Personalized Prediction of Trust Links in Social Networks (Student Abstract)

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Abstract

In this paper we show how integrating both domain specific and generic trust indicators into a prediction of trust links between users in social networks can improve upon methods for recommending content to users and how clustering of users to deliver personalized solutions offers even greater advantages.

Introduction

This work introduces the concept of Personalized Multi-Faceted Trust Modeling (PMFTM) to predict trust links between members of a social network. A *trust link* is an explicit or implicit signal of goal and preference alignment between users. For instance, an explicit trust link between users of a social network is mutual friendship, an implicit trust link is a strong correlation in the content which two users rate positively. In Multi-Faceted Trust Modeling (MFTM), arbitrarily many indicators of user reputation and trust between pairs of users are aggregated in order to predict likely trust links and filter out unlikely ones.These *trust indicators* are quantified aspects of a user or the relationships between users which may add or detract from the probability that there is a trust link between users. For instance, the popularity of a user, the degree to which two users' social circles overlap, and the ratio of positive to negative feedback a user has received may all be relevant trust indicators. These trust indicators are combined (often using logistic regression) to produce accurate predictors of trust links. We propose to isolate a rich set of domain specific and generic trust indicators as predictors. We *personalize* this process (PMFTM) by clustering users into sets of highly similar users and learn distinct predictors for each set of users. This personalization encodes the intuition that individuals and groups have distinct methods of weighting evidence when deciding whether or not to trust someone.

In order to test the effectiveness of this procedure, we ran multiple recommendation experiments using trust-aware recommender systems on user data available in the Yelp dataset. The Yelp data set includes information about the users of the Yelp restaurant review website, including the scores users have given to particular restaurants and the graph of friendship links between users. Trust aware recommender systems integrate trust-link information into their optimization process, producing recommendations based both on the similarity of user's previous content rating behaviour and the notion that users who trust each other are likely to enjoy similar content. We evaluate our trust link predictors by showing noticeable improvements in the context of the TrustMF system for content recomendation (Yang et al. 2013).

Our work shows that, when recommending content to users in a trust-aware context, 1) trust links predicted with our MFTM outperform explicit trust links available in the data set and 2) trust links predicted with PMFTM show improvements on both methods.

Proposed Solution and Results

At a high level, we aim to examine the performance of (P)MFTM by contrasting multiple methods of predicting trust links in a data set and evaluating the accuracy of these links by measuring their impact on the performance of a trust aware recommender system. The process is separated into three steps, which we will describe at a high level here.

1. **Clustering**
   - **Input:** All users U and a user-user distance matrix.
   - **Output:** An assignment of every user to a cluster.
   - **Description:** Using a simple greedy clustering system, partition the users into groups of highly similar users. We used social circle overlap (Jaccard Similiarty) and review score correlation (Pearson Correlation Coefficient) as inverse distance measures.
2. **Trust Link Prediction**
   - **Input:** Clusters of users and all user trust indicators $\mathbf{x}_i$.
   - **Output:** A matrix of trust link predictions.
   - **Description:** For each cluster c_l of users a logistic regression learns a distinct weight vector, $\mathbf{w}_{c_l}$, for that cluster. We experimented with predicting friendship links and positive review score correlation. Output a $|U| \times |U|$ matrix where, $u_{ij} = 1$ if the classifier for the i'th user's cluster predicts a trust link between users i and j and 0 otherwise.

3. **Recommendation Evaluation**

- **Input:** User-item rating matrix, $|U| \times |U|$ trust matrix.
- **Output:** A user-item matrix of predicted review scores.
- **Description:** Given reviews present in the original data set and the predictions from Step 2, train a trust-aware recommender system to predict review scores. After training, we evaluate the correctness of the recommender on a reserved testing set.

We used a simple one-shot greedy clustering algorithm for step 1, dividing a set of 10000 users into 20 groups. In step 2, 18 features were extracted from the profiles and histories of the Yelp users. These features combined generic and domain specific perspectives, taking inspiration from the works of (Mauro, Ardissono, and Hu 2019) and (Fang, Guo, and Zhang 2015) (and moving beyond these solutions by taking a data driven approach to MFTM and employing more than a small set of general purpose indicators). One of the principal advantages of MFTM is its capability to process many features. After step 3, evaluations of recommendation accuracy were computed according to Mean Squared Error (MSE) and Mean Average Error (MAE) metrics. A full descriptions of the features we computed and the details of these steps can be found in the supplemental material.

We tested prediction accuracy in a number of experiments, only varying which set of trust links the recommender system was given. We tested the actual friend links on Yelp (RealFriends), the predictions of friendship of a MFTM system (FriendPredictions), the predictions of positive review score correlation between users in a MFTM system (PCCPrediction), and four PMFTM experiments, varying the basis for clustering and the type of prediction being done (e.g. PCCCluster_FriendPredict corresponds to clustering users with the most similar review behaviour, then training predictors of friendship links for each cluster).

Figures 1 and 2 summarize results for the *best performing* prediction task in the three experiment classes (RealFriends, MFTM, PMFTM). Metrics are Mean Squared Error and Mean Average Error, measured on the predicted review score on a test set of user ratings. The line labelled *RealFriends* shows results when using the actual friend links between users in the Yelp dataset. The lines *PccPrediction* and *FriendPrediction* are results for MFTM prediction of positive review score correlation and friend links respectively. The line labelled *PCCCluster_PCCPredict* shows results for PMFTM, when users are clustered based on similar review behaviour then a predictor for review score similarity is learned for each cluster of users. The X-axis of each figure corresponds to a social regulation parameter, which controls how heavily trust-links are weighted in the optimization. That is, it is a hyperparemter that could be tuned via cross validation, and we are largely interested in which of the lines reaches the lowest minimum anywhere on the range. Broadly, our results show that prediction of trust links can outperform actual trust links and that personalization of trust link prediction (PMFTM) can significantly improve on the MSE measure[1].

[1]Supplemental material is available upon request.

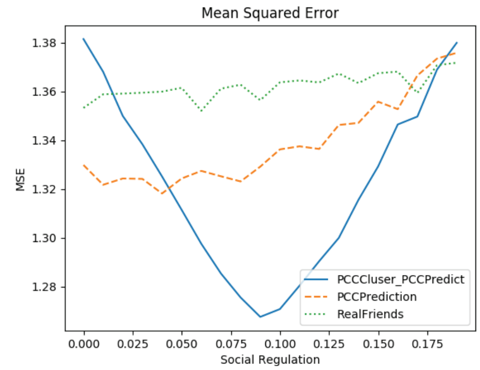

Figure 1: MSE results

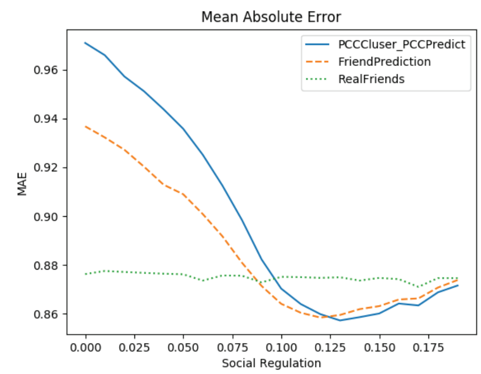

Figure 2: MAE results.

Conclusion

In this work we showed that personalized prediction of trust links between users on a social network leads to enhanced prediction accuracy in a trust-aware recommendation context. This lends support to the intuition that individuals and groups weight evidence differently when forming trust links, which can be of value for curating social network content. We stress that while we chose a recommendation task to demonstrate the efficacy of this approach, we are broadly concerned with improving experiences on social networks and are encouraged by the flexibility of PMFTM for modeling trust in diverse contexts. This work is part of a thesis aimed at promoting pro-social behaviour in social networks through the integration of trust modeling.

References

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