ICML 2018
Workshop TLLLEIB,
July 13 (Fri),
Stockholm, Sweden

CoNet: Collaborative Cross Networks for Cross-Domain Recommendation

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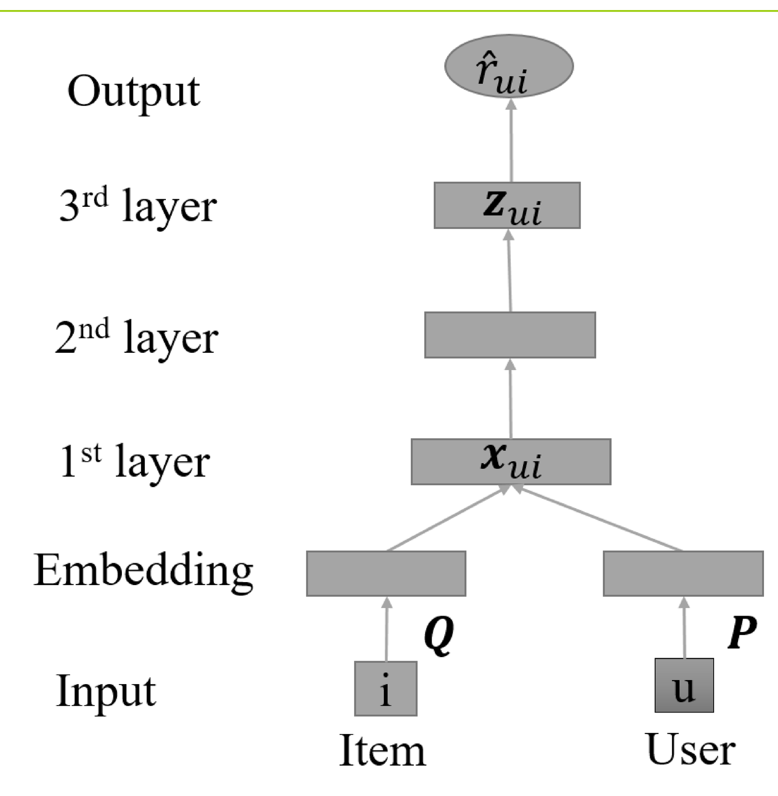
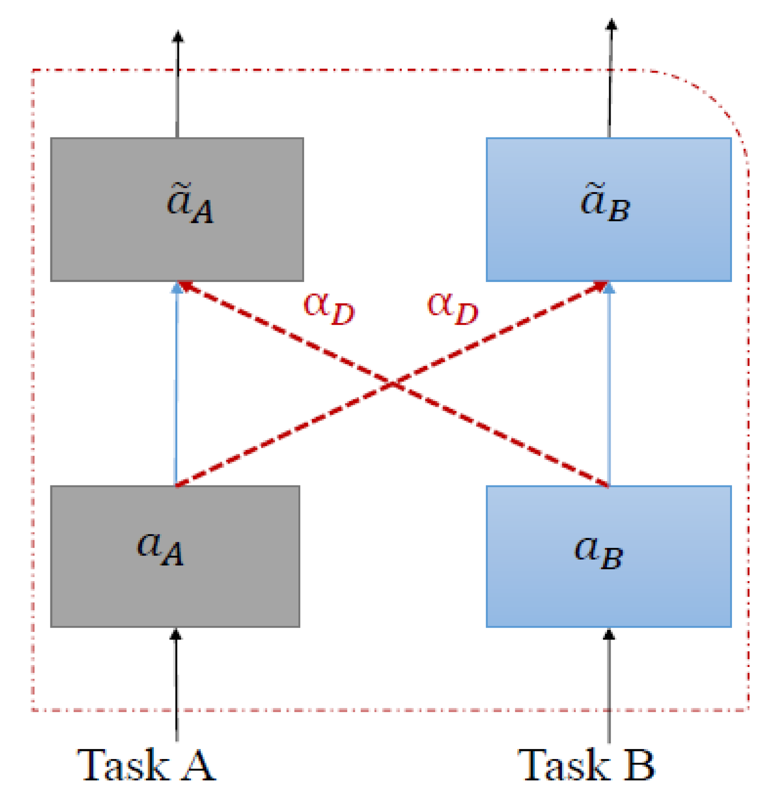
1 Motivation

Collaborative filtering techniques for recommendation:

- Deep collaborative filtering has the power to learn the complex/nonlinear relationship between the user and item from their interactions.
  - Requires many examples to learn a good predictor. Or, it faces the data *sparsity issue*.



- Cross-domain recommendation reduces the data sparsity in the target domain (e.g. App domain) by leveraging the knowledge from a related source domain (e.g. News domain)
  - Assumes *equally important* weights and *all useful* for transferred knowledge.



2 The Collaborative Cross Networks

We propose a novel deep transfer learning method, Collaborative Cross Networks, to both alleviate the data sparsity issue faced by the deep collaborative filtering and relax the strong assumptions faced by the existing cross-domain recommendation.

Contributions

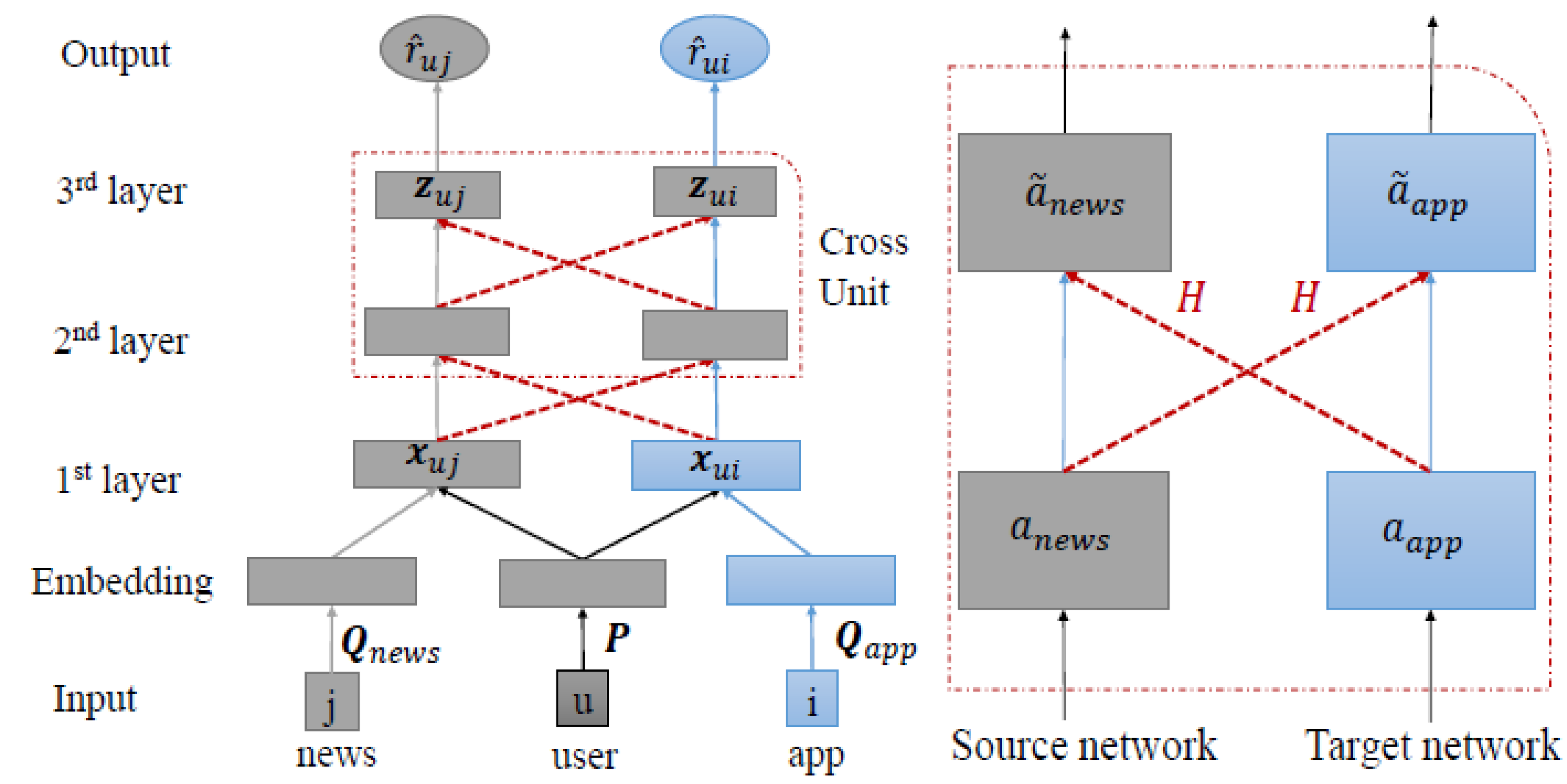
- Our model can reduce tens of thousands training examples by comparing with non-transfer methods without performance degradation.
- We demonstrate the necessity of adaptively selecting representations to transfer. Naïve transfer learning approach may confront the negative transfer.
- The proposed model outperforms various baselines on two large real-world datasets under three ranking metrics.

Dataset	#Users	Target Domain #Items	Target Domain #Interactions	Target Domain Density	Source Domain #Items	Source Domain #Interactions	Source Domain Density
Mobile	23,111	14,348	1,164,394	0.351%	29,921	617,146	0.089%
Amazon	80,763	93,799	1,323,101	0.017%	35,896	963,373	0.033%

2 The Collaborative Cross Networks (cont.)

The Architecture (CoNet)

Idea 1: Using a matrix rather than a scalar to transfer.



Adaptive Variant (SCoNet)

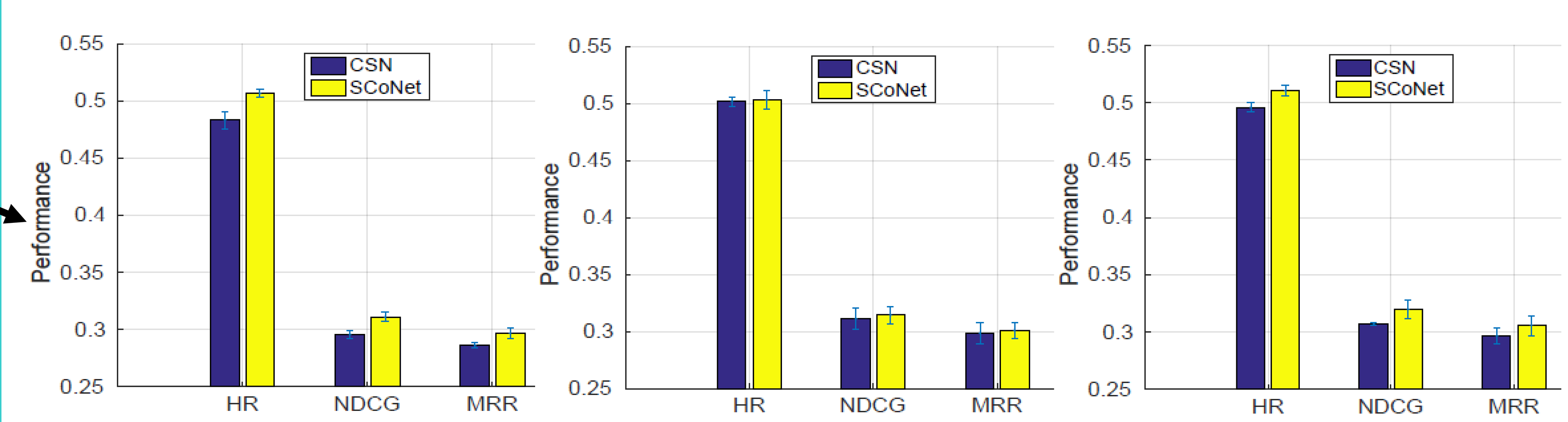
Idea 2: Sparsity-induced regularization for selecting representations.

$$\Omega(\boldsymbol{H}^l) = \lambda \sum\nolimits_{i=1}^{r} \sum\nolimits_{j=1}^{p} |h_{ij}|$$

3 Experiments

Baselines	Shallow method	Deep method
Single-domain	BPRMF [40]	MLP [13]
Cross-domain	CDCF [27], CMF [43]	MLP++, CSN [30]

Dataset	Method	Reduction percent	Reduction amount	HR	NDCG	MRR
Mobile	MLP	0%	0	.8405	.6615	.6210
	SCoNet	0%	0	.8547	.6802	.6431
		2.05%	23,031	.8439	.6640	.6238
		4.06%	45,468	.8347*	.6515*	.6115*
Amazon	MLP	0%	0	.5014	.3143	.3113
	SCoNet	0%	0	.5338	.3424	.3351
		1.11%	12,850	.5110	.3209	.3080*
		2.18%	25,318	.4946*	.3082*	.2968*



Dataset	Metric	BPRMF	CMF	CDCF	MLP	MLP++	CSN	CoNet	SCoNet	improve
Mobile	HR	.6175	.7879	.7812	.8405	.8445	.8458*	.8480	**.8583**	1.47%
	NDCG	.4891	.5740	.5875	.6615	.6683	.6733*	.6754	**.6887**	2.29%
	MRR	.4489	.5067	.5265	.6210	.6268	.6366*	.6373	**.6475**	1.71%
Amazon	HR	.4723	.3712	.3685	.5014	.5050*	.4962	.5167	**.5338**	5.70%
	NDCG	.3016	.2378	.2307	.3143	.3175*	.3068	.3261	**.3424**	7.84%
	MRR	.2971	.1966	.1884	.3113*	.3053	.2964	.3163	**.3351**	7.65%