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

## Introduction

Recommendation system often employs Collaborative Filtering (CF) 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 addition to that, trust is used increase the explainablity as well improve robustness of CF based recommenders [para 1, chapter2, F].

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. Several trust inference models have been proposed to increase the accuracy of the recommender system […add any number of references here]. The focus of our study is explicitly on implicit trust inference.

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 trusted 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.

Addressing the issues of using similarity in kNN CF, Lathia et al.[Lathia] proposed a similar trust-based k-nearest neighbour CF method. The trust between two users is calculated as the average of 1 minus absolute rating difference over the maximum of rating scale for all the co-rated items. Thus, trust value is ranged from 0 to 1. If the target user does not have co-rated items, then trust between them is 0. The predictions are then made using the trust matrix rather than the similarity. This method assumes a recommender with negative similarity correlation is more trustworthy, to the target user, than those who have not yet rated the item. Similar to [odnovan’s method], this method depends on prediction to be calculated in order to generate the trust matrix.

Simialrly Pitsilis & Marshall derived trust by measuring the uncertainty in the similarity values. The users’ inability to make accurate predictions is modelled as *uncertainty*. The similarity matrix is then scaled to according the user’s belief and disbelief on the rating provider (trustee). The sum of belief, disbelief, uncertainty adds up to 1. Although inclusion of belief in this model inclines to subjective probability, the essence of prediction depends on the correlation of users. In this aspect, the model is similar to our proposed model.

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

Most trust inference methods we discussed earlier requires predictions to be calculated before generating the trust matrix. This involves use of a similarity matric. Inspired by O’Donovan’s model, we propose AgreeTrust, a much simpler method in which trust is inferred directly from the user preferences. The users’ positive and negative preferences are used to generate trust between them.

Preliminaries and Model

Let be users and be the items and the rating represents user ’s evaluation on item . The predictions are calculated using the Resnik prediction 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:

Similarly, let Iu and Iv be the set of items rated by user u and user v respectively, and tu,v be the trust between them. The trust tu,v ,can be calculated as the ratio of agreements, i.e. sum of positive agreements and negative agreements, in co-rated items as in the following equation

where , k is the maximum of the rating scale (often 5). Trust value is in the range of [0,1] where 0 means no trust and 1 is completely trustworthy. Positive agreements are the number of items both users have liked, similarly negative agreements contain items both users disliked. Predictions are then made by replacing the similarity with trust:

Trust matrix calculation 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 all other users get the co-rated item

Positives 🡪 length(common > )

Negtivae 🡪 length(common < )

Agreement 🡪 negative + postive

Trust 🡪 agreement/length(co-rated item)

Experiment and Result

Dataset

To evaluate our method, we use publicly available Movielense 100k benchmark 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. As a baseline, we choose classic CF with k neighbour. We compare the results of AgreeTrust with Odvnova, PitsMarsh and baseline KNN. We used *surprise* framework, a well-known python framework for recommendation, to implement our algorithm.

The ratings are divided into a training set containing 80% of the rating and a test set containing 20% rating. In [] odnvan’s used the same ratio to test their model.

For reproducibility, the code for the experiment is available http://github.com/xahiru/ agreerecom.

Most recommender use MAE and RMSE as evaluate the efficiency of the recommender. Therefore, we adopt these two matrices to measure the prediction accuracy. Root Mean Square Error (RMSE) punishes more on higher diviataion from ground truth. RMS is calculated as:

Results

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

[GRAPH K fold]

[Trust distribution]

Discussion

We set r = l = 10, m = 10, and ξ = 10−6 in our experiments unless otherwise stated.

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 AgreeTrust model, Odnovan model is prohibitively expensive since it requires additional O(KN2) time as there is a prediction step for each user.

In contrast to most implicit trust inference methods that uses rating as primary source trust [odnovan, pistmarsh, Yuan et a], our method takes into account the direction of agreement. Unfortunately, our 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.

Conclusion

In this paper, we have proposed AgreeTrust, an implicit inference model for Collaborative Filtering system. The basic idea is that trust relationship between trustor and trustee relies on the ratio of agreed number of rating (considering both positive and negatives) and total number of co-rated items. By incorporating AgreeTrust in CF based recommender, we have shown our experimental evaluations on real benchmark data sets show that it leads to significant improvement in prediction accuracy. As future work, we plan to investigate integration trust in deep learning models. Most trust implicit models use same prediction method for both trust generation and model evaluation. Another, direction for future work is to explore the efficiency of trust models under different prediction methods for trust generation. In this work, we used users’ direct rating for trust inference. Alternatively, we could have used predicted rating.

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

The Role of Trust in Collaborative Filtering

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

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

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