Recommendation of Faculty Web Pages

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Abstract. A task of valuable importance for universities is the assignment of reviewers and panel members for assessing theses and dissertations. This is not a trivial task as the topics covered in a theses or a dissertation could be quite diverse and the research could be multidisciplinary. We further might have constraints such as reviewer's preferences, conflicts of interest and reviewer's workload as well. Here, we provide an overview of variants based on ESA and the evaluation methods for these variants.

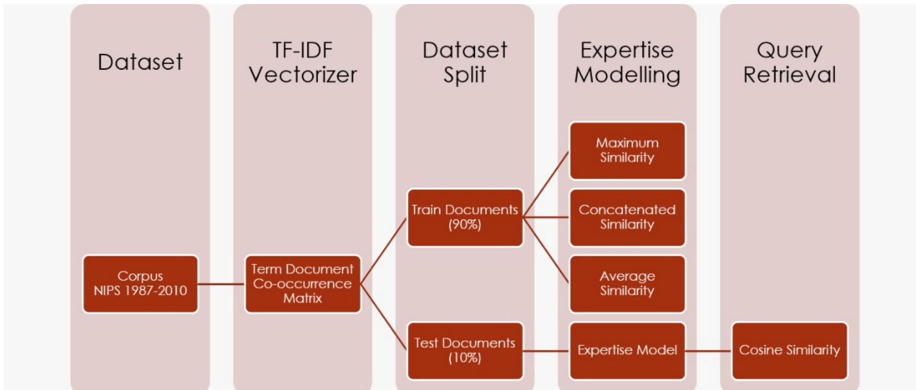
1 Introduction

In this project, we attempt to solve the problem of automatically recommending faculty members as reviewers for theses and dissertations submitted by research scholars, based on the faculty member's previous research work. This is an important as typically there are many hundreds of thesis and dissertations every year, each of which could potentially require multiple reviewers. Manually assigning reviewers is both a tedious and time consuming task. Also, assigning theses and dissertations to a set of apt reviewers requires knowing both the area of topics explored in the theses and also the expertise of the reviewers and will be very difficult for a single person to accomplish. The research could be overlap between multiple disciplines in which case, assigning reviewers becomes much more complicated too. Constraints such as workload of the reviewer and conflicts of interest have to taken into account and also every theses or dissertation has to be reviewed by at least a certain number of reviewers. The motivation is to decrease the time manually spent in assigning the faculty members to assess the research work of scholars.

2 Approaches and Evaluation Methods

Our idea for the solution consists of two steps. In the first step, we model the expertise of the faculty members. In the second step, we retrieve and rank the faculty members as potential reviewers for a given thesis or dissertation based on the learned expertise model. We have used a few variants of ESA to model the expertise of faculty members.

And since we do not have target reviewers for the query articles for evaluation, we take the contributors of the target thesis or dissertation as the target reviewers since the current article would be in their field of expertise.



2.1 Vanilla ESA

2.1.1 Variant 1: We first pre-process data stemming all the words present in the articles using Porter stemmer. Next, we generate the TF-IDF matrix of the articles present in the dataset. Then, to model the expertise of a faculty member, we group all of his articles and to find the similarity of a faculty member with a new theses or dissertation, we take the maximum of cosine similarity of all of the faculty member's documents with the new thesis or dissertation. Finally, we take the faculty member with highest maximum similarity with the query document.

For evaluating this variant, we use the usual accuracy metric and mean reciprocal rank. After we generate the rankings of the reviewers, we classify a certain output as correct in the usual accuracy metric if the top ranked reviewer is one of the contributors of the article. We then find the accuracy based on these correct outputs. Similarly, we also find the mean reciprocal rank based on rankings retrieved.

2.1.2 Variant 2: In the second variant, we concatenate all the articles of a contributor which is effectively summing up the corresponding rows of the TD-IDF matrix and normalizing. Then, we compute cosine similarity of the query article with each such concatenated representation of every faculty member and rank them.

After rankings are generated, we follow the method of evaluation as in the earlier case.

2.1.3 Variant 3: In the third variant, instead of maximum of the cosine similarities, we take the average of cosine similarity of all of the faculty member's documents with the new thesis or dissertation. While taking maximum of similarities is one extreme case as it requires the author to have just a single very relevant document, concatenating all documents is another extreme case. So, we use average similarity to balance them out. Then, the faculty members are ranked based on the values of their average similarities.

Once the ranking are generated, the evaluation method is identical to the earlier case.

2.2 Grouped ESA

Similar to the earlier, we pre-process the dataset using Porter Stemmer and then generate the TF-IDF matrix. Here, to model the expertise of a faculty member we concatenate all the corresponding articles similar to what was done in the third variant of the earlier approach. To find the similarity of a researcher with a new articles, we take the average of cosine similarity of all his articles with the new article. The researchers are then ranked based on their values of average similarities.

For evaluating the approach, we first group the articles based on their similarities with each other, with a certain threshold for similarity as a parameter. Again, we take cosine similarity as the similarity measure between the articles using the TF-IDF matrix. We then group the contributors of the grouped documents into the corresponding groups as well. After we generate rankings of the reviewers, we classify a certain output as correct if the top ranked reviewer and any of the contributors are of the same group. We then find the accuracy based on these correct outputs. Similarly, we also find the mean reciprocal rank based on rankings retrieved.

We estimate the possible number of groups that could be present in the given field of study and tune the threshold or we could use it just as a heuristic.

3 Datasets

We have used conference papers from NIPS (Neural Information Processing Systems) 1987 - 2017 from Kaggle source. The dataset contains about 7,284 documents. Since the computational time was too high for such high number of documents, we have taken NIPS papers up to 2010. This has about 3,513 documents with a vocabulary of 135,761 words. The dataset consists of the conference year, title, the type of event, abstract and text. There are about 10000 different contributors in the dataset.

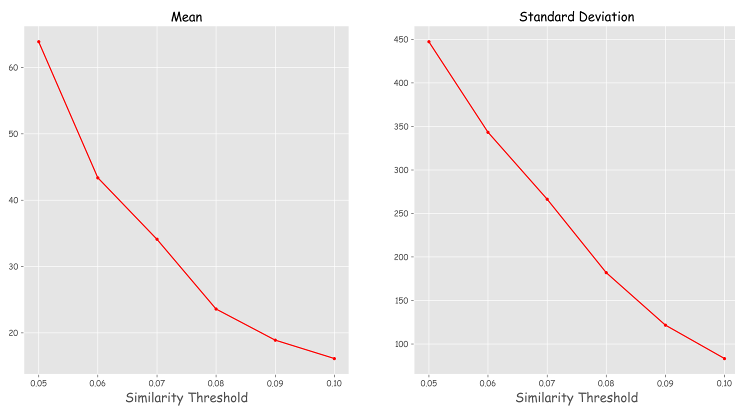
4 Results and Discussion

4.1 Vanilla ESA

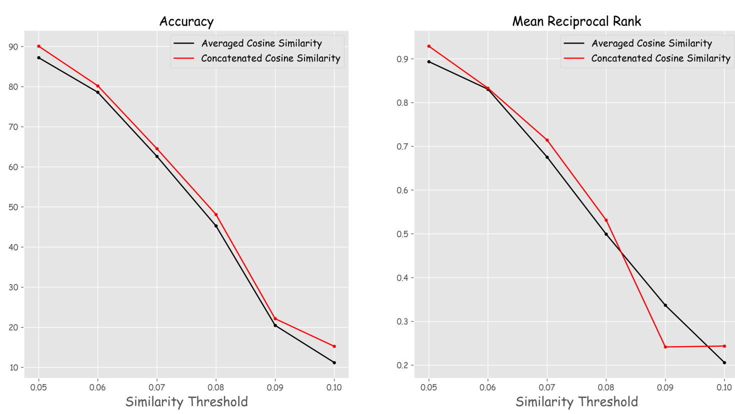
In the first variant of ESA, we have gotten an accuracy of 25.18%. For the concatenated cosine similarity variant, a top-1 accuracy of 24.19% was obtained while the top-3 accuracy was 37.23%, the mean reciprocal rank for this was 0.2592. For the average cosine similarity variant, we obtain an accuracy of 16.79% and mean reciprocal rank of 0.2011.

4.2 Grouped ESA

We vary the threshold of the similarity and observe the mean and standard deviation of the number of groups generated. For a very low similarity threshold, the groups are skewed with a very high standard deviation meaning that most of the contributors are in a single group with the other groups being very sparse.



Mean and Standard Deviation of Number of Groups



Here, we see the variations of accuracy and mean reciprocal rank as we vary the threshold.

4.3 Example

For illustration, we have chosen the paper "Improved Switching among Temporally Abstract Actions" by Prof. Balaraman Ravindran. The top 4 ranked reviewers for this are Doina Precup (Specialization: Artificial Intelligence, Thesis: Temporal Abstraction in Reinforcement Learning, Doctoral Advisor: Richard S. Sutton), Anna Koop (Director of Applied Machine Learning, AMII, Specialization: Artificial intelligence, Machine Learning, Reinforcement Learning), Richard S. Sutton (One of the founding fathers of Modern Computational Reinforcement Learning, having several significant contributions to the field, includingtemporal difference learning andpolicy gradient methods) and Cosmin Paduraru (PhD work: Investigating the properties of value function estimators in batch Reinforcement Learning).

5 Conclusion

Grouped ESA in general tends to give more generalized results compared the other approaches. We could also sample from the top few ranked reviewers instead of selecting the top ranked reviewer.

References

1. Gabrilovich, Evgeniy, and Shaul Markovitch, *Computing Semantic Relatedness Using Wikipedia-based Explicit Semantic Analysis.*. IJCAI. Vol. 7. 2007.
2. Mimno, David, and Andrew McCallum, *Expertise modeling for matching papers with reviewers.*. Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2007.
3. Laurent Charlin, and Richard S. Zemel, *The Toronto Paper Matching System: An automated paper-reviewer assignment system.*. Proceedings of the 30th International Conference on Machine Learning, Atlanta, Georgia, USA, 2013.