Personalized Academic Research Paper Recommendation System

Joonseok Lee, Kisung Lee, Jennifer G. Kim
Georgia Institute of Technology
Atlanta, GA 30318
{jlee716,kslee,jkim693}@gatech.edu

Abstract

A huge number of academic papers are coming out from a lot of conferences and journals these days. In these circumstances, most researchers rely on key-based search or browsing through proceedings of top conferences and journals to find their related work. To ease this difficulty, we propose a Personalized Academic Research Paper Recommendation System, which recommends related articles, for each researcher, that may be interesting to her/him. In this paper, we first introduce our web crawler to retrieve research papers from the web. Then, we define similarity between two research papers based on the text similarity between them. Finally, we propose our recommender system developed using collaborative filtering methods. Our evaluation results demonstrate that our system recommends good quality research papers.

1 Introduction

Recommender systems are widely used these days in e-commerce, for the purpose of personalized recommendation. Based on each user’s profile, previous purchase history, and online behavior, they suggest products which they are likely to prefer. For example, Amazon.com is using recommender systems for books. When a user logs-in to the system, it suggests books similar to previously bought ones by the user.

Personalized recommendation can be applied to outside of commercial applications. These days, many academic papers are coming out from a lot of conferences and journals. Academic researchers should go through all the conferences and journals which are related to their field of research and find out if there is any new articles that may relate to their current works. Sometimes they search the articles from Google scholars or Citeseer with the key words that might show interesting articles to them. However, these two methods require users to commit their time to search articles, which is labor-intensive, and also do not guarantee that they will find the exact articles related to their field of research.

In order to reduce their workload, we suggest developing the scholarly paper recommendation system for academic researchers, which will automatically detect their research topics they are interested in and recommend the related articles they may be interested in based on similarity of the works. We believe this system will save the researchers’ time to search the articles and increase the accuracy of finding the articles they are interested in.

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2 Related Work

In this section we briefly present some of the research literature related to recommender systems in general, academic paper recommendation system, and evaluation of recommender systems.

Recommender systems are broadly classified into three categories[7]: collaborative filtering, contents-based methods, and hybrid methods. First, collaborative filtering uses only user-item rating matrix for predicting unseen preference[21][1]. It can be categorized into memory-based CF, which contains the whole matrix on memory, and model-based CF, building a model for estimation[2]. The most effective memory-based algorithms known so far is item-based CF[19]. Recently, making use of matrix factorization, a kind of model-based approach[14, 16, 18, 4, 24], is known as the most efficient and accurate, especially after those approaches won the Netflix prize in 2009. Content-based methods, on the other hand, recommend items based on their characteristics as well as specific preferences of a user[7]. Pazzani[15] studied this approach in depth, including how to build user and item profiles. Last category, hybrid approach, tries to combine both collaborative and content-based recommendation. Koren[8] suggested effectively combining rating information and user, item profiles for more accurate recommendation.

Recommender systems have concentrated on recommending media items such as movies, but recently they are extending to academy. Most popular application is citation recommendation[5, 12, 23, 20]. Recently, Matsatsinis[11] introduced scientific paper recommendation using decision theory. Sugiyama[22] extended scholarly paper recommendation with citation and reference information.

Although recommender systems are very popular in commercial applications these days, it is still difficult to evaluate them due to the lack of standard methods. Traditional recommender systems[4, 17, 6] were usually introduced in Human-Computer Interaction community, so they have been evaluated by user study. This approach is still used, especially for verifying improvement in terms of user experience.

3 Methodology

Figure 1 shows the flow of our system. First, our system gathers data and preprocess it, by applying Bag-of-word model to the corpus. In actual learning process, we apply lazy learning method similar to k-Nearest Neighbors (kNN). Thus, we estimate preference of a target user and recommend the most preferred papers, when the system gets a query, specifying the target user. For this task, we applied clustering and neighbor-based recommendation algorithm. Finally, the result is conveyed to the user by visualizer. In this section, we describe each component in detail.

Figure 1: Recommendation Flow

3.1 Data Gatherer

To get information of research papers, we have implemented a web data gatherer for two research paper search engines and storage: IEEE Xplore and ACM Digital Library.

IEEE Xplore Digital Library provides a unique web page for conferences or journals, of a specific year or edition respectively. On each page, there is a list of published papers, so we retrieve the list of URLs using regular expression matching. After getting the URL list, our data gatherer retrieves the information of all research papers in the list by iterating each URL in the list.
ACM Digital Library also provides a unique web page for conferences or journals published by ACM. The data gatherer finds a list of URLs which have information for each research paper using regular expression matching. Unlike IEEE Xplore, since the single page includes URLs of all the papers, our data gatherer does not need to traverse multiple pages for one conference or journal. With the URL list, the data gatherer gathers the information of all research papers in the list by iteratively visiting each URL in the list.

We have experienced a challenge while developing the data gatherer. There are different representations for same researcher’s name. To solve this problem, we have developed several rules to handle any orders of first name, last name, middle name and suffix. Also, we have implemented a function to infer authors’ full name using the co-occurrence with other authors.

### 3.2 Data Model

#### 3.2.1 Bag-of-word model

With the gathered data, we modeled them by a bag-of-word model. In this model, each word appeared in the whole document corpora becomes an attribute. Then, each document is represented by a bit vector, indicating whether each word appears or not. This model is based on two assumptions: 1) word probabilities for one text position are independent of the words that occur in other positions (Naive Bayes Assumption) and 2) the probability of encountering a specific word is independent of its position. (Independent Identical Distribution Assumption) This assumption is incorrect, but it is known that this does not seriously affect classification or learning task. We combined title, key words, and abstract to construct a set of words representing a paper.

#### 3.2.2 Heuristics

For more efficient processing, we applied some heuristics. First, we removed stop words such as “the” or “of”. These words appear in almost every document in English, so they are not useful for classifying or filtering some specific documents, but just slow down computation speed by increasing the text length. We removed about 140 words which were selected manually. This process reduces the length of dictionary, resulting in reduced dimension of the clustering work, so we expect speed improvement.

The other heuristic applied is stemming. In English, same word can be used as different parts, usually in a slightly different form. For example, “clear”, “clearly”, and “cleared” have same meaning, but used in different forms for its position or role in the sentence. It is much better to deal with these minor changes of forms as same words, as it can dramatically reduce the dimension. However, this work is not straightforward. As a first step, we just removed last "ed", "ly", and "ing" from the word, whenever encountered.

### 3.3 Learner (Recommender)

Using the crawled documents and data model discussed so far, we are ready to proceed to our main goal: personalized recommendation of academic papers. As a perspective of recommendation system, we can consider authors as users and papers as items. We will use these terms interchangeably henceforth. We can think of recommendation system as a task to fill out missing preference data on a user-item matrix, based on observed values. There can be lots of schemes to decide proper values for missing preference. Filling with the user’s average or item’s average can be a simple baseline. In this section, we discuss fundamental characteristics of our problem, and then describe our algorithm.

#### 3.3.1 Inherent Characteristics of Problem

The information we gather contains each paper’s title, list of authors, key words, and abstract. In order to build a user-item matrix with this data, we assume that users are interested in their own papers. Thus, we set high score (in this paper, 5) to every <author, paper> pair that the paper is written by the author. We use 1-5 scale as it is widely used in recommendation systems in literature.

We claim that this user-item matrix we use is extremely sparse, which means most of values are missing while only small portion of them are observed. This situation is common in recommendation, though. According to Netflix Prize data, only 1% of cells of the user-item matrix are observed
values. Nonetheless, it has been shown that it is possible to accurately estimate missing data only using small amount of observed data. In our situation, however, the sparsity can be worse. Regularly, one author writes only one or two papers in one conference proceeding. There are only at most two or three top-level conferences in each field, the maximum number of papers one author can publish a year is about 10. This is an ideal case, and most researchers may have only one or two papers. Thus, our matrix have only a few number of preference data.

More serious problem is that we do not have "dislike" information. When we request users to explicitly rate items in a common recommendation system, we can get both positive and negative feedback from the user. For example, we can get "very like" feedback for the movie "Titanic" as well as "very hate" one for the "Shrek 2." Based on this variety, we can infer that the user may prefer romantic movies to animations. In our data, however, we do not have negative feedback. This problem makes difficult us to use widely-used collaborative filtering algorithms.

3.3.2 Naive Recommender

We basically assume that authors will like papers similar to ones they wrote before. In this context, we note that similar papers mean ones dealing with similar topic. In our Naive Recommender, we just apply this assumption. When we try to recommend a set of papers to a specific user, we first calculate similarity between every paper and the user’s own papers. Then, we take the highest similarity as the score of that paper. This process is similar to k-Nearest Neighbors (kNN) algorithm. That is, we can easily select and recommend most similar $n$ papers to the target user’s previous paper. We used vector cosine of our data model (bit vector) as the similarity measure.

However, the real situation is a little bit more complicated, as the user may have written more than one paper. It is still kNN, but we can have more than one queried point. Thus, we applied clustering first. All candidate papers are assigned to only one of the most similar paper written by the target user. This process is similar to K-means, but the centroids are also papers, so their geometric location in the space cannot change. Thus, we do not need to iterate in our case. After assigned to a cluster, the score is calculated based on the distance between the candidate paper and its centroid. For example, as shown in Figure 2 each big circle represents a centroid of a cluster and small circles connected to the centroid are members of its cluster. Using the calculated score as a distance metric for kNN, we select $k$ papers for recommendation to the target user.

![Figure 2: Visualization of Clustering and kNN](image)

To illustrate, assume that the user $u$ wrote only two papers ($x_1$ and $x_2$, respectively) until now. We calculate estimated preference of new paper $p$ by the user $u$. First, we calculate similarity between $p$ and $x_1$. Let’s say this similarity as $s_1$. We also calculate similarity between $p$ and $x_2$, namely $s_2$. Then, we compare $s_1$ and $s_2$. We set estimated preference of $p$ by user $u$ as $\max(x_1, x_2)$. This is because the user may like a paper when it is related to his one of the interested topics. Although it is not related to other papers, the author may still like it if it is related to at least one of the topic in which he is interested. More formal formula for estimating preference of user $u$ for item $i$ is given as:

$$\max_i \left( \frac{\text{sim}(x, i) \times 5}{\max_{i, k} \text{sim}(j, k)} \right)$$

(1)
where, $x$ is index of papers which the user $u$ published, and $i, j, k$ are index of all papers. The score is scaled to 5 as we set 5 points for authorship. This scale will be lowered for referenced papers.

### 4 Evaluation

#### 4.1 Classification Accuracy

First, we measured accuracy of our system by the following simple classification scheme. As we crawled papers (and authors) from three different areas (ML, HCI, DB), we observed how many papers are actually recommended from the researcher’s own area, when the corpus is mixed. For this experiment, we recommended 10 papers each among the overall 10,386 papers to 10 ML researchers, 10 HCI researchers, and 10 DB researchers. This task can be seen as a kind of classification of each researcher, based on the papers recommended to them. The result is shown in Figure [1] In overall, our system recommended papers from correct area with accuracy of 89%. One thing to note is that, however, recommendation from different area may not an incorrect result, as some researchers actually do research cross over other areas. For example, robotics research is highly related to ML as well as HCI. Thus, fine detail of evaluation should be conducted with real users, as described in the next subsection.

| Area           | ML Paper | HCI Paper | DB Paper | Accuracy |
|----------------|----------|-----------|----------|----------|
| ML Researchers | 84       | 0         | 16       | 84%      |
| HCI Researchers| 3        | 88        | 9        | 88%      |
| DB Researchers | 4        | 1         | 95       | 95%      |

#### 4.2 User Study Design

Our system is aimed to recommend similar papers to the target user’s previously published papers, assuming that researchers will like similar papers to their previous research topics. In order to verify whether this assumption is true, we evaluated the content relevance between the target users previous published papers and the papers recommended by our system. We conducted focus group user study by interviewing three professors from all different fields of Computer Science area, i.e., Machine learning, Data Base, and Human-Computer Interaction. One professor is a junior professor, and the other two are senior professors. The data we used in this evaluation is summarized in Table [2]

| Area | Paper | Author | Conferences (Years) | Time (sec) |
|------|-------|--------|---------------------|------------|
| ML   | 3,644 | 5,786  | ICML(04-09), KDD(04-10), COLING(04-10), UAI(04-09), SIGIR(04-10), JML(04-11) | 38.8       |
| HCI  | 2,557 | 4,728  | CHI(03-09), ASSETS(02-09), CSCW(04-11), Ubicomp(07-10), UIST(04-10) | 33.5       |
| DB   | 4,156 | 7,213  | ICDE(06-10), SIGMOD(06-10), VLDB(06-10), EDBT(08-11), PODS(06-10), CIKM(06-10) | 92.2       |

We provided 10 papers, to each participant, recommended by our system. The survey listed title, authors, proceedings name, and abstract of those papers. The participants are asked to read and indicate how the papers are relevant to their research. We used a Likert-scale between 1 (not relevant at all) and 6 (perfectly relevant), in order to prevent voting to middle-way. After evaluating all 10 papers, we asked how much the list of papers was relevant to the researchers previous research and current research separately. One more thing we wanted to evaluate is the usefulness of recommended papers. We asked the subjects to indicate the number of papers they would take time to read and get useful information among 10 recommended papers. Lastly, we asked how they are satisfied with the system in overall and how much they are willing to use the system. Here, we also used 1-6 Likert-scale question.
4.3 Result

As shown in Table 3, three subjects indicated recommended papers tend to relate to their previous and current research. When we asked how the recommended paper list is related to their previous research in overall, all gave higher than 5 point. (5.5, 5.0, 5.5) However, for the relevance of their current research topic, even though two professors gave 5.0 and 5.5, respectively, the other gave 2 point. In this case, she has worked on so many various topics before, so our system recommended papers that are relevant to every topic she has been interested in. In this way, for her, among 10 recommended papers there were only two papers related to current research topics. Overall, all the professors were satisfied with the results of the recommended papers in respect of the topic relevance to their research.

For senior professors, our system recommended four papers that their previous students published. Since their previous students now graduated, they did not publish the recommended papers together with the professor, but the papers topics were relevant to what they have done with the professor. The fact that our system is able to recommend these papers also ensures good performance of our system in recommending relevant topics papers.

When we asked the subjects the number of papers to read, they replied, realistically they would read only the papers that are highly related to their research, which was about two papers among 10 papers since they do not have enough time to read all the papers. This result is also very satisfied, when we consider the fact that we did not use any other users profile information and just only used content based on their previous research. Lastly, all of the subjects marked 6.0 point out of 6.0 to use this recommendation system, indicating that our research is valuable for real users.

| Subjects      | Average | Standard Deviation |
|---------------|---------|--------------------|
| Subject 1     | 4.40    | 1.26               |
| Subject 2     | 4.00    | 1.56               |
| Subject 3     | 3.25    | 1.72               |
| Total         | 3.88    | 1.52               |

5 Discussion

5.1 Contribution and User Interface

In this study, we investigated the way to reduce academic researchers’ labor-intensive workload, going through all the conferences and journals to find out any scholarly papers that might relate to their research topic. Our system provides simple Graphical User Interface (GUI), shown in Figure 3, that requires two input fields, name of researcher and the number of academic papers the user wants to be recommended.

5.2 Limitation and Future Work

Even though our system showed good performance on recommending relevant topic’s paper, we identified two limitations on our content-based recommendation. First, we cannot distinguish the meaning of topics that are narrowed by few specific words. In other words, our system recommends papers based on the words’ frequency, so our system will recommend papers that contain many words that the user may be interested in. This cannot discover few words that restrict meaning of its topic, so it causes recommending the paper that has not relevant topic to the user. Also, there are users who have worked previous study on various topics, but are not interested in anymore. Also in this case, because our system does not have any additional information about whether the user is still interested in the paper or not, it is hard to distinguish the papers that recommend to users. We may be able to extend by applying publication year in some way.

To overcome these limitations we need to recommend papers based on not only relevant topics but also other user information. We suggest obtaining a user input about whether they like the recommended papers or not would be helpful information to differentiate the papers that users would be
interested in more accurately. Also, through the focus group interview we discovered the interesting fact that even though the topics are not as much as relevant to their research topic, they showed great interest to the papers that their peer researchers, i.e., their former students or the researchers they have done research together before, wrote. In this way, it will be important to include the information about relevant researchers to users and recommend papers that they found interesting or they have wrote. Also, the subjects replied, if we provide information about which researcher liked this papers, it would also give them great reason and motivation to read that paper.

For the perspective of machine learning, we may need to consider about scalability. Although our current system runs within a few minutes, it may take more time when we crawl more data. First, we can improve accuracy of similarity measure by allowing counting the frequency of each word in a document, instead of bit vector model. TF-IDF model [10] can be a great candidate to implement. In this model, we give more weight for frequently used words in a specific document, but not in other ones. Also, we may need to speed up the calculation. For this, dimension reduction will be helpful. Specifically, it would be better to add more stemming logic because this can deal with more words as same ones, so we can successfully reduce dimension. We may use L-Distance algorithm [9] for calculating similarity of each word pair, and decide whether they are same or not.

6 Conclusion

In this paper, we have presented a Personalized Academic Research Paper Recommendation System, which recommends related articles for each researcher. Thanks to our system, researchers can get their related papers without searching keywords on Google or browsing top conferences’ proceedings. Our system makes three contributions. First, we have developed a web crawler to retrieve a huge number of research papers from the web. Second, we define a similarity measure for research papers. Third, we have developed our recommender system using collaboration filtering methods. Evaluation results show the usefulness of our system.

References

[1] G. Adomavicius and A. Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering,
[2] J. S. Breese, D. Heckerman, and C. Kadie. Empirical analysis of predictive algorithms for collaborative filtering. pages 43–52. Morgan Kaufmann, 1998.

[3] L. D. D. Algoritms for nonnegative matrix factorization. Advances in Neural Information Processing Systems, 13:556–562, 2001.

[4] D. Goldberg, D. Nichols, B. M. Oki, and D. Terry. Using collaborative filtering to weave an information tapestry. Commun. ACM, 35:61–70, December 1992.

[5] Q. He, J. Pei, D. Kifer, P. Mitra, and L. Giles. Context-aware citation recommendation. In Proceedings of the 19th international conference on World wide web, WWW ’10, pages 421–430, New York, NY, USA, 2010. ACM.

[6] W. Hill, L. Stead, M. Rosenstein, and G. Furnas. Recommending and evaluating choices in a virtual community of use. In Proceedings of the SIGCHI conference on Human factors in computing systems, CHI ’95, pages 194–201, New York, NY, USA, 1995. ACM Press/Addison-Wesley Publishing Co.

[7] D. Jannach, M. Zanker, A. Felfernig, and G. Friedrich. Recommender Systems – An Introduction. Cambridge, 2011.

[8] Y. Koren. Factorization meets the neighborhood: a multifaceted collaborative filtering model. In Proceeding of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, KDD ’08, pages 426–434, New York, NY, USA, 2008. ACM.

[9] V. I. Levenshtein. Binary codes capable of correcting deletions, insertions, and reversals. Soviet Physics Doklady, 10(8):707–710, 1966.

[10] C. D. Manning, P. Raghavan, and H. Schutze.

[11] N. F. Matsatsinis, K. Lakiotaki, and P. Delias. A system based on multiple criteria analysis for scientific paper recommendation. 2007.

[12] S. M. Mcnee, I. Albert, D. Cosley, P. Gopalkrishnan, S. K. Lam, A. M. Rashid, J. A. Konstan, and J. Riedl. On the recommending of citations for research papers. In Proceedings of the 2002 ACM conference on Computer supported cooperative work, CSCW ’02, pages 116–125, New York, NY, USA, 2002. ACM.

[13] T. M. Mitchell. Machine Learning. McGraw-Hill, 1997.

[14] A. Paterek. Improving regularized singular value decomposition for collaborative filtering. Statistics, 2007:2–5.

[15] M. Pazzani and D. Billsus. Content-based recommendation systems. In P. Brusilovsky, A. Kobsa, and W. Nejdl, editors, The Adaptive Web, volume 4321 of Lecture Notes in Computer Science, pages 325–341. Springer Berlin, Heidelberg, 2007.

[16] J. D. M. Rennie and N. Srebro. Fast maximum margin matrix factorization for collaborative prediction. In Proceedings of the 22nd international conference on Machine learning, ICML ’05, pages 713–719, New York, NY, USA, 2005. ACM.

[17] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl. GroupLens: an open architecture for collaborative filtering of netnews. In Proceedings of the 1994 ACM conference on Computer supported cooperative work, CSCW ’94, pages 175–186, New York, NY, USA, 1994. ACM.

[18] R. Salakhutdinov and A. Mnih. Probabilistic matrix factorization. 2008.

[19] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl. Item-based collaborative filtering recommendation algorithms. pages 285–295, 2001.

[20] T. Strohman, W. B. Croft, and D. Jensen. Recommending citations for academic papers. In Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval, SIGIR ’07, pages 705–706, New York, NY, USA, 2007. ACM.

[21] X. Su and T. M. Khoshgoftaar. A survey of collaborative filtering techniques. Adv. in Artif. Intell., 2009:4:2–4:2, January 2009.

[22] K. Sugiyama and M.-Y. Kan. Scholarly paper recommendation via user’s recent research interests. In Proceedings of the 10th annual joint conference on Digital libraries, JCDL ’10, pages 29–38, New York, NY, USA, 2010. ACM.

[23] J. Tang and J. Zhang. A discriminative approach to topic-based citation recommendation. In T. Theeramunkong, B. Kijsirikul, N. Cercone, and T.-B. Ho, editors, Advances in Knowledge Discovery and Data Mining, volume 5476 of Lecture Notes in Computer Science, pages 572–579. Springer Berlin / Heidelberg, 2009.

[24] K. Yu, S. Zhu, J. Lafferty, and Y. Gong. Fast nonparametric matrix factorization for large-scale collaborative filtering. In Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval, SIGIR ’09, pages 211–218, New York, NY, USA, 2009. ACM.