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A novel confidence estimation method for heterogeneous implicit feedback

Key words: Recommender systems; Heterogeneous implicit feedback; Confidence; Collaborative filtering; E-commerce

Corresponding author: Jing WANG
E-mail: cswangjing@zju.edu.cn
ORCID: http://orcid.org/0000-0002-0149-2049

Motivation

1. Implicit feedback has gained increasing attention in recommender system communities, and in real-world applications, there are usually various types of implicit feedback, which can be referred to as heterogeneous implicit feedback.

2. Most existing methods work well only when just one type of implicit feedback is available, and cannot efficiently infer confidence levels of preference from heterogeneous implicit feedback.

Main idea

1. Implicit feedback can be classified into: certain feedback such as purchase, which indicates full confidence of preference; uncertain feedback, such as click, collect, and cart, which indicates uncertain preference.

2. Certain feedback and uncertain feedback are related.

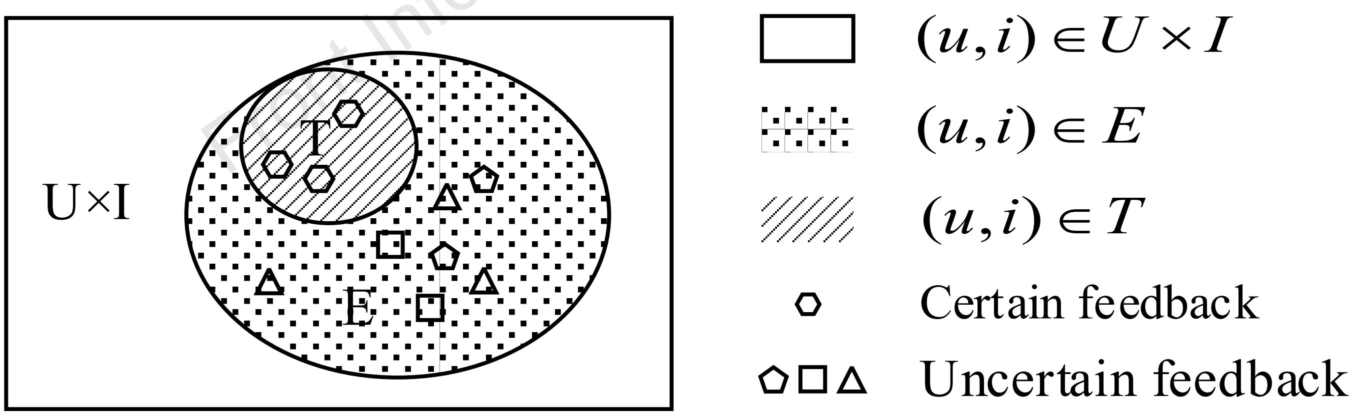

Fig. 1 Heterogeneous implicit feedback.

Main idea

3. We can infer the probability of the existence of certain feedback from uncertain feedback, which can be treated as the confidence of preference, thus we can represent the degree of confidence for uncertain feedback.

$$c_{ui} = \begin{cases} 1 & (u,i) \in T \\ p_{(u,i)\in T'} & (u,i) \in E, (u,i) \notin T \end{cases}$$

$(u,i) \in T'$ means although certain feedback is not observed in historical data, but it may happen in the future.

Method

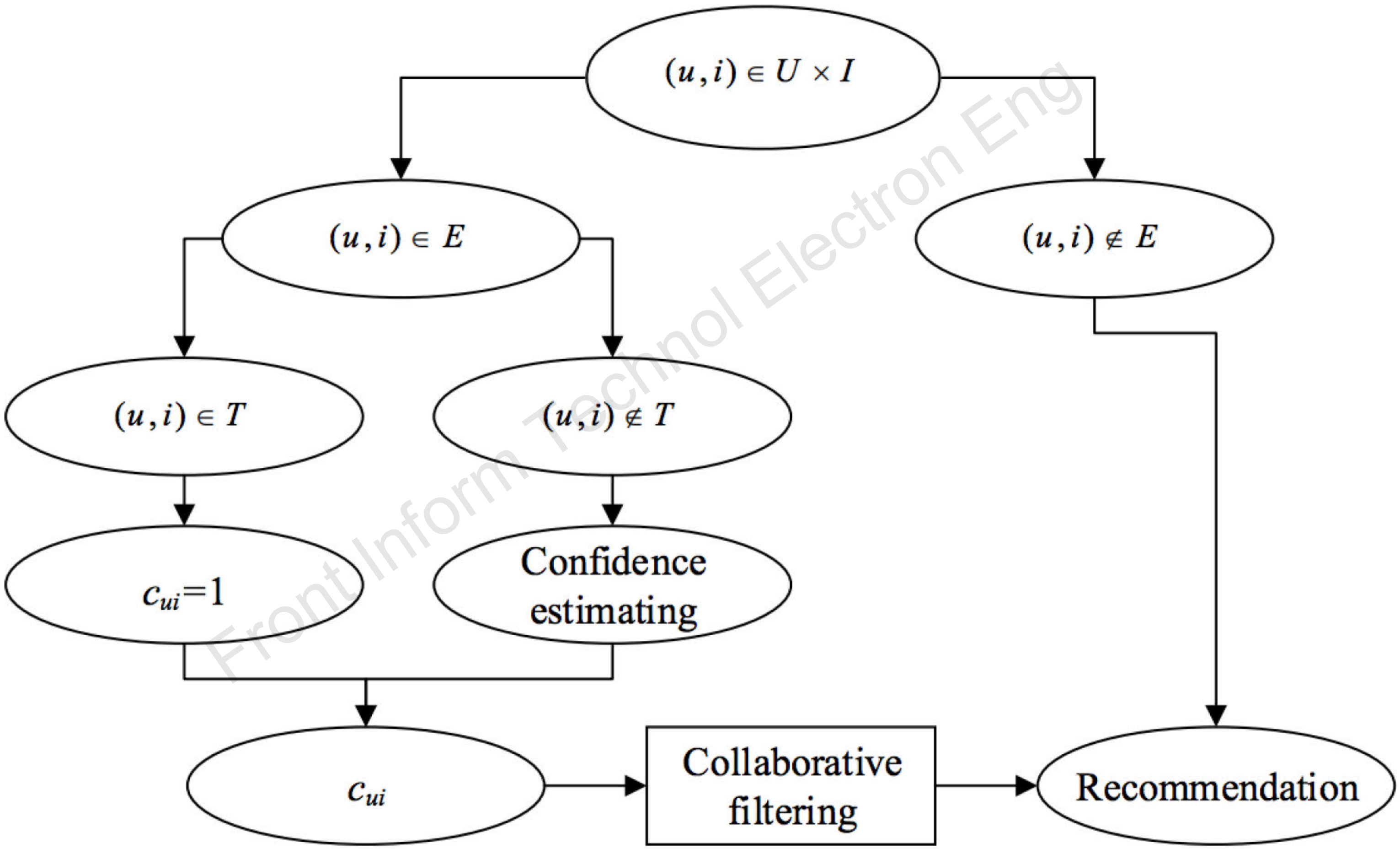

Fig. 2. Framework.

Major results

Table 4 Recommendation performance of point-wise methods with the REC-TMALL dataset

Algorithm	P@5	P@10	R@5	R@10	AUC	MAP	NDCG	MRR
ImplicitALS(T)	0.0158	0.0112	0.0664	0.0857	0.5511	0.0336	0.0483	0.0416
ImplicitALS($T \cup E$)	0.0158	0.0125	0.0664	0.0903	0.5572	0.0339	0.0499	0.0428
CL-ImplicitALS	0.0211	0.0158	0.0725	0.1091	0.5763	0.0472	0.0676	0.0681

Table 5 Recommendation performance of point-wise methods with the IJCAI-15 dataset

Algorithm	P@5	P@10	R@5	R@10	AUC	MAP	NDCG	MRR
ImplicitALS(T)	0.0131	0.0094	0.0097	0.0140	0.5364	0.0063	0.0139	0.0317
ImplicitALS($T \cup E$)	0.0103	0.0082	0.0076	0.0122	0.5295	0.0054	0.0118	0.0256
CL-ImplicitALS	0.0212	0.0156	0.0155	0.0231	0.5576	0.0110	0.0233	0.0522

Table 6 Recommendation performance of pair-wise methods with the REC-TMALL dataset

Algorithm	P@5	P@10	R@5	R@10	AUC	MAP	NDCG	MRR
BPR(T)	0.0172	0.0152	0.0634	0.1098	0.5603	0.0350	0.0554	0.0439
BPR($T \cup E$)	0.0198	0.0165	0.0634	0.0867	0.5721	0.0352	0.0538	0.0541
ABPR	0.0211	0.0165	0.0662	0.1041	0.5759	0.0372	0.0592	0.0612
CL-BPR	0.0238	0.0185	0.0725	0.1135	0.5821	0.0459	0.0683	0.0688

Table 7 Recommendation performance of pair-wise methods with the IJCAI-15 dataset

Algorithm	P@5	P@10	R@5	R@10	AUC	MAP	NDCG	MRR
BPR(T)	0.0156	0.0129	0.0116	0.0191	0.5401	0.0090	0.0184	0.0376
BPR($T \cup E$)	0.0177	0.0133	0.0138	0.0208	0.5498	0.0091	0.0196	0.0408
ABPR	0.0162	0.0094	0.0115	0.0182	0.5429	0.0056	0.0139	0.0350
CL-BPR	0.0203	0.0157	0.0149	0.0233	0.5535	0.0116	0.0240	0.0529

Major results

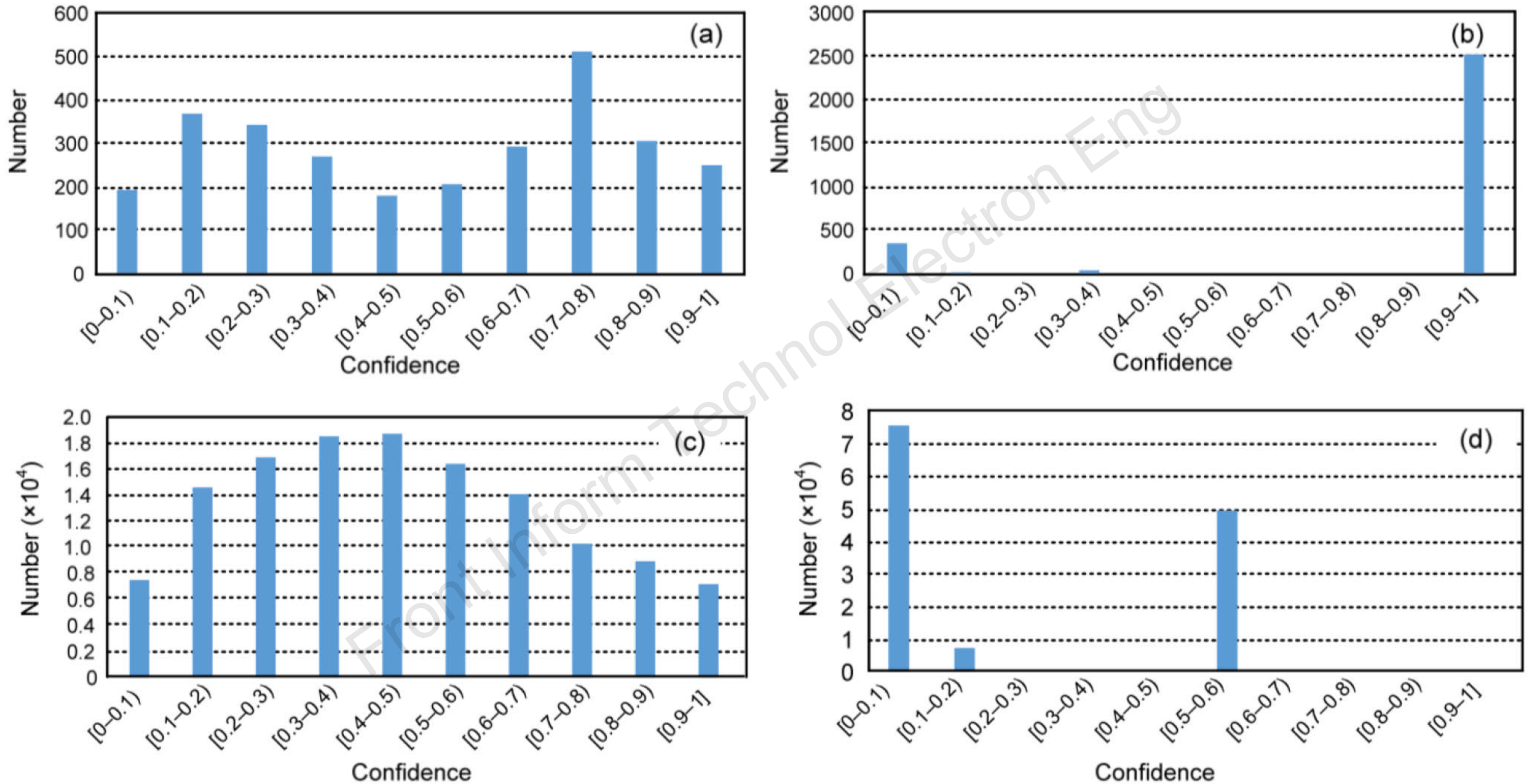

Fig. 3 Distributions of confidence: (a) confidence learned by our method on REC-TMALL; (b) confidence learned by ABPR on REC-TMALL; (c) confidence learned by our method on IJCAI-15; (d) confidence learned by ABPR on IJCAI-15

Conclusions

1. We propose a novel confidence-estimation method to quantify the confidence of user preference based on heterogeneous implicit feedback, by studying the internal relations of certain feedback and uncertain feedback.

2. We also propose CL-BPR, which generalizes BPR and can construct more effective training samples from the heterogeneous implicit feedback data.

3. Experiments on two real-world e-commerce datasets show that our methods outperform the baseline approaches.