

An Explainable Recommendation Based on Acyclic Paths in an Edge-Colored Graph

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1 Introduction

An explainable recommendation provide **recommendation reasons**.

Explainability improves Transparency, Effectiveness, Trustworthiness, Satisfaction, Persuasiveness

2 Existing explainable recommendation

Recommendation	Explanation
collaborative filtering [Herlocker et al., 2000, Chen et al., 2016]	Present similar users and items
deep neural networks [Li et al., 2017]	Extract words contributed to the recommendation in reviews by CNNs text analysis
graph-based [Xian et al., 2019]	Track the objects (items and attributes) contributed to the recommendation

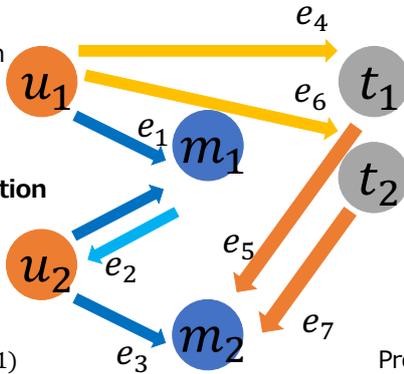
Explanation based on various relation is possible

3 Objective

Develop a graph-based explainable recommendation system that can show various contributed relations between users and contributed items

4 Edge-Weighted Edge-Colored Graph

- Vertex** v is an **object** such as a user, item, tag
- Edge** e is the **relation** between vertices
ex) user u_1 rated item m_1
- Color** c is the **type of relation**
ex) user u_1 **rated** item m_1
user u_1 **tagged** item m_1
- Weight** $p((u, v, c)) > 0$ is **strength of relation** represented by edge (u, v, c)
※ $(\sum_{(v,c):(u,v,c) \in E} p((u, v, c)) = 1)$



5 Acyclic-Path from user to item

- Acyclic-Path $e_1 e_2 \dots e_n$ has probability
ex) $\mathbb{P}(e_1 e_2 e_3) = p(e_1) \times p(e_2) \times p(e_3)$
- Color sequence of path from a user to an item represents relation between them

ex) (blue, light blue, blue) represents a concatenated relation like
"Items rated by users who rated the same item"

6 Item score for recommendation

P_t : Score of the item (for each user s)

$P_t \stackrel{\text{def}}{=} \text{probability sum of paths to the item } t \text{ whose probability is greater than the threshold } \theta$

ex) Item m_2 score for user u_1

$$P_{m_2} = p(e_1) \times p(e_2) \times p(e_3) + p(e_4) \times p(e_5) + p(e_6) \times p(e_7)$$

7 Color sequence score for explanation

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"Items rated by users who rated the same item"

color sequence c_2 (yellow, orange)

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"Items with the same tag as the one you tagged"

8 How to efficiently calculate score

- Do depth-first search from each user s
- In the search, keep the probability of the current path and add it to the score for the current item t unless the path is cyclic
- Bound search space on acyclic paths whose probability is at least threshold θ

9 Experiment

Dataset	#users	#items	#tags	#ratings	#taggings
Movielens 20M	138493	27278	38644	20000263	465564
Food.com	6389	197317	532	719548	2798545

Comparison methods

- AVE(Average)
- IBCF(Item-Based Collaborative Filtering)
- MRH(Music Recommendation via Hypergraph)
- BPR(Bayesian Personalized Ranking)

Dataset	method	nDCG	Precision	Recall	F1
Movielens	AVE	0.4508	0.3658	0.3625	0.3106
	IBCF	0.7667	0.6901	0.5239	0.4926
	MRH	0.7354	0.6478	0.4991	0.4657
	BPR	0.6885	0.6123	0.4770	0.4419
	APBRec	0.7023	0.6241	0.4799	0.4474
Food.com	AVE	0.8328	0.8587	0.5673	0.6094
	IBCF	0.8745	0.8785	0.5755	0.6199
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	APBRec	0.8735	0.8777	0.5752	0.6196

Proposed method (APBRec) outperforms baseline model AVE and has performance close to the other three major unexplainable methods

10 Conclusion

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