Recommendation as Language Processing (RLP): A Unified Pretrain, Personalized Prompt & Predict Paradigm (P5)

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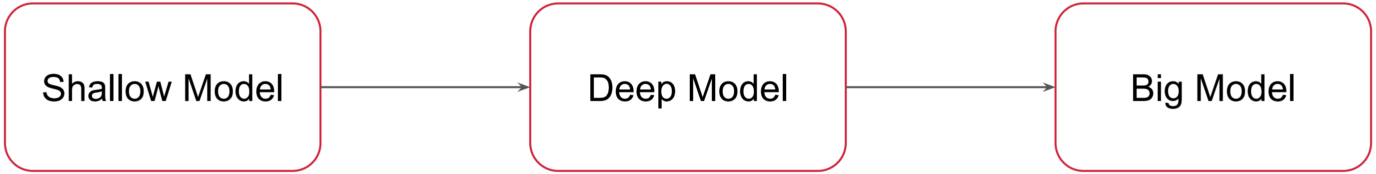
Development Trend of Recommender Systems

- Recommender Systems have advanced from shallow models to deep models and now entering the stage of big models (or foundation models).



Development Trend of Recommender Systems

- In retrospect of the past decades, we can summarize the development trend of recommender systems as a more comprehensive system that accommodates
  - **more diverse features**
    - For feature engineering / learning:
      - user-item interaction records **->**
      - rich contextual features **->**
      - directly utilize raw data contains natural language
  - **wider spectrum of application scenarios**
    - For real-world applications:
      - user-item matching-based recommendation, rating prediction, CTR prediction **->**
      - sequential recommendation, session-based recommendation, conversational recommendation, explainable recommendation

Motivation

- Though achieving great success, current recommendation systems still **need** to design **specific model architectures** & **training objectives** for different recommendation tasks

- Since recommendation tasks usually share a common user–item pool and have overlapping contextual features

- It's promising to merge more recommendation tasks into a unified framework thus they can implicitly transfer knowledge and better benefit each other

Motivation (Cont'd)

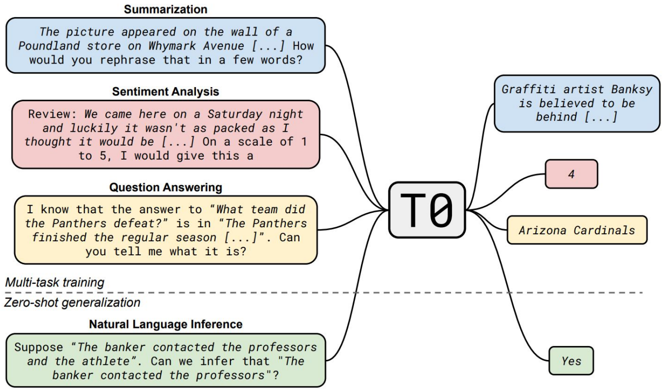
- Considering **language** is a powerful medium to describe and represent various problems / tasks as well as the rich natural language raw data

- We believe language models are a good candidate for building such unified framework for recommender systems and can enable recommendation models a better generalization ability

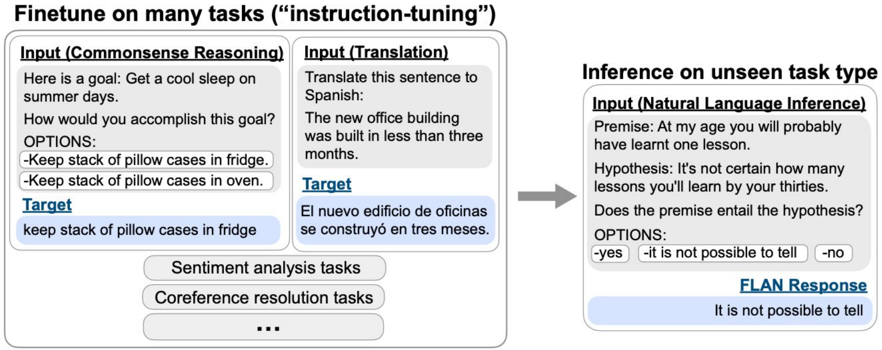
- **Challenges**: how to convert all data (such as user-item interactions, item metadata, and user reviews) & different tasks into a common format – natural language sequence

- We get inspiration from recent progress in multitask prompt-based training with large language models

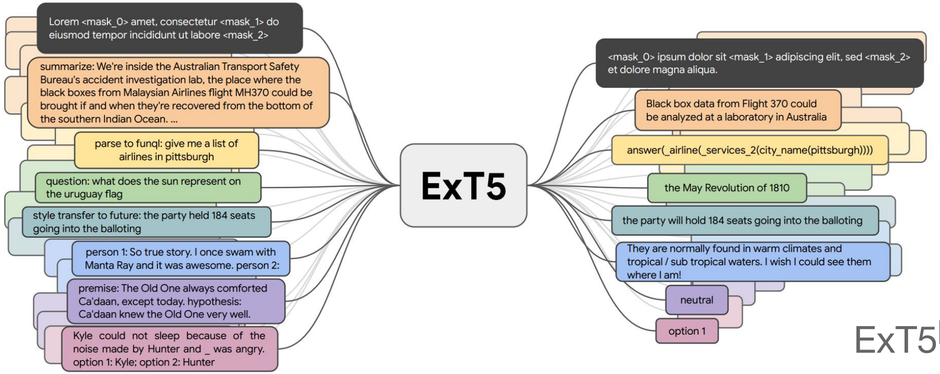
Multitask Prompt-based Training with LLMs



T0[1]



FLAN[2]

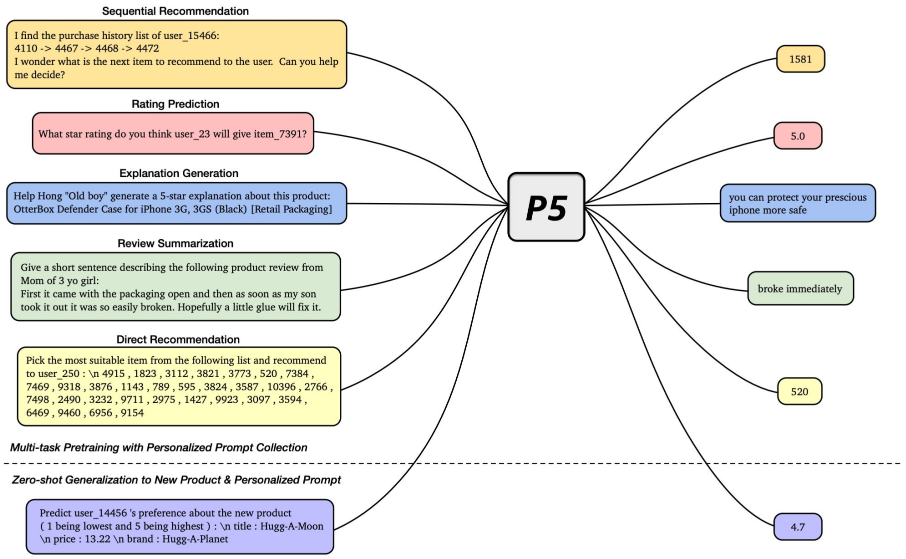


ExT5[3]

[1] Sanh, Victor et al. "Multitask prompted training enables zero-shot task generalization." ICLR. 2022
[2] Wei, Jason et al. "Finetuned language models are zero-shot learners." ICLR. 2022
[3] Aribandi, Vamsi et al. "Ext5: Towards extreme multi-task scaling for transfer learning." ICLR. 2022

A Unified Pretrain, Personalized Prompt & Predict Paradigm (P5)

- Learns multiple recommendation related 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 prompt templates as model inputs



Main Advantage of P5

- Immerses recommendation models into a full language environment; Thanks to the flexibility and expression ability 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

- P5 attains sufficient zero-shot performance when generalizing to novel personalized prompts or unseen items in other domains

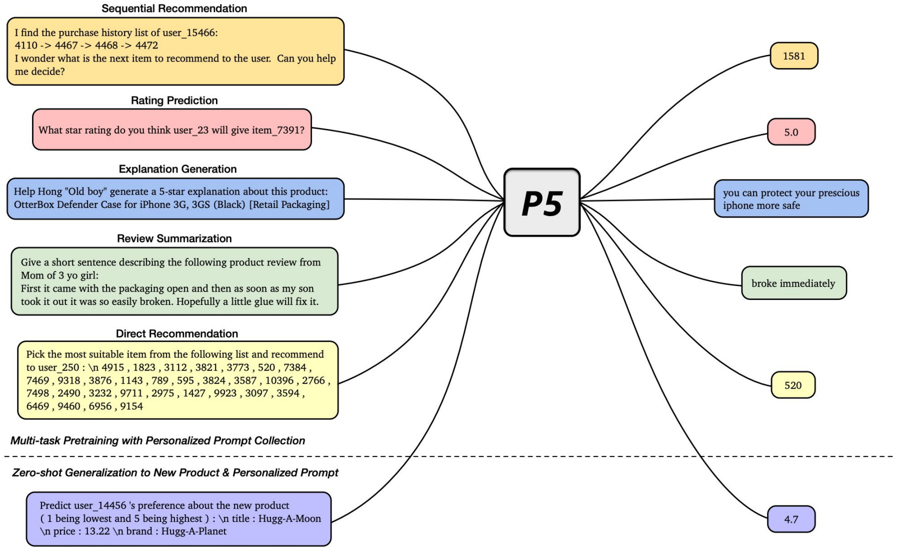
Challenges to Adopt Multitask Prompt-based Training to Recommendation

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

C1. Recommendation Tasks Covered by P5

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

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



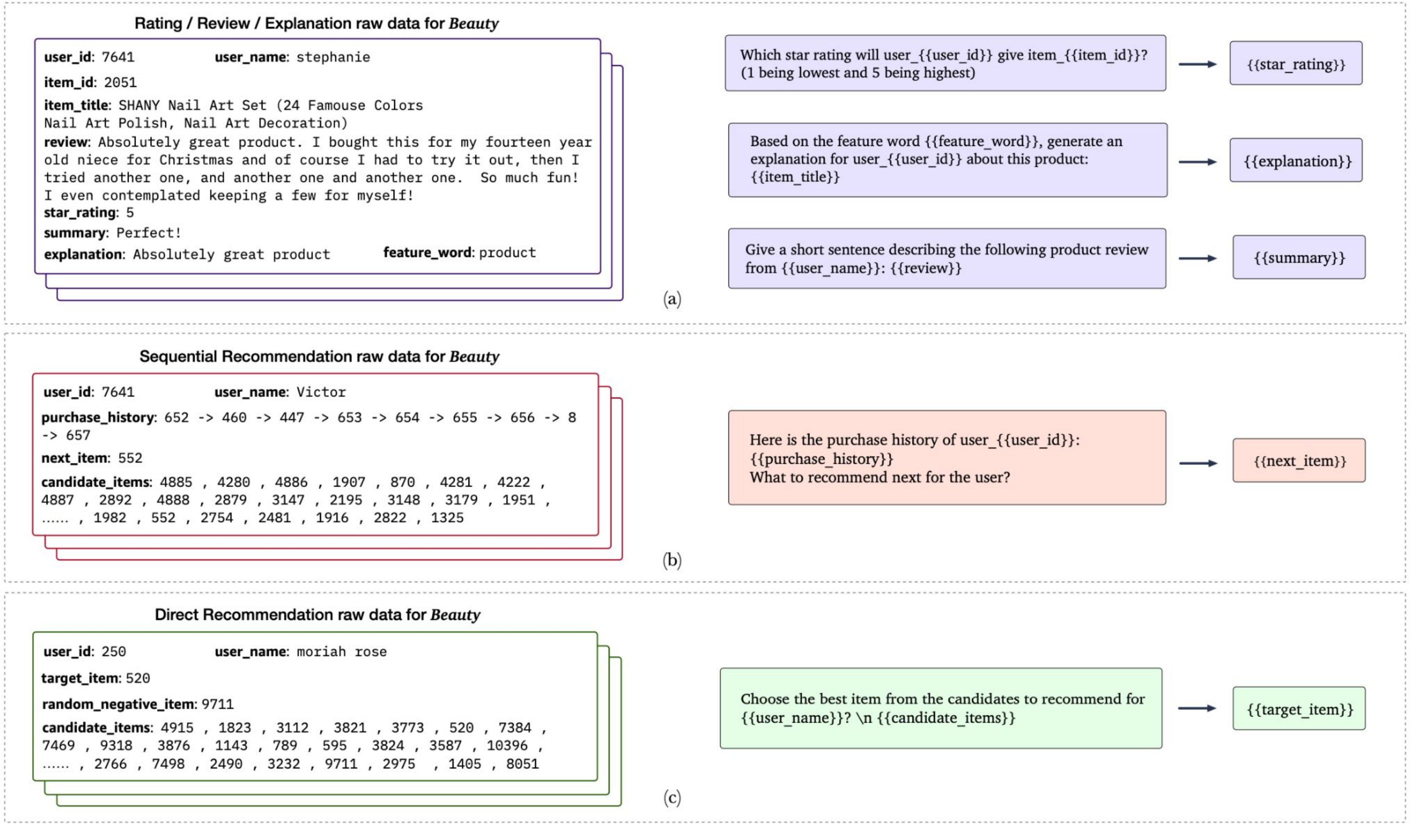
C2. Represent Personalization in Prompts

- 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 number** (e.g., "user_23")
  - a **description of the user** such as name, gender, age, etc

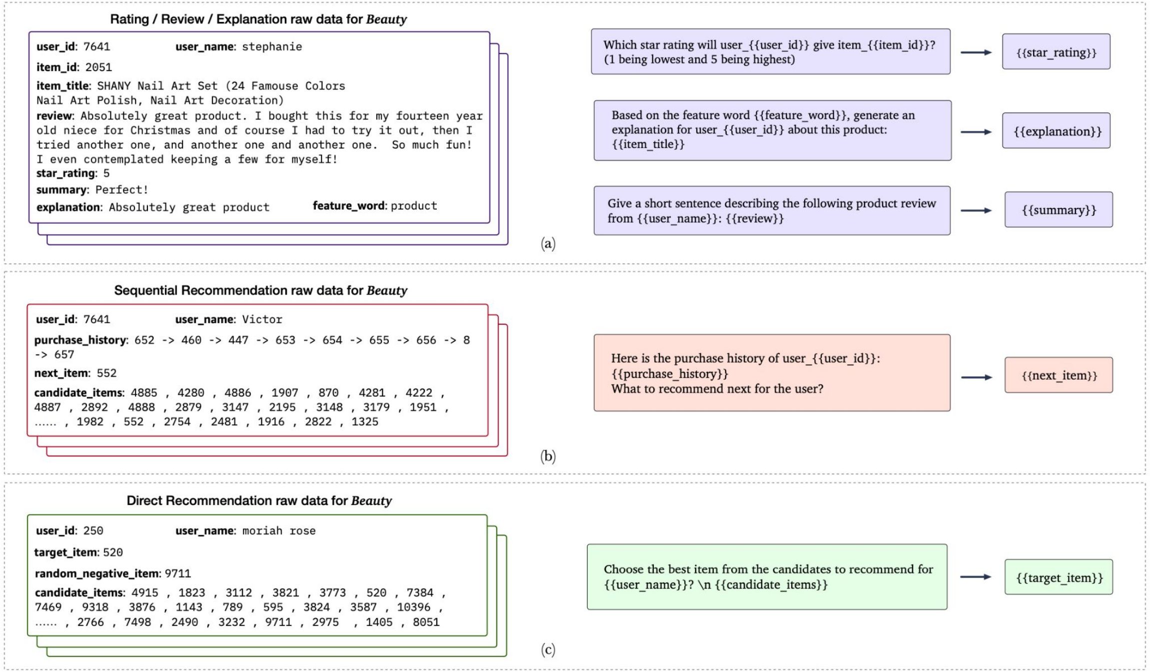
- Item field can be represented by
  - an **item ID number** (e.g., "item_7391")
  - **item** metadata that contains **detailed descriptions**

C3. Design of Personalized Prompt Templates

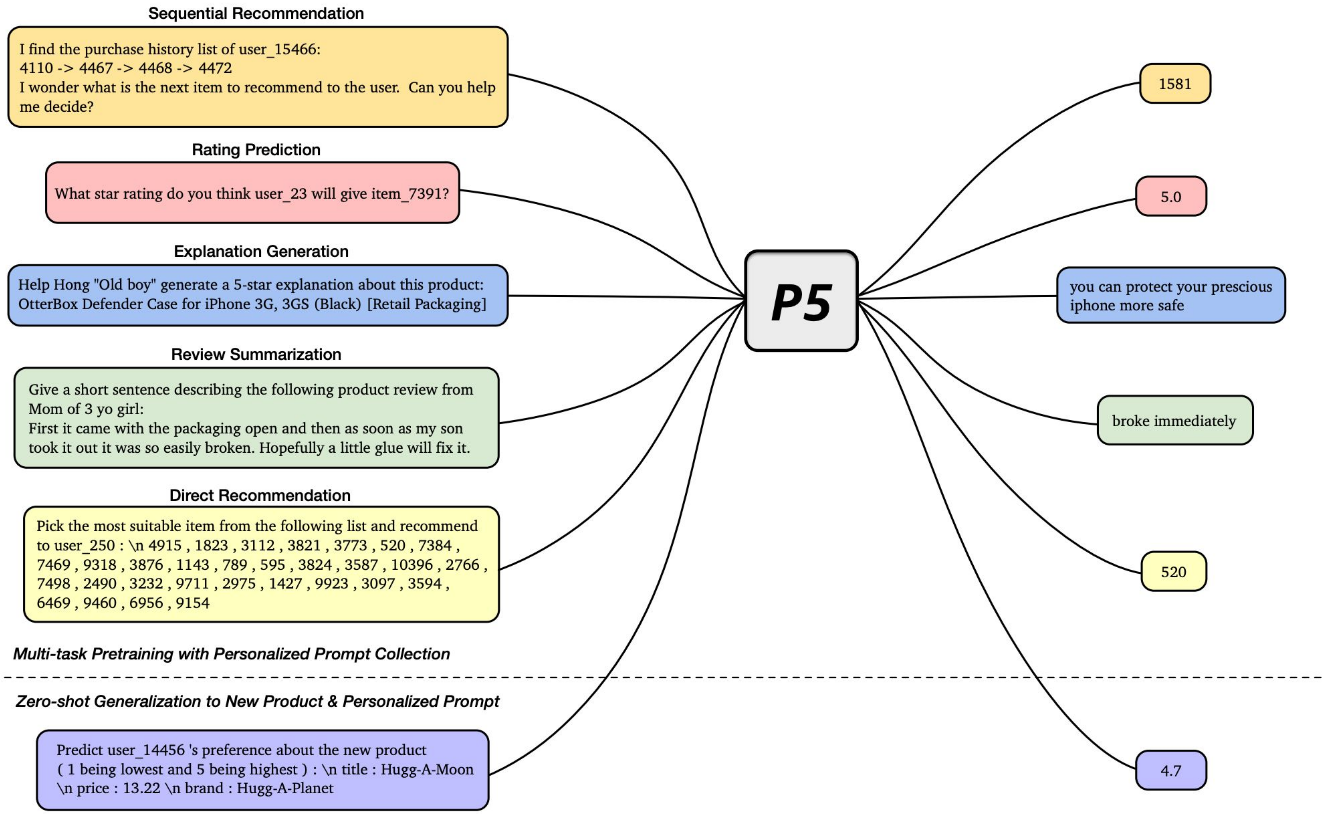


C3. Personalized Prompts

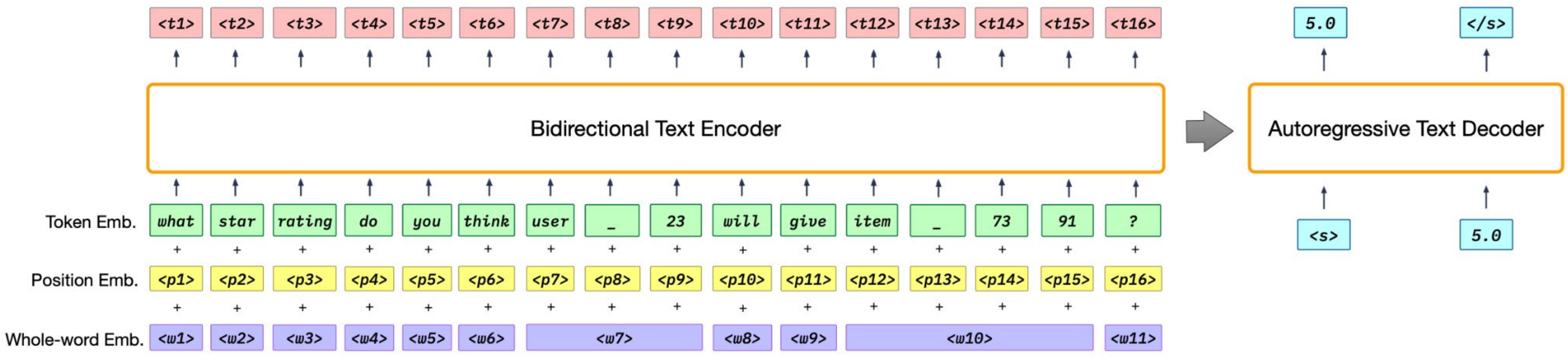
- Design various personalized prompts for each category can help improve P5's generalization ability; Finally, we created 47 personalized prompts to cover 5 task families
- Then we can construct training prompts from personalized prompt templates by simply filling raw data:



A Unified Pretrain, Personalized Prompt & Predict Paradigm (P5)



C4. Architecture of P5



- P5 is built on top of pretrained 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

C5. Pretraining & Inference of P5

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

- As a result, we unify recommendation tasks with **one model, one loss, and one data format**

- Inference with pretrained P5 on seen or unseen prompts / items
  - For rating, explanation, and review tasks, we simply use **greedy decoding** to generate answer
  - For sequential recommendation, we apply **beam search** to generate a list of potential next items and evaluate it under the all-item setting
  - For direct recommendation, we predict the recommended items from a candidate set, and also use **beam search** to decode a list of potential target items with the highest scores and then conduct evaluation

Research Questions

1. How does our unified P5 framework perform compared with task-specific methods on all five task families?

2. Does P5 have enough zero-shot generalization ability when transferring to unseen personalized prompts for either existing or new items?

seen prompts unseen prompts

RQ1: Performance of P5

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)	0.5902	**60.8892**	17.7514	18.0010	2.4094	**62.0077**	21.4176	25.1863	1.0794	59.4588	18.9272	19.8567
P5-B (3-3)	0.6213	58.7260	**18.5533**	**18.4670**	**2.6606**	61.7001	**22.3824**	**25.9821**	1.5248	**60.0415**	**19.9905**	**20.8306**
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)	**7.2129**	**67.4004**	**36.1417**	**30.8359**	5.8239	**68.6839**	**37.1359**	31.4482	**8.5465**	**69.7741**	40.0564	**34.0364**
P5-B (3-9)	3.5598	64.7683	34.0162	26.3184	6.5846	68.3067	37.0722	31.7545	7.7315	69.2266	39.7407	33.3348
P5-S (3-12)	5.8446	66.5976	35.5160	29.2766	5.3233	68.3174	36.8730	30.7071	8.2840	69.7158	**40.1340**	33.9770
P5-B (3-12)	4.6977	65.4562	34.9379	27.7223	**6.9169**	68.2195	36.9858	**32.1314**	7.2597	68.8920	39.5056	32.8794

seen prompts unseen prompts

RQ1: Performance of P5 (Cont'd)

Review-base Preference Prediction:

Methods	Sports		Beauty		Toys	
	RMSE	MAE	RMSE	MAE	RMSE	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				Beauty				Toys			
	BLUE4	ROUGE1	ROUGE2	ROUGEL	BLUE4	ROUGE1	ROUGE2	ROUGEL	BLUE4	ROUGE1	ROUGE2	ROUGEL
T0 (4-1)	**8.0881**	43.4226	13.9629	19.4267	6.1775	41.4487	13.2033	18.2904	7.1445	44.8651	15.1572	18.9544
GPT-2 (4-1)	2.6586	43.6313	15.2021	5.2144	2.2032	41.0148	13.5772	4.2457	2.0760	43.0985	14.4126	4.4048
P5-S (4-1)	7.1781	44.6943	20.0491	26.5941	**7.5644**	**44.0703**	**18.3076**	**26.4375**	**7.3916**	**46.0153**	**19.3441**	**27.1528**
P5-B (4-1)	7.5727	**47.7859**	**21.6872**	**28.1312**	7.0708	44.0486	18.1725	26.2031	6.0264	43.7403	17.3446	25.0362

Direct Recommendation:

Methods	Sports					Beauty					Toys				
	HR@1	HR@5	NDCG@5	HR@10	NDCG@10	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	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

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

RQ2: Zero-shot Generalization of P5

Part 1: Transfer to Unseen Personalized Prompts

Concluion: Multitask prompted pretraining empowers P5 **enough robustness** to understand **unseen prompts** with wording variations

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)	0.5902	**60.8892**	17.7514	18.0010	2.4094	**62.0077**	21.4176	25.1863	1.0794	59.4588	18.9272	19.8567
P5-B (3-3)	0.6213	58.7260	**18.5533**	**18.4670**	**2.6606**	61.7001	**22.3824**	**25.9821**	1.5248	**60.0415**	**19.9905**	**20.8306**
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)	**7.2129**	**67.4004**	**36.1417**	**30.8359**	5.8239	**68.6839**	**37.1359**	31.4482	**8.5465**	**69.7741**	40.0564	**34.0364**
P5-B (3-9)	3.5598	64.7683	34.0162	26.3184	6.5846	68.3067	37.0722	31.7545	7.7315	69.2266	39.7407	33.3348
P5-S (3-12)	5.8446	66.5976	35.5160	29.2766	5.3233	68.3174	36.8730	30.7071	8.2840	69.7158	**40.1340**	33.9770
P5-B (3-12)	4.6977	65.4562	34.9379	27.7223	**6.9169**	68.2195	36.9858	**32.1314**	7.2597	68.8920	39.5056	32.8794

Direct Recommendation:

Methods	Sports					Beauty					Toys				
	HR@1	HR@5	NDCG@5	HR@10	NDCG@10	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	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

RQ2: Zero-shot Generalization of P5 (Cont'd)

Part 2: Transfer to Items in New Domain

Example Zero-shot Prompts:

Prompt ID: Z-1

Input template: Given the facts about the new product, do you think user {{user_id}} will like or dislike it? title: {{item_title}} brand: {{brand}} price: {{price}}

Target template: {{answer_choices[label]}} (like/dislike) – like (4,5) / dislike (1,2,3)

Prompt ID: Z-6

Input template: Based on the word {{feature_word}}, help user_{{user_id}} write a {{star_rating}}-star explanation for this new product: title: {{item_title}} price: {{price}} brand: {{brand}}

Target template: {{explanation}}

RQ2: Zero-shot Generalization of P5 (Cont'd)

Part 2: Transfer to Items in New Domain

Table 8. Statistics on domain transfer evaluation sets.

Dataset	Sports	Beauty	Toys
#Users	290	439	487
#Items	381	586	886
#Reviews	478	1,237	1,183

Table 9. Performance on zero-shot domain transfer.

Directions	Z-1 & Z-4	Z-2 & Z-3	Z-5 & Z-7		Z-6	
	Accuracy	MAE	BLUE4	ROUGE1	BLUE4	ROUGE1
Toys -> ***Beauty***	0.7922	0.8244	1.8869	61.1919	5.4609	66.4931
Toys -> ***Sports***	0.8682	0.6644	0.7405	60.9575	2.2601	62.0353
Beauty -> ***Toys***	0.8073	0.7792	0.0929	41.3061	11.8046	64.8701
Beauty -> ***Sports***	0.8676	0.6838	0.0346	39.7191	6.6409	66.9222
Sports -> ***Toys***	0.8230	0.7443	0.0687	42.9310	13.3408	69.7910
Sports -> ***Beauty***	0.8057	0.8102	0.0790	41.0659	13.1690	66.7687

Concluion: P5 still **maintains sufficient performances for most tasks** such as rating prediction, like/dislike prediction, as well as explanation generation with feature word

RQ2: Zero-shot Generalization of P5 (Cont'd)

Toys -> Beauty

	Input	Output
Case 1	**Input**: Based on the word color , help user_4549 write a 5-star explanation for this new product : \n title : Bain De Terre Serum Anti-Frizz Recovery Complex 1.7 oz. \n price : 3.86 \n brand : Bain de Terre	**Target Output**: I have color treated fine hair but lots of it **P5's Output**: The colors are bright
Case 2	**Input**: Based on the word shampoo , help user_1491 write a 1-star explanation for this new product : \n title : CLEAR SCALP & HAIR BEAUTY Volumizing Root Boost Nourishing Shampoo, 12.9 Fluid Ounce \n price : 1.66 \n brand : Clear	**Target Output**: I tried the shampoo and it hardly foams up **P5's Output**: Not worth the price

Beauty -> Sports

	Input	Output
Case 3	**Input**: Based on the word tool , help user_3877 write a 5-star explanation for this new product : \n title : SOG Specialty Knives & Tools TF6-CP Trident Knife with Straight Edge Assisted Folding 3.75-Inch Steel Tanto Shape Blade and GRN Handle, Satin Finish \n price : 57.6 \n brand : SOG Specialty Knives	**Target Output**: this is an excellent tool **P5's Output**: This is a great tool tool
Case 4	**Input**: Based on the word saw , help user_326 write a 2-star explanation for this new product : \n title : Rome's #1705 Square Pie Iron with Steel and Wood Handles \n price : 20.26 \n brand : Rome Industries	**Target Output**: After looking closely we saw 2 of the rivots that are supposed to hold it on were missing **P5's Output**: I saw no visible improvement

Sports -> Toys

	Input	Output
Case 5	**Input**: Based on the word game , help user_29782 write a 3-star explanation for this new product : \n title : Deal Breaker Coaster Card Game \n price : 13.95 \n brand : Zobmondo!!	**Target Output**: I think this game could prove interesting if played while drinking **P5's Output**: I'm a big fan of this game and it is a great game
Case 6	**Input**: Based on the word cars , help user_2121 write a 5-star explanation for this new product : \n title : Ridemakerz Marvel Universe Spiderman and Venom Xtreme Customz Swap Set \n price : 14.89 \n brand : RIDEMAKERZ	**Target Output**: These are great looking little plastic cars **P5's Output**: I have several cars and this one is the best

Fig. 4. Example cases of zero-shot domain transfer on Z-6 task. We demonstrate three transfer directions: *Toys* to *Beauty*, *Beauty* to *Sports*, and *Sports* to *Toys*.

Concluion: P5 is able to catch different users' rating preferences and hint feature words, then integrate them with the knowledge learned from previous domain to **generate plausible explanations**

Conclusions

- **P5**: unifies different recommendation tasks into **a shared language modeling and natural language generation framework**
- **List of personalized prompts**: covers five recommendation task families **->** **all raw data are transferred to the same format**
- **P5 beats or achieves similar performances** with several **task-specific representative approaches**
- **P5 shows the generalization ability** on performing **zeroshot transfer to new items, new domains, and new personalized prompts**
- In the future, **P5** can be further **extended to more diverse modalities and personalized tasks**

Thanks for listening!