Recommending the Recommenders
Demo Project

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1. What is exactly the function of your tool? That is, what will it do?

The main goal of recommender systems is to suggest items to the user that are most likely to align with their interest. The performance of the recommender systems in a target domain A can be augmented using the information from a source domain B.

For example, we can recommend movies (target domain) to a person who is a frequent buyer of books (source domain). Their ratings in the books domain can be used to approximate genres which could then be used to recommend relevant movies to users.

Current cross-domain recommenders suggest recommendations on the basis of some pre-selected source domains all of which have equal importance in the calculation of the final recommendation. We propose to bring more interpretability in the recommendation algorithms by calculating an importance score with the embeddings of source domain in a cross-domain recommender system.

$$f(x) = \frac{1}{2} \sum_{i,j}$$

2. Why would we need such a tool and who would you expect to use it and benefit from it?

The cross-domain recommendation techniques proposed in the current literature work takes a set of source domains and extrapolates the ratings of cold-start users in the target domain. However, the methodology used to choose the source domains has not yet been explored.

An apt selection of source domains might improve the cross-domain recommendation and provide insights of inter-domain correlation of interest. The proposed design is presented to investigate this issue.

The cross-domain recommenders with source domain selection can be used by online services such as Amazon, Netflix to recommend items to the users.

3. Does this kind of tools already exist? If similar tools exist, how is your tool different from them? Would people care about the difference? How hard is it to build such a tool? What is the challenge?

Sahebi et. al [1] finds the correlation between the source domain and target domain in a one-to-one mapping setting. However, the analysis is limited in the sense that it trains separate models for each mapping from source to target domain for showing this correlation.

4. How do you plan to build it? You should mention the data you will use and the core algorithm that you will implement.

We are planning to use CCCFNet, a combination of collaborative and content-based filtering technique, as our baseline model. The purposed CCCFNet model uses a source-target domain pair and predicts the rating of a new item in the target domain. We plan to use it as base model, but instead of estimating the rating of a a new item in the target domain we plan to ascertain which source domains are mostly correlated to the target domain by using weight attention model.

The idea is not to simply average the embeddings from the different source domains rather calculate the weighted average of the different source domains' embedding. This attention/importance parameter will be completely learned in our model. This makes our model interpretable i.e. we can see the attention score and say which source domains are more important for a particular target domain.

5. What existing resources can you use?

We are planning to evaluate our recommendation system model on the following available datasets:

- Douban
- MovieLens
- Amazon dataset released by UCSD

Amazon dataset from UCSD provides an ample collection of different domains such as books, movies, music etc. We can perform cross-domain recommendation analysis over these data sets.

6. How will you demonstrate the usefulness of your tool?

We will use RMSE (Root Mean Squared Error) as our primary evaluation measure, along with Average Recall and MAP (Mean Average Precision) metrics. Using the Lian et al [2] and Sahebi et al [1] results as our baseline, we will compare the performance of our proposed recommendation engine.

References

[1] Shaghayegh Sahebi, Peter Brusilovsky, and Vladimir Bobrokov. Cross-domain recommendation for large-scale data. 2017.

[2] Jianxun Lian, Fuzheng Zhang, Xing Xie, and Guangzhong Sun. Cccfnet: a content-boosted collaborative filtering neural network for cross domain recommender systems. In *Proceedings of the 26th International Conference on World Wide Web Companion*, pages 817–818. International World Wide Web Conferences Steering Committee, 2017.