Learning to Rank with Trust and Distrust in Recommender Systems

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1 Problem being addressed

We prefer items that are preferred/recommended by our friends, and have less preference to those preferred to foes (or the people we distrust). We can exploit these relationships to improve the prediction accuracy. It also helps deal with sparsity issues of user preferences in collaborative filtering strategies.

Challenge: $\text{Pref}_i \neq \text{Pref}_j$ for a user i and friend j. This implies we need to incorporate trust degrees to identify correlation between user preferences.
Focus on top-N recommendation instead of rating prediction accuracy.

2 Key ideas and contributions

- Developed a *Learning to Rank* model where objective is to minimize the distances of latent features between trust users and maximize the distance in case of distrust. (similar to social regularization)

  Optimize Mistakes made for a particular user (irrelevant items for user i ranked above a relevant item) + this relevance gap for friends - this relevance gap for foes.

  Push relevant items of user i and friend j above irrelevant items of user i. Also, push relevant items of foe below relevant items of user i.

- For n users, *LTRW* uses:
  $A^+, A^- \in \mathbb{R}^{n \times n}$ for weights of trust and distrust
  Neighborhoods N_i^+, N_i^- for friends and foes of i.
  Weighting matrices $W^+, W^- \in \mathbb{R}^{n \times n}$ express correlation between user i and each friend/foe (to be learnt).
  Ranking functions r is decomposed to user and item factor matrices U and V.
  Three user factor matrices U, U^+, U^- - 3 latent spaces.

- Weighting strategy:
  $W^+ = U \times M^+ \times {U^+}^T$ using trust preference user factor matrix M^+
  $W^- = U \times M^- \times {U^-}^T$ using distrust preference user factor matrix M^-
  $\forall i$, friend j, maximize similarity in U, U^+, M^+
  $\forall i$, foe j, minimize similarity in U, M^-, maximize similarity in U, U^-

- **Training data** - Epinions
  Evaluation metric - Recall, Normalized Discounted Cumulative Gain (NDCG)
  Baselines CofiRank, Social Poisson Factorization , JSCR.

3 Strong points

- Successfully implements LTRW model and demonstrates superiority over other models without trust or weighting strategy. Beneficial weighting strategy (along with LTR) to incorporate user preferences.
- The study of missing relationships indicate that there is a significant reduction in recall. This implies that incorporation of social relationships is beneficial.

4 Weak Points

- **Expertise and trust**: Can a friend ("trust") be a foe ("distrust") in a different context? A person can be very reliable on his recommendations for headphones, but say he is not reliable on *fantasy books*. The model builds the intermediate trust and distrust preference latent spaces,but friend and foe of a person are disjoint sets. This notion of contextual trust along with granularity levels could be modelled.
  This is further strengthened by the fact that "influence" of a person depends on item, user preference and time. Currently a *global* model.
- **Trust evolution and temporal dynamics**: Trust can change over time. Modeling this evolution in the neighborhoods and intermediate latent factor matrices can be beneficial.
- A better comparison can be done with **metric spaces** to see if there is a benefit in factorizing over representations in the metric spaces.
- Relies on predefined A^+, A^- matrices to prepare neighborhood matrices. The nature of these matrices and their generation is not known.

5 Questions

1. How would you incorporate temporal and item dynamics in the weighting strategy as well as neighborhoods?
2. Handling hierarchical categories of items could be implicitly captures in (1) above.

6 Misc

Easy read. Creative.
ACM ref:
Dimitrios Rafailidis and Fabio Crestani. 2017. Learning to Rank with Trust and Distrust in Recommender Systems. In Proceedings of the Eleventh ACM Conference on Recommender Systems (RecSys '17). ACM, New York, NY, USA, 5-13. DOI: https://doi.org/10.1145/3109859.3109879