AgreeTrust, A simple trust inference method for memory-based CF recommenders

## Introduction

Recommendation system often employs Collaborative Filtering method to make predictions. The preferences of the similar users are aggregated to predict a personalized recommendation [huang]. The intuition is that users who had similar preference in the past would have a similar presence in the future. Similarities are calculated as correlation between users’ rating profiles. Most common form similarity measures include Pearson, cosine, and jacquard correlation. Trust is often used as replacement for similarity in recommenders. The intuition behind using trust is that users are more likely to accept a recommendation from trustworthy partner.

Application of incorporating trust in computer model have been shown successful in various context, such as reputation systems [epinion, amazon], dynamic network [19 of f]and mobile environment [20 of F]. For an overview of various trust models interested readers can refer to [josang]. In order to increase the efficiency of recommender system, researchers have been incorporating various aspects of social relationship among the users. Recently, there has been a growing number of work on trust based recommender systems. Use of trust in recommenders has also been shown to alleviate problems such as cold start and data sparcity [5 in A].

In general, trust computation methods are broadly classified as two types; implicit trust, where trust between two users are inferred from their rating profiles, and explicit trust, where existing social links are used for trust calculation. The goal of both methods is to use the underlying trust relationship to aggregate the user preferences in such a way that more weight is given to trustworthy partners.

Although, intuitively it is more reasonable to use explicit trust, in many real-world recommender systems it is difficult to get the social link data among the users. For instance, many online shops do not require users to be registered, in order to buy products. In addition to that, using social network data increases the risk of exposing the users’ privacy. [ include film in C]. Furthermore, number of ratings available is far greater than number of explicit trust link which often comes in the form of binary value. It is possible to generate real values for the binary data however it could add noise to the preferences.

In this paper, we propose a novel approach for calculating implicit trust in recommenders. We have shown this method performs reasonably better than the traditional memory-based methods as well as other implicit trust models. The rest of the paper is organized as follow. The related work section explores the background of incorporating trust in recommenders found in the literature. Next, we propose details the problem and discusses our model. In the experiment and result section, we compare the performance of the proposed with the baseline method. We have chosen, O’dnonvan’s item-trust-profile as baseline method, since we draw motivation for the proposed model from their model.

Related Work

Similar to traditional brick-and-mortar businesses, trust plays a vital role in the success e-commerce business [Trust worthiness in ecommerce 4, 5, 13]. Mase & Avane showed that incorporating trust increase the efficiency of the recommender system.

Most CF literature assumes the implicit meaning of trust without a definition, thus, there is no room for argument. In this work, we borrow the definition of trust form sociology research. Gamabata[1982] states *Trust as the subjective probability by which an individual,* A*, expects that another individual,* B*, performs a given action on which its welfare depends*

Odnovan [] proposed a method based on recommender’s contribution to prediction accuracy. The trust is calculated as the ratio of the correct number of recommendation or total number of recommendation. Higher the contribution to the accuracy, trust between two users increases. Similar to our approach, Resnick formula is used to calculate the predictions. The algorithm defines [alpha] contribution threshold to filter the neighbours. The main disadvantage of this method is time complexity of trust matrix generation. For each user, the algorithm requires to make a prediction for all other users, in order to calculate the absolute difference between the predicted rating and ground truth. Similar to many other similarity measures, [alpha] does not accounts for how two agree on positivity or negativity of the item. In contrast, our model measures it as degree of agreeableness.

Li et. al [Yung-Ming Li] improvised O’dnovan’s model by including preference similarity, recommendation trust, and social relations into the recommendation algorithm. In their recommendation trust analysis module, trust is calculated exactly as O’dnovan proposed model. Therefore, we argue that replacing their trust module with ours would increase the performance of the recommender.

Preliminaries and Model

Let be users and be the item and the rating represents ’s evaluation on . The predictions are calculated using K nearest neighbour version of Resnik formula as in Eq.1

where is the predicted rating of item j for the user u. and are the mean ratings of user u and v respectively. The similarity between u and v is using the Pearson correlation given by:

Trust between user u and user v can be calculated as the ratio of agreements in co-rated items as in the following equation

where , k is the upper bound of the rating value (often 5), Ia and Ib are user a and b’s rating vector respectively. Trust value is in the range of [0,1] where 0 means no trust and 1 is completely trust worthy. In contrast to using predication accuracy most trust inference methods that uses rating as primary source trust [odnovan], this method takes into account of expectation drawn from past agreement. However, this trust inference method counts the non-co-rated items. If any two users have no common item, then the trust between them is 0, and it is very common to find user pairs who do not have common item ratings.

We address this issue by searching the trust matrix for common user of user’s immediate friends. Take the most reliable friend and assign new trust value by discounting the friends trust value. If there is more than one max value, one is chosen randomly. Similar to Film trust, a breadth search first can be utilized to fill the rest of the trust matrix. Since the trust values are in the range of 0-1, the values can be multiplied along the path.

algorithm 1

Get number the co-rated item positively co-rated items and negatively co-rated items

For each user get the rated items

For allother users get the co-rated item

Positives 🡪 length(common > k)

Negtivae 🡪 length(common <k)

Agreement 🡪 negative + postive

Trust 🡪 agreement/length(co-rated item)

Experiment and Result

Dataset

We use publicly available benchmark movielense 100k data set. The data set contains 100,00 ratings from 943 users on 1682 movies. Similar to Odnovan’s model, we chose 20/80 trustor/trustee ratio. Note that the data set is very sparse. Since our model is based on the common ratings by both trustor and trustee, trust values between users who does not have a common rating will be 0. I

As a baseline, we choose classic CF with k neighbour. We compare our results with two baseline method HUI [Quasi] and Odvan’s method.

Results

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Method | AgreeTrust | O’dnovans | PitstMarsh | KNN |  |
| RMSE |  |  |  |  |  |
| MAE |  |  |  |  |  |
| RMSE |  |  |  |  |  |
| MAE |  |  |  |  |  |

Complexity analysis

The pairwise trust calculation requires O(N2) time as model loops through each user for rating comparison with other users. In contrast to our Agree model, Odnovan model is prohibitively expensive since it requires additional O(KN2) time as there is a prediction step for each user.

Huang, Applying Associative Retrieval Techniques to Alleviate the Sparsity Problem in Collaborative Filtering

Quasi, An effective recommender system by unifying user and item trust information for B2B applications

Yung-Ming Li ⁎, Chun-Te Wu, Cheng-Yang Lai , A social recommender mechanism for e-commerce: Combining similarity, trust, and relationship

F = [https://pdfs.semanticscholar.org/d550/f9437c22d72be8fcadd3ad0fd77c66752a65.pdf

A = <http://www.ntu.edu.sg/home/ZhangJ/paper/sac14-guibing.pdf>

C = trust file:///Users/xahiru/Downloads/sac14-guibing.pdf