Learning to Warm Up Cold Item Embeddings for Cold-start Recommendation with Meta Scaling and Shifting Networks

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Motivation

Item Cold-start Problem

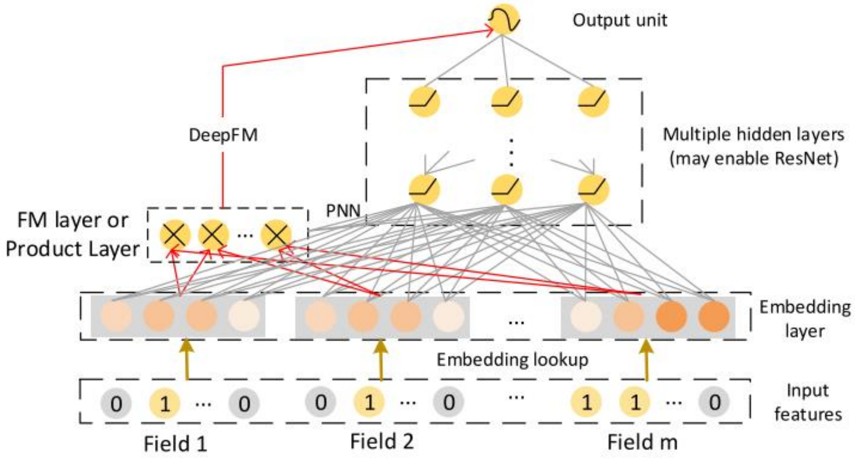
New item

How to recommend these new(cold-start) items to potential users?

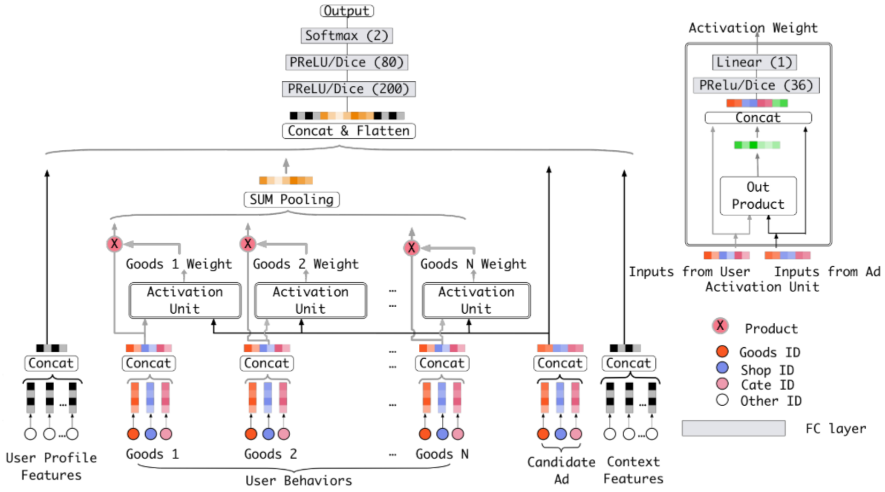
No History Data For Recommendation

Motivation

Embedding Technology



DeepFM



DIN

Deep recommendation models:

- Embedding layer
- Deep model

Item ID embedding is transformed from an item identifier (item ID).

Motivation

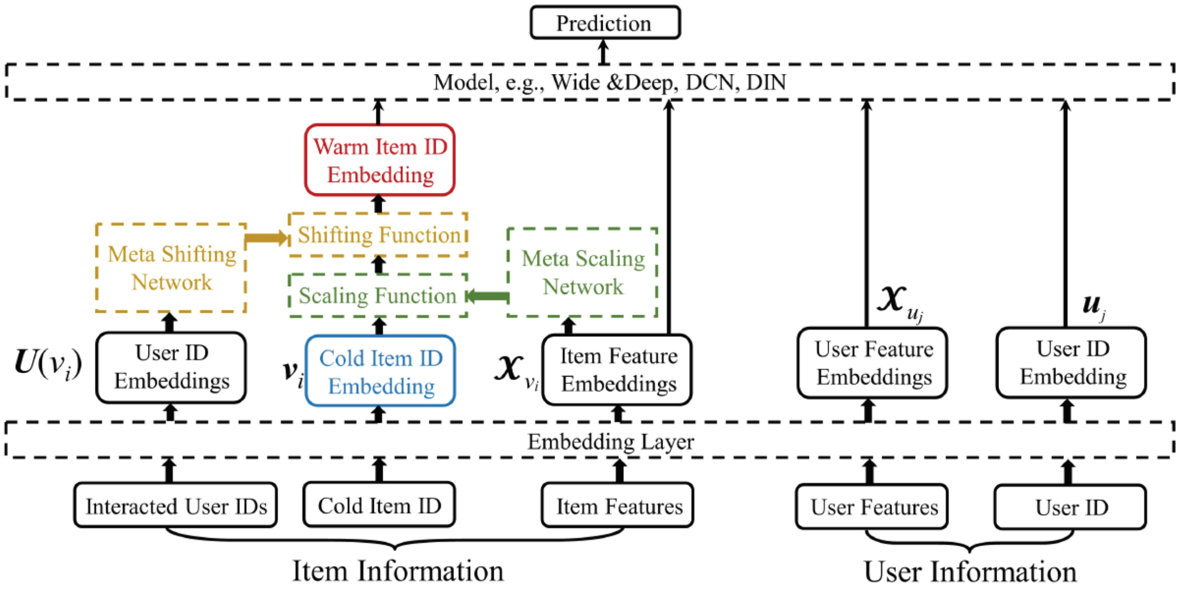
Challenges

- A gap is existing between the cold ID embedding and the deep model.
- The cold item ID embedding would be seriously influenced by noise.

Solution

- Fast adaptation (Meta Scaling Network)
- Alleviate the influence of noise (Meta Shifting Network)

Meta Warm Up Framework (MWUF)



- Common initialization
- Meta Scaling Network

$$\tau_{v_i}^{scale} = h(\mathcal{X}_{v_i}; w_{scale}),\ \tau^{scale} \in \mathbb{R}^k,$$

- Meta Shifting Network

$$\tau_{v_i}^{shift} = g(\mathcal{G}(U(v_i)); w_{shift}),\ \tau^{shift} \in \mathbb{R}^k,$$

Warm Embedding

$$v_i^{warm} = v_i \odot \tau_{v_i}^{scale} + \tau_{v_i}^{shift}$$

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Meta Warm Up Framework (MWUF)

Overall procedure

- Train the deep model and embedding layer
- Train two meta networks with the common initial embeddings

$$\hat{y}^{cold} = f(\hat{v}_i, \mathcal{X}_{v_i}, u_j, \mathcal{X}_{u_j}; \theta)$$

$$\hat{y}^{warm} = f(\hat{v}_i^{warm}, \mathcal{X}_{v_i}, u_j, \mathcal{X}_{u_j}; \theta)$$

$$\min_{\phi_{id}^{new}} \mathcal{L}^{cold}, \qquad \min_{w^{scale}, w^{shift}} \mathcal{L}^{warm}$$

Algorithm 1 Meta Warm Up Framework (MWUF).

Input: f_θ: A pre-trained model.
Input: $h_{w_{scale}}$, $g_{w_{shift}}$: Two meta networks.
Input: ϕ_{id}^{new}: An initialized item ID embedding layer.
Input: $\mathcal{D}$: A dataset sorted by timestamp.

(1) randomly initialize $h_{w_{scale}}$, $g_{w_{shift}}$.
(2) **while** not converge **do**:
(3) Sample batch of samples $\mathcal{B}$ from $\mathcal{D}$
(4) Obtain cold ID embeddings v of items in $\mathcal{B}$
(5) Obtain warm ID embeddings v^{warm} by Equation(5)
(6) Evaluate $\mathcal{L}^{cold}$ with v
(7) Update ϕ_{id}^{new} by minimizing $\mathcal{L}^{cold}$
(8) Evaluate $\mathcal{L}^{warm}$ with v^{warm}
(9) Update $h_{w_{scale}}$, $g_{w_{shift}}$ by minimizing $\mathcal{L}^{warm}$
(10) **end while**

Experiments

Datasets

- MovieLens-1M
- Taobao Display Ad Click
- CIKM2019 EComm AI

Metrics: AUC, RelaImpr

Baselines

- Popular CF methods: FM, Wide & Deep, PNN, DCN, AFN
- Cold-start methods: DropoutNet, MeLU, MetaEmb
- Sequential methods: GRU4Rec, DIN

Experiments

Research questions

- RQ1 How do different methods (popular CF models, sequential methods, cold-start methods) perform in the cold-start setting?
- RQ2 How does MWUF upon various deep recommendation models perform?
- RQ3 What are the effects of Initialization, Meta Scaling, and Meta Shifting Networks in our proposed MWUF?
- RQ4 Can the initialization methods (MetaEmb, MWUF) alleviate the cold-start problem?

Dataset splits

- Old items
- New items

Implementation Details

- Pre-train the base model with the data of old items.
- Train extra modules or initialize the new item ID.
- Compute evaluation metrics on the warm-a set; (**cold phase**)
- Update the embeddings of new items IDs with warm-a set and compute evaluation metrics on the warm-b set; (**warm-a phase**)
- Update the embeddings of new items IDs with warm-b set and compute evaluation metrics on the warm-c set; (**warm-b phase**)
- Update the embeddings of new items IDs with warm-c set and compute evaluation metrics on the test set; (**warm-c phase**)

Experiments

Results (RQ1)

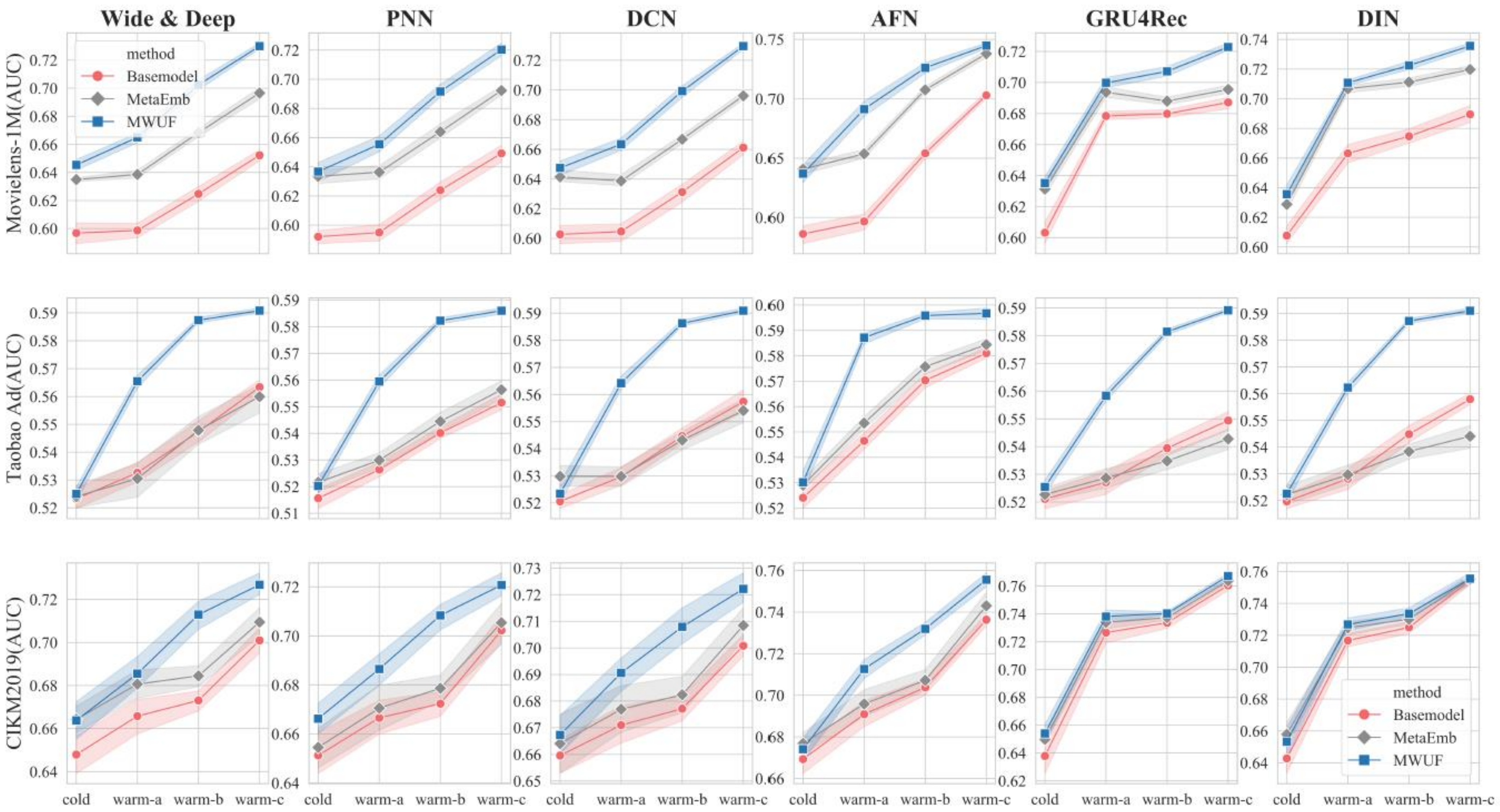
- The effectiveness of SOTA deep CF method.
- The effectiveness of various kinds of cold-start approaches.
- The effectiveness of sequential models.
- Recommendation performance on different phases.
- The effectiveness of MWUF.

Dataset	Methods	cold AUC	cold RelaImpr	warm-a AUC	warm-a RelaImpr	warm-b AUC	warm-b RelaImpr	warm-c AUC	warm-c RelaImpr
MovieLens-1M	FM	0.5250	-74.2%	0.5296	-70.0%	0.5406	-67.4%	0.5525	-65.5%
	Wide & Deep	0.5968	0.0%	0.5987	0.0%	0.6247	0.0%	0.6523	0.0%
	PNN	0.5920	-5.0%	0.5949	-3.9%	0.6240	-0.6%	0.6493	-2.0%
	DCN	0.6027	6.1%	0.6046	6.0%	0.6312	5.2%	0.6612	5.8%
	AFN	0.5862	-11.0%	0.5966	-2.1%	0.6541	23.6%	0.7029	33.2%
	DropoutNet	0.6432	47.9%	0.6499	51.9%	0.6565	25.5%	0.6628	6.9%
	MeLU	**0.6434**	**48.1%**	0.6400	41.8%	0.6643	31.8%	0.6760	15.6%
	MetaEmb	0.6369	41.4%	0.6349	36.7%	0.6686	35.2%	0.6983	30.2%
	GRU4Rec	0.6032	6.6%	0.6784	80.7%	0.6799	44.3%	0.6872	22.9%
	DIN	0.6077	11.3%	0.6632	65.3%	0.6747	40.1%	0.6895	24.4%
	MWUF(Wide & Deep)	0.6339	38.3%	0.6569	59.0%	0.6999	60.3%	0.7273	49.2%
	MWUF(GRU4Rec)	0.6298	34.1%	**0.6962***	**98.8%**	0.7033	63.0%	0.7160	41.8%
	MWUF(AFN)	0.6370	41.5%	0.6913	93.8%	**0.7261***	**81.3%**	**0.7447***	**60.7%**
Taobao Display AD	FM	0.5020	-91.4%	0.5064	-80.4%	0.5096	-79.7%	0.5126	-80.1%
	Wide & Deep	0.5233	0.0%	0.5326	0.0%	0.5474	0.0%	0.5634	0.0%
	PNN	0.5156	-33.0%	0.5264	-19.0%	0.5401	-15.4%	0.5515	-18.8%
	DCN	0.5206	-11.6%	0.5296	-9.2%	0.5446	-5.9%	0.5574	-9.5%
	AFN	0.5241	3.4%	0.5465	42.6%	0.5703	48.3%	0.5810	27.8%
	DropoutNet	0.5214	-8.2%	0.5318	-2.5%	0.5515	8.6%	0.5655	3.3%
	MeLU	0.5226	-3.0%	0.5223	-31.6%	0.5256	-46.0%	0.5360	-43.2%
	MetaEmb	0.5250	7.3%	0.5345	5.8%	0.5506	6.8%	0.5633	-0.2%
	GRU4Rec	0.5211	-9.4%	0.5271	-16.9%	0.5394	-16.9%	0.5494	-22.1%
	DIN	0.5197	-15.5%	0.5281	-13.8%	0.5448	-5.5%	0.5580	-8.5%
	MWUF(Wide & Deep)	0.5255	9.4%	0.5718	120.2%	0.5890	87.8%	0.5919	45.0%
	MWUF(GRU4Rec)	0.5208	-10.7%	0.5626	92.0%	0.5842	77.6%	0.5867	36.8%
	MWUF(AFN)	**0.5302**	**29.6%**	**0.5872***	**167.5%**	**0.5958***	**102.1%**	**0.5965***	**45.3%**
CIKM2019	FM	0.5386	-73.9%	0.5420	-74.7%	0.5510	-70.5%	0.5598	-70.2%
	Wide & Deep	0.6479	0.0%	0.6657	0.0%	0.6730	0.0%	0.7010	0.0%
	PNN	0.6512	2.2%	0.6665	0.5%	0.6723	-0.4%	0.7022	0.6%
	DCN	0.6596	7.9%	0.6710	3.2%	0.6771	2.4%	0.7008	-0.1%
	AFN	0.6693	14.5%	0.6909	15.2%	0.7038	17.8%	0.7363	17.6%
	DropoutNet	0.6555	5.1%	0.6719	3.7%	0.6854	7.2%	0.6980	-1.5%
	MeLU	0.6595	7.8%	0.6697	2.4%	0.6762	1.8%	0.7032	1.1%
	MetaEmb	0.6642	11.0%	0.6746	5.4%	0.6795	3.8%	0.7095	4.2%
	GRU4Rec	0.6378	-6.8%	0.7266	36.8%	0.7337	35.1%	0.7635	31.1%
	DIN	0.6428	-3.4%	0.7168	30.8%	0.7250	30.1%	0.7545	26.6%
	MWUF(Wide & Deep)	0.6637	10.7%	0.6855	11.9%	0.7097	21.2%	0.7236	11.2%
	MWUF(GRU4Rec)	0.6540	4.1%	**0.7381***	**43.7%**	**0.7404**	**39.0%**	**0.7672**	**32.9%**
	MWUF(AFN)	**0.6741**	**17.7%**	0.7126	28.3%	0.7320	34.1%	0.7556	27.2%

Experiments

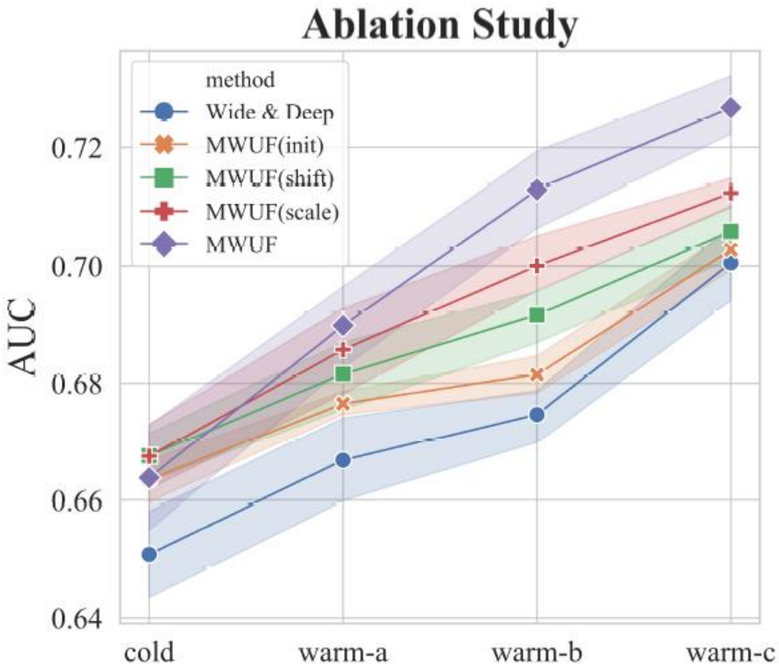
Generalization Experiments (RQ2)

- Compatibility.
- The effectiveness of MWUF.

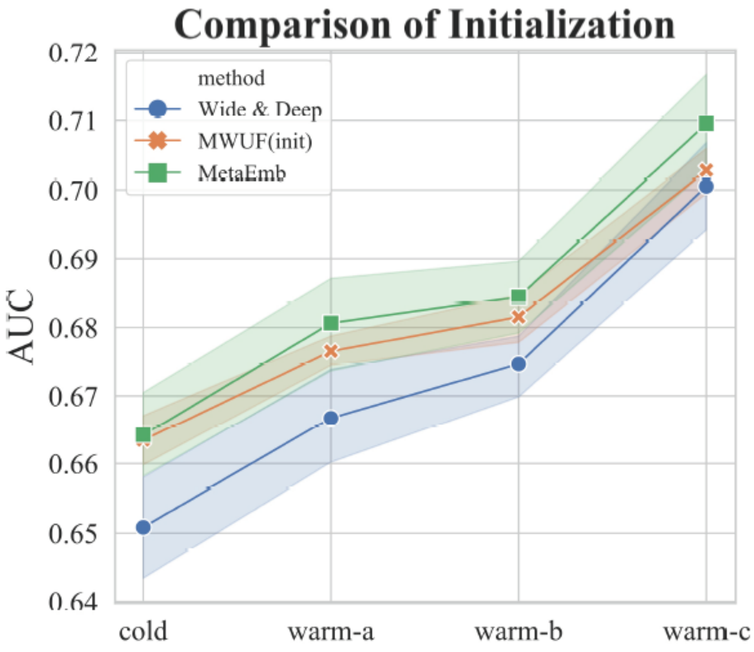


Experiments

Ablation Study (RQ3)



Comparison of Initialization (RQ4)



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Thanks Q & A

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