Towards Universal Sequence Representation Learning for Recommender Systems

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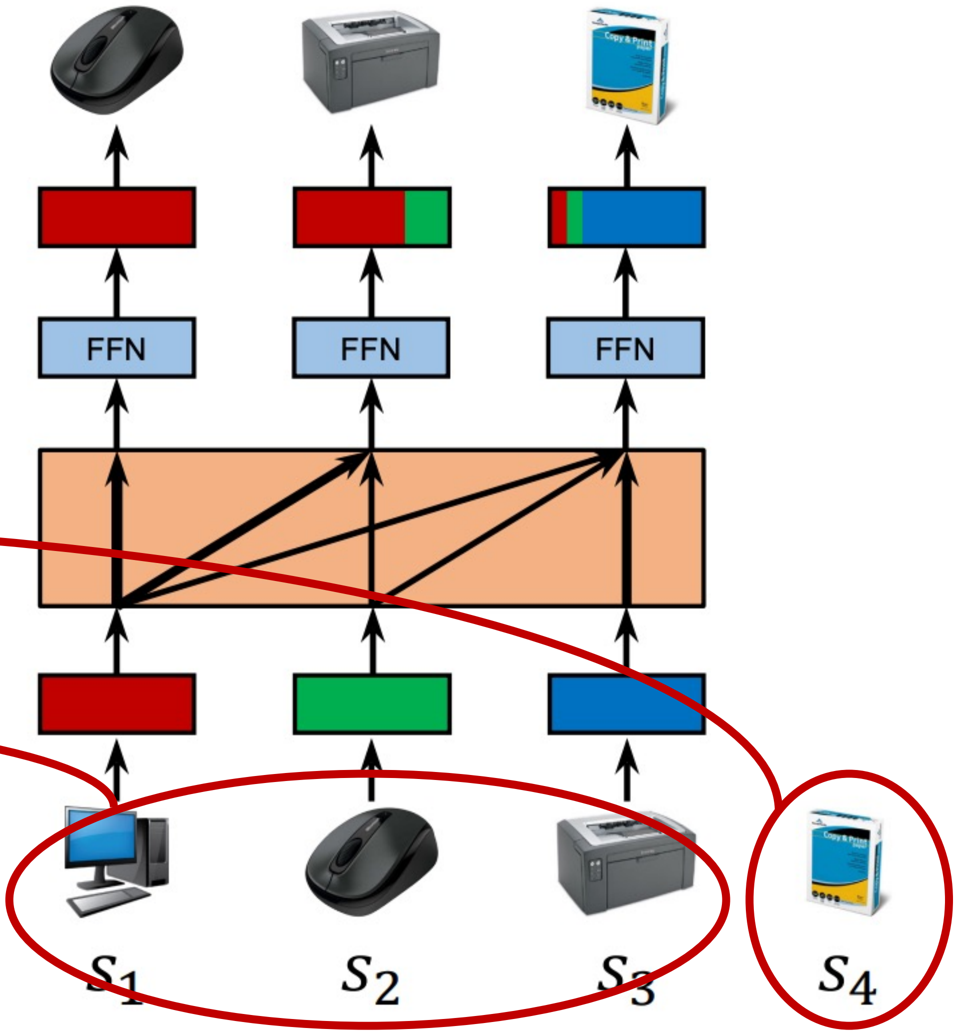
Motivation

- Sequential Recommendation

Next Item Prediction

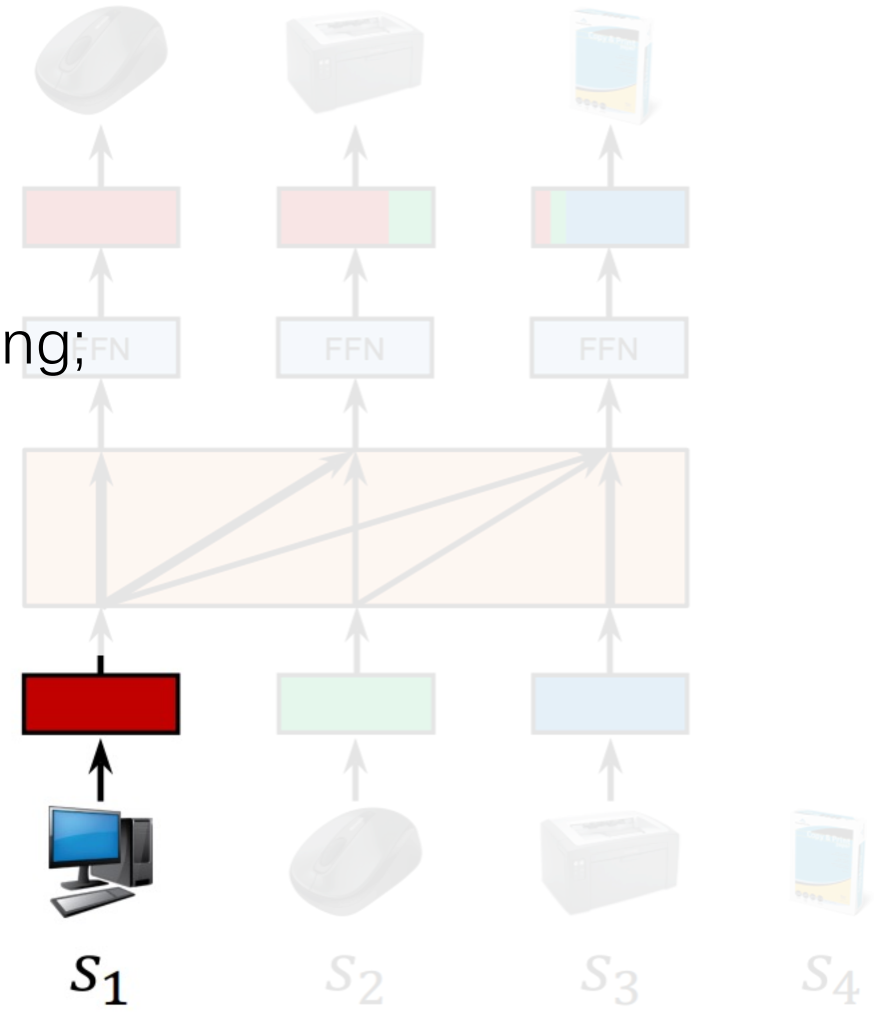
Historical Behavior Sequences



Kang and McAuley. Self-Attentive Sequential Recommendation. ICDM 2018.

Motivation

- Sequential Recommendation
  - Existing methods: explicit item ID modeling;



Sequence Model

ID Embedding

Item ID, B00TNNWMXI

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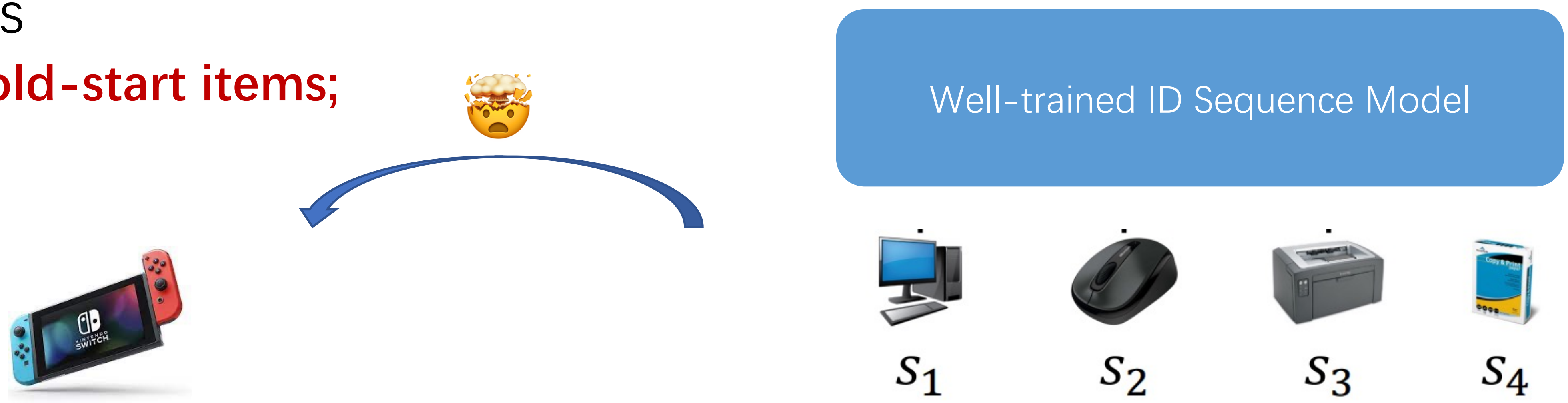
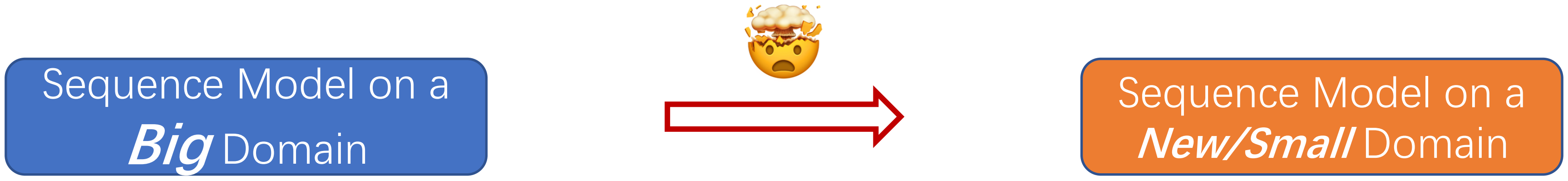
- Issues
  - **Cold-start items;**



New Item!

Motivation

- Sequential Recommendation
  - Existing methods: explicit item ID modeling;
- Issues
  - Cold-start items;
  - **New domains;**



Motivation

- Solution for small data: Transfer Learning
  - Foundation Models
    - Pre-training on large scale corpus;
    - Transfer to downstream tasks;

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- Can we build foundation models for RecSys? 🤔

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  - Foundation Models
    - Pre-training on large scale corpus;
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- Can we build foundation models for RecSys? 🤔
  - ✅ **Same data format;**

s_1 s_2 s_3 s_4

Motivation

- Solution for small data: Transfer Learning
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    - Pre-training on large scale corpus;
    - Transfer to downstream tasks;

- Can we build foundation models for RecSys? 🤔
  - ✅ Same data format;
  - ✅ **Large corpus;**

amazon HUAWEI

Motivation

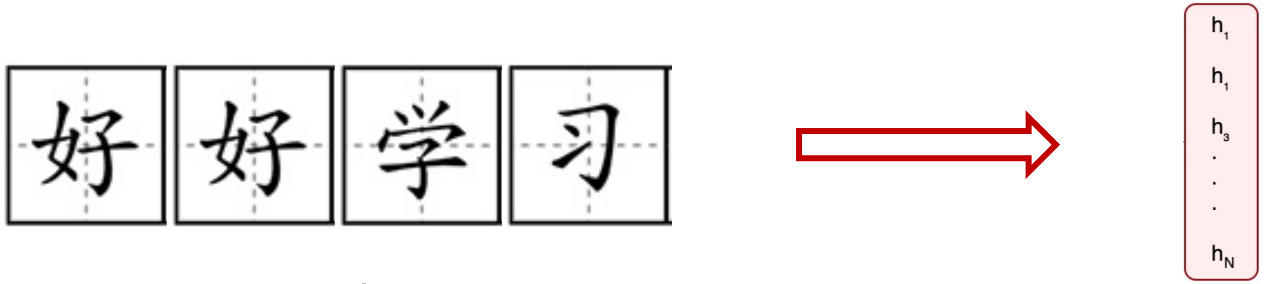
- Solution for small data: Transfer Learning
  - Foundation Models
    - Pre-training on large scale corpus;
    - Transfer to downstream tasks;

- Can we build foundation models for RecSys? 🤔
  - ✅ Same data format;
  - ✅ Large corpus;

  - ❌ **Different item ID dictionaries;**

Motivation

- Foundation Models for NLP (**Universal**)

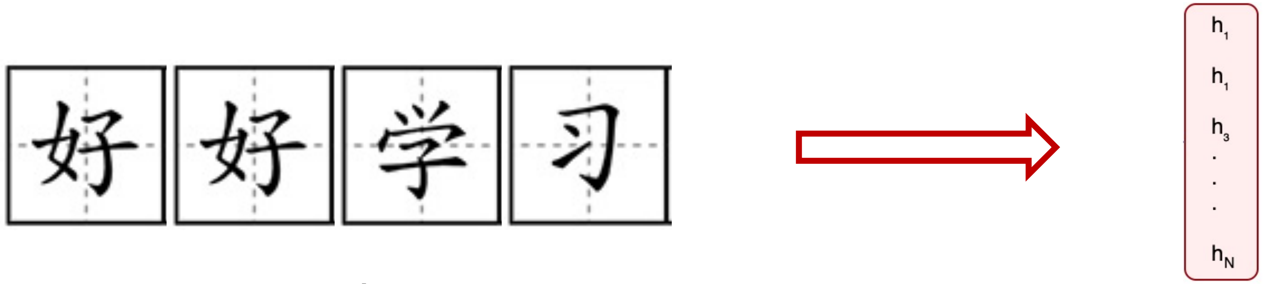


Word ID

Word Emb

Motivation

- Foundation Models for NLP (Universal)

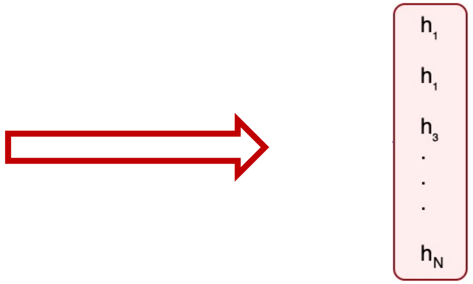


Word ID

Word Emb

- **Universal Sequence/Item Representations** for RecSys?

?



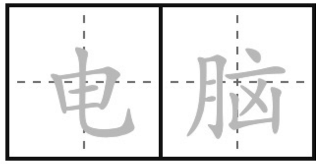
Item Emb

Sequence Emb

Idea

- **Universal Sequence/Item Representations** for RecSys?

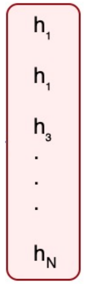
Item ID



Item Text

(natural language,

e.g., Title, Description, Brand, ……)



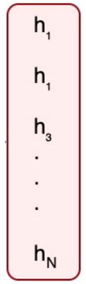
Item Emb

Sequence Emb

Idea

- Item text -> Transferable representations

- Challenges:

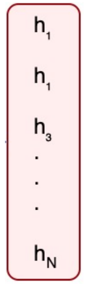


Textual representations **for Rec**?

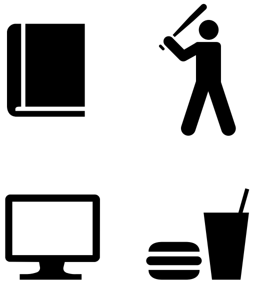
Idea

- Item text -> Transferable representations

- Challenges:

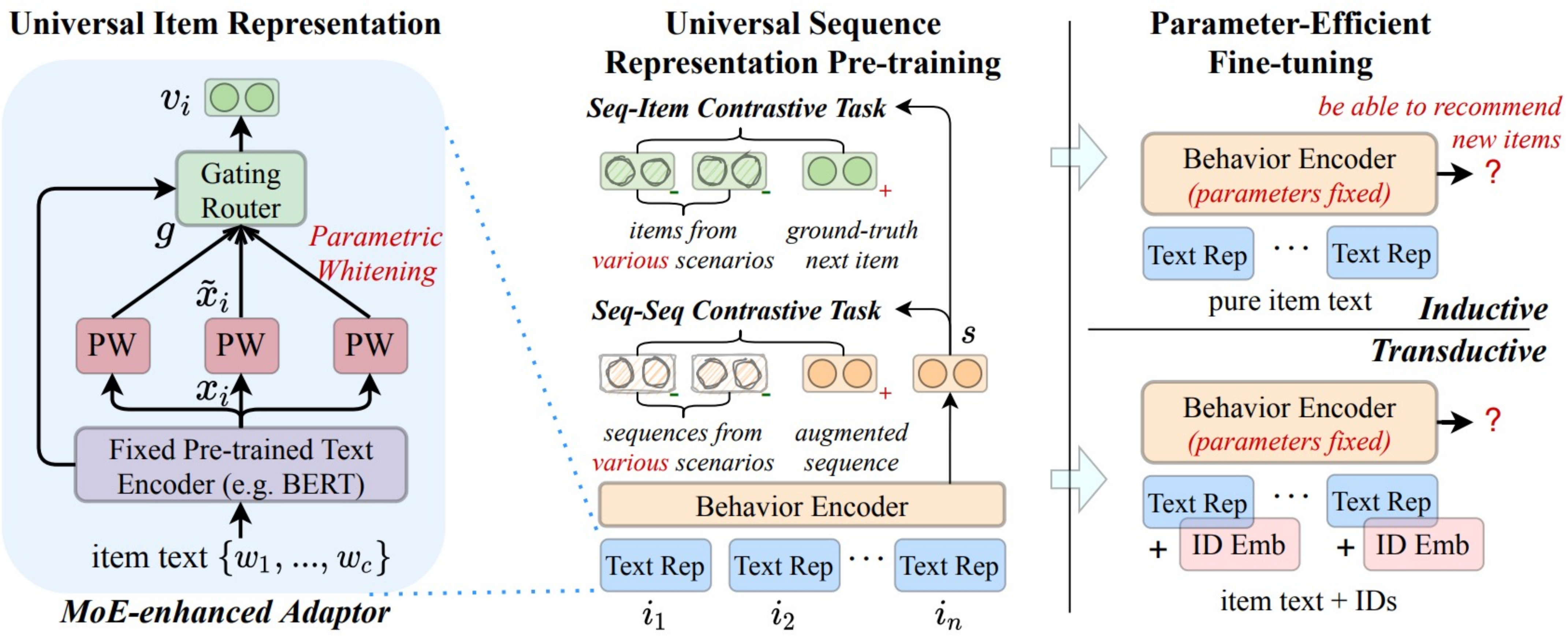


Textual representations **for Rec**?

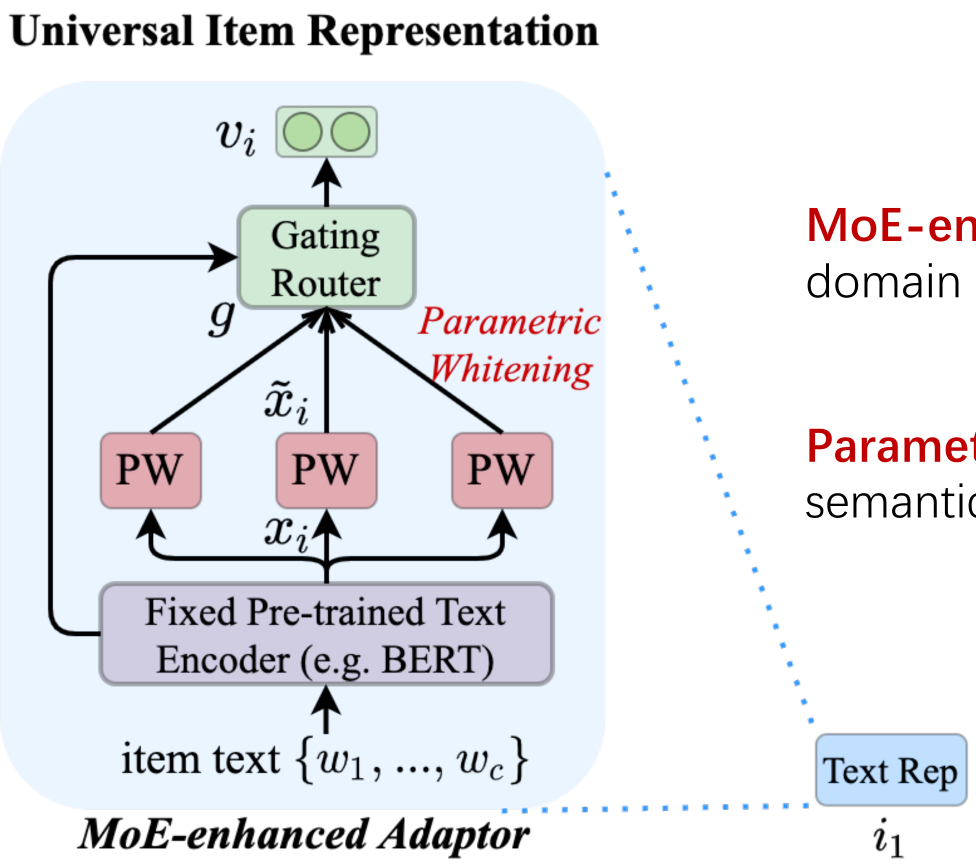


Learning from **multiple domains**?

UniSRec, universal sequence representation learning approach



UniSRec



MoE-enhanced Adaptor for domain fusion & adaptation

$$\boldsymbol{v}_i = \sum_{k=1}^{G} g_k \cdot \widetilde{\boldsymbol{x}}_i^{(k)},$$

Parametric Whitening for semantic transformation

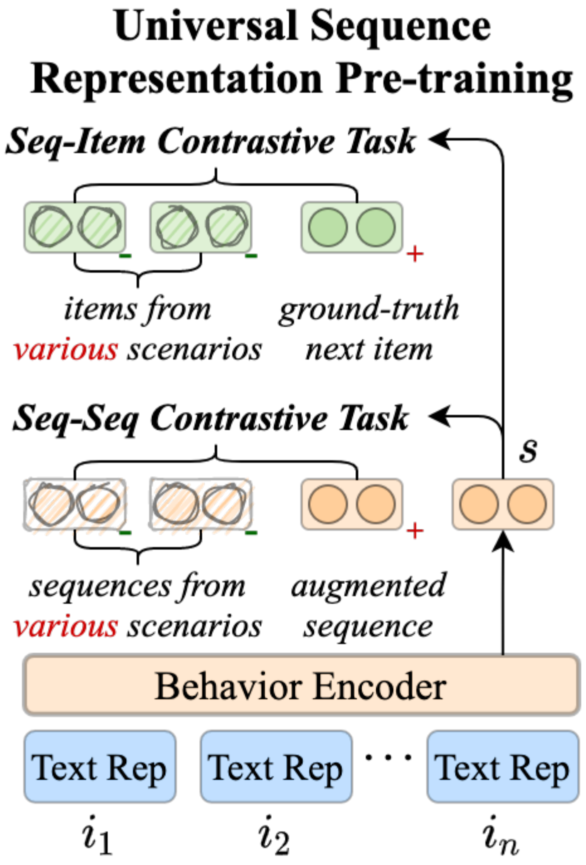
$$\widetilde{\boldsymbol{x}}_i = (\boldsymbol{x}_i - \boldsymbol{b}) \cdot \boldsymbol{W}_1,$$

UniSRec

Pre-training on multi-domain sequences

$$\ell_{S-I} = -\sum_{j=1}^{B} \log \frac{\exp\left(\boldsymbol{s}_j \cdot \boldsymbol{v}_j / \tau\right)}{\sum_{j'=1}^{B} \exp\left(\boldsymbol{s}_j \cdot \boxed{\boldsymbol{v}_{j'}} / \tau\right)},$$

$$\ell_{S-S} = -\sum_{j=1}^{B} \log \frac{\exp\left(\boldsymbol{s}_j \cdot \widetilde{\boldsymbol{s}}_j / \tau\right)}{\sum_{j'=1}^{B} \exp\left(\boldsymbol{s}_j \cdot \boxed{\boldsymbol{s}_{j'}} / \tau\right)}.$$

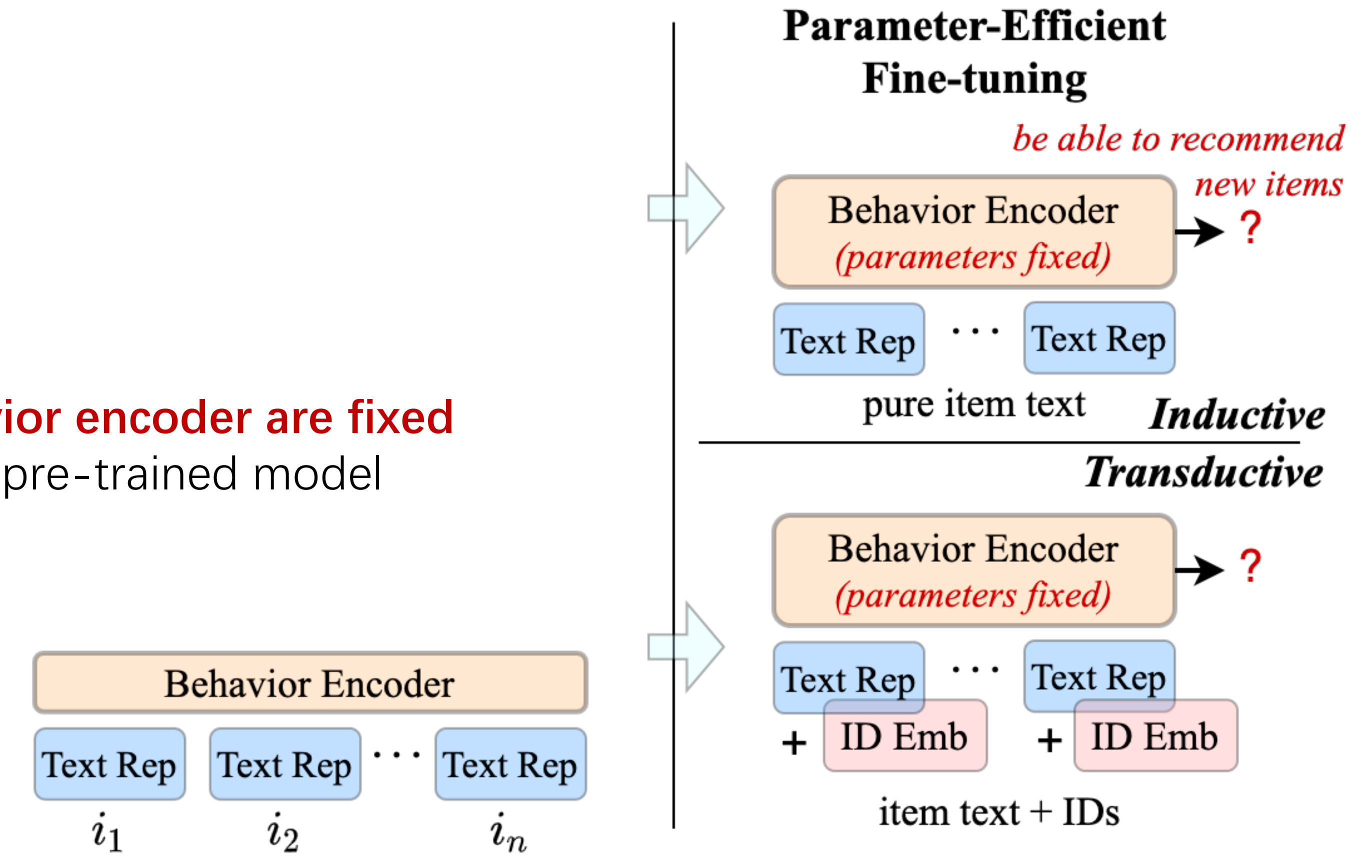


Sequence model
e.g., Transformer encoder

Negative samples from multiple domains
alleviate the seesaw phenomenon and capture their semantic correlation

UniSRec

Parameters in behavior encoder are fixed
while fine-tuning the pre-trained model



Experiments – Setting

One UniSRec model

Pre-trained on

Amazon:
Food, CDs, Kindle, Movies, Home

Fine-tuned to

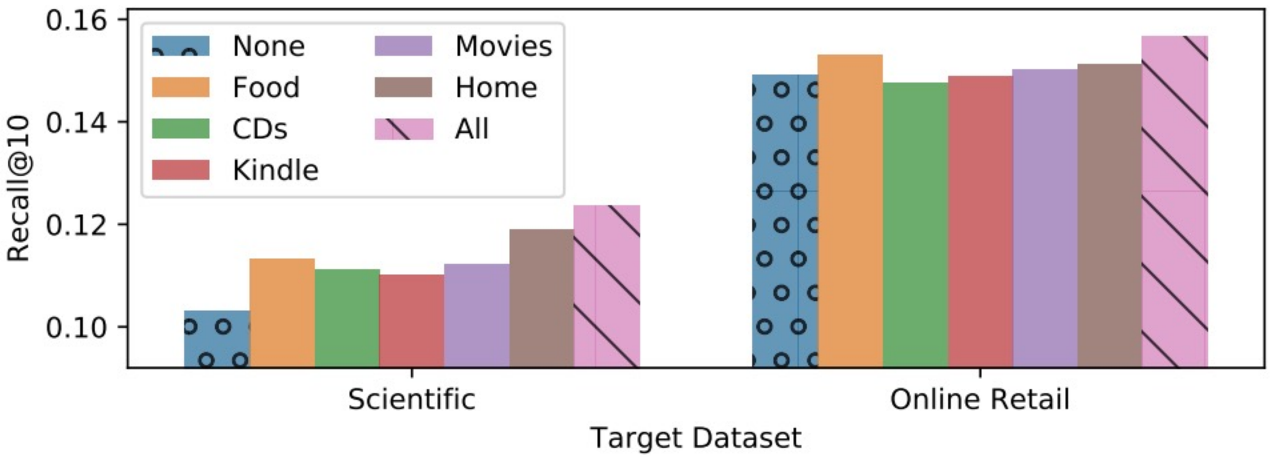
New domains
Scientific, Pantry, Instruments, Arts, Office

New platform
Online Retail in UK

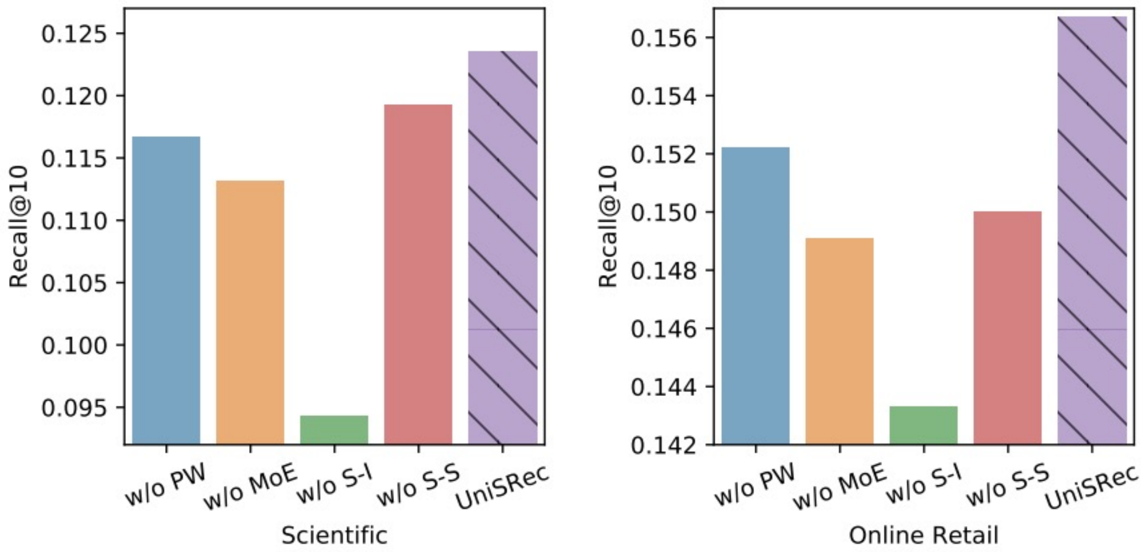
Experiments – Overall

Scenario	Dataset	Metric	SASRec	BERT4Rec	FDSA	S^3-Rec	CCDR	RecGURU	ZESRec	UniSRec$_t$	UniSRec$_{t+ID}$	Improv.
Cross-Domain	Scientific	Recall@10	0.1080	0.0488	0.0899	0.0525	0.0695	0.1023	0.0851	0.1188*	**0.1235***	+14.35%
		NDCG@10	0.0553	0.0243	0.0580	0.0275	0.0340	0.0572	0.0475	**0.0641***	0.0634*	+10.52%
		Recall@50	0.2042	0.1185	0.1732	0.1418	0.1647	0.2022	0.1746	0.2394*	**0.2473***	+21.11%
		NDCG@50	0.0760	0.0393	0.0759	0.0468	0.0546	0.0786	0.0670	0.0903*	**0.0904***	+15.01%
	Pantry	Recall@10	0.0501	0.0308	0.0395	0.0444	0.0408	0.0469	0.0454	0.0636*	**0.0693***	+38.32%
		NDCG@10	0.0218	0.0152	0.0209	0.0214	0.0203	0.0209	0.0230	0.0306*	**0.0311***	+35.22%
		Recall@50	0.1322	0.1030	0.1151	0.1315	0.1262	0.1269	0.1141	0.1658*	**0.1827***	+38.20%
		NDCG@50	0.0394	0.0305	0.0370	0.0400	0.0385	0.0379	0.0378	0.0527*	**0.0556***	+39.00%
	Instruments	Recall@10	0.1118	0.0813	0.1070	0.1056	0.0848	0.1113	0.0783	0.1189*	**0.1267***	+13.33%
		NDCG@10	0.0612	0.0620	**0.0796**	0.0713	0.0451	0.0681	0.0497	0.0680	0.0748*	–
		Recall@50	0.2106	0.1454	0.1890	0.1927	0.1753	0.2068	0.1387	0.2255*	**0.2387***	+13.34%
		NDCG@50	0.0826	0.0756	0.0972	0.0901	0.0647	0.0887	0.0627	0.0912	**0.0991***	+1.95%
	Arts	Recall@10	0.1108	0.0722	0.1002	0.1003	0.0671	0.1084	0.0664	0.1066	**0.1239***	+11.82%
		NDCG@10	0.0587	0.0479	**0.0714**	0.0601	0.0348	0.0651	0.0375	0.0586	0.0712	–
		Recall@50	0.2030	0.1367	0.1779	0.1888	0.1478	0.1979	0.1323	0.2049*	**0.2347***	+15.62%
		NDCG@50	0.0788	0.0619	0.0883	0.0793	0.0523	0.0845	0.0518	0.0799	**0.0955***	+8.15%
	Office	Recall@10	0.1056	0.0825	0.1118	0.1030	0.0549	0.1145	0.0641	0.1013	**0.1280***	+11.79%
		NDCG@10	0.0710	0.0634	**0.0868**	0.0653	0.0290	0.0768	0.0391	0.0619	0.0831	–
		Recall@50	0.1627	0.1227	0.1665	0.1613	0.1095	0.1757	0.1113	0.1702	**0.2016***	+14.74%
		NDCG@50	0.0835	0.0721	0.0987	0.0780	0.0409	0.0901	0.0493	0.0769	**0.0991**	+0.41%
Cross-Platform	Online Retail	Recall@10	0.1460	0.1349	0.1490	0.1418	0.1347	0.1467	0.1103	0.1449	**0.1537***	+3.15%
		NDCG@10	0.0675	0.0653	0.0719	0.0654	0.0620	0.0658	0.0535	0.0677	**0.0724**	+0.70%
		Recall@50	0.3872	0.3540	0.3802	0.3702	0.3587	**0.3885**	0.2750	0.3604	**0.3885**	0.00%
		NDCG@50	0.1201	0.1131	0.1223	0.1154	0.1108	0.1188	0.0896	0.1149	**0.1239***	+1.31%

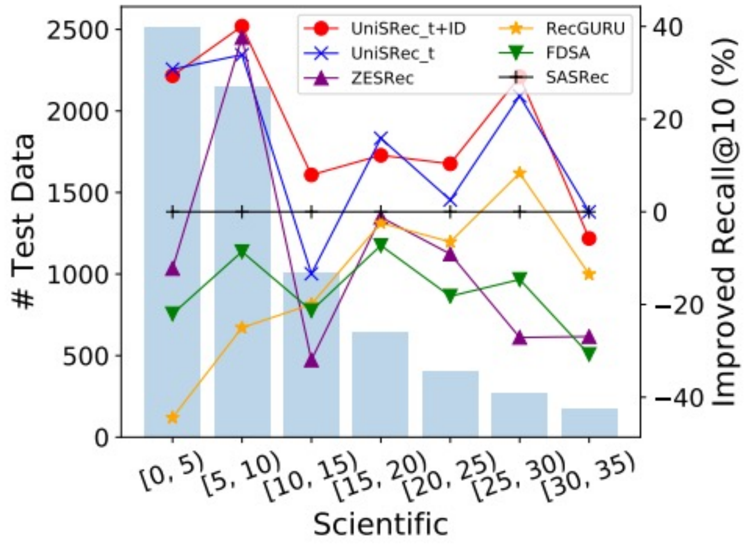
Experiments – Pre-trained datasets

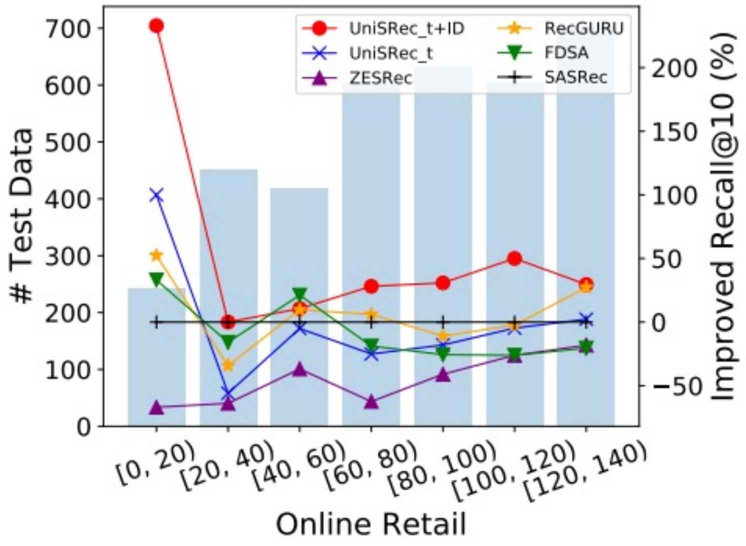


Experiments – Ablation study

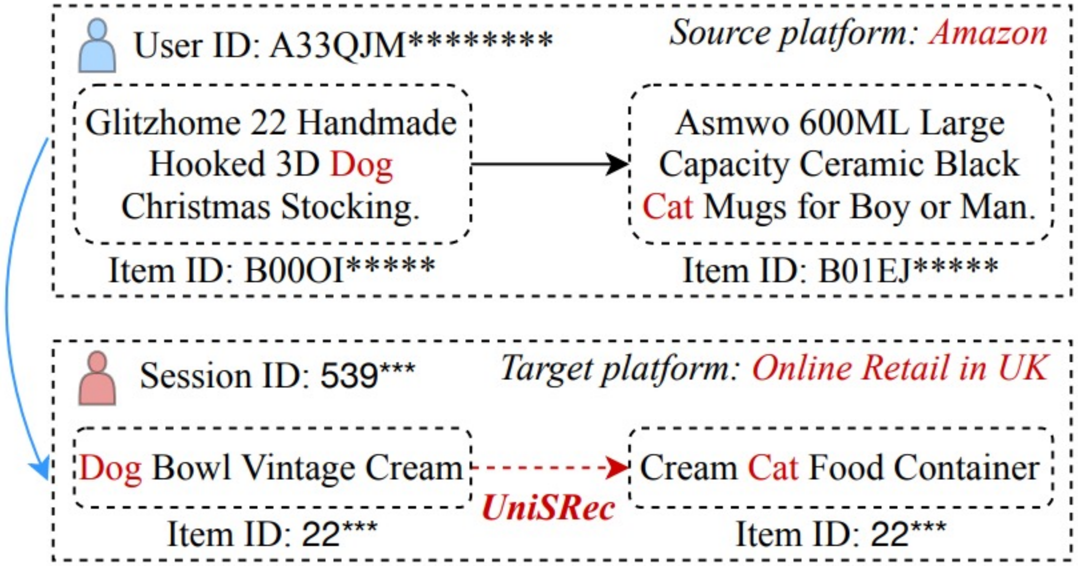


Experiments – Long-tail items





Experiments – Case study



Conclusion & QA

presented by Yupeng Hou, houyupeng@ruc.edu.cn

https://github.com/RUCAIBox/UniSRec

All implemented by RecBole

- Issues
  - **Cold-start items;**

New Item!

  - **New domains;**

Sequence Model on a *Big* Domain

Sequence Model on a *New/Small* Domain

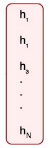
Well-trained ID Sequence Model

- **Universal Sequence/Item Representations** for RecSys?

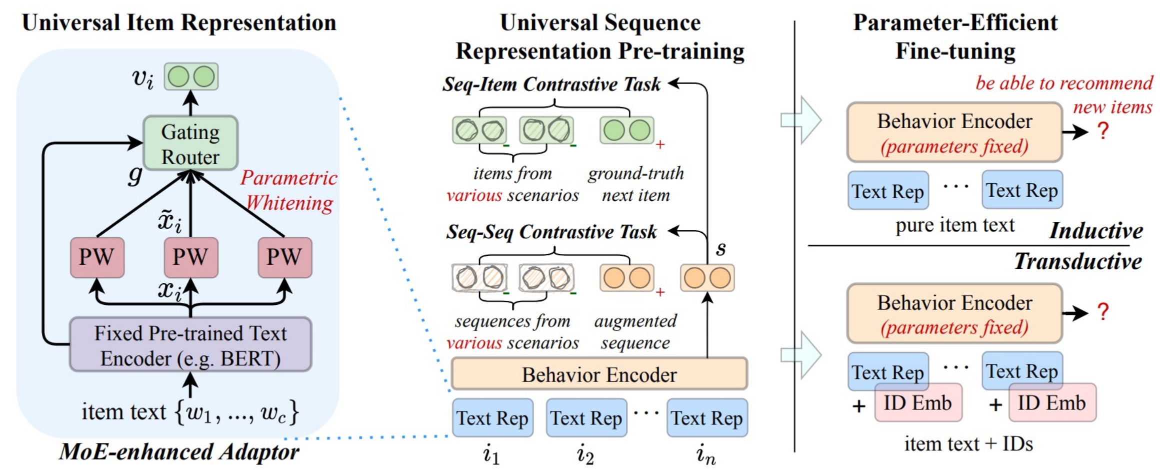
Item ID

电脑

Item Text
(natural language,
e.g., Title, Description, Brand, ……)



Item Emb
Sequence Emb



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