MTNet: A Neural Approach for Cross-Domain Recommendation with Unstructured Text

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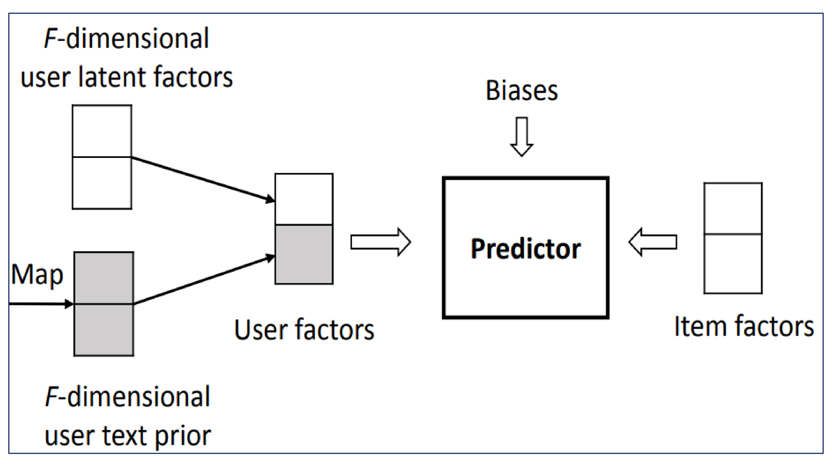
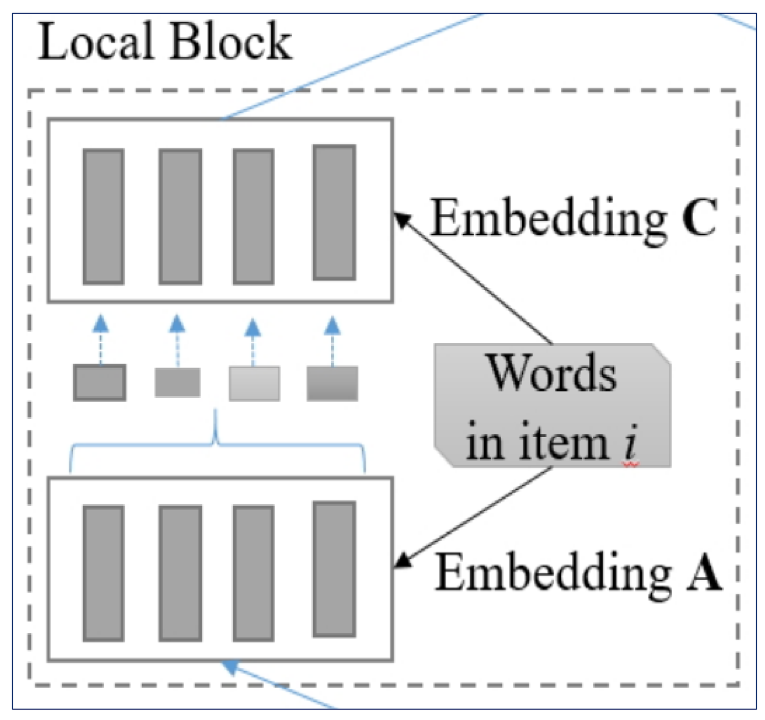
1 Motivation

Two threads to alleviate the sparsity in collaborative filtering:

- Hybrid filtering methods integrate the content information, e.g. product reviews and news titles.

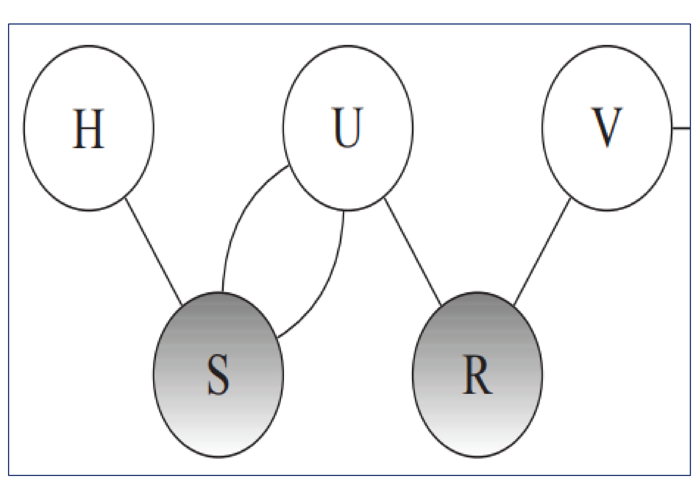


TBPR, Hu et al, PAKDD'17

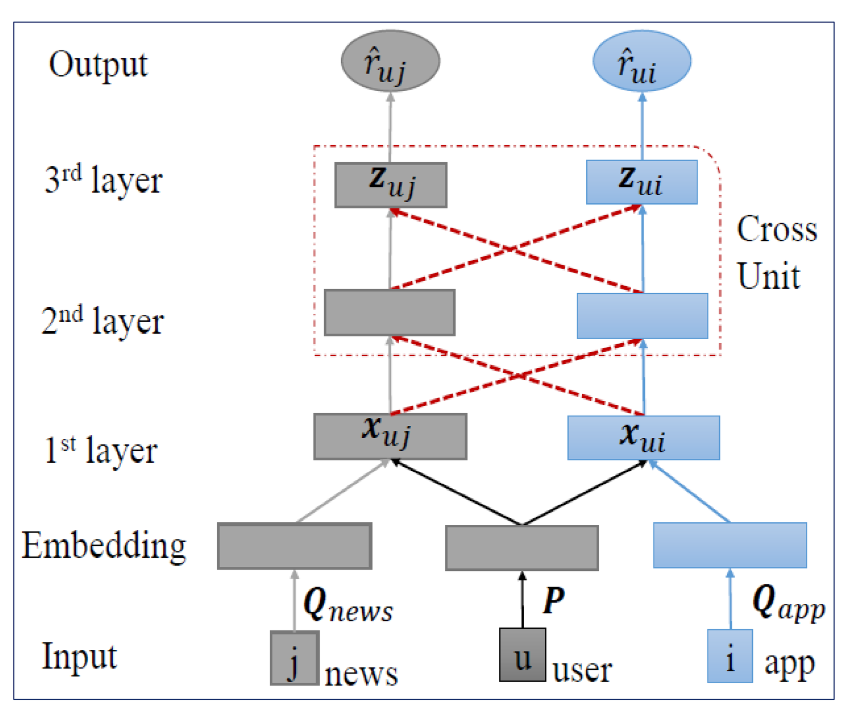


LCMR, Hu et al, arXiv'18

- Cross-domain methods leverage the knowledge from a related domain, e.g. from App to News



eSMF, Hu et al, IJCAI'15



CoNet, Hu et al, CIKM'18

2 MTNet: Memory and Transfer Networks

We propose a novel neural model, MTNet ("M" for memory and "T" for transfer), for cross-domain recommendation with unstructured text.

Contributions

- The proposed model can alleviate the sparsity issue including cold-user and cold-item start.
- The proposed model outperforms various baselines on two real-world datasets under three ranking metrics.

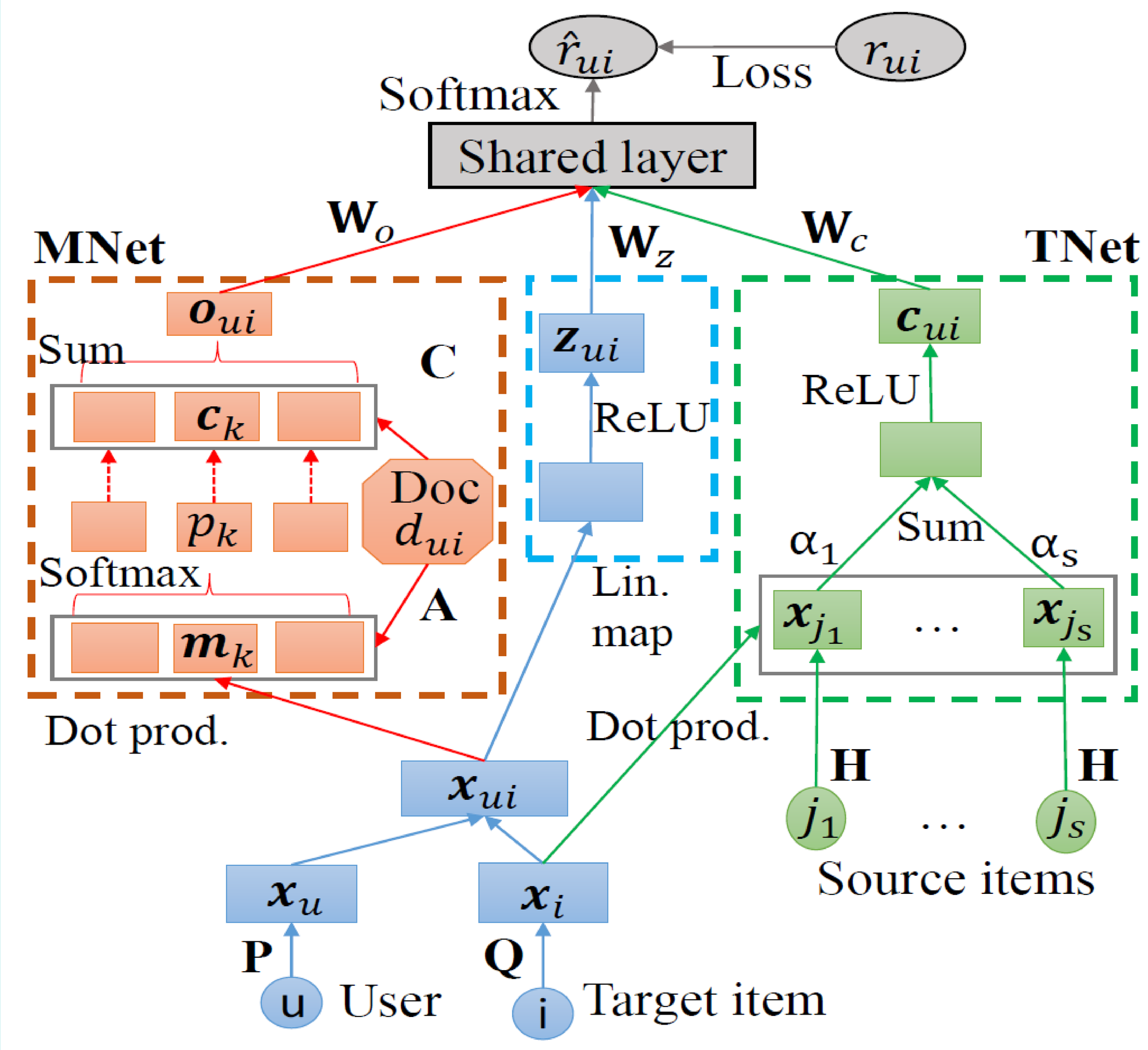
Components

- MNet can learn high-level representations of unstructured text with respect to the given user-item interaction.
- TNet can selectively transfer knowledge via learning adaptive weights over source items.

Baselines	Shallow method	Deep method
Single-Domain	BPRMF	MLP
Cross-Domain	CDCF, CMF	MLP++, CSN
Hybrid	HFT, TextBPR	LCMR
Cross + Hybrid	CDCF++	MTNet (ours)

2 MTNet: Memory and Transfer Networks (cont.)

Architecture



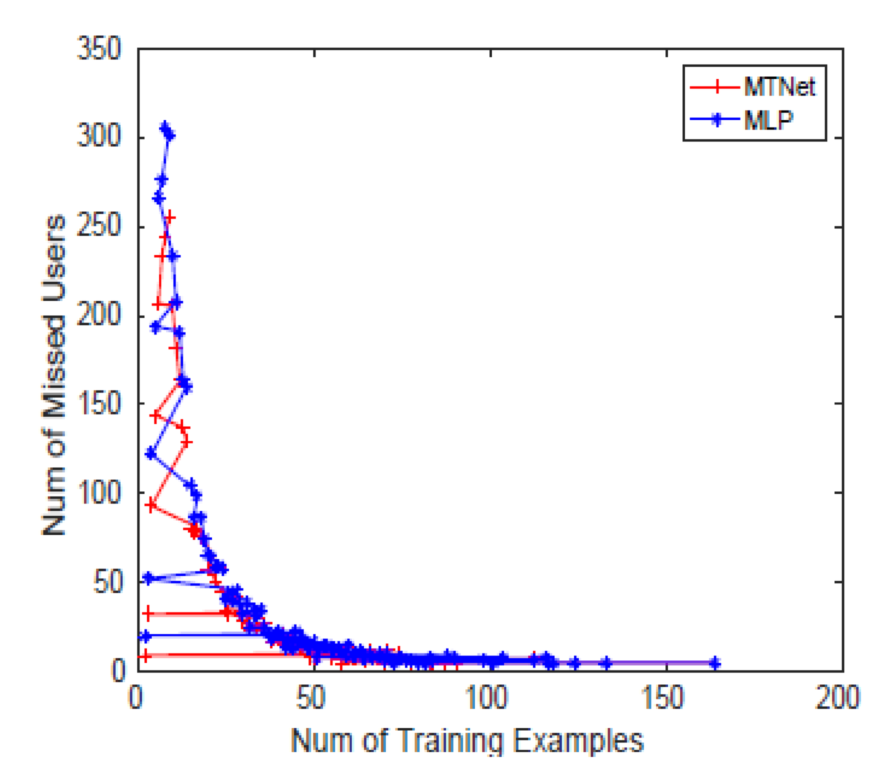
$$\hat{r}_{ui} = \frac{1}{1+\exp(-\boldsymbol{h}^T \boldsymbol{y}_{ui})}$$

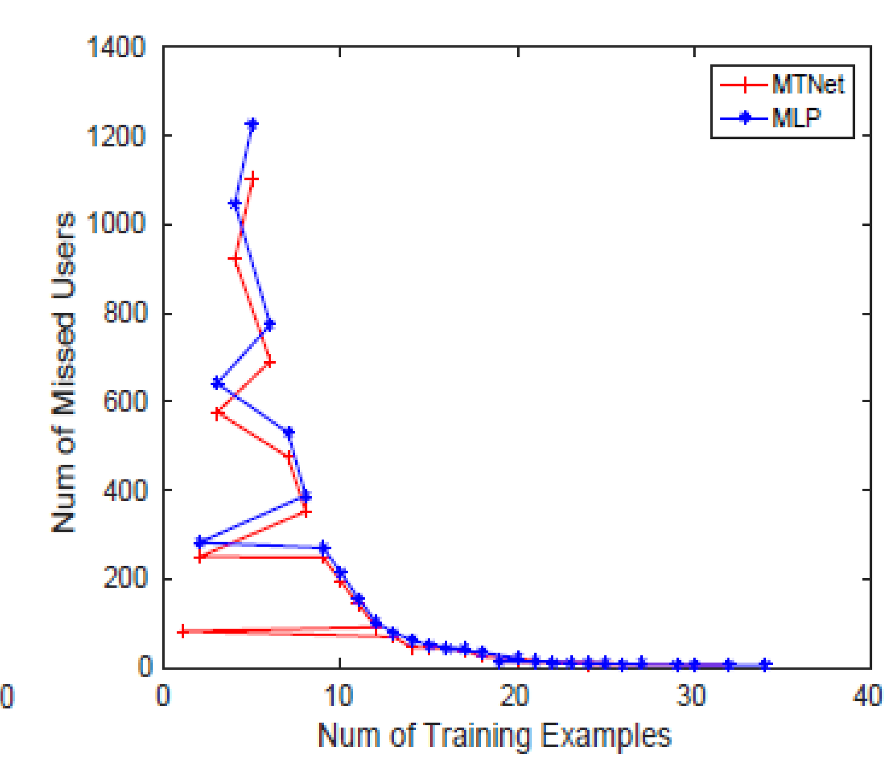
$$\boldsymbol{y}_{ui} = [\boldsymbol{W}_o \boldsymbol{o}_{ui}, \boldsymbol{W}_z \boldsymbol{z}_{ui}, \boldsymbol{W}_c \boldsymbol{c}_{ui}].$$

$$a_j^{(i)} = \boldsymbol{x}_i^T \boldsymbol{x}_j$$

3 Experiments

Method	topK = 5 HR	NDCG	MRR	topK = 10 HR	NDCG	MRR	topK = 20 HR	NDCG	MRR
BPRMF	.0810	.0583	.0509	.1204	.0710	.0561	.1821	.0864	.0602
CDCF	.1295	.0920	.0797	.2070	.1167	.0897	.3841	.1609	.1015
CMF	.1498	.0950	.0771	.2224	.1182	.0863	.3573	.1521	.0957
HFT	.1077	.0815	.0729	.1360	.0907	.0767	.2782	.1252	.0854
TextBPR	.1517	.1208	.1104	.1777	.1291	.1138	.2268	.1414	.1171
CDCF++	.1314	.0926	.0800	.2102	.1177	.0901	.3822	.1605	.1016
MLP	.2100	.1486	.1283	.2836	.1697	.1371	.3820	.1899	.1426
MLP++	.2263	.1626	.1417	.2992	.1862	.1514	.3810	.2069	.1570
CSN	.2340*	.1680*	.1462*	.3018*	.1898*	.1552*	.3944*	.2091*	.1605*
LCMR	.2024	.1451	.1263	.2836	.1678	.1356	.3951	.1918	.1420
MTNet	**.2575**	**.1796**	**.1550**	**.3490**	**.2077**	**.1666**	**.4443**	**.2311**	**.1727**
Improvement of MTNet	10.04%	6.90%	6.01%	15.63%	9.43%	7.34%	12.65%	10.52%	7.60%





Dataset	Domain	Statistics	Amount
Mobile News	Shared	#Users	15,890
	Target	#News	84,802
		#Reads	477,685
		Density	0.035%
		#Words	612,839
		Avg. Words Per News	7.2
	Source	#Apps	14,340
		#Installations	817,120
		Density	0.359%
Amazon Men	Shared	#Users	8,514
	Target	#Clothes (Men)	28,262
		#Ratings/#Reviews	56,050
		Density	0.023%
		#Words	1,845,387
		Avg. Words Per Review	32.9
	Source	#Products (Sports)	41,317
		#Ratings/#Reviews	81,924
		Density	0.023%

$$HR = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \delta(p_u \le topK)$$

$$NDCG = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \frac{\log 2}{\log(p_u + 1)},$$

$$MRR = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \frac{1}{p_u}.$$