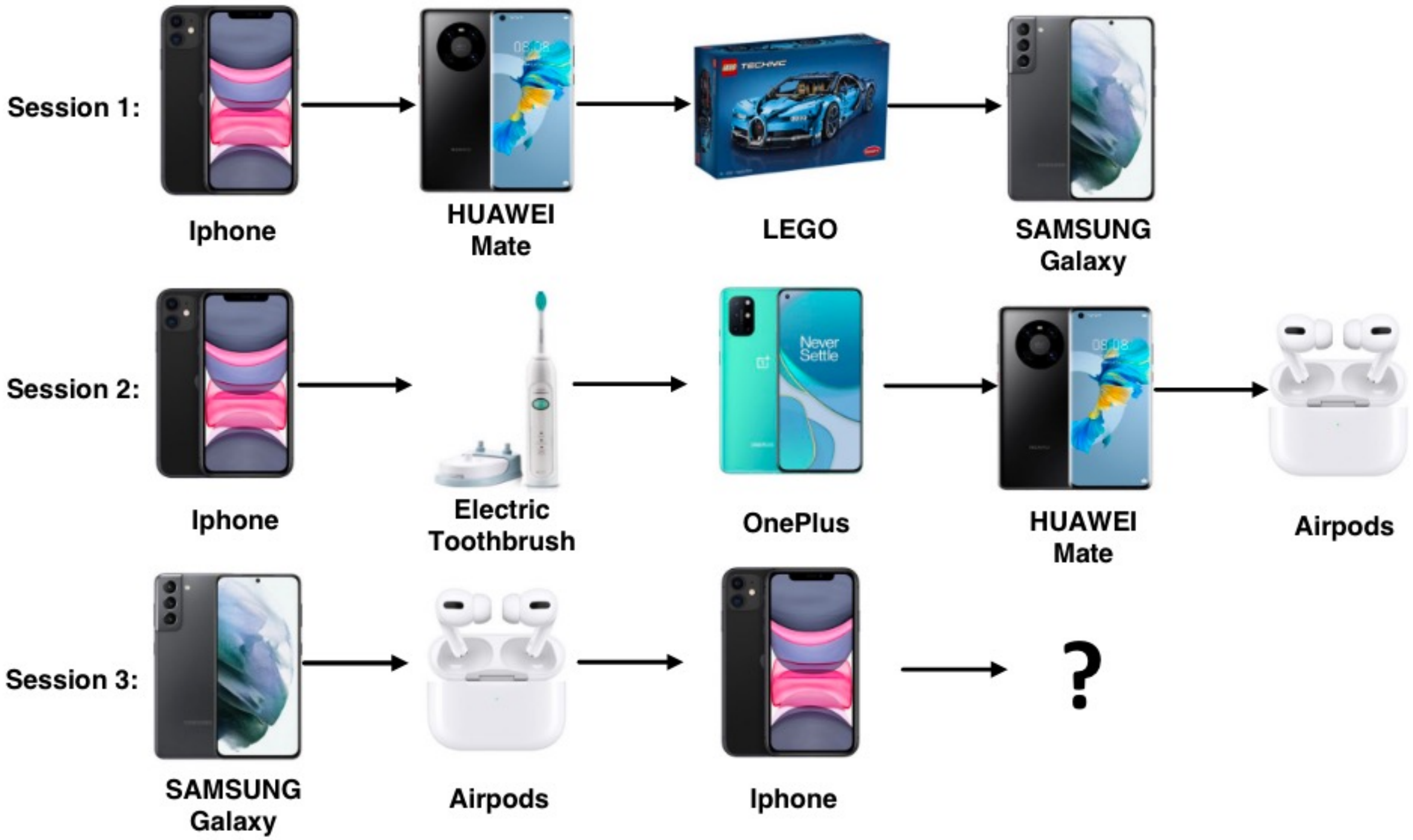
CORE:
Simple and Effective Session-based Recommendation within Consistent Representation Space

Yupeng Hou, Binbin Hu, Zhiqiang Zhang, Wayne Xin Zhao.

SIGIR 2022, short paper.

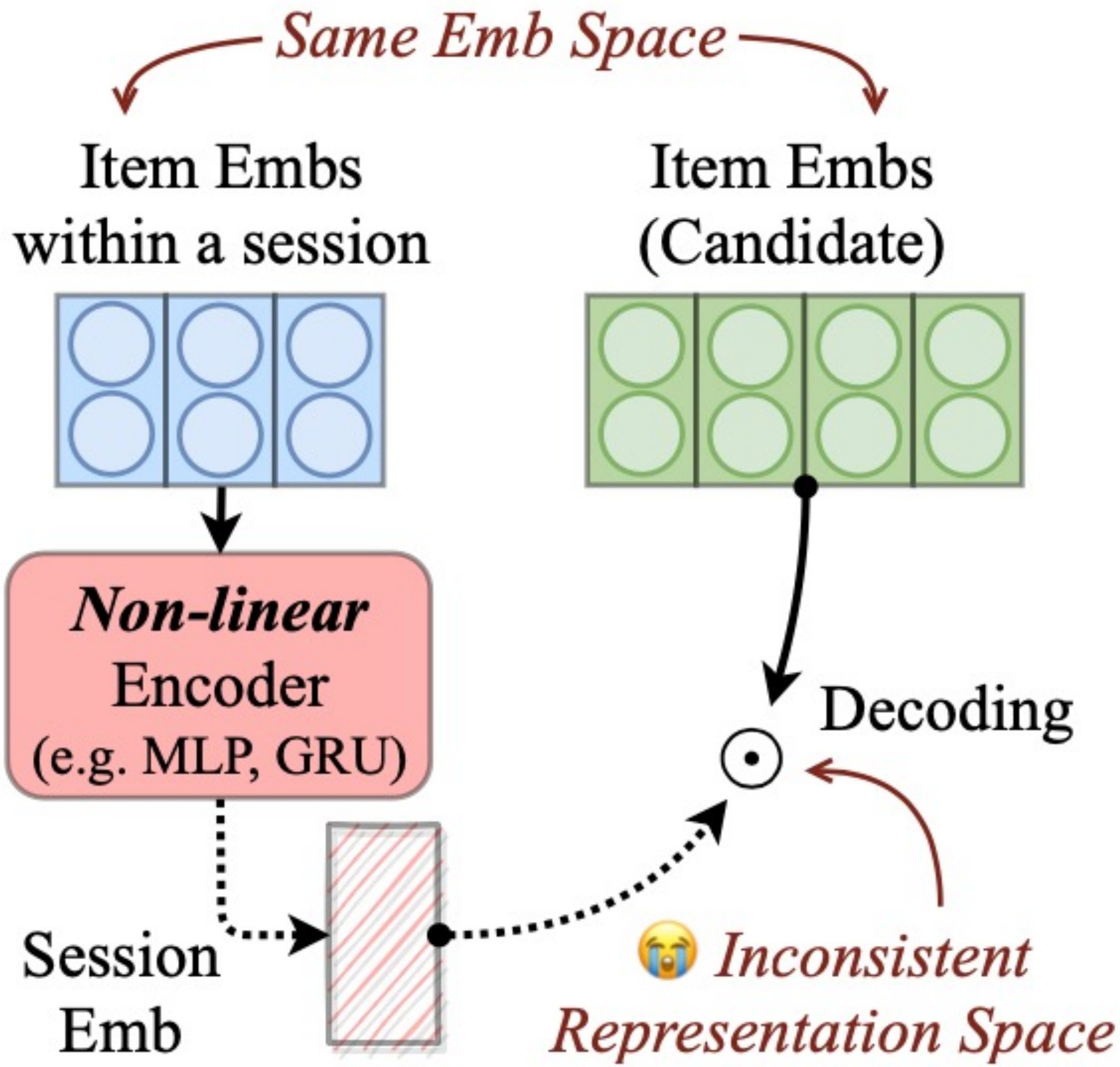
Background - Session-based Rec

- Next-item prediction;
- Anonymous sessions;
- Short-term Interest;



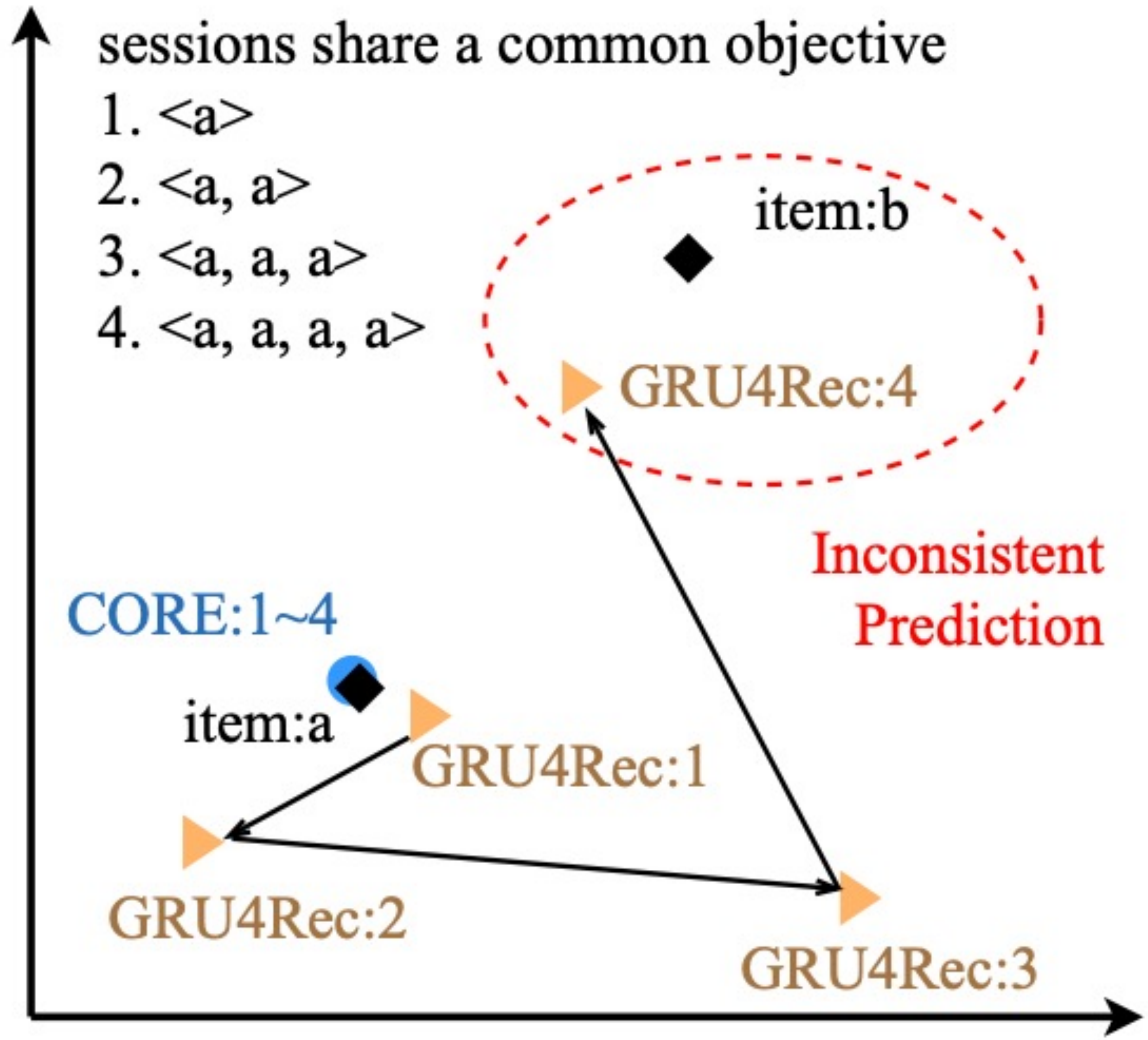
Observation

- Encoder-Decoder



Issue

- Inconsistent Prediction
- (a toy example)



Idea

- What if encoding-decoding in consistent representation space mandatorily? 🤔
- Basically, linear combination as encoder 💡

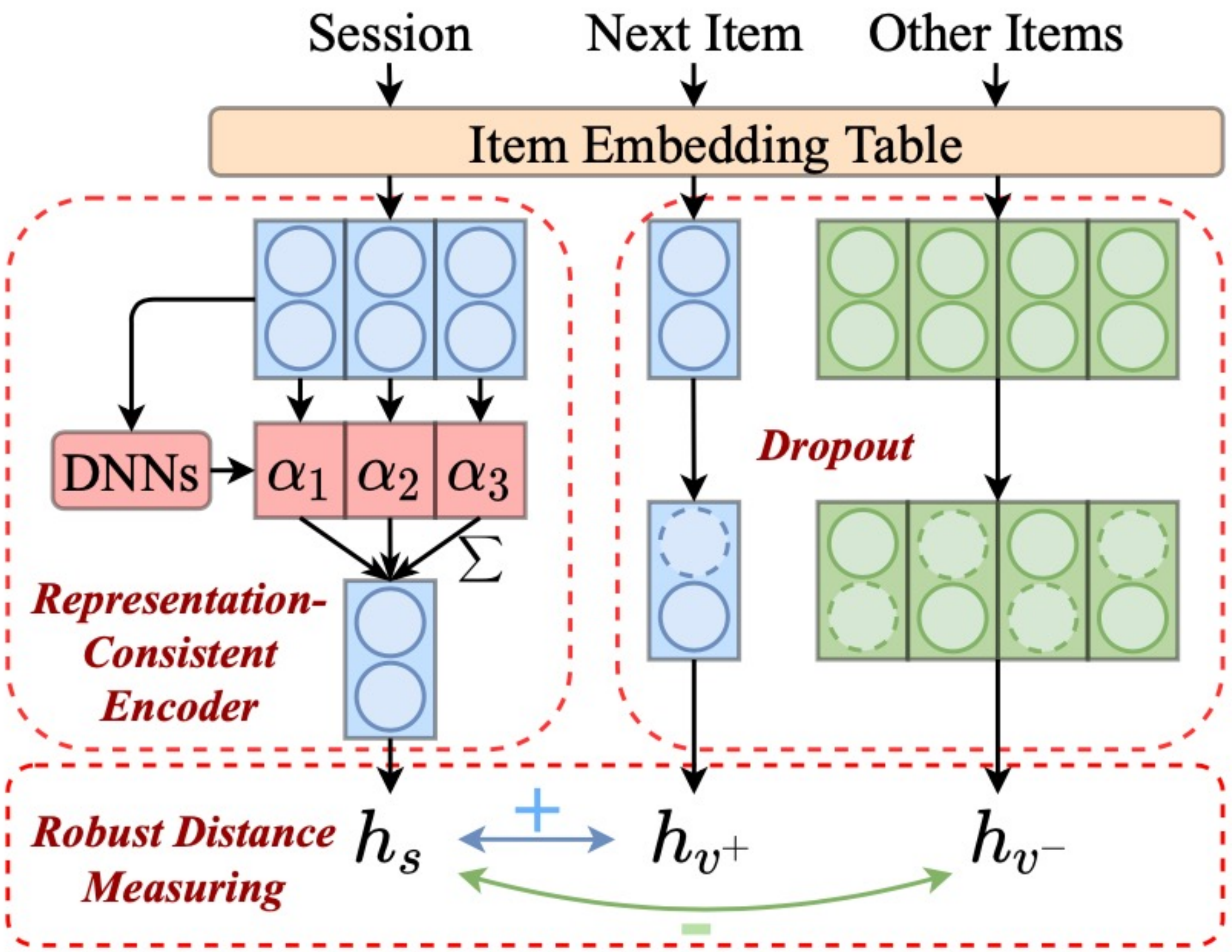
Challenge

- Strong power of DNNs + consistent representation space;

- Prevent overfitting of item embeddings;
  (in consistent representation space)

COnsistent REpresentation - RCE

(Representation-Consistent Encoder)



$$\boldsymbol{\alpha} = \mathrm{DNNs}([\boldsymbol{h}_{s,1}; \boldsymbol{h}_{s,2}; \ldots; \boldsymbol{h}_{s,n}])$$

$$\boldsymbol{h}_s = \sum_{i=1}^{n} \alpha_i \boldsymbol{h}_{s,i}.$$

DNNs can be:

- Pooling;
- Transformers;
- … …

COnsistent REpresentation - RDM

(Robust Distance Measuring)

- Traditional cross-entropy loss

$$\ell_{\text{ori}} = -\log \frac{\exp(\boldsymbol{h}_s \cdot \boldsymbol{h}_{v^+})}{\sum_{i=1}^{m} \exp(\boldsymbol{h}_s \cdot \boldsymbol{h}_{v_i})}$$

$$\propto \sum_{v^- \in \mathcal{V} \setminus \{v^+\}} \left(\|\boldsymbol{h}_s - \boldsymbol{h}_{v^+}\|^2 - \|\boldsymbol{h}_s - \boldsymbol{h}_{v^-}\|^2 + 2 \right).$$

$(N-1)$ –tuplet loss with L2-distance & fixed margin 2

COnsistent REpresentation - RDM

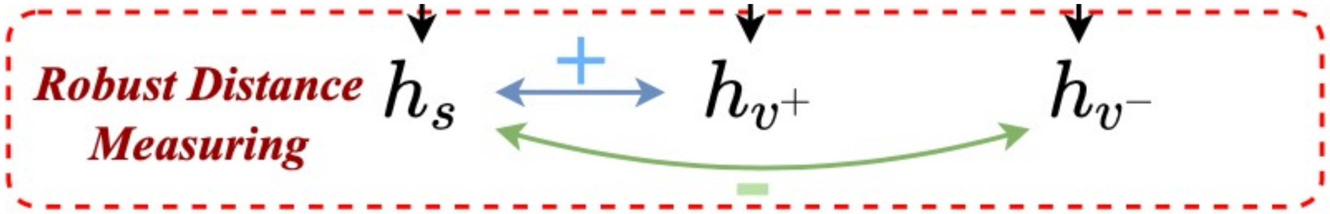
(Robust Distance Measuring)

$(N-1)$ −tuplet loss with L2-distance & fixed margin 2

Dropout & cosine distance & tunable margin τ

$$\ell = -\log \frac{\exp\left(\cos(\boldsymbol{h}_s, \boldsymbol{h}'_{v^+})/\tau\right)}{\sum_{i=1}^{m} \exp\left(\cos(\boldsymbol{h}_s, \boldsymbol{h}'_{v_i})/\tau\right)},$$

(contrastive learning)
Sessions <-> Next items



CORE experiments

RecBole

RecBole-GNN

- 5 widely-used public datasets

Dataset	# Interactions	# Items	# Sessions	Avg. Length
Diginetica	786,582	42,862	204,532	4.12
Nowplaying	1,085,410	59,593	145,612	9.21
RetailRocket	871,637	51,428	321,032	6.40
Tmall	427,797	37,367	66,909	10.62
Yoochoose	1,434,349	19,690	470,477	4.64

- Carefully hyper-parameter tuning for all baselines
- https://github.com/RUCAIBox/CORE

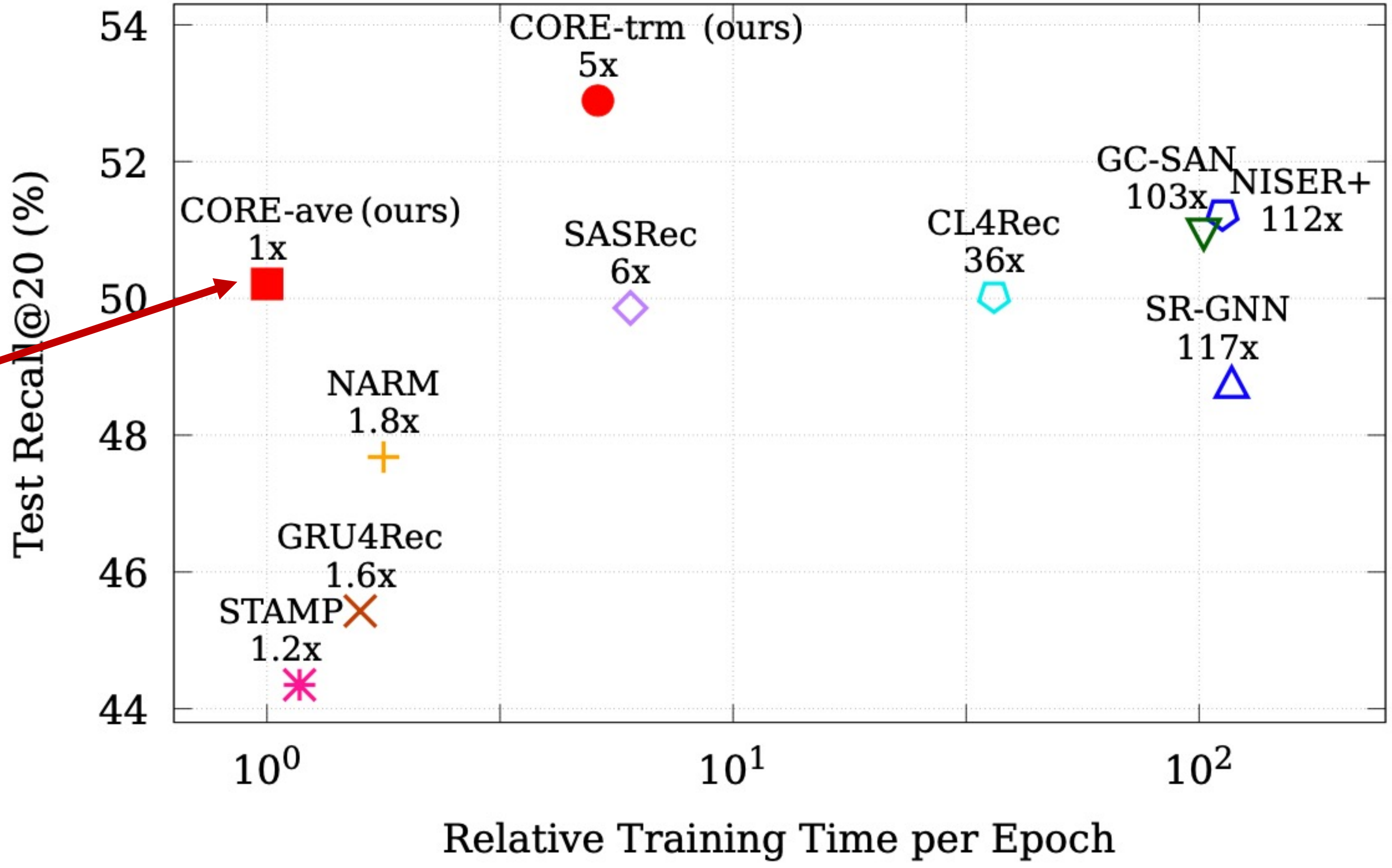
CORE experiments (1)

Dataset	Metric	FPMC	GRU4Rec	NARM	SR-GNN	NISER+	LESSR	SGNN-HN	SASRec	GC-SAN	CL4Rec	CORE-ave	CORE-trm	Improv.
Diginetica	R@20	31.83	45.43	47.68	48.76	<u>51.23</u>	48.80	50.89	49.86	50.95	50.03	50.21	**52.89***	+3.24%
	M@20	8.79	14.77	15.58	16.93	<u>18.32</u>	16.96	17.25	17.19	17.84	17.26	18.07	**18.58***	+1.42%
Nowplaying	R@20	10.18	13.80	14.17	15.28	16.55	17.60	16.75	<u>20.69</u>	18.30	20.59	20.31	**21.81***	+5.41%
	M@20	4.51	5.83	6.11	6.10	7.14	7.13	6.13	**8.14**	<u>8.13</u>	8.21	6.62	7.35	–
RetailRocket	R@20	46.04	55.32	58.65	58.71	<u>60.36</u>	56.22	58.82	59.81	60.18	59.69	59.18	**61.85***	+2.47%
	M@20	21.95	33.18	34.69	36.42	37.43	37.11	35.72	36.03	36.85	35.95	<u>37.52</u>*	**38.76***	+3.55%
Tmall	R@20	20.30	23.25	31.67	33.65	35.97	32.45	39.14	35.82	35.32	35.59	**44.67***	<u>44.48</u>*	+14.13%
	M@20	13.07	15.78	21.83	25.27	27.06	23.96	23.46	25.10	23.48	25.07	**31.85***	<u>31.72</u>*	+17.70%
Yoochoose	R@20	–	60.78	61.67	61.84	62.99	62.89	62.49	63.55	63.24	<u>63.61</u>	58.83	**64.61***	+1.57%
	M@20	–	27.27	27.82	28.15	<u>28.98</u>	28.59	28.24	28.63	**29.00**	28.73	25.05	28.24	–

CORE experiments (2)

- Efficiency

Variant with
only item embs



Conclusion

https://github.com/RUCAIBox/CORE