Collaborative Filtering Course Project

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Abstract. We have implemented the paper Trust aware Recommender Systems by Paolo Massa and Paolo Avesani and tried another approach(Tidal Trust approach) on the same dataset(Epinions Dataset) and have produced results.

1 Trust Aware RS

1.1 Motivation

In regular recommender systems based on collaborative filtering techniques, a user can be considered as neighbour for the active user only if it is possible to compute the similarity weight of her and the active user. In this sense this first step is very important in order to be able to generate recommendations. Two users can be compared with a correlation coefficient only if they have rated in common at least few items. But in general cases there are so many items that there are generally no overlap between items rated by two different users. Hence this data sparsity is the first major weakness of neighbourhood based techniques. This is especially evident in cold start users. The second major weakness of this type of recommender systems is its vulnerability to attacks like the copy profile attack.

1.2 Methodology

Authors have compared different user-item prediction techniques on the Epinions dataset[3]. Epinions dataset provides us with the ratings which different users(40000) have provided for different items(40000). We are also provided with a user to user trust dataset which contains the trust value which user u assigns to user v. The authors then suggest a novel technique to use trust coverage instead of neighbourhood method in regular Collabrative filtering techniques.
Authors have compared the following methods:

- User-User similarity
- Item-Item similarity
- Moletrust-1,2,3

Moletrust Moletrust is an adaptation of algorithm found in (Rici et al, 2011). It is a graph based approach where we find a weight between two users who have not rated each other. It is an approach where we find a path from a source user to a sink user using neighbours and calculate weight.[2]

Tidal-Trust It is a similar algorithm as Moletrust but instead of average we take the maximum of minimum(edge_weight, weight[predecessor]) for all the predecessors for each node.[2]

1.3 Discounted Method Novel

Other than just simple algorithms discussed above, inspired from Reinforcement Learning, we have tried using a discounted trust approach where we discount the trust value by a fixed discount factor after each level traversal. We have shown results using symbol DX where X could be Moletrust(MT) or Tidal Trust(TT).

1.4 Node2Vec

We got to know about another technique Node2Vec but too late. We can also use this feature to find out results and this might prove to be a better technique. We weren't able to train but we produced the feature vector(128 features) for 1000 users using an implementation on Github[1]. We can use this to train neural networks and then use that as a classifier on test data. We have attached the feature vectors in the file 'epinions/sub_graph.embs'.

2 Results

Algorithms	All	Cold Start
User-User	0.847274	1.2610
Item-Item	0.86636	1.2541
MT1	0.93755	0.85187
MT2	0.95526	1.1655
MT3	0.95667	1.04890
DMT1	0.89165	0.821659
DMT2	0.91673	1.12638
DMT3	0.95436	1.15595
Tidal Trust(TT)	0.99742	1.03130
DTT	1.01520	1.2645

References

1. Node2vec implementation, https://github.com/aditya-grover/node2vec
2. Tidal trust and moletrust algorithms, https://www.fer.unizg.hr/_download/repository/Master_Thesis_-_Mirjam_Situm.pdf
3. Massa, P., Avesani, P.: Trust-aware recommender systems. In: Proceedings of the 2007 ACM Conference on Recommender Systems. pp. 17–24. RecSys '07, ACM, New York, NY, USA (2007). https://doi.org/10.1145/1297231.1297235, http://doi.acm.org/10.1145/1297231.1297235