A Graph-Based Recommendation Framework for Price-Comparison Services

Sang-Chul Lee
Computer Science Department
Carnegie Mellon University
Pittsburgh, PA, USA
sclee12@cs.cmu.edu

Sang-Wook Kim*
Dept. of Electronics and Computer Engineering
Hanyang University
Seoul, Korea
wook@hanyang.ac.kr

Sunju Park
School of Business
Yonsei University
Seoul, Korea
boxenju@yonsei.ac.kr

ABSTRACT

In this paper, we propose a set of recommendation strategies and develop a graph-based framework for recommendation in online price-comparison services. We verify the superiority of the proposed framework by comparing it with existing methods using real-world data.

1. INTRODUCTION

Price-comparison services are widely used in online shopping. Personalized recommendation would aid the user to find items of his interest in price-comparison shopping [1]. Existing recommendation methods, however, cannot be directly applicable to price-comparison services because of the unique characteristics of the services. To solve these problems, we propose three recommendation strategies and develop a recommendation framework based on them. We evaluate the performance of the proposed framework by comparing it to those of existing methods through various experiments.

2. OUR APPROACH

Existing recommendation systems cannot be directly applicable to price-comparison services because of the following three distinct characteristics of price-comparison services. First, most price-comparison services keep no record of user feedbacks (such as item ratings). Second, different titles are often used for the same or quite similar items in online shopping malls, which makes it difficult to differentiate whether two users have clicked or searched for the same item or different items. Third, since most users use a price-comparison service without log-in, a price-comparison service provider cannot collect enough data about users' history on clicked or searched items.

To address these problems, we propose three recommendation strategies in the following.

*The corresponding author

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(1) *Utilizing click-log data*: Since no explicit feedback is available, we use click log as a surrogate of users' *implicit* preferences. This is justifiable because a user tends to click on items of his interest.

(2) *Grouping similar items as a unit of a user's preference*: Instead of individual items, we group similar items, which we call an *interest field*, and use it as a unit of a user's preference. Because of the sheer number of distinct items sold online, it is often difficult to find a set of users who have clicked the same item. By using a group of similar items as a unit of a user's preference, we have more chance to identify a set of users with similar preferences.

(3) *Expanding the unit of a user's preference using similar groups*: Items in online shopping malls are generally classified into a multi-level category hierarchy, and they are searched by keywords. We use these two features, keywords used in search and a category hierarchy, of an interest field to expand the user's preference. That is, an interest field is considered to be related to another if they share common keywords or they belong to the same higher-level category.

Based on the three strategies, we propose a graph-based recommendation framework. The graph consists of three types of nodes: users, interest fields, and features. It captures two types of relationships: (1) between user u and interest field i (denoted by $L_i(u)$) and (2) between interest field i and its feature f (denoted by $L_i(f)$).

Figure 1 shows an example graph generated by our framework. In our framework, the lowest-level categories are used as interest fields. Higher-level categories and search keywords are used as the features of interest fields.

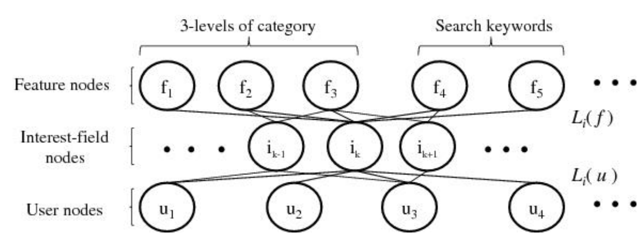

Figure 1: An example graph built by our framework.

We experimentally set the weights of links by trial and error[1]. We use the number of clicks on an interest field to adjust the weight of links between the interest-field node and the user node. That is, $\Sigma_{\forall u} L_{i_k}(u) = 1$. We set the weight of

[1]Due to the page limit, we omit details of how to set the weights of links.

$L_{i_k}(f)$ to be the same normalized value if the link belongs to the same type. We set the weight ratio between two feature nodes (i.e., links from interest fields to category nodes and those to keyword nodes) to be 2:1.

We use *Random Walk with Restart* (*RWR*) to compute a personalized rank of interest fields for the target user [2]. An element in the restart vector is set as 1 for the node corresponding to the target user; it is set as 0 otherwise. We select top-k ranked interest fields, and recommend the most popular item in each interest field to the user.

3. EXPERIMENTS

To evaluate the proposed framework, we used anonymized log data crawled from *Naver Shopping*, one of the biggest price-comparison service sites in Korea. The log data consists of 9,997 users and 310,841 items. The proposed framework was compared to user-based collaborative filtering (user-CF), item-based collaborative filtering (item-CF), and RWR-based collaborative filtering (rwr-CF) methods [1, 2, 3]. For evaluation, we measured *recall*, *precision*, and *coverage* of each method.

From the entire log data, we randomly chose 100 users among those who had clicked on items from more than 10 interest fields. We made each method recommend top 10 or 20 interest fields to a user. Table 1 shows the result of accuracy comparison. It is observed that the proposed framework improves over the existing methods up to 129% of recall and up to 87% of precision when 10 interest fields are recommended. When 20 interest fields are recommended, our framework improves up to 87% of recall and up to 48% of precision.

Table 1: Accuracy comparisons

Methods	Recall, %		Precision, %	
	at 10	at 20	at 10	at 20
our approach	23.83	27.67	3.70	2.15
user-CF	16.16	21.87	3.15	2.19
item-CF	12.00	19.06	2.25	1.68
rwr-CF	10.43	14.83	1.98	1.45

The *cold-start user* is a user who has clicked on only a few items. It is difficult to evaluate the accuracy if we use real cold-start users because they do not have enough interest fields for training and test sets. Thus, for accuracy comparison with cold-start users, we generated cold-start users from normal users as follows. We chose 700 users among those who had clicked items from more than 30 interest fields. Then, we randomly pulled interest fields out of the entire set until 5 interest fields were remained. The pulled out interest fields were used as a test set and remaining ones were used as a training set.

Table 2 shows the result of accuracy comparison for cold-start users. It is observed that the proposed framework improves over the existing methods up to 72% of recall and up to 79% of precision when 10 interest fields are recommended. When 20 interest fields are recommended, it is observed that ours improves up to 40% of recall and up to 43% of precision.

Figure 2 shows the result of *coverage* comparison for cold-start users while increasing the number of interest fields from which the target user had clicked on items. The proposed framework provided *all* users with recommendation, while the compared existing methods were not able to produce recommendation for up to 35% of cold-start users. All existing methods achieved close to 100% of the coverage with the increase in the number of lowest-level categories the target user had clicked. It is important to produce the recommendation for cold-start users, and thus the proposed method is more suitable for price-comparison services.

Table 2: Accuracy comparisons for cold-start users

Methods	Recall, %		Precision, %	
	at 10	at 20	at 10	at 20
our approach	2.74	4.12	6.09	4.61
item-CF	1.61	3.05	3.40	3.23
user-CF	1.60	3.06	3.52	3.29
rwr-CF	1.59	2.95	3.53	3.30

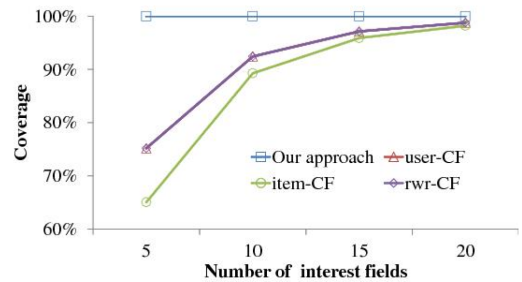

Figure 2: Coverage comparison for cold-start users.

4. CONCLUSIONS

In this paper, we proposed three recommendation strategies and a framework for recommendation in price-comparison services. We showed that the proposed framework improves 87% and 129% in precision and recall for normal users, and 79% and 72% for cold-start users, compared to existing methods. We also verified that our framework provides high coverage even for cold-start users.

5. ACKNOWLEDGMENTS

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