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AgreeTrust, a simple implicit trust inference model for memory-based Collaborative Filtering recommender systems.

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**Abstract:** A single paragraph of about 200 words maximum. For research articles, abstracts should give a pertinent overview of the work. We strongly encourage authors to use the following style of structured abstracts, but without headings: 1) Background: Place the question addressed in a broad context and highlight the purpose of the study; 2) Methods: Describe briefly the main methods or treatments applied; 3) Results: Summarize the article's main findings; and 4) Conclusions: Indicate the main conclusions or interpretations. The abstract should be an objective representation of the article, it must not contain results which are not presented and substantiated in the main text and should not exaggerate the main conclusions.

**Keywords:** trust 1; collaborative filtering 2; recommender system 3

1. Introduction

Recommendation systems often employ 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 preferences in the past would have similar preferences in the future. Preference similarities are calculated as correlation between users’ rating profiles. Most common similarity measures include Pearson, cosine, and Jacquard correlation. Correlation matrices suffer various problems []. In order address the issues with 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 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 a detailed survey of various computational trust models, interested readers can refer to [josang]. In order to increase the efficiency of recommender system, researchers have been incorporating many aspects of social relationship between 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 sparsity [5 in A]. Furthermore, trust has been used for increase the explainability as well as to improve the 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 inference. The goal of both methods is to use the underlying trust relationship to aggregate the user preferences in such a way, so that more weight is given to trustworthy partners.

Although, intuitively it is more sensible to use explicit trust for prediction, 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 [Stanford] [ 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 that proposed 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 detail the problem and formalized 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.

2. 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, by various researches in the field, to increase the accuracy of the recommender system, see e.g. […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 a contribution threshold , to filter the trusted neighbours. The main disadvantage of this method is the 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. Also, the method does not consider the direction of agreement, but simply the accuracy either by sum of squared errors or mean absolute error. In contrast, our proposed trust model takes direction of agreement into consideration

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 ours.

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 for making initial predictions. 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.

3. Preliminaries and Model

Let be users, be the items, the rating represents user ’s evaluation on item , and is the maximum of the rating scale (often 5). The predictions are calculated using the Resnik method as in Eq. (1):

(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:

(2)

3.1. AgreeTrust

Similarly, let and be the set of items rated by user and user respectively, and be the trust between them. The trust , can be calculated as the ratio of agreements, i.e. sum of positive agreements and negative agreements, in co-rated items as:

(3)

(4)

(5)

where , separates positive and negative ratings. Trust value is in the range of [0,1] where 0 means no trust and 1 is completely trustworthy. The positive agreements do not overlap with negative agreements, thus, guarantees that trust value would not grow beyond 1. 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 in equation 1 with trust of k-nearest neighbors:

(6)

where is the predicted rating.

4. Experiment

4.1 Data set

In order to evaluate our method, we used publicly available Movielense 100k benchmark data set. The data set contains 100,000 ratings from 943 users on 1682 movies. The ratings are scaled from 1 to 5. In order to reproduce results of O’Donovan’s model, the ratings are divided into a training set containing 80% of the rating and a test set containing 20% rating.

Note that the data set is very sparse. Since our model is based on the co-rated items for trust calculation, trust values between users who does not have a common rating will be 0. We compare the results of AgreeTrust with two benchmark methods; O’Donovan’s trust model (denoted as O’Donovan), the trust model proposed by Pits and Marsh (denoted as PitsMarsh), and with baseline kNN.

We used *surprise* framework, a well-known python framework for recommendation, to implement our algorithm. We set r = 5 (since the maximum rating scale of ml-100k data set is 5), =40, and trust threshold = 0.2 (for O’Dnovan’s) in our experiments unless otherwise stated.

We have also explored the effect of combining trust and similarity. In [] O’Donovan adopted harmonic mean to combine trust and similarity. However, we found our model gives best accuracy when using simple athematic mean as in Eq. (7):

(7)

where and are the trust matrix and similarity matrix, respectively. is generated using the Eq. (3) and is calculated using the Pearson correlation formula as in Eq. (2).

4.2 Evaluation Metrics

Most commonly used accuracy metrics in CF are Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Therefore, we adopt these two matrices to measure the prediction accuracy our model. MAE treats all errors equally while RMSE punishes more on higher deviation from ground truth. RMSE is calculated as:

(8)

Mean Absolute Error (MAE) is a calculated as:

(9)

where is the predicted rating, is the actual rating of the *jth* item, and is the predicted rating matrix. MAE and RMSE will be equal if there are no variance in errors.

5. Results and Discussion

5.1 Results

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Method** | **AgreeTrust** | **SimTrust** | **Odnovan** | **PitsMarsh** | **kNNmeans** |
| RMSE (item) | 0.9355 | **0.9283** | data | 0.9353 | 0.9394 |
| MAE (item) | 0.7358 | **0.7293** | data | 0.7349 | 0.7364 |
| RMSE (user) | 0.9547 | 0.9409 |  | 0.9430 | 0.9438 |
| MAE (user) | 0.7539 | 0.7374 |  | 0.7381 | 0.7381 |

Table 1. Accuracy of the prediction algorithms

We can observe from the result table 1. that all the RMSE values are higher than MAE. The difference in error matrices shows that variance within set of error values. For all the methods, item-based predictions have better accuracy than user-based prediction. There is a clear improvement in prediction accuracy for all the trust-based method, except user-based AgreeTrust, although the improvement is not significant. For instance, MAE for PitsMarsh is equal with kNNmeans, however PistMarsh has a lower RMSE, suggesting that PitsMarsh has low variance in errors. The results, further confirm finding of previous researches that claim inclusion of trust in the CF based recommender increases the accuracy.

User-based AgreeTrust performs worse than all the other methods. However, item-based AgreeTrust results are better than kNNwithMeans

The best result is achieved when similarity is combined with AgreeTrust. SimTrust outperforms with an average increased accuracy of 0.6%. Although, PistMash method performs better than AgreeTrust, we should note that belief calculation in their method involves aggregation of similarity.

5.2 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. Thus, all the models, that requires prediction during trust matrix generation, requires O(kN2 + N2) time. Due to the expensive time requirement of the O’Donovan’ trust matrix generation, the only practical way to implement the method in a real-world system is to pre-calculate the trust matrices. On the other hand, AgreeTrust takes far less time to generate the trust matrix.

6. Conclusion and Future works

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. We have shown, by experimental evaluations on real benchmark data set, that AgreeTrust improves prediction accuracy. In contrast to most implicit trust inference methods that uses rating as primary source trust, our model takes into account the direction of rating agreement between users. Unfortunately, our trust inference method does not count 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 ratings. As future work, we plan to explore ways to address the sparsity of trust matrix.

Modern recommenders are heavily relying on deep learning models. However, not much work has been done to incorporate trust in deep learning models. Therefore, we plan to investigate the effect of incorporating trust in deep learning models. Furthermore, most trust implicit models use same prediction method for both trust generation and model evaluation. In this work, we have used users rating for trust inference. Alternatively, we could have used predicted ratings. Another direction for future work is to explore the efficiency of trust models under different prediction methods for trust generation.

**Supplementary Materials:** For the purpose of reproducibility, we have published the code for our experiment at http://github.com/xahiru/agreerecom.

**Author Contributions:** For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used “conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y.”, please turn to the [CRediT taxonomy](http://img.mdpi.org/data/contributor-role-instruction.pdf) for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

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