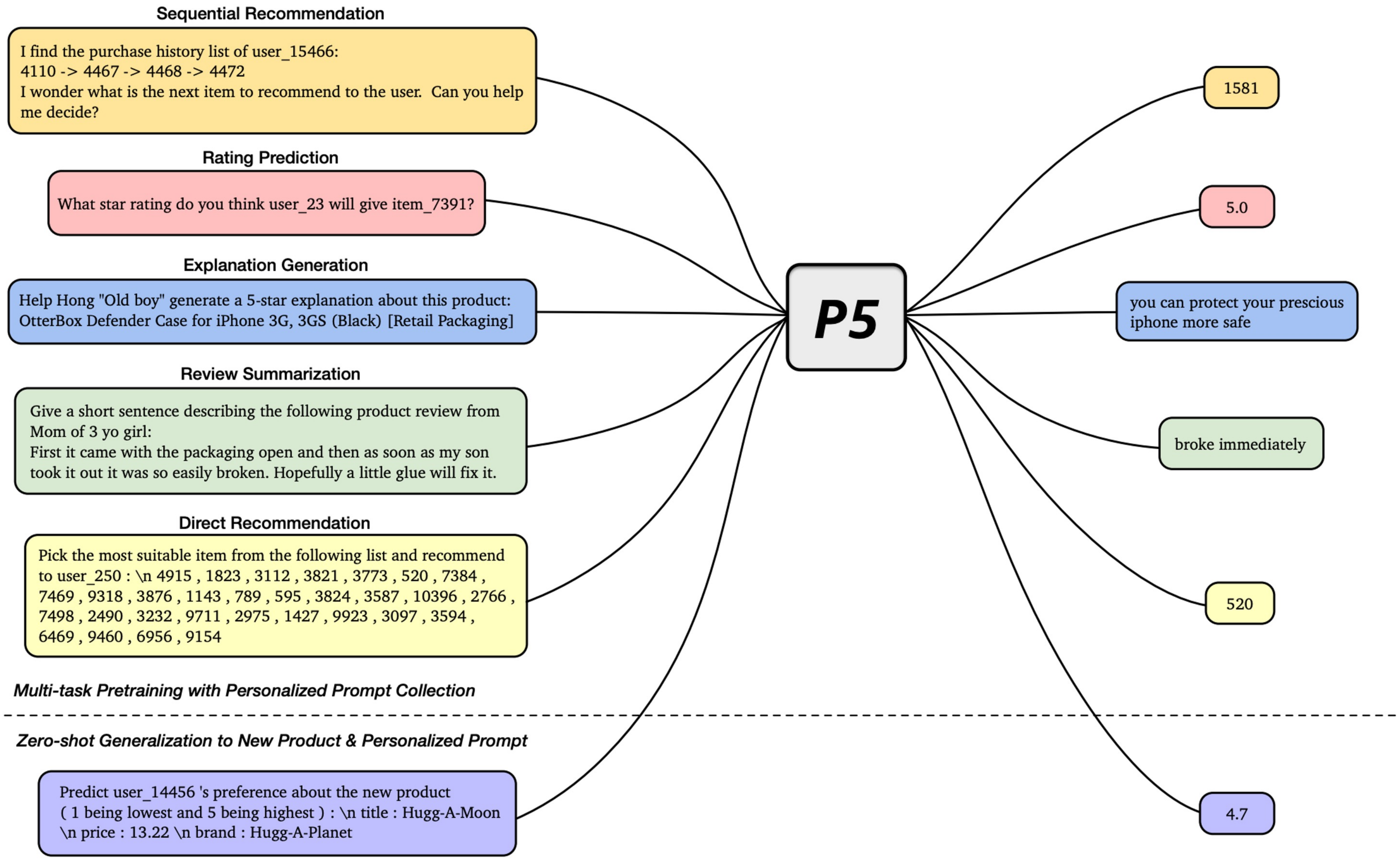
Prompt ID: 2-6

```
Input template: Here is the purchase history of {{user_desc}}:
{{purchase_history}}
What to recommend next for the user?

Target template: {{next_item}}
```

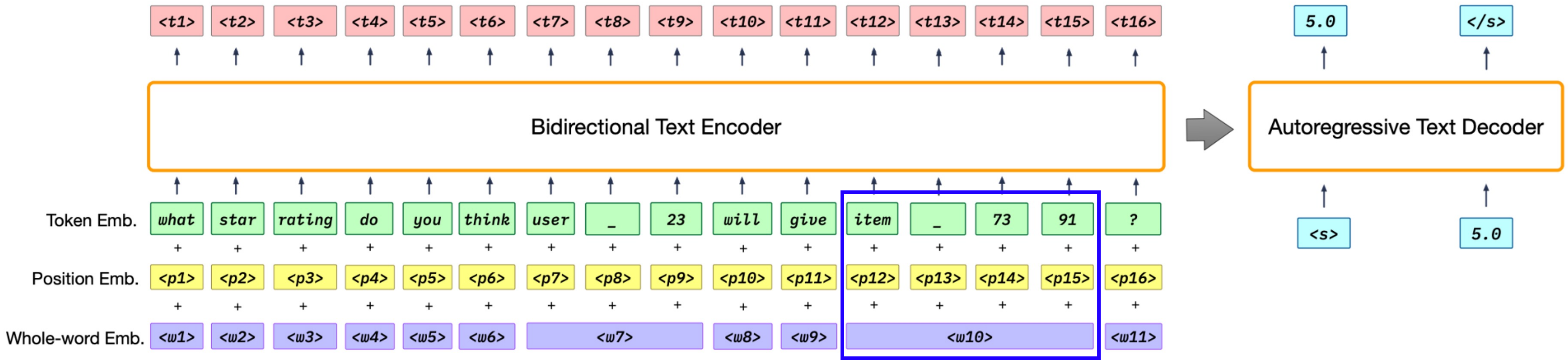
Text-to-Text Training Data



Multi-Task Pre-training



Multi-Task Pre-training



- P5 is pre-trained on top of T5 checkpoints (to enable P5 basic ability for language understanding)
  - So P5 is a sequence-to-sequence model
- By default, we use multiple sub-word units to represent personalize fields (e.g., [“item”, “_”, “73”, “91”])
- To help the model to understand [“item”, “_”, “73”, “91”] is a complete field, we apply whole-word embedding in P5

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Generative Recommendation

- The encoder takes input sequence
- The decoder autoregressively generates next words:
  - **Autoregressive LM loss** is shared by all tasks: $\mathcal{L}_{\theta}^{\mathrm{P5}} = -\sum_{j=1}^{|\mathbf{y}|} \log P_{\theta}\left(\mathbf{y}_j \mid \mathbf{y}_{<j}, \mathbf{x}\right)$

- We can unify various recommendation tasks with **one model, one loss, and one data format**

- Inference with pretrained P5
  - Simply apply **beam search** to generate a list of potential next items
  - Since item IDs are tokenized (e.g., [“item”, “_”, “73”, “91”]), beam search is limited on width
    - E.g., 100 tokens width: ⟨00⟩, ⟨01⟩, ⟨02⟩, …, ⟨98⟩, ⟨99⟩

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Advantages of P5 Generative Recommendation

- Immerses recommendation models into a full language environment
  - With the flexibility and expressiveness of language, there is no need to design feature-specific encoders
- P5 treats all personalized tasks as a conditional text generation problem
  - One data format, one model, one loss for multiple recommendation tasks
  - No need to design data-specific or task-specific recommendation models
- P5 attains sufficient zero-shot performance when generalizing to novel personalized prompts or unseen items in other domains

Performance of P5 under seen Prompts

Rating Prediction:

Methods	Sports		Beauty		Toys	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
MF	**1.0234**	0.7935	**1.1973**	0.9461	**1.0123**	0.7984
MLP	1.1277	0.7626	1.3078	0.9597	1.1215	0.8097
P5-S (1-6)	1.0594	**0.6639**	1.3128	**0.8428**	1.0746	0.7054
P5-B (1-6)	1.0357	0.6813	1.2843	0.8534	1.0544	0.7177
P5-S (1-10)	1.0522	0.6698	1.2989	0.8473	1.0550	0.7173
P5-B (1-10)	1.0292	0.6864	1.2870	0.8531	1.0245	**0.6931**

Sequential Recommendation:

Methods	Sports				Beauty				Toys			
	HR@5	NDCG@5	HR@10	NDCG@10	HR@5	NDCG@5	HR@10	NDCG@10	HR@5	NDCG@5	HR@10	NDCG@10
Caser	0.0116	0.0072	0.0194	0.0097	0.0205	0.0131	0.0347	0.0176	0.0166	0.0107	0.0270	0.0141
HGN	0.0189	0.0120	0.0313	0.0159	0.0325	0.0206	0.0512	0.0266	0.0321	0.0221	0.0497	0.0277
GRU4Rec	0.0129	0.0086	0.0204	0.0110	0.0164	0.0099	0.0283	0.0137	0.0097	0.0059	0.0176	0.0084
BERT4Rec	0.0115	0.0075	0.0191	0.0099	0.0203	0.0124	0.0347	0.0170	0.0116	0.0071	0.0203	0.0099
FDSA	0.0182	0.0122	0.0288	0.0156	0.0267	0.0163	0.0407	0.0208	0.0228	0.0140	0.0381	0.0189
SASRec	0.0233	0.0154	0.0350	0.0192	0.0387	0.0249	0.0605	0.0318	0.0463	0.0306	0.0675	0.0374
S^3-Rec	0.0251	0.0161	0.0385	0.0204	0.0387	0.0244	0.0647	0.0327	0.0443	0.0294	0.0700	0.0376
P5-S (2-3)	0.0272	0.0169	0.0361	0.0198	0.0503	0.0370	0.0659	0.0421	**0.0648**	**0.0567**	**0.0709**	**0.0587**
P5-B (2-3)	0.0364	0.0296	0.0431	0.0318	**0.0508**	**0.0379**	**0.0664**	**0.0429**	0.0608	0.0507	0.0688	0.0534
P5-S (2-13)	0.0258	0.0159	0.0346	0.0188	0.0490	0.0358	0.0646	0.0409	0.0647	0.0566	0.0705	0.0585
P5-B (2-13)	**0.0387**	**0.0312**	**0.0460**	**0.0336**	0.0493	0.0367	0.0645	0.0416	0.0587	0.0486	0.0675	0.0536

Explanation Generation:

Methods	Sports				Beauty				Toys			
	BLUE4	ROUGE1	ROUGE2	ROUGEL	BLUE4	ROUGE1	ROUGE2	ROUGEL	BLUE4	ROUGE1	ROUGE2	ROUGEL
Attn2Seq	0.5305	12.2800	1.2107	9.1312	0.7889	12.6590	1.6820	9.7481	1.6238	13.2245	2.9942	10.7398
NRT	0.4793	11.0723	1.1304	7.6674	0.8295	12.7815	1.8543	9.9477	1.9084	13.5231	3.6708	11.1867
PETER	0.7112	12.8944	1.3283	9.8635	1.1541	14.8497	2.1413	11.4143	1.9861	14.2716	3.6718	11.7010
P5-S (3-3)	**1.0447**	**14.9048**	**2.1297**	**11.1778**	**1.2237**	**17.6938**	**2.2489**	**12.8606**	2.2892	**15.4505**	3.6974	**12.1718**
P5-B (3-3)	1.0407	14.1589	2.1220	10.6096	0.9742	16.4530	1.8858	11.8765	**2.3185**	15.3474	**3.7209**	12.1312
PETER+	**2.4627**	**24.1181**	5.1937	**18.4105**	**3.2606**	25.5541	5.9668	19.7168	**4.7919**	28.3083	9.4520	**22.7017**
P5-S (3-9)	1.4101	23.5619	**5.4196**	17.6245	1.9788	**25.6253**	**6.3678**	**19.9497**	4.1222	**28.4088**	9.5432	22.6064
P5-B (3-9)	1.4689	23.5476	5.3926	17.5852	1.8765	25.1183	6.0764	19.4488	3.8933	27.9916	9.5896	22.2178
P5-S (3-12)	1.3212	23.2474	5.3461	17.3780	1.9425	25.1474	6.0551	19.5601	4.2764	28.1897	9.1327	22.2514
P5-B (3-12)	1.4303	23.3810	5.3239	17.4913	1.9031	25.1763	6.1980	19.5188	3.5861	28.1369	**9.7562**	22.3056

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Performance of P5 under seen Prompts

Review-base Preference Prediction:

Methods	Sports RMSE	Sports MAE	Beauty RMSE	Beauty MAE	Toys RMSE	Toys MAE
T0 (4-2)	0.6728	0.3140	0.6925	0.3324	0.8282	0.4201
T0 (4-4)	0.6503	0.2984	0.7066	0.3663	0.8148	0.4230
P5-S (4-2)	0.7293	0.3529	**0.6233**	**0.3051**	**0.6464**	**0.3125**
P5-B (4-2)	**0.6487**	**0.2847**	0.6449	0.3168	0.6785	0.3342
P5-S (4-4)	0.7565	0.3395	0.6262	0.3113	0.6577	0.3174
P5-B (4-4)	0.6563	0.2921	0.6515	0.3106	0.6730	0.3342

Review Summarization:

Methods	Sports BLUE2	Sports ROUGE1	Sports ROUGE2	Sports ROUGEL	Beauty BLUE2	Beauty ROUGE1	Beauty ROUGE2	Beauty ROUGEL	Toys BLUE2	Toys ROUGE1	Toys ROUGE2	Toys ROUGEL
T0 (4-1)	2.1581	2.2695	0.5694	1.6221	1.2871	1.2750	0.3904	0.9592	2.2296	2.4671	0.6482	1.8424
GPT-2 (4-1)	0.7779	4.4534	1.0033	1.9236	0.5879	3.3844	0.6756	1.3956	0.6221	3.7149	0.6629	1.4813
P5-S (4-1)	2.4962	11.6701	2.7187	10.4819	**2.1225**	**8.4205**	**1.6676**	**7.5476**	**2.4752**	**9.4200**	**1.5975**	**8.2618**
P5-B (4-1)	**2.6910**	**12.0314**	**3.2921**	**10.7274**	1.9325	8.2909	1.4321	7.4000	1.7833	8.7222	1.3210	7.6134

Direct Recommendation:

Methods	Sports HR@1	Sports HR@5	Sports NDCG@5	Sports HR@10	Sports NDCG@10	Beauty HR@1	Beauty HR@5	Beauty NDCG@5	Beauty HR@10	Beauty NDCG@10	Toys HR@1	Toys HR@5	Toys NDCG@5	Toys HR@10	Toys NDCG@10
BPR-MF	0.0314	0.1404	0.0848	0.2563	0.1220	0.0311	0.1426	0.0857	0.2573	0.1224	0.0233	0.1066	0.0641	0.2003	0.0940
BPR-MLP	0.0351	0.1520	0.0927	0.2671	0.1296	0.0317	0.1392	0.0848	0.2542	0.1215	0.0252	0.1142	0.0688	0.2077	0.0988
SimpleX	0.0331	**0.2362**	**0.1505**	0.3290	0.1800	0.0325	0.2247	0.1441	0.3090	0.1711	0.0268	**0.1958**	**0.1244**	**0.2662**	**0.1469**
P5-S (5-1)	0.0638	0.2096	0.1375	0.3143	0.1711	0.0600	0.2021	0.1316	0.3121	0.1670	0.0405	0.1538	0.0969	0.2405	0.1248
P5-B (5-1)	0.0245	0.0816	0.0529	0.1384	0.0711	0.0224	0.0904	0.0559	0.1593	0.0780	0.0187	0.0827	0.0500	0.1543	0.0729
P5-S (5-4)	0.0701	0.2241	0.1483	**0.3313**	**0.1827**	**0.0862**	**0.2448**	**0.1673**	**0.3441**	**0.1993**	0.0413	0.1411	0.0916	0.2227	0.1178
P5-B (5-4)	0.0299	0.1026	0.0665	0.1708	0.0883	0.0506	0.1557	0.1033	0.2350	0.1287	0.0435	0.1316	0.0882	0.2000	0.1102
P5-S (5-5)	0.0574	0.1503	0.1050	0.2207	0.1276	0.0601	0.1611	0.1117	0.2370	0.1360	0.0440	0.1282	0.0865	0.2011	0.1098
P5-B (5-5)	0.0641	0.1794	0.1229	0.2598	0.1488	0.0588	0.1573	0.1089	0.2325	0.1330	0.0386	0.1122	0.0756	0.1807	0.0975
P5-S (5-8)	0.0567	0.1514	0.1049	0.2196	0.1269	0.0571	0.1566	0.1078	0.2317	0.1318	**0.0451**	0.1322	0.0889	0.2023	0.1114
P5-B (5-8)	**0.0726**	0.1955	0.1355	0.2802	0.1627	0.0608	0.1564	0.1096	0.2300	0.1332	0.0389	0.1147	0.0767	0.1863	0.0997

Observation: P5 **achieves promising performances** on the five task families when taking **seen prompt** templates as model inputs

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Performance of P5 under unseen Prompts

Observation: Multitask prompted pretraining empowers P5 good robustness to understand **unseen prompts** with wording variations

Sequential Recommendation:

Methods	Sports HR@5	Sports NDCG@5	Sports HR@10	Sports NDCG@10	Beauty HR@5	Beauty NDCG@5	Beauty HR@10	Beauty NDCG@10	Toys HR@5	Toys NDCG@5	Toys HR@10	Toys NDCG@10
Caser	0.0116	0.0072	0.0194	0.0097	0.0205	0.0131	0.0347	0.0176	0.0166	0.0107	0.0270	0.0141
HGN	0.0189	0.0120	0.0313	0.0159	0.0325	0.0206	0.0512	0.0266	0.0321	0.0221	0.0497	0.0277
GRU4Rec	0.0129	0.0086	0.0204	0.0110	0.0164	0.0099	0.0283	0.0137	0.0097	0.0059	0.0176	0.0084
BERT4Rec	0.0115	0.0075	0.0191	0.0099	0.0203	0.0124	0.0347	0.0170	0.0116	0.0071	0.0203	0.0099
FDSA	0.0182	0.0122	0.0288	0.0156	0.0267	0.0163	0.0407	0.0208	0.0228	0.0140	0.0381	0.0189
SASRec	0.0233	0.0154	0.0350	0.0192	0.0387	0.0249	0.0605	0.0318	0.0463	0.0306	0.0675	0.0374
S^3-Rec	0.0251	0.0161	0.0385	0.0204	0.0387	0.0244	0.0647	0.0327	0.0443	0.0294	0.0700	0.0376
P5-S (2-3)	0.0272	0.0169	0.0361	0.0198	0.0503	0.0370	0.0659	0.0421	**0.0648**	**0.0567**	**0.0709**	**0.0587**
P5-B (2-3)	0.0364	0.0296	0.0431	0.0318	**0.0508**	**0.0379**	**0.0664**	**0.0429**	0.0608	0.0507	0.0688	0.0534
P5-S (2-13)	0.0258	0.0159	0.0346	0.0188	0.0490	0.0358	0.0646	0.0409	0.0647	0.0566	0.0705	0.0585
P5-B (2-13)	**0.0387**	**0.0312**	**0.0460**	**0.0336**	0.0493	0.0367	0.0645	0.0416	0.0587	0.0486	0.0675	0.0536

Explanation Generation:

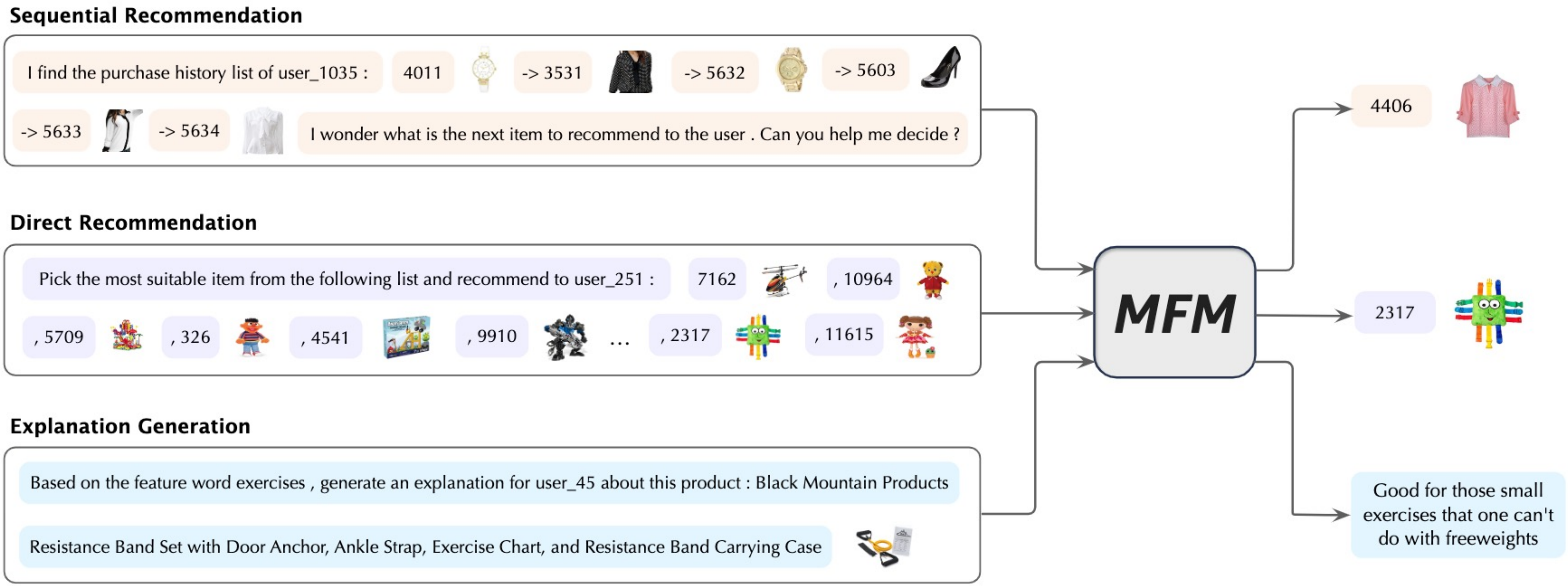
Methods	Sports BLUE4	Sports ROUGE1	Sports ROUGE2	Sports ROUGEL	Beauty BLUE4	Beauty ROUGE1	Beauty ROUGE2	Beauty ROUGEL	Toys BLUE4	Toys ROUGE1	Toys ROUGE2	Toys ROUGEL
Attn2Seq	0.5305	12.2800	1.2107	9.1312	0.7889	12.6590	1.6820	9.7481	1.6238	13.2245	2.9942	10.7398
NRT	0.4793	11.0723	1.1304	7.6674	0.8295	12.7815	1.8543	9.9477	1.9084	13.5231	3.6708	11.1867
PETER	0.7112	12.8944	1.3283	9.8635	1.1541	14.8497	2.1413	11.4143	1.9861	14.2716	3.6718	11.7010
P5-S (3-3)	**1.0447**	**14.9048**	**2.1297**	**11.1778**	**1.2237**	**17.6938**	**2.2489**	**12.8606**	2.2892	**15.4505**	3.6974	**12.1718**
P5-B (3-3)	1.0407	14.1589	2.1220	10.6096	0.9742	16.4530	1.8858	11.8765	**2.3185**	15.3474	**3.7209**	12.1312
PETER+	**2.4627**	**24.1181**	5.1937	**18.4105**	**3.2606**	25.5541	5.9668	19.7168	**4.7919**	28.3083	9.4520	**22.7017**
P5-S (3-9)	1.4101	23.5619	**5.4196**	17.6245	1.9788	**25.6253**	**6.3678**	**19.9497**	4.1222	**28.4088**	9.5432	22.6064
P5-B (3-9)	1.4689	23.5476	5.3926	17.5852	1.8765	25.1183	6.0764	19.4488	3.8933	27.9916	9.5896	22.2178
P5-S (3-12)	1.3212	23.2474	5.3461	17.3780	1.9425	25.1474	6.0551	19.5601	4.2764	28.1897	9.1327	22.2514
P5-B (3-12)	1.4303	23.3810	5.3239	17.4913	1.9031	25.1763	6.1980	19.5188	3.5861	28.1369	**9.7562**	22.3056

Direct Recommendation:

Methods	Sports HR@1	Sports HR@5	Sports NDCG@5	Sports HR@10	Sports NDCG@10	Beauty HR@1	Beauty HR@5	Beauty NDCG@5	Beauty HR@10	Beauty NDCG@10	Toys HR@1	Toys HR@5	Toys NDCG@5	Toys HR@10	Toys NDCG@10
BPR-MF	0.0314	0.1404	0.0848	0.2563	0.1220	0.0311	0.1426	0.0857	0.2573	0.1224	0.0233	0.1066	0.0641	0.2003	0.0940
BPR-MLP	0.0351	0.1520	0.0927	0.2671	0.1296	0.0317	0.1392	0.0848	0.2542	0.1215	0.0252	0.1142	0.0688	0.2077	0.0988
SimpleX	0.0331	**0.2362**	**0.1505**	0.3290	0.1800	0.0325	0.2247	0.1441	0.3090	0.1711	0.0268	**0.1958**	**0.1244**	**0.2662**	**0.1469**
P5-S (5-1)	0.0638	0.2096	0.1375	0.3143	0.1711	0.0600	0.2021	0.1316	0.3121	0.1670	0.0405	0.1538	0.0969	0.2405	0.1248
P5-B (5-1)	0.0245	0.0816	0.0529	0.1384	0.0711	0.0224	0.0904	0.0559	0.1593	0.0780	0.0187	0.0827	0.0500	0.1543	0.0729
P5-S (5-4)	0.0701	0.2241	0.1483	**0.3313**	**0.1827**	**0.0862**	**0.2448**	**0.1673**	**0.3441**	**0.1993**	0.0413	0.1411	0.0916	0.2227	0.1178
P5-B (5-4)	0.0299	0.1026	0.0665	0.1708	0.0883	0.0506	0.1557	0.1033	0.2350	0.1287	0.0435	0.1316	0.0882	0.2000	0.1102
P5-S (5-5)	0.0574	0.1503	0.1050	0.2207	0.1276	0.0601	0.1611	0.1117	0.2370	0.1360	0.0440	0.1282	0.0865	0.2011	0.1098
P5-B (5-5)	0.0641	0.1794	0.1229	0.2598	0.1488	0.0588	0.1573	0.1089	0.2325	0.1330	0.0386	0.1122	0.0756	0.1807	0.0975
P5-S (5-8)	0.0567	0.1514	0.1049	0.2196	0.1269	0.0571	0.1566	0.1078	0.2317	0.1318	**0.0451**	0.1322	0.0889	0.2023	0.1114
P5-B (5-8)	**0.0726**	0.1955	0.1355	0.2802	0.1627	0.0608	0.1564	0.1096	0.2300	0.1332	0.0389	0.1147	0.0767	0.1863	0.0997

Easy Handling of Multi-modality Information

- Item images can be directly inserted into prompts



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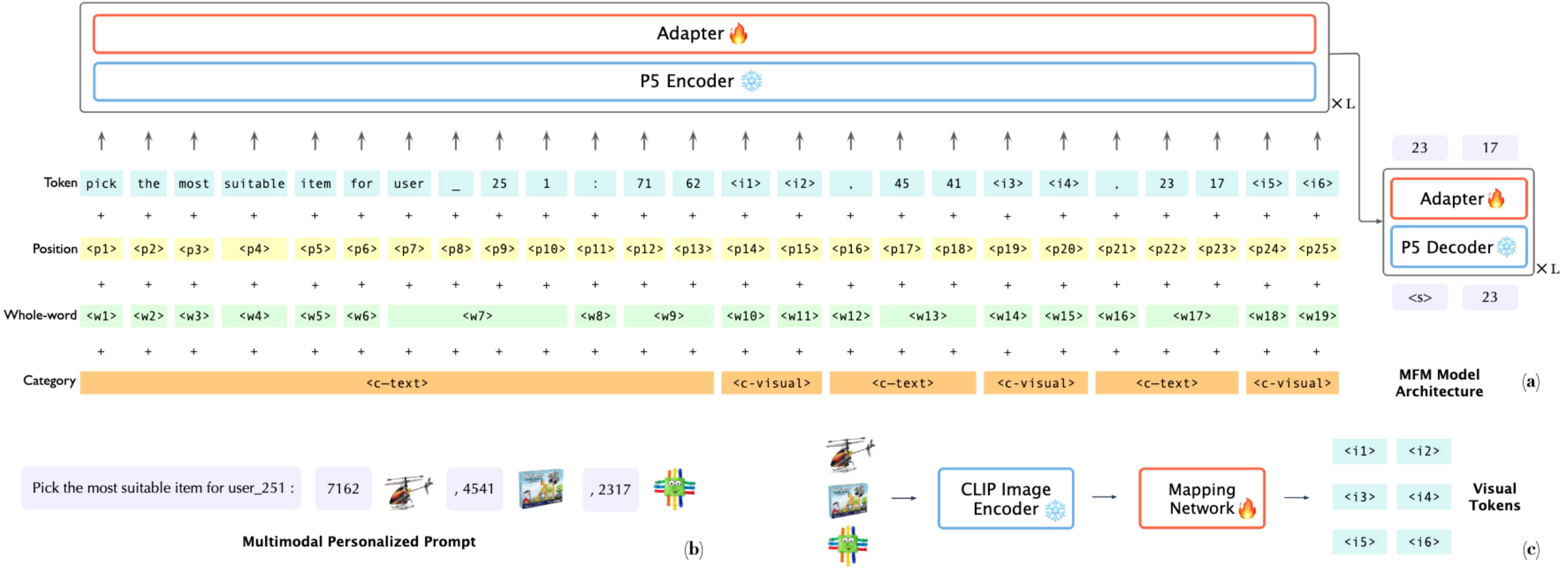
Easy Handling of Multi-modality Information

- Item images can be directly inserted into prompts



Easy Handling of Multi-modality Information

- Item images can be directly inserted into prompts
  - Multi-modality information further improves performance

Methods	Sports				Beauty			
	HR@5	NDCG@5	HR@10	NDCG@10	HR@5	NDCG@5	HR@10	NDCG@10
HGN	0.0189	0.0120	0.0313	0.0159	0.0325	0.0206	0.0512	0.0266
SASRec	0.0233	0.0154	0.0350	0.0192	0.0387	0.0249	0.0605	0.0318
S^3-Rec	0.0251	0.0161	0.0385	0.0204	0.0387	0.0244	0.0647	0.0327
P5 *(A-3)*	0.0272	0.0169	0.0361	0.0198	0.0503	0.0370	0.0659	0.0421
MFM *(A-3)*	**0.0412**	**0.0345**	**0.0475**	**0.0365**	**0.0556**	**0.0427**	**0.0677**	**0.0467**
P5 *(A-9)*	0.0258	0.0159	0.0346	0.0188	0.0490	0.0358	0.0646	0.0409
MFM *(A-9)*	0.0392	0.0327	0.0456	0.0347	0.0529	0.0413	0.0655	0.0454

Methods	Clothing				Toys			
	HR@5	NDCG@5	HR@10	NDCG@10	HR@5	NDCG@5	HR@10	NDCG@10
HGN	0.0107	0.0071	0.0175	0.0092	0.0321	0.0221	0.0497	0.0277
SASRec	0.0107	0.0066	0.0194	0.0095	0.0463	0.0306	0.0675	0.0374
S^3-Rec	0.0076	0.0045	0.0135	0.0063	0.0443	0.0294	0.0700	0.0376
P5 *(A-3)*	0.0478	0.0376	0.0554	0.0401	0.0655	0.0570	0.0726	0.0593
MFM *(A-3)*	**0.0603**	**0.0564**	**0.0632**	**0.0573**	**0.0662**	**0.0577**	**0.0749**	**0.0604**
P5 *(A-9)*	0.0455	0.0359	0.0534	0.0385	0.0631	0.0547	0.0701	0.0569
MFM *(A-9)*	0.0569	0.0531	0.0597	0.0540	0.0641	0.0556	0.0716	0.0580

Sequential Recommendation Performance

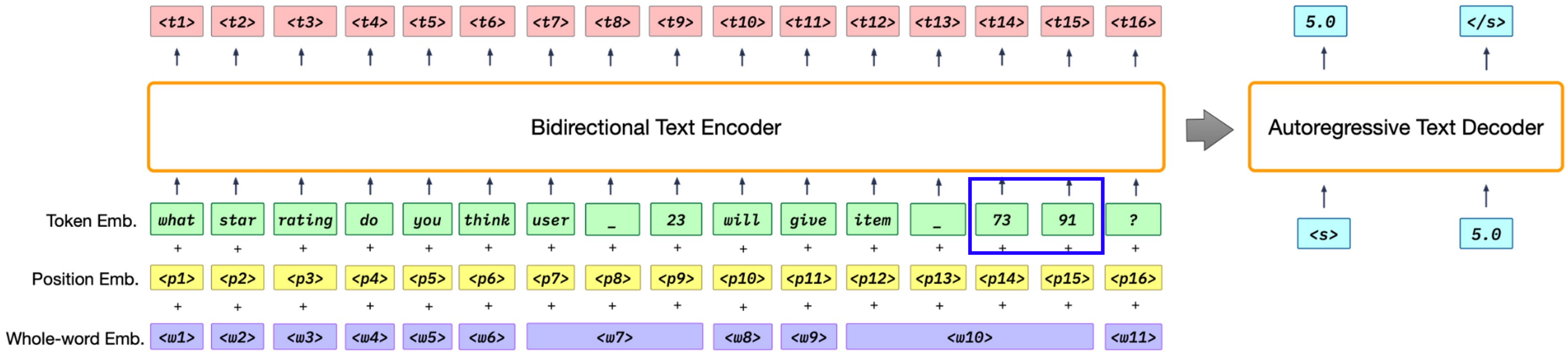
Methods	Sports					Beauty				
	HR@1	HR@5	NDCG@5	HR@10	NDCG@10	HR@1	HR@5	NDCG@5	HR@10	NDCG@10
BPR-MF	0.0314	0.1404	0.0848	0.2563	0.1220	0.0311	0.1426	0.0857	**0.2573**	0.1224
BPR-MLP	0.0351	0.1520	0.0927	0.2671	0.1296	0.0317	0.1392	0.0848	0.2542	0.1215
VBPR	0.0262	0.1138	0.0691	0.2060	0.0986	0.0380	0.1472	0.0925	0.2468	0.1245
P5 *(B-5)*	0.0574	0.1503	0.1050	0.2207	0.1276	0.0601	0.1611	0.1117	0.2370	0.1360
MFM *(B-5)*	0.0606	0.1743	0.1185	0.2539	0.1441	0.0580	0.1598	0.1099	0.2306	0.1327
P5 *(B-8)*	0.0567	0.1514	0.1049	0.2196	0.1269	0.0571	0.1566	0.1078	0.2317	0.1318
MFM *(B-8)*	**0.0699**	**0.1882**	**0.1304**	**0.2717**	**0.1572**	**0.0615**	**0.1655**	**0.1147**	0.2407	**0.1388**

Methods	Clothing					Toys				
	HR@1	HR@5	NDCG@5	HR@10	NDCG@10	HR@1	HR@5	NDCG@5	HR@10	NDCG@10
BPR-MF	0.0296	0.1280	0.0779	0.2319	0.1112	0.0233	0.1066	0.0641	0.2003	0.0940
BPR-MLP	0.0342	0.1384	0.0858	0.2327	0.1161	0.0252	0.1142	0.0688	0.2077	0.0988
VBPR	0.0352	0.1410	0.0877	**0.2420**	0.1201	0.0337	0.1294	0.0808	**0.2199**	0.1098
P5 *(B-5)*	0.0320	0.0986	0.0652	0.1659	0.0867	0.0418	0.1219	0.0824	0.1942	0.1056
MFM *(B-5)*	0.0481	0.1287	0.0890	0.1992	0.1116	0.0428	0.1225	0.0833	0.1906	0.1051
P5 *(B-8)*	0.0355	0.1019	0.0688	0.1722	0.0912	0.0422	0.1286	0.0858	0.2041	0.1099
MFM *(B-8)*	**0.0552**	**0.1544**	**0.1058**	0.2291	**0.1297**	**0.0433**	**0.1301**	**0.0875**	0.2037	**0.1110**

Direct Recommendation Performance

How to Index Items

- Item ID: item needs to be represented as a sequence of tokens
  - e.g., an item represented by two tokens <73> <91>



- Different item indexing gives very different performance

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Why do we need to create Item IDs?

- LLM-based Generative Recommendation Paradigm
  - We want to directly generate the recommended item
  - Avoid one-by-one ranking score calculation

- However, item descriptions can be very long
  - e.g., product description: >100 words
  - e.g., news article: >1,000 words

RUTGERS

Why do we need to create Item IDs?

- Generating long text is difficult, especially for recommendation
  - Hallucination problem
  - Generated text does not correspond to a real existing item in database
  - Calculating similar between generated text and item text?
  - Goes back to one-by-one similarity calculation for ranking!

- Item ID: A short sequence of tokens for an item
  - Easy generation, and can be indexed!

- Item ID can take various forms
  - A sequence of numerical tokens <73><91><26>
  - A sequence of word tokens <the><lord><of><the><rings>

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How to Index Items (create Item IDs)

- Three properties for good item indexing methods
  - Items are distinguishable (different items have different IDs)
  - Similar items have similar IDs (more shared tokens in their IDs)
  - Dissimilar items have dissimilar IDs (less shared tokens in their IDs)
- Three naïve Indexing methods
  - Random ID (RID): Item ⟨73⟩⟨91⟩, item ⟨73⟩⟨12⟩, …
  - Title as ID (TID): Item ⟨the⟩⟨lord⟩⟨of⟩⟨the⟩⟨rings⟩, …
  - Independent ID (IID): Item ⟨1364⟩, Item ⟨6321⟩, …

Method	Amazon Sports				Amazon Beauty				Yelp			
	HR@5	NCDG@5	HR@10	NCDG@10	HR@5	NCDG@5	HR@10	NCDG@10	HR@5	NCDG@5	HR@10	NCDG@10
SASRec	0.0233	0.0154	0.0350	0.0192	0.0387	0.0249	0.0605	0.0318	0.0170	0.0110	0.0284	0.0147
S^3-Rec	0.0251	**0.0161**	0.0385	**0.0204**	0.0387	0.0244	**0.0647**	0.0327	0.0201	0.0123	0.0341	0.0168
RID	0.0208	0.0122	0.0288	0.0153	0.0213	0.0178	0.0479	0.0277	0.0225	**0.0159**	0.0329	0.0193
TID	0.0000	0.0000	0.0000	0.0000	0.0182	0.0132	0.0432	0.0254	0.0058	0.0040	0.0086	0.0049
IID	**0.0268**	0.0151	**0.0386**	0.0195	**0.0394**	**0.0268**	0.0615	**0.0341**	**0.0232**	0.0146	**0.0393**	**0.0197**

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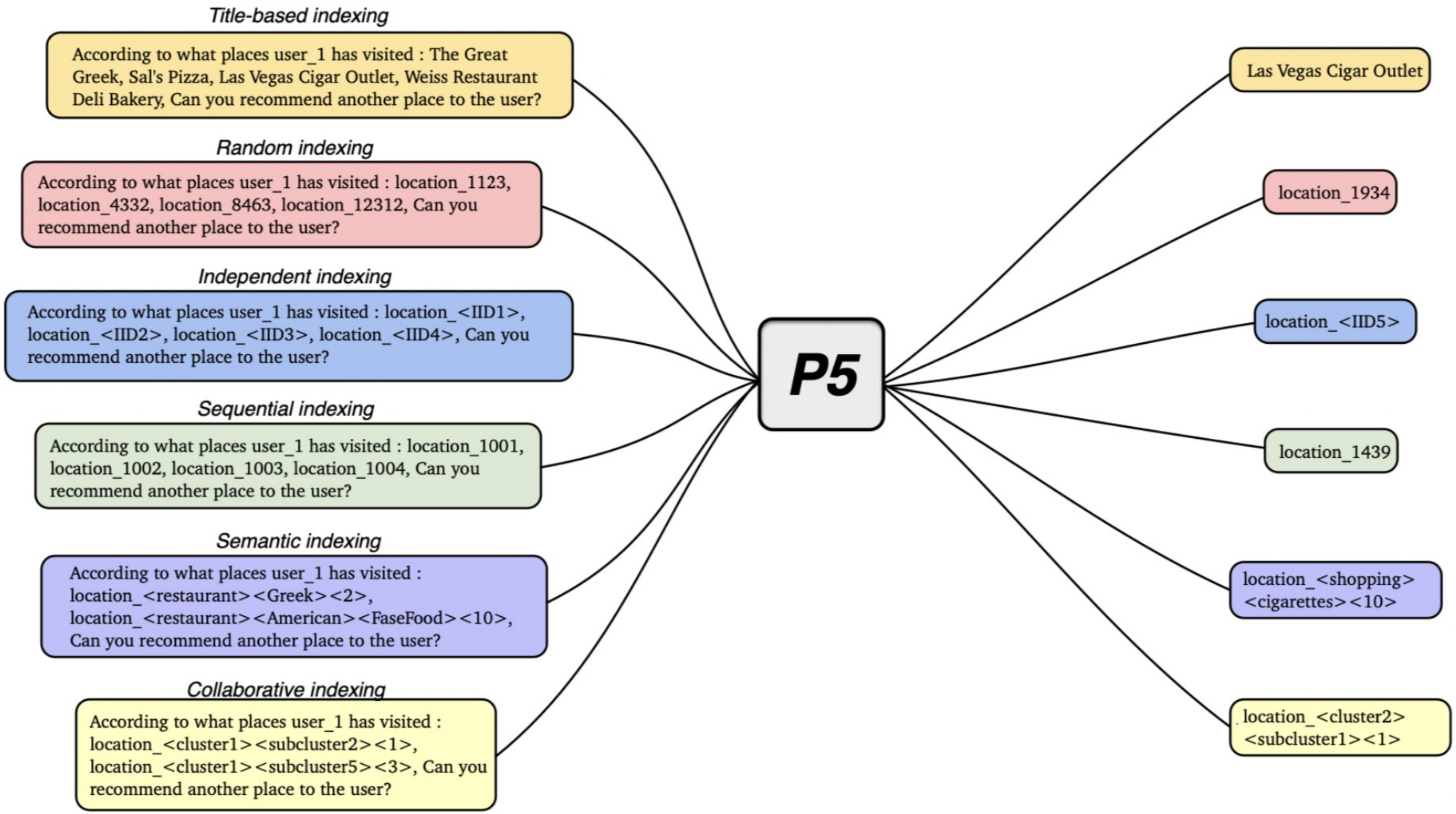
How to Index Items (create Item IDs)

- Three naïve Indexing methods
  - Random ID (RID): Item ⟨73⟩⟨91⟩, item ⟨73⟩⟨12⟩, …
    - Very different items may share the same tokens
    - Mistakenly making them semantically similar
  - Title as ID (TID): Item ⟨the⟩⟨lord⟩⟨of⟩⟨the⟩⟨rings⟩
    - Very different movies may share similar titles
      - **Inside Out** (animation) and **Inside Job** (documentary)
      - **The Lord of the Rings** (epic fantasy) and **The Lord of War** (crime drama)
  - Independent ID (IID): Item ⟨1364⟩, Item ⟨6321⟩, …
    - Too many out-of-vocabulary (OOV) new tokens need to learn
    - Computationally unscalable

Meticulous Item Indexing Methods are Needed



Sequential Indexing (SID)

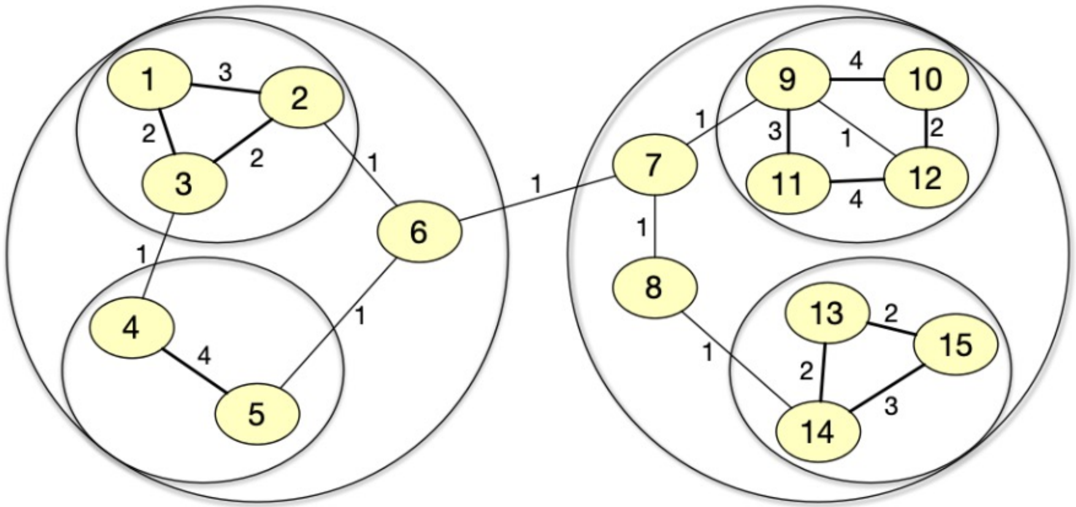
- Leverage the local co-appearance information between items

	Training Sequence										Validation	Testing
User 1	1001	1002	1003	1004	1005	1006	1007	1008	1009		1018	1019
User 2	1010	1011	1001	1012	1008	1009	1013	1014			1022	1023
User 3	1015	1016	1017	1007	1018	1019	1020	1021	1009		1015	1016
User 4	1022	1023	1005	1002	1006	1024					1002	1008
User 5	1025	1026	1027	1028	1029	1030	1024	1020	1021	1031	1033	1034

- After tokenization, co-appearing items share similar tokens
  - Item 1004: ⟨10⟩⟨04⟩
  - Item 1005: ⟨10⟩⟨05⟩

Collaborative Indexing (CID)

- Leverage the global co-appearance information between items
  - Spectral Matrix Factorization over the item-item co-appearance matrix
  - Hierarchical Spectral Clustering



(a) Recursive spectral clustering on item co-appearance graph

$$
\begin{array}{c c}
 & \begin{array}{cccccccc} 1 & 2 & 3 & 4 & 5 & 6 & \cdots \end{array} \\
\begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ \vdots \end{array} &
\begin{bmatrix}
0 & 3 & 2 & 0 & 0 & 0 & \cdots \\
3 & 0 & 2 & 0 & 0 & 1 & \cdots \\
2 & 2 & 0 & 1 & 0 & 0 & \cdots \\
0 & 0 & 1 & 0 & 4 & 0 & \cdots \\
0 & 0 & 0 & 4 & 0 & 1 & \cdots \\
0 & 1 & 0 & 0 & 1 & 0 & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots &
\end{bmatrix}
\end{array}
$$

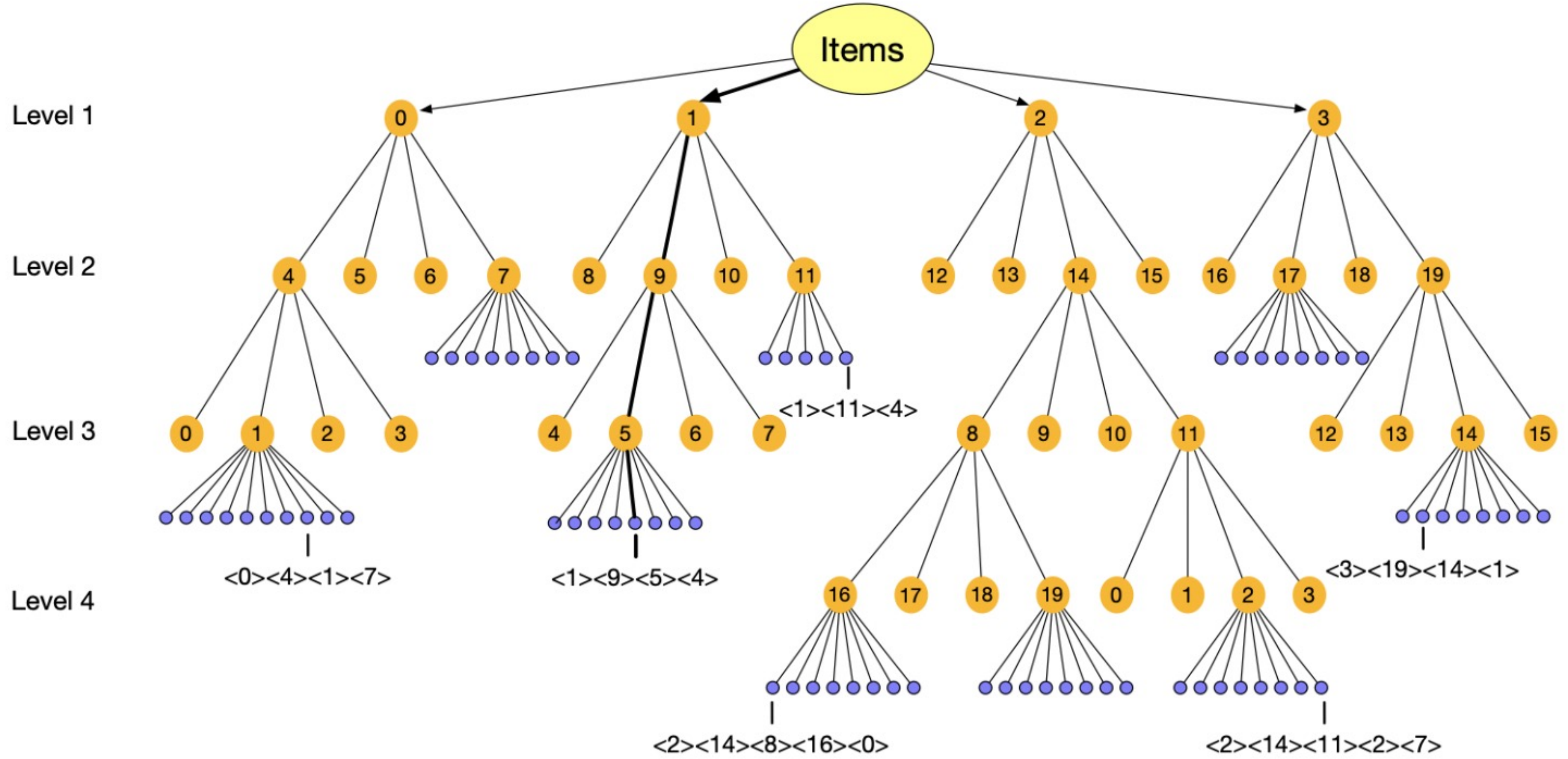
(b) Adjacency matrix

$$
\begin{array}{c c}
 & \begin{array}{cccccccc} 1 & 2 & 3 & 4 & 5 & 6 & \cdots \end{array} \\
\begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ \vdots \end{array} &
\begin{bmatrix}
5 & -3 & -2 & 0 & 0 & 0 & \cdots \\
-3 & 6 & -2 & 0 & 0 & -1 & \cdots \\
-2 & -2 & 6 & -1 & 0 & 0 & \cdots \\
0 & 0 & 1 & 5 & -4 & 0 & \cdots \\
0 & 0 & 0 & -4 & 5 & -1 & \cdots \\
0 & 1 & 0 & 0 & -1 & 2 & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots &
\end{bmatrix}
\end{array}
$$

(c) Laplacian matrix

Collaborative Indexing (CID)

- Leverage the global co-appearance information between items
  - Root-to-Leaf Path-based Indexing
  - Items in the same cluster share more tokens



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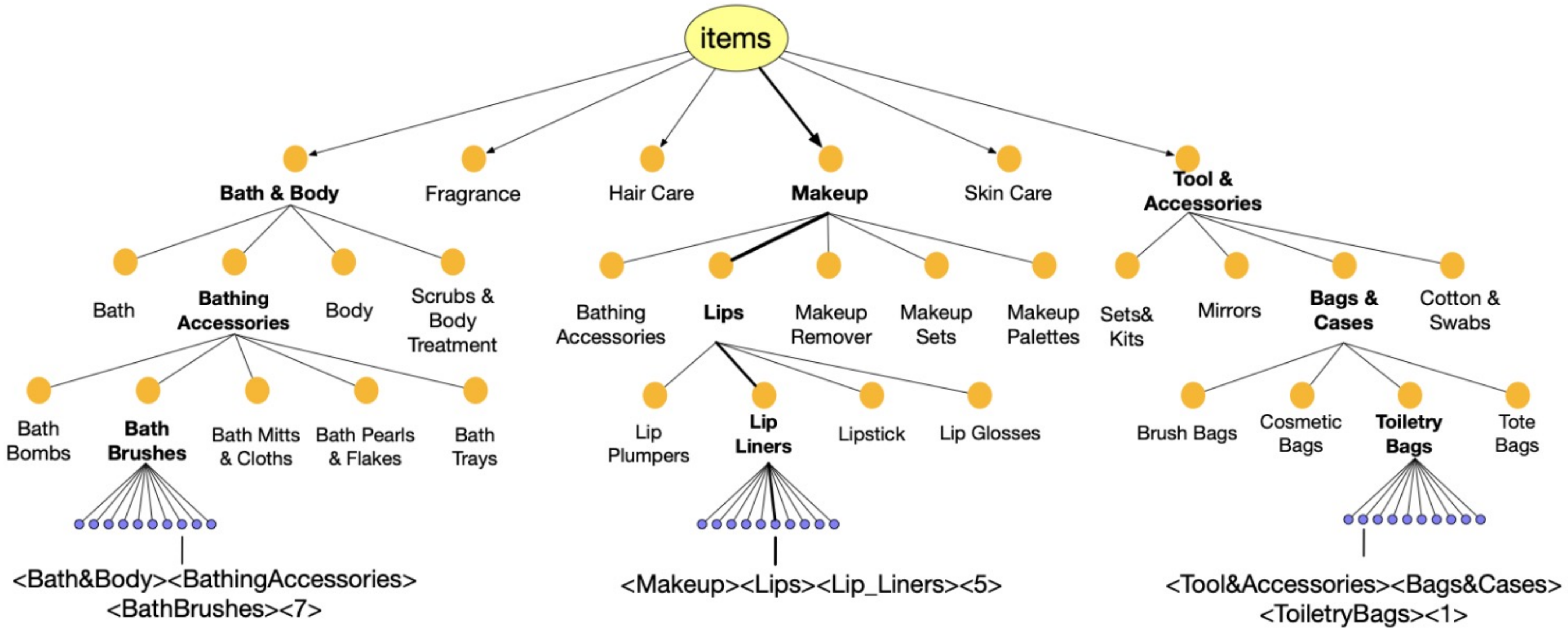
Semantic (Content-based) Indexing (SemID)

- Leverage the item content information for item indexing
  - e.g., the multi-level item category information in Amazon



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Hybrid Indexing (HID)

- Concatenate more than one of the following indices
  - Random ID (RID)
  - Title as ID (TID)
  - Independent ID (IID)
  - Sequential ID (SID)
  - Collaborative ID (CID)
  - Semantic ID (SemID)

  - For example, if an item's Semantic ID and Collaborative ID are as follows:
    - SemID: ⟨Makeup⟩⟨Lips⟩⟨Lip_Liners⟩⟨5⟩
    - CID: ⟨1⟩⟨9⟩⟨5⟩⟨4⟩
  - Then its Hybrid ID is ⟨Makeup⟩⟨Lips⟩⟨Lip_Liners⟩⟨1⟩⟨9⟩⟨5⟩⟨4⟩

Different Item Indexing Gives Different Performance

	Method	Amazon Sports				Amazon Beauty				Yelp			
		HR@5	NCDG@5	HR@10	NCDG@10	HR@5	NCDG@5	HR@10	NCDG@10	HR@5	NCDG@5	HR@10	NCDG@10
	Caser	0.0116	0.0072	0.0194	0.0097	0.0205	0.0131	0.0347	0.0176	0.015	0.0099	0.0263	0.0134
	HGN	0.0189	0.0120	0.0313	0.0159	0.0325	0.0206	0.0512	0.0266	0.0186	0.0115	0.0326	0.159
	GRU4Rec	0.0129	0.0086	0.0204	0.0110	0.0164	0.0099	0.0283	0.0137	0.0176	0.0110	0.0285	0.0145
	BERT4Rec	0.0115	0.0075	0.0191	0.0099	0.0203	0.0124	0.0347	0.0170	0.0051	0.0033	0.0090	0.0090
	FDSA	0.0182	0.0122	0.0288	0.0156	0.0267	0.0163	0.0407	0.0208	0.0158	0.0098	0.0276	0.0136
	SASRec	0.0233	0.0154	0.0350	0.0192	0.0387	0.0249	0.0605	0.0318	0.0170	0.0110	0.0284	0.0147
	S^3-Rec	0.0251	0.0161	0.0385	0.0204	0.0387	0.0244	0.0647	0.0327	0.0201	0.0123	0.0341	0.0168
Naïve indexing methods	RID	0.0208	0.0122	0.0288	0.0153	0.0213	0.0178	0.0479	0.0277	0.0225	0.0159	0.0329	0.0193
	TID	0.000	0.000	0.000	0.000	0.0182	0.0132	0.0432	0.0254	0.0058	0.0040	0.0086	0.0049
	IID	0.0268	0.0151	0.0386	0.0195	0.0394	0.0268	0.0615	0.0341	0.0232	0.0146	0.0393	0.0197
Advanced indexing methods	SID	0.0264	0.0186	0.0358	0.0216	0.0430	0.0288	0.0602	0.0368	**0.0346**	**0.0242**	**0.0486**	**0.0287**
	CID	0.0313	0.0224	0.0431	0.0262	0.0489	0.0318	0.0680	0.0357	0.0261	0.0171	0.0428	0.0225
	SemID	0.0274	0.0193	0.0406	0.0235	0.0433	0.0299	0.0652	0.0370	0.0202	0.0131	0.0324	0.0170
Hybrid indexing methods	SID+IID	0.0235	0.0161	0.0339	0.0195	0.0420	0.0297	0.0603	0.0355	0.0329	0.0236	0.0465	0.0280
	CID+IID	**0.0321**	**0.0227**	**0.0456**	**0.0270**	**0.0512**	**0.0356**	**0.0732**	**0.0427**	0.0287	0.0195	0.0468	0.0254
	SemID+IID	0.0291	0.0196	0.0436	0.0242	0.0501	0.0344	0.0724	0.0411	0.0229	0.0150	0.0382	0.0199
	SemID+CID	0.0043	0.0031	0.0070	0.0039	0.0355	0.0248	0.0545	0.0310	0.0021	0.0016	0.0056	0.0029

- Advanced indexing methods are better than naïve methods
- Hybrid indexing can further improve performance

The Future of Generative Recommendation

- Recommendation as Personalized On-demand Generation
  - Recommend existing items vs. recommend newly generated items
    - Traveling in Hawaii, want to make a post on Instagram
    - Personalized generation of candidate images for users to consider



*Image generated with Midjourney

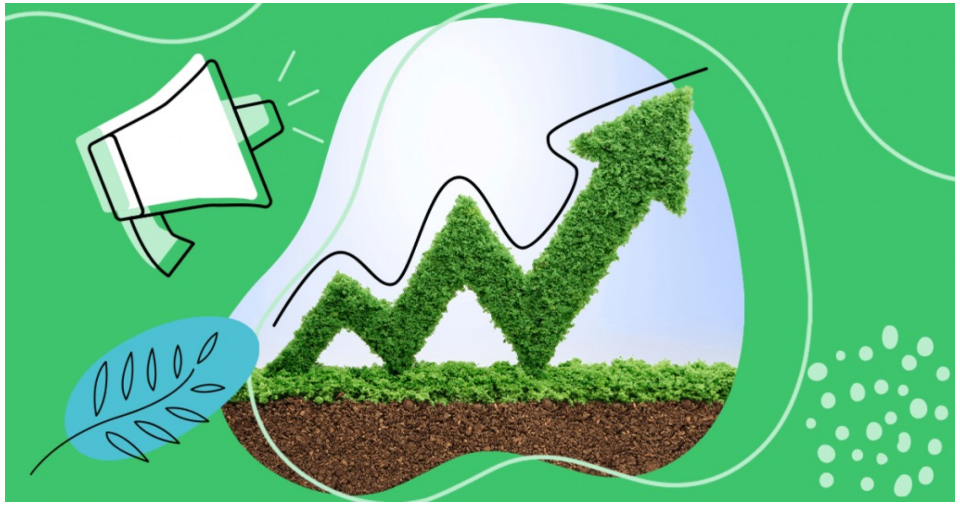
The Future of Generative Recommendation

- Recommendation as Personalized On-demand Generation
  - Personalized Advertisement Generation
  - Same ad, different wording, real-time generation given user's context
    - e.g., an environmental protection ad for an NGO

For Children:

Join us in protecting our planet. Let's work together to make the world a better place for ourselves and for future generations.

For Business Leaders:



Join the movement towards sustainability and create a brighter future for your business and our planet. By adopting environmentally-friendly practices, you can reduce your costs, attract new customers, and enhance your reputation as a responsible business leader.

*Text generated with ChatGPT

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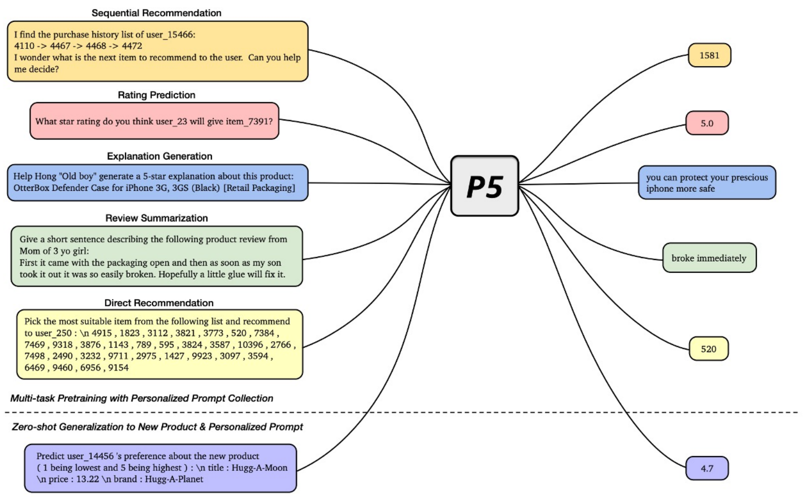
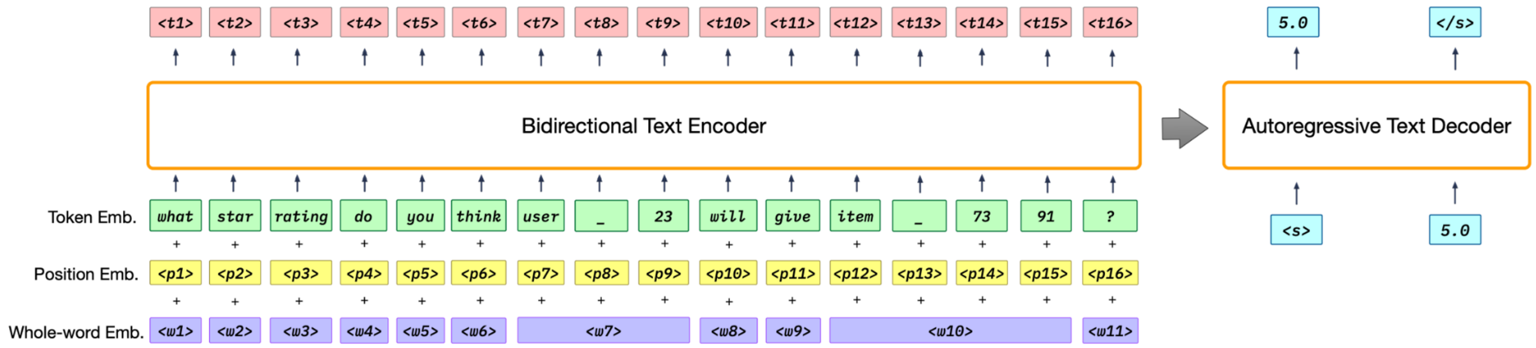
Summary

- From Discriminative Recommendation to Generative Recommendation
  - From multi-stage ranking to single-stage ranking
  - Multi-task learning with the same foundation model
  - Easily handle multi-modality data
  - Various item indexing methods for recommendation foundation models
  - Recommendation as Personalized On-demand Generation
    - From recommending existing items to recommending newly generated items





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