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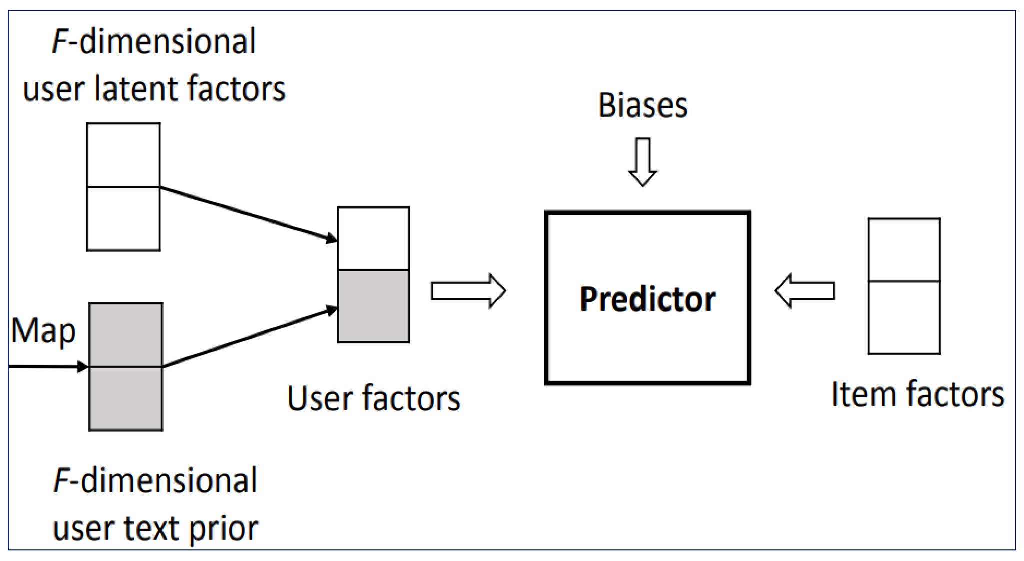
Personalized Neural Embeddings for Collaborative Filtering with Unstructured Text

Guangneng Hu and **Yu Zhang**
Department of Computer Science and Engineering, Hong Kong University of Science and Technology, Hong Kong
njuhgn@gmail.com, yu.zhang.ust@gmail.com

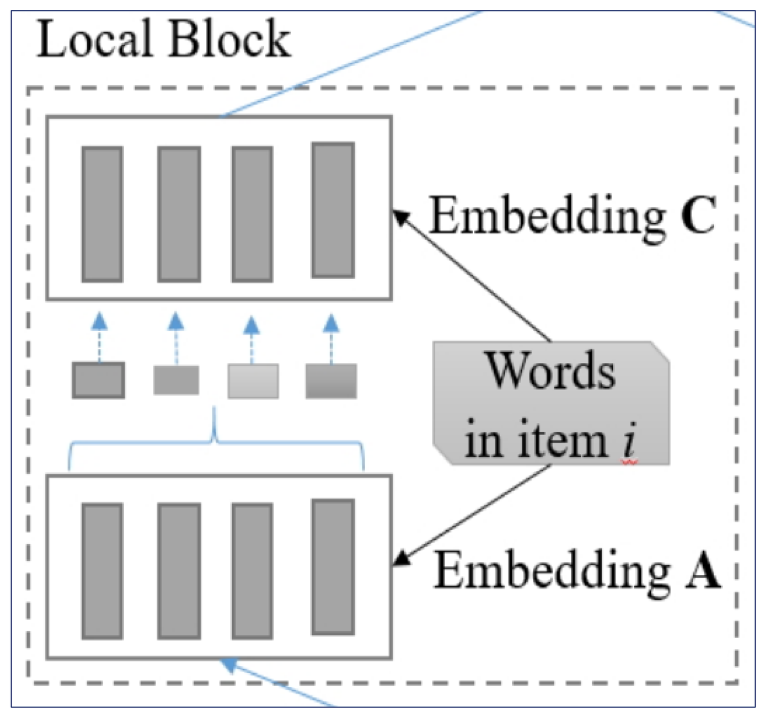
香港科技大學 THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

1 Motivation

Existing hybrid methods to alleviate the sparsity in collaborative filtering:



TBPR, Hu et al, PAKDD'17



LCMR, Hu et al, arXiv'18

- TBPR treats different words in the item document as equal importance:

$$\boldsymbol{f}_i = \frac{1}{|d_{ui}|} \sum_{w \in d_{ui}} \boldsymbol{e}_w$$

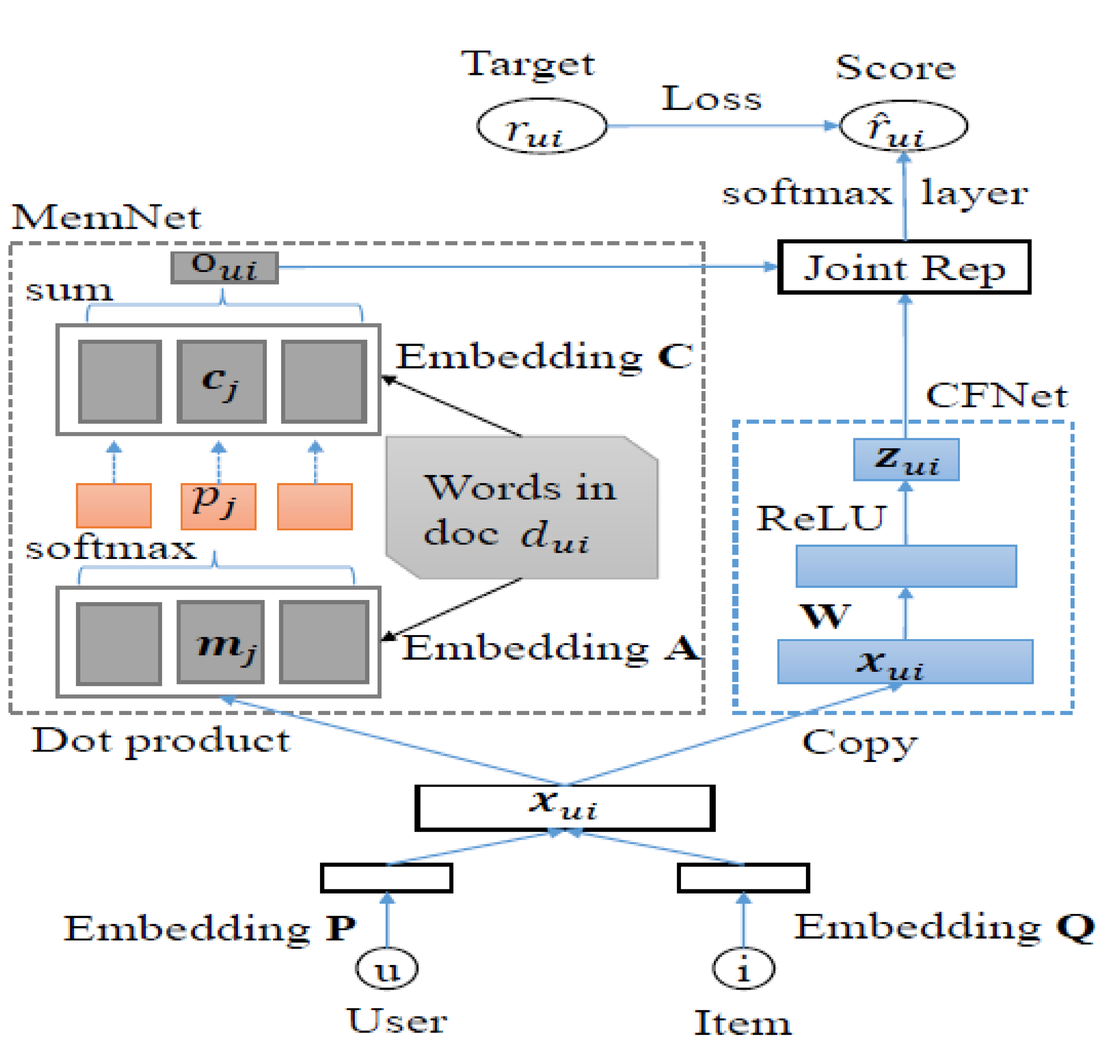
- Where ***e*** is the word embedding and ***f*** is the text feature for item
- LCMR uses a softmax (NOT sigmoid) activation function between two hidden layers
- The values would be fairly small causing a vanishing gradient since it would be normalized to a probability distribution

2 Personalized Neural Embeddings

A personalized neural embedding (PNE) model to learn embeddings of users, items, and words jointly, and predict the user preferences on items based on these learned representations

Contributions

- The first neural embedding model that integrates relational interactions data with unstructured text by bridging neural CF and memory networks
- PNE learns meaningful word embeddings which raising a rethinking the social impact of language technology



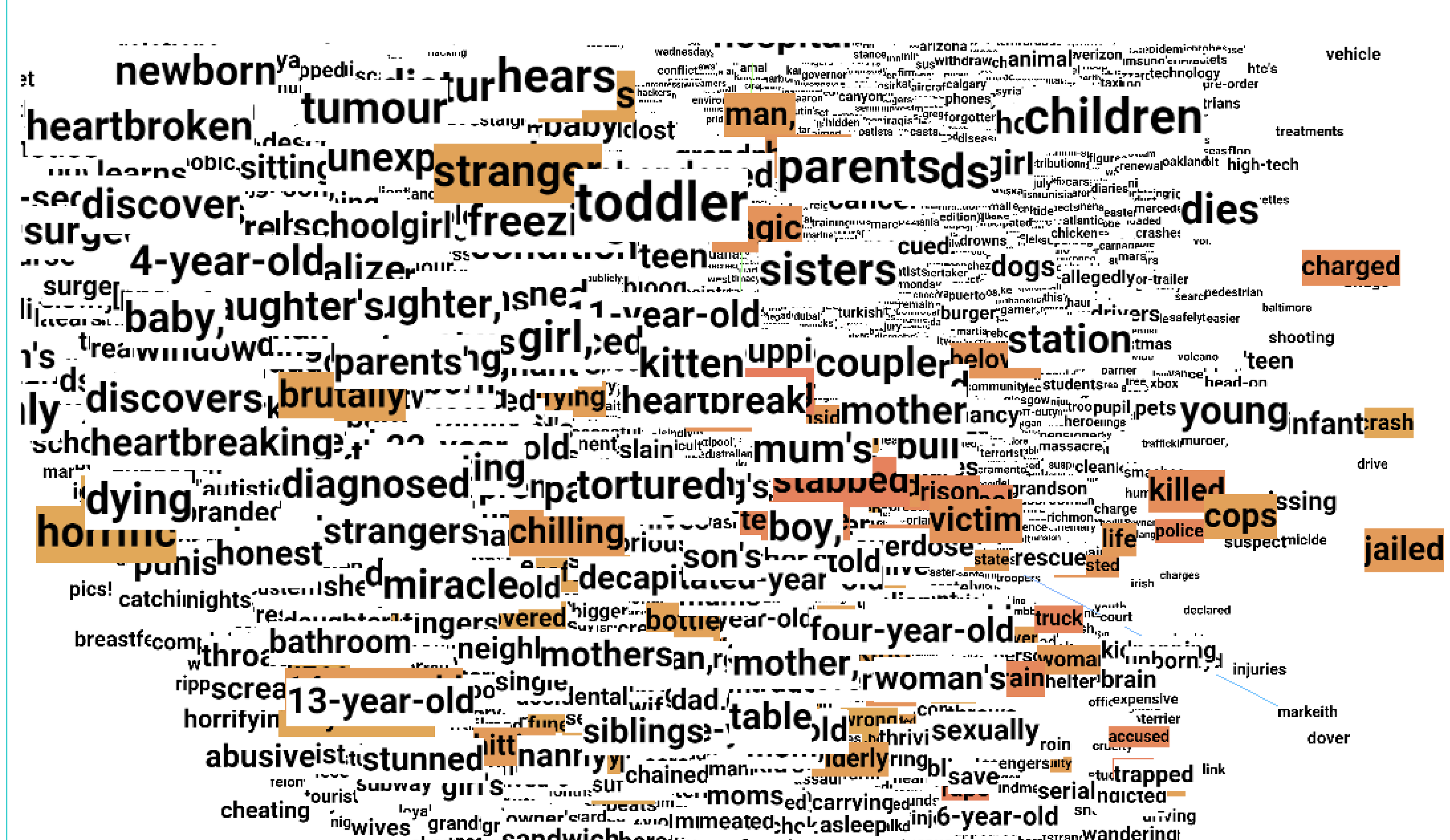
3 Result

Dataset	#user	#item	#rating	#word	#density	avg. words
Amazon	8,514	28,262	56,050	1,845,387	0.023%	65.3
Cheetah	15,890	84,802	477,685	612,839	0.035%	7.2

Amazon	Metric	Method					
		BPR	HFT	TBPR	MLP	LCMR	PNE
topK=5	HR	.0810	.1077	.1517	.2100*	.2024	**.2352**
	NDCG	.0583	.0815	.1208	.1486*	.1451	**.1646**
	MRR	.0509	.0729	.1104	.1283*	.1263	**.1413**
topK=10	HR	.1204	.1360	.1777	.2836*	.2836*	**.3186**
	NDCG	.0710	.0907	.1291	.1697*	.1678	**.1915**
	MRR	.0561	.0767	.1138	.1371*	.1356	**.1524**
topK=20	HR	.1821	.2782	.2268	.3820	.3951*	**.4221**
	NDCG	.0864	.1252	.1414	.1899	.1918*	**.2175**
	MRR	.0602	.0854	.1171	.1426*	.1420	**.1595**

Cheetah	Metric	Method					
		BPR	HFT	TBPR	MLP	LCMR	PNE
topK=5	HR	.4380	.4966	.4948	.5380	.5476*	**.5648**
	NDCG	.3971	.3617	.4298*	.4121	.4189	**.4345**
	MRR	.3606	.3175	.3826*	.3702	.3762	**.3911**
topK=10	HR	.4941	.5580	.5466	.6176	.6311*	**.6424**
	NDCG	.4182	.4093	.4499*	.4381	.4460	**.4598**
	MRR	.3694	.3365	.3913*	.3810	.3874	**.4016**
topK=20	HR	.5398	.6547	.6123	.6793	.6927*	**.6952**
	NDCG	.4316	.4379	.4682*	.4529	.4619	**.4732**
	MRR	.3730	.3445	.3958*	.3851	.3918	**.4053**

4 Analysis



- Nearest neighbors of *drug* are: *shot, shoots, gang, murder, killing, rape, stabbed, truck, school, police, teenage*
- Meaningful semantics for word embeddings such that words are to cluster when they have relevant semantics
- May infer that school teenagers have high relationships to the drug issue from the corpus and this should raise a concern for the whole society which shows the social impact of natural language processing

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