Where to Go Next for Recommender Systems? ID- vs. Modality-based Recommender Models Revisited

Zheng Yuan¹, Fajie Yuan¹, Yu Song¹, Youhua Li¹, Junchen Fu¹, Fei Yang², Yunzhu Pan¹, Yongxin Ni¹

¹Westlake University; ²Zhejiang Lab



Framework and Training Details

Experiments and Findings

Future Works



(1) Cold-start setting











Rethink the potential of MoRec



Rethink the potential of MoRec (1/4)



Rethink the potential of MoRec (1/4)



Q(i): Equipped with strong modality encoders, can MoRec be comparable to or even surpass IDRec in no-cold setting?

Rethink the potential of MoRec (2/4)



Rethink the potential of MoRec (2/4)



 $\mathsf{Q}(\mathsf{ii}):$ Can the recent technical advances developed in NLP and CV fields

translate into improvement in MoRec?

Rethink the potential of MoRec (3/4)



Rethink the potential of MoRec (3/4)



Q(iii): How can we effectively use the item modality representations derived from a pre-training NLP or CV encoder?

Rethink the potential of MoRec (4/4)



Rethink the potential of MoRec (4/4)



Q(iv): Several key challenges that remain unexplored for MoRec training.

Framework and Training Details

Experiments and Findings

Future Works

Framework



Illustration of IDRec vs MoRec.

Datasets and Loss Function



(a) Item cases on ImageNet1K.



(b) Item cases on HM.





(c) Item cases on Bili.

Item cases on datasets.

Image:

Datasets and Loss Function



(a) Item cases on ImageNet1K.









(c) Item cases on Bili.

Item cases on datasets.

$$\begin{array}{ll} \text{Binary cross entropy loss} \\ & \left\{ \begin{array}{l} \min - \sum_{u \in \mathcal{U}} \sum_{i \in [2, \dots, L]} \left\{ \log(\sigma(\hat{y}_{ui})) + \log(1 - \sigma(\hat{y}_{uj})) \right\} \right\} \\ & \left\{ \min - \sum_{< u, i, j > \in \mathcal{R}} \left\{ \log(\sigma(\hat{y}_{ui})) + \log(1 - \sigma(\hat{y}_{uj})) \right\} \right\} \\ \end{array} \right\} \\ \end{array}$$

Framework and Training Details

Experiments and Findings

Future Works



• Q(i): Equipped with strong modality encoders, can MoRec be comparable to or even surpass IDRec in no-cold setting?



• Q(i): Equipped with strong modality encoders, can MoRec be comparable to or even surpass IDRec in no-cold setting?

Dataset	Metrics	DSSM				Improv			
		IDRec	BERT _{base}	RoBERTa _{base}	IDRec	BERT _{small}	BERT _{base}	RoBERTa _{base}	
MINID	HR@10	3.58	2.68	3.07	17.71	18.50	18.23	18.68	+5.48%
WIIND	NDCG@10	1.69	1.21	1.35	9.52	9.94	9.73	10.02	+5.25%
		IDRec	ResNet50	Swin-T	IDRec	ResNet50	Swin-T	Swin-B	
ЦМ	HR@10	4.93	1.49	1.87	6.84	6.67	6.97	7.24	+5.85%
	NDCG@10	2.93	0.75	0.94	4.01	3.56	3.80	3.98	-0.75%
Bili	HR@10	1.14	0.38	0.57	3.03	2.93	3.18	3.28	+8.25%
	NDCG@10	0.56	0.18	0.27	1.63	1.45	1.59	1.66	+1.84%

MoRec vs IDRec (Regular Setting)



• Q(i): Equipped with strong modality encoders, can MoRec be comparable to or even surpass IDRec in no-cold setting?



Dataset	N	IIND	H	IM	Bili		
Dutubet	IDRec	BERT _{base}	IDRec	Swin-T	IDRec	Swin-T	
Warm-20	20.12	20.19	7.89	8.05	3.48	3.57	
Warm-50	20.65	20.89	8.88	8.83	4.04	4.02	
Warm-200	22.00	21.73	11.15	11.10	10.04	9.98	

MoRec vs IDRec (Warm Item Settings)



• Q(ii): Can the recent technical advances developed in NLP and CV fields translate into accuracy improvement in MoRec?



• Q(ii): Can the recent technical advances developed in NLP and CV fields translate into accuracy improvement in MoRec?



MaDaa



• Q(iii): How can we effectively use the item modality representations derived from an pre-training NLP or CV encoder?



• Q(iii): How can we effectively use the item modality representations derived from an pre-training NLP or CV encoder?

Dataset	IDRec	ME	TS		,	TS-DNN	ſ		E2E
				2	6	8	10	12	
MIND	17.71	BERT _{base}	13.93	15.20	16.26	<u>16.66</u>	16.32	16.14	18.23
HM	6.84	ResNet50 Swin-T	4.03 3.45	4.64 4.46	$\frac{5.40}{5.28}$	5.39 <u>5.55</u>	<u>5.40</u> 5.40	5.02 5.38	6.67 6.97
Bili	3.03	ResNet50 Swin-T	0.72 0.79	1.23 1.40	<u>1.62</u> 1.81	1.47 <u>2.10</u>	1.28 1.95	1.24 1.64	2.93 3.18

E2E vs TS with additional MLP layers



• Q(iv): Several key challenges that remain unexplored for MoRec training.

Q(iv):

• Q(iv): Several key challenges that remain unexplored for MoRec training.

Dataset	Method	#Param.	FLOPs	Time/E	MU	GPU
	IDRec	47M	0.12G	2.7m	3G	V100-32G(1)
MIND	BERT _{tiny}	11M	0.63G	10m	4G	V100-32G(1)
	BERT _{small}	35M	16G	42m	13G	V100-32G(1)
	BERT _{base}	116M	107G	102m	52G	V100-32G (2)
HM	IDRec	114M	1G	4.3m	5G	V100-32G(1)
	ResNet18	18M	40G	95m	23G	V100-32G(1)
	ResNet34	29M	81G	136m	30G	V100-32G(1)
	ResNet50	31M	91G	83m	80G	V100-32G (4)
	Swin-T	34M	96G	107m	157G	A100-40G (4)
	Swin-B	94M	333G	102m	308G	A100-40G (8)

The training cost of IDRec and End2end MoRec

• Q(iv): Several key challenges that remain unexplored for <u>MoRec training</u>

Dataset	ME		TS		E2E			
		w/o	$\mathbf{w}/$	Improv.	w/o	$\mathbf{w}/$	Improv.	
MIND	BERT _{base}	13.93	14.68	+5.38%	18.23	18.63	+2.19%	
HM	MAE _{base}	2.50	2.79	+11.60%	7.03	7.07	+0.57%	
Bili	MAE _{base}	0.57	0.57	0.00%	3.18	3.17	-0.31%	

Performing a second round of pre-training for ME



(a) MoRec with BERT_{base} on MIND.

(b) MoRec with Swin-T on HM.

• Q(iv): Several key challenges that remain unexplored for

Dataset	ME	DRec	TS	W	w/o		7/	Improv.
				ADD	CON	ADD	CON	
MIND	BERT _{base}	17.71	13.93	16.10	17.20	<u>17.66</u>	17.57	-0.28%
HM	Swin-T	6.84	3.45	<u>5.75</u>	4.89	5.37	5.40	-15.94%
Bili	Swin-T	3.03	0.79	3.01	2.61	<u>3.02</u>	2.86	-0.33%

	ID+TS-DNN						ID+E2E		
TS-DNN	w/o		w/		Improv.	E2E	w/o		Improv.
	ADD	CON	ADD	CON			ADD	CON	
16.66	14.93	16.58	17.29	17.55	-0.90%	18.23	16.25	17.12	-6.09%
5.55	5.27	4.00	4.77	5.11	-22.95%	6.97	5.40	4.95	-22.53%
2.10	2.86	2.35	2.50	2.72	-5.61%	3.18	<u>2.94</u>	2.55	-7.55%

co-training ID and modality.

Framework and Training Details

Experiments and Findings

Future Works



- 3. Improved networks;
- 4. Scale up training data
- 5. Large Language Models: ChatGPT, GPT4

Where to Go Next for Recommender Systems? ID- vs. Modality-based Recommender Models Revisited

Zheng Yuan¹, Fajie Yuan¹, Yu Song¹, Youhua Li¹, Junchen Fu¹, Fei Yang², Yunzhu Pan¹, Yongxin Ni¹

Q&A

