Knowledge-enhanced Collaborative Meta Learner for Long-tail Recommendation

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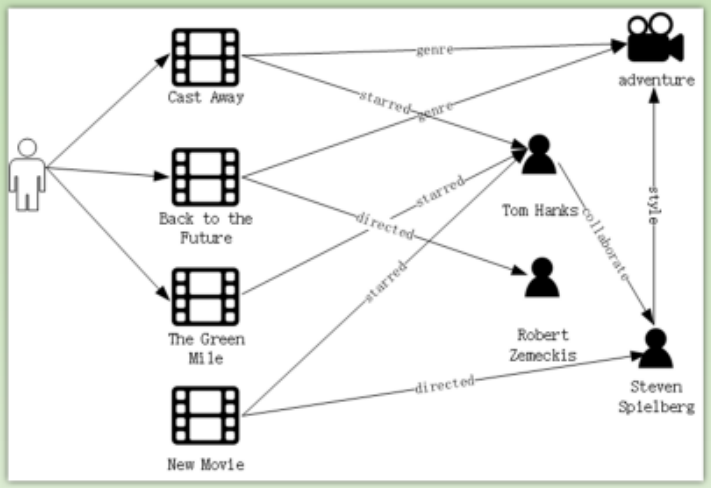
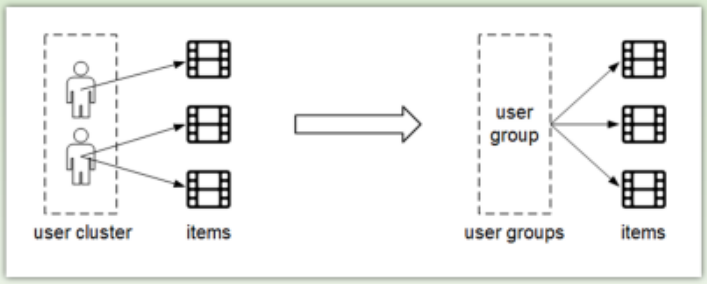
Motivation

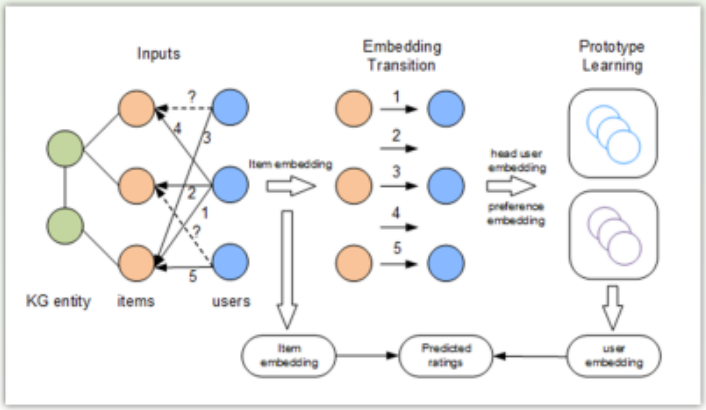
Modern recommender systems usually suffer from long tail effect, we argue that this can be solved by

- Knowledge-enhanced decomposing and reassembling from KG
- User prototype learning for user group





Model Overview

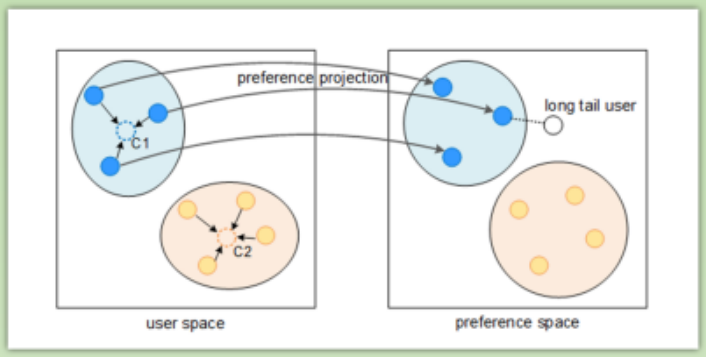


Methodology

Item Representation Learning

We use TransE method to learn item representation in linked knowledge graph with:

$$\mathcal{L} = \sum_{(h,r,t)\in S} \sum_{(h',r,t')\in S'_{(h,r,t)}} [\gamma + d(V_h + V_r, V_t) - d(V_{h'} + V_r, V_{t'})]_+$$



User Representation learning

- For head user representation learning, $\mathcal{V}^T$ is fixed and $\mathcal{U}_{\text{head}}$ is learned with:

$$\mathcal{L}_{\text{head}} = (\mathcal{U}_{\text{head}}\mathcal{V}^T - \mathcal{R}_{\text{head}})^2 + \lambda\|\mathcal{U}_{\text{head}}\|$$

- For long tail user representation learning, to transfer preference learned from head users and capture user group's preference, preference space embedding is defined as:

$$h_{U_i} = \frac{\sum_{j\in R_u} r_{ij} v_j}{\sum_{R_{U_i}}}$$

- By conducting head user oriented clustering, we treat clustering center representation as prototype user embedding.

Recommendation for long tail users

User space embedding of target user's nearest neighbor in preference space are used as long tail user's embedding. And the final prediction output is computed by:

$$R_{pred} = \mathcal{U}\mathcal{V}^T$$

Experiments

Experiment result on MovieLens-1M dataset

Method	MSE	MSE-tail
MF	1.731	2.345
NFM	1.712	2.324
Hitting Time	1.753	2.315
MELU	1.685	2.297
KCML(Random)	1.718	2.240
KCML(GCN)	1.684	2.212
KCML	**1.544**	**2.046**

Experiment result on Recsys2020 Twitter dataset

Method	PR-AUC			
	Reply	Retweet	Retweet-wc	Like
MF	0.011	0.201	0.003	0.794
NFM	0.031	0.284	0.004	0.908
Hitting Time	0.033	0.293	0.006	0.900
MELU	0.034	0.221	0.006	0.907
KCML	**0.046**	**0.310**	**0.008**	**0.912**

Method	RCE			
	Reply	Retweet	Retweet-wc	Like
MF	-940.354	-43.285	-2950.675	-34.538
NFM	1.617	1.741	0.872	9.220
Hitting Time	1.626	1.728	0.871	9.240
MELU	2.235	**2.621**	0.870	9.564
KCML	**4.625**	1.736	**0.881**	**20.542**