Using Association Rules to Solve the Cold-Start Problem in Recommender Systems

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Abstract. Recommender systems are widely used online to help users find other products, items etc that they may be interested in based on what is known about that user in their profile. Often however user profiles may be short on information and thus it is difficult for a recommender system to make quality recommendations. This problem is known as the cold-start problem. Here we investigate using association rules as a source of information to expand a user profile and thus avoid this problem. Our experiments show that it is possible to use association rules to noticeably improve the performance of a recommender system under the cold-start situation. Furthermore, we also show that the improvement in performance obtained can be achieved while using non-redundant rule sets. This shows that non-redundant rules do not cause a loss of information and are just as informative as a set of association rules that contain redundancy.

1 Introduction

Recommender systems are designed to understand a user's interests, learn from them and recommend items (whether they be products, books, movies etc) that will be of interest to the user. This requires them to personalise their recommendations. Recommendation systems usually work most effectively when user profiles are extensive and/or the applicable dataset has a high information density. When the dataset is sparse or user profiles are short, then recommender systems struggle to provide quality recommendations. This is often known as the cold-start problem.

We propose expanding a user profile (eg. so it contains more ratings) through the use of association rules derived from the dataset. By doing so we expand profiles based on patterns and associations of items, topics, categories etc and thus give more information to a recommender system. This would reduce the effect of the cold-start problem and result in better quality recommendations earlier on. We also investigate the performance of both non-redundant rules and rules that contain redundancy. The idea behind non-redundant rules is that the removed redundant rules should not cause a loss of information [11] [12]. If there is no information loss, then the performance should be similar to that of a ruleset with redundant rules.

M.J. Zaki et al. (Eds.): PAKDD 2010, Part I, LNAI 6118, pp. 340–347, 2010.

The paper is organised as follows. Section 2 discusses related works. Our proposed approach for solving the cold-start problem is presented in Section 3. In Section 4 we outline our experiments to test our approach. Lastly, Section 5 concludes the paper.

2 Related Work

Here we briefly review works related to our proposed approach. We consider works that have focused on recommender systems and redundancy in association rules.

Much work has been done in the area of recommender systems. A survey undertaken in [1] details many different approaches that have been proposed. It is shown that the cold-start problem heavily affects content-based and collaborative-based systems [1]. In the case of collaborative-based systems, proposed solutions include getting the user to rate specific items [1]. However this places a burden on the user. Our proposed approach does not. Thus work focusing on solving the cold-start problem includes collaborative & content hybrids [2] [7], ontology based systems [5] and taxonomy driven recommender systems [10] [13]. However, all of these proposals have drawbacks. Hybrid systems can lack novelty, resulting in recommendations that are excessively content centric [13]. Onotolgy based system requires a well defined ontology to be created, something that can be difficult and limiting. Taxonomy based systems work better, but still have low performance. Also the HTR system proposed in [10] performs only marginally better than the TPR system proposed in [13], although it is more time efficient. The taxonomy based approach in [13] does have the advantage of being able to be applied to many domains. Work in [4] proposed a system that uses fuzzy cross-level rules to enhance a collaborative based recommender to solve this cold-start problem. Our work focuses on the cold-start problem of users not items.

Much work in the field of association rule mining has focused on finding more efficient ways to discover all of the rules. However, complete rule enumeration is often intractable in datasets with a very large number of multi-valued attributes. One approach is to determine which rules are redundant and remove them, reducing the number of rules a user has to deal with while not reducing information content [6] [11] [12]. The MinMax algorithm proposed in [6] uses the closure of the Galois connection to define non-redundant rules. These non-redundant rules have a minimal antecedent and maximal consequent and were selected as the most relevant because they are the most general. The ReliableBasis algorithm proposed in [11] [12] argued that MinMax still contained redundant rules. They propose that by using the same technique as MinMax, but relaxing the definition for redundancy, further redundant rules could be removed. Work in [11] shows a reduction of over 80% can be achieved in some situations. Recent work in [8] [9] proposed taking the MinMax and ReliableBasis approaches developed for single level datasets and extend them to remove hierarchical redundancy found in multi-level datasets. The proposed extensions, MinMax with HRR and

ReliableBasis with HRR [8] [9] were developed to find rules that not only had a minimal antecedent and maximum consequent, but also comprimsed of high level concepts or items. These approaches have been shown to yield further reductions in the size of rule sets. In this paper we demostrate an application where non-redundant rule sets can be used in place of other rule sets which are redundant.

3 Using Association Rules to Expand User Profiles

In this section we outline our proposed approach and investigation into solving the cold-start problem in recommender systems.

For our investigation we use the Taxonomy-driven Product Recommender (TPR) system first proposed in [13]. The user profiles are created through the process described in [13] (which has been omitted here due to space) to generate taxonomy-driven profiles. A taxonomy T containing topics (or categories) t in a multi-level structure, where each topic has one parent or supertopic, but may have many children or subtopics. Thus the taxonomy can be visualised as a tree. By doing this the profiles represent the user's interests in topics, rather than items. Although we have used the taxonomy in the profile generation, we still have the issue of short profiles. By using the rules to expand the profile we bring other topics in that similar users have shown an interest in.

From the user profiles we can construct a transactional dataset, where each transaction is a user and each topic is an attribute. Thus each transaction consists of the topics that a user is interested in. We then mine the transactional dataset for frequent patterns and derive association rules from these patterns. This will give us association rules between topics that interest users. These rules allow us to discover topics that frequently appear together as part of a user's interest. This rule set will then be used to expand user profiles to solve the cold-start problem.

Finally, we expand the user profiles. For this we take the set of user profiles P and the association rule set we derived in the second step. For each user profile $p(u_x)$ we extract all of the topics t within and generate a list of all the combinations possible from the group of topics. Each combination represents a possible antecedent of an association rule. We take each combination and search the set of association rules for any rules that have a matching antecedent. If such a rule exists we can then take the topics in its consequent and add them to the profile $p(u_x)$. Each new topic added is assigned a weight, which is calculated based on the weights of the topics in that rule's antecedent.

$$Weight_{t_x} = \frac{\sum_{i=1}^{|A|} Weight_{t_i}}{|A|} \times R_{conf} \tag{1}$$

where $|A|$ represents the number of topics in the antecedent of the rule $R : A \rightarrow C$. Then as per the design of the TPR approach the values of the topics in the expanded profile need to be normalised. All topic scores within a profile p are normalised through the following formula.

$$NormalisedWeight_{t_x} = \frac{Weight_{t_x}}{\sum_{i=1}^{n} Weight_{t_i}} \times Limit \quad (2)$$

where *Limit* is the value to which a profile of normalised topic values is to sum to. Thus this generates a set of expanded user profiles which we show in our experiments have the potential to improve recommendations over profiles that have not been expanded.

We have outlined our proposal for using association rules to expand user profiles in order to improve recommender system quality. However, it is possible that we may want to place limitations on the expansion of user profiles.

1. Restrict the expansion to short profiles. The idea behind this proposal is to expand users who have very few ratings and thus suffer from the cold-start problem. Users with many ratings do not have this problem. Thus a restriction should be imposed on how many topics can be in the user profile p before there is too many to warrant expansion.
2. Restrict the number of rules used when expanding a user profile. It is entirely possible that when deriving the association rules from the transactional dataset that a large list may be generated. It is also possible that from this, when expanding a user profile that a large number of rules and their consequents will be considered for inclusion in the expanded user profile. This may lead to poorer performance as many more topics are added and more items from a wider selection become recommended. Our experiments will test the effect of using 1 to 5 rules during expansion.

4 Experiments and Evaluation of User Profile Expansion

Here we outline the experiments we undertook to study the value of our proposal to use association rules in expanding user profiles to improve recommendation quality, as well as the effect redundant and non-redundant rule sets have. We aim to show that non-redundant rule sets give a similar improvement when compared to rule sets containing redundant rules.

4.1 Evaluation Metrics and Datset

In order to evaluate the performance of the baseline set of profiles and the expanded set of profiles we follow the same approach detailed in [10]. The past ratings of each user $u \in U$ have been randomly divided into training and test components. For the experiments, the recommender system will recommend a list of n items for user u_i based on the training set and will be evaluated against the test set. For our experiments we use exactly the same training and test sets as used in [10].

To evaluate redundant and non-redundant rule sets we use 4 different rule mining algorithms to extract a set of rules. The algorithms used are the ones previously introduced in Section 2; MinMax [6], ReliableBasis [11] [12], MinMax with HRR [8] [9] and ReliableBasis with HRR [8] [9].

In our work we use precision, recall and F1-measure to determine the overall performance of the recommender system [3]. This allows us to compare the standard approach against our proposal of using association rules for user profile expansion.

For this investigation we use the BookCrossing dataset (obtained from http://www.informatik.uni-freiburg.de/˜cziegler/BX/) which contains users, books and the ratings given to those books by the user. The taxonomy tree and descriptors are orginally sourced from Amazon.com and are exactly the same as those used in [10]. From this we build a transactional dataset that contains 92,005 users (transactions) and 12,147 topics from the taxonomy. The dataset is populated using the descriptors that belonged to 270,868 unique books. This dataset is then mined to derive the association rules from it. For our experiments here, all ratings of items are considered to be positive. From the BookCrossing dataset we also build the base set of user profiles P. This set of profiles contains 85,415 distinct users. As already mentioned the ratings for each user are divided into a training set and a test set. The set of user profiles P is based on the training set. The average number of ratings in a user profile is 27.08. This set of user profiles will serve as the baseline input in our experiments and is also the set that will be expanded.

4.2 Experiment Results

To validate our proposal we conducted a series of experiments to see whether using association rules to expand user profiles improves recommendation quality. From the transactional dataset we set the minimum confidence threshold to 50% and are able to derive 37,827 association rules using the MinMax algorithm [6]. We then go through the user profiles in the training set and for any profile $p \in P(train)$ that has 5 or less ratings we attempt to expand our approach. This yields a total of 15,912 user profiles which we consider to be short profiles. We chose to restrict profile expansion to those with 5 ratings or less as these are the users most likely to suffer from the cold-start problem. This falls in line with the first restriction proposed in section 3. Long profiles do not usually suffer from the cold-start problem, so expanding them is likely to result in a high computation cost for minimal gain. We then make up to 10 recommendations for these 15,912 users and measure the overall performance of the recommender system. We compare our approach against the baseline of the same 15,912 user profiles with no expansion. All experiments use the TPR recommender[13].

As shown in Table 1 the baseline set of user profiles (no expansion) scores only 0.00619, 0.0571 and 0.0112 for precision, recall and F1-measure respectively. When using expanded profiles we manage to achieve up to 0.00815, 0.0754 and 0.0147 for precision, recall and F1-measure. This is an improvement of around 31.5% over the baseline. Also the efficiency of the recommender is not negatively impacted, as while our expanded profiles naturally take longer to make recommendations for, it is no different to that of a longer profile without expansion.

Table 1. Results for TPR using the short user profiles with rules ranked by confidence

Approach	Precision	%	Recall	%	F1-Measure	%
Baseline	0.00619		0.0571		0.0112	
Expanded (1 Top Rule)	0.00649	4.77%	0.0595	4.28%	0.0117	4.72%
Expanded (2 Top Rules)	0.00714	15.21%	0.0655	14.66%	0.0128	15.16%
Expanded (3 Top Rules)	0.00732	18.15%	0.0672	17.77%	0.0132	18.12%
Expanded (4 Top Rules)	0.00792	27.79%	0.0729	27.75%	0.0143	27.79%
Expanded (5 Top Rules)	0.00815	31.54%	0.0749	31.22%	0.0147	31.51%

To test the hypothesis that non-redundant rule sets perform as well as rule sets that contain redundancy we conducted a series of experiments to determine the improvement in a recommender system obtained using various rule sets.

We mine the transactional dataset using four different rule mining algorithms all with the same minimum support and confidence thresholds. Initially we used the MinMax algorithm to extract all of the possible rules, including redundant ones by using the proposed recovery algorithms [6]. However, the entire ruleset and the non-redundant ruleset generated by the MinMax algorithm are actually identical. This means that none of the rules discovered by the MinMax algorithm are considered redundant and thus the ruleset derived using MinMax becomes our baseline ruleset, which based on the ReliableBasis redundancy definition, contains redundant rules.

The other three algorithms all derive smaller rule sets indicating that they deem some of the rules that MinMax derived to actually be redundant. The ReliableBasis with HRR [8] [9] derives the smallest set of rules and thus ReliableBasis and MinMax with HRR still contain some redundant rules. Table 2 shows the size of each ruleset derived using these algorithms. Again we follow the same procedure previously outlined. The same 15,912 'short profile' users are then used to test the performance of the TPR recommender.

Table 3 clearly shows that the performance of the four algorithms is not that different, except for the case of the top 3 rules, where ReliableBasis with HRR (RBHRR) outperformed the worst rule mining algorithm, MinMax (MM) by 8%. We believe Table 3 strongly support our hypothesis that non-redundant rule sets can be used in place of larger rule sets which contain redundancy, without degrading performance. It also supports the theory behind these algorithms.

Table 2. Size of ruleset derived for each algorithm

Algorithm	No. of rules	Reduction
MinMax	37,827	
ReliableBasis	36,852	2.58%
MinMax with HRR	37,555	0.72%
ReliableBasis with HRR	36,604	3.23%

Table 3. Results for TPR using the short user profiles with different derived rule sets and rules ranked by confidence

Approach	Precision	%	Recall	%	F1-Measure	%
Baseline	0.00619		0.0571		0.0112	
Expanded (1 Top Rule) - MM	0.00649	4.77%	0.0596	4.28%	0.01171	4.72%
Expanded (1 Top Rule) - RB	0.00649	4.77%	0.0596	4.28%	0.01171	4.72%
Expanded (1 Top Rule) - MMHRR	0.0066	6.49%	0.0606	6.04%	0.0119	6.45%
Expanded (1 Top Rule) - RBHRR	0.0066	6.49%	0.0606	6.04%	0.0119	6.45%
Expanded (2 Top Rules) - MM	0.00714	15.21%	0.0655	14.66%	0.0129	15.16%
Expanded (2 Top Rules) - RB	0.00714	15.21%	0.0655	14.66%	0.0129	15.16%
Expanded (2 Top Rules) - MMHRR	0.00717	15.72%	0.0658	15.21%	0.01293	15.67%
Expanded (2 Top Rules) - RBHRR	0.0072	16.13%	0.066	15.65%	0.01298	16.08%
Expanded (3 Top Rules) - MM	0.00732	18.15%	0.0673	17.77%	0.0132	18.12%
Expanded (3 Top Rules) - RB	0.00734	18.46%	0.0674	18.1%	0.01323	18.42%
Expanded (3 Top Rules) - MMHRR	0.00772	24.65%	0.0711	24.57%	0.01393	24.64%
Expanded (3 Top Rules) - RBHRR	0.00782	26.17%	0.0721	26.17%	0.01411	26.17%
Expanded (4 Top Rules) - MM	0.00792	27.79%	0.073	27.75%	0.01428	27.79%
Expanded (4 Top Rules) - RB	0.00798	28.8%	0.0736	28.8%	0.0144	28.8%
Expanded (4 Top Rules) - MMHRR	0.00805	29.92%	0.0741	29.78%	0.0145	29.91%
Expanded (4 Top Rules) - RBHRR	0.00802	29.41%	0.0738	29.21%	0.01446	29.39%
Expanded (5 Top Rules) - MM	0.00815	31.54%	0.0749	31.22%	0.0147	31.51%
Expanded (5 Top Rules) - RB	0.00819	32.15%	0.0754	31.97%	0.0148	32.13%
Expanded (5 Top Rules) - MMHRR	0.00808	30.43%	0.0743	30.07%	0.01458	30.39%
Expanded (5 Top Rules) - RBHRR	0.00811	30.83%	0.0745	30.51%	0.01462	30.8%

5 Conclusions

In this paper we proposed the idea of using association rules to expand user profiles in order to improve recommendations. We outline an approach whereby the rules can be discovered and used, increasing the number of topics in a user profile that only has a few existing ratings. Our experiments show that the proposed approach can improve the performance of a recommender system under the cold-start problem. We also argued that the performance of non-redundant and redundant rulesets in this application should be very similar. Results obtained show that non-redundant rulesets, which contain fewer rules, performing on par with larger rulesets still containing redundancy.

Acknowledgements. Computational resources and services used in this work were provided by the HPC and Research Support Unit, Queensland University of Technology, Brisbane, Australia.

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