A REVIEW OF HYBRID RECOMMENDER SYSTEMS

[a]BABAK JOZE ABBASCHIAN, [b]SAMIRA KHORSHIDI

[a]University of Louisville, 2301 S 3rd St, Louisville, KY 40208, USA
[b]Indiana University Purdue University, 420 University Blvd. Indianapolis, IN 46202, USA
Email: [a]b0joze01@louisville.edu, [b]sakhors@iu.edu

Abstract: Due to the huge amount of information available online, the need of personalization and filtering systems is growing permanently. In today's world recommender systems are increasingly used to make suggestions and provide information about items for users. Also recommendation systems constitute a specific type of information filtering technique that attempt to present items according to the interest expressed by a user. There are many techniques that can be applied for personalization in recommender systems. All these techniques have complementary strengths and weaknesses. A hybrid recommender system combines two or more recommendation techniques to gain better system performance and mitigate the weaknesses of individual ones. In this review paper, we prepared a brief introduction on hybrid recommendation systems, components of recommendation systems, various approaches of recommendation systems such as collaborative approach, content-based approach, hybrid approach and demographic approach.

Keywords: hybrid approach, collaborative approach, content-based approach, demographic approach.

1 Introduction

It is typically necessary to possess a certain sufficient amount of information to make good decisions in any situation. Technologies enable us to easily obtain more information, especially on the Internet. For example, if an individual want to rent a movie online, there are numerous choices available. However, too much information can make decision-making inefficient, leading to information overload. Personalization technologies and recommender systems help to overcome this problem by providing personalized suggestions regarding which information is most relevant to users. [1]

Recommender systems are used in various online applications from e-commerce to search engines. There are a number of techniques used to implement recommender systems, each with its advantages and disadvantages. Hybrid systems intend to combine two or more of these techniques in order to obtain better results. [2]

Recommender systems [3] reached a broad acceptance and attracted public interest during the last decade, also expanding the field for new sales opportunities in e-commerce [4, 5].

Recommender systems are divided into two categories in term of their approach to rating estimation: content-based and collaborative recommender systems. Content-based recommendations [6] based on item similarity of the user preferred to objects in the past. Moreover, collaborative recommendation systems [7] depend on the ratings given by individuals with similar taste and preference. However, both techniques exhibit specific strong and weak points.

Collaborative filtering recommender systems are the most commonly used systems [8]. They involve the use of the information provided by other users to make suggestions to a particular user. This can be compared to what happens in real life when an item is purchased based on the recommendation. Collaborative filtering systems differ in the way they use the information provided by other users to link it to the information available about the user that it needs to make a prediction for. A type of collaborative filtering is the use of association rules.

Development of recommender systems depends on e-commerce but there are also other applications for them such as search results and news portals customization. Different techniques have been used, including the nearest neighbor algorithm [9], association rule mining [10] and neural networks [11].

Hybrid techniques were implemented to overcome some challenges in the above-mentioned techniques. The challenges include some aspects of performance, trust security and privacy issues.

Hybrid approaches unifying collaborative and content-based filtering less than one single framework, reducing synergetic effects and mitigating inherent challenges of either paradigm. Finally, hybrid recommenders operate on both product rating information and descriptive features. In fact, numerous ways for combining collaborative and content-based aspects are conceivable; [8] lists an entire plethora of hybridization methods. However most widely adopted among these, is the so-called "collaboration via content" paradigm [12], where content-based are built to detect similarities among users.

2 A review on the recommendation systems: approaches and limitations

This section is a review on the basic approaches of recommendation systems. The approaches include content-based, collaborative filtering, demographic, and hybrid approaches. Also there are limitations for the recommendation approaches are described in details.

Today there are different approaches to recommendation systems that are used to serve in different contexts based on system needs. The content-based approach deals with item profiles and user profiles, and it is designed to recommend text-based items. The collaborative filtering approach is widely used in commercial areas. Amazon uses the collaborative filtering approach to recommend books and other products to its customers [13]. Recommendation systems based on collaborative filtering recommend items to a particular user based on the similar items that have been rated by some other users, and the target user and the other users share the same preferences of items or products. The demographic approach recommender systems use demographic information such as the gender, age, and date of birth of respective users in order to recommend items [13].

3 Content-based approach

Content-based approach is one of the most widely used recommendation approaches. One main component of content-based is the user modeling process, because the interests of users are inferred from the items that users interacted with. Items are usually textual, for instance emails or webpages [14]. There are actions that are typically established interaction through downloading, buying, authoring, or tagging an item. Items are showed containing the items' features. Features are typically word-based. Some recommender systems use non-textual features, such as writing style, layout information, and XML tags [15].

In content-based approach, the user rates the items, that mean the recommender system should understand the common characteristics among the items that the user has rated in the past. The system then recommends the items that have a high degree of similarity to the user's preferences and tastes. For example, in a movie recommendation system, a content-based approach tries to understand the common characteristics such as actors, directors, genres, etc. among the movies that the user has given high ratings in the past. Then, the system recommends the movies that have a high degree of similarity to the user's preferences [13].

In a content-based recommendation system, a user profile contains the user's preferences of items. A user profile can be obtained by analyzing the content of all rated items [5]. Specifically, this profile is constructed by using the content (keyword) that has been analyzed using the methods that are mentioned in the item profile section. Each item in the user's profile has a weight that denotes the importance of keyword Ki to the user [5]. This weight can be computed using average approach through a variety of techniques such as Rocchio algorithm, Bayesian classifier, Winnow algorithm, and cosine similarity measure [5]

In the recommender systems, content-based approach is the important approach among 62 tested approaches, 34 (55%) applied the idea of content-based approach [16]. There is an authorship relationship between users and items [17], having papers in one's personal collection, adding social tags [18], or downloading, reading, and browsing papers [19].

Most of the reviewed approaches use plain words as features, although some use n-grams, topics (words and word combinations that occurred as social tags on CiteULike) and concepts that were inferred from the Anthology Reference Corpus (ACL ARC) via Latent Dirichlet Allocation [20], and assigned to papers through machine learning. A few approaches utilize non-textual features, and if they did then these non-textual features were typically utilized in addition to words.

Giles et al. declared same method as words were used and weighted the citations with the standard TF-IDF measure so-called CC-IDF. Others used the idea of CC-IDF as a baseline. Moreover, Beel recently developed some initial evidence that CC-IDF might not be an ideal weighting scheme [21].

Zarrinkalam and Kahani considered authors as features and determined similarities by the number of authors two items share [22].

Here we can refer to some weakness of content-based approach such as low serendipity and overspecialization, lack of quality and popularity of items. For example, two research papers may be considered by a content-based approach recommender system. This relevance might not always be justified, for example if one paper was written by an authority, while another paper was written by a student. So a recommender system should recommend only the first paper but a content-based approach system would fail to do so.

Another criticism of content-based approach is limited access to the item's features. For research-paper recommendations, usually PDFs must be processed and converted to text, document fields must be identified, and features, such as terms must be extracted. None of these tasks are trivial and they may introduce errors into the recommendations [23].

4 Collaborative filtering approaches

The term collaborative filtering approaches was developed by Goldberg et al (1992), who proposed that "information filtering can be more effective when humans are involved in the filtering process" [24]. The concept of collaborative filtering was introduced two years later by Resnick et al. Their theory was that users like what like-minded users like, where two users were considered like-minded when they rated items alike. Items that one user rated positively were recommended to the other user, and vice versa. [25].

Collaborative filtering approaches are widely used in e-commerce. They have been successful in many e-commerce applications such as Amazon and Netflix. It is a popular approaches used to reduce information overload [9]. Amazon recommends books to their customers using the collaborative filtering approach. A recommendation system based on collaborative filtering recommends items to a particular user based on the similar items that have been rated by some other users. For example, in movie recommendation systems that are based on the collaborative filtering approach, the system finds a group of users that have similar preferences as a query user. Then, the system recommends the movies that they have rated highly in the past by those users to the target user [13].

Collaborative filtering approaches are grouped into two general categories:

- Memory-based approaches: They use the entire collection of the rated items in order to make recommendations or predictions.
- Model-based approaches: They allow systems to learn to recognize patterns in the data sets in order to make recommendations or predictions.

In a memory-based approach, it is important to measure the similarities between users or items. There are many different similarity measures that are used to compute the similarities between users or items [9].

In model-based approaches, classification, clustering, and regression algorithms can be used. For example, the Bayesian classification and K-Means clustering algorithm are used in model based of collaborative filtering approach [8].

There are three advantages to comparison of content-based approach, collaborative filtering approach. First; collaborative filtering approach is content independent, second, because humans do the ratings, collaborative filtering approach considered real quality assessments. Finally, collaborative filtering approach is supposed to provide serendipitous recommendations are not based on item similarity but on user similarity [26].

From the reviewed approaches, only 11 (18%) applied collaborative filtering [27]. Yang et al. intended to let user's rate research papers, but users were "too lazy to provide ratings" [28].

Naak et al. faced the same problem and created artificial ratings for their evaluation [29]. This illustrates one of the main problems that collaborative filtering approach requires user participation, but often the motivation to participate is low. This problem is referred to as the "cold-start" problem. If a new user rates few or no items, the system cannot find like-minded users and therefore cannot provide recommendations. If an item is new in the system and has not been rated yet by at least one user, it cannot be recommended. In a new community, no users have rated items, so no recommendations can be made and as a result, the incentive for users to rate items is low.

A general problem of collaborative filtering in the domain of research-paper recommender systems is sparsity. Vellino compared the implicit ratings on Mendeley (research papers) and Netflix (movies), and found that sparsity on Netflix was three orders of magnitude lower than on Mendeley [30]. This is caused by the different ratio of users and items. In domains like movie recommendations, there are typically few items and many users.

There are further critiques of collaborative filtering approach. Computing time for collaborative filtering approach tends to be higher than for content-based approach. Collaborative filtering approach is generally less scalable and requires more offline data processing than content-based approach.

Torres et al. believed that collaborative filtering approach creates similar users [31] and Sundar et al. observe that collaborative filtering approach dictates opinions [32].

Lops criticized that collaborative filtering approach systems cannot explain why an item is recommended except that other users liked it. Other problem of collaborative filtering approach is manipulation, collaborative filtering approach is based on user opinions, and blackguards might try to manipulate ratings to promote their products so they are recommended more often. [33].

4.1 Limitation of collaborative filtering approaches

- Collaborative filtering has the problem which is new users entering the system. In order to make recommendations to a user, the system needs to know the user's preferences from the ratings that the user makes. Since the user is new in the system, he has not rated items yet. Thus, the system will not be able to provide accurate recommendations.

- The systems should contain rated items in order to recommend some items to the users. When a new item enters the systems, the item has not rated by users yet. Therefore, the systems will not be able to recommend it to the users.
- Sparsity is a major problem for collaborative filtering approach. The total number of ratings is important in the recommendation systems. In order to provide accurate recommendations by the recommendation systems, sufficient number of ratings should exist in the systems. For example, in movie recommendation systems, there are many movies that have been rated by only a few people. The systems will rarely recommend these movies [13].
- In many practical collaborative filtering recommendation systems, the number of users and items increase rapidly in the system [8]. Therefore, the system needs to provide more and complicated computational process, and this leads the computational resources going beyond the acceptable levels.

5 Demographic approach

A demographic approach recommends items to the user based on the user's demographic information such as gender, age, and date of birth. It puts the users into groups based on their demographic characteristics. The system will put the users who belong to a certain zip code into one group. Also, the users of ages ranging from 18 to 25 years-old will be in one group. The recommendation systems based on demographic approaches assume that the users in the same group or category share the same interests and preferences [13]. The demographic approach tracks the buying or rating behavior of the users within the same group or category. If there is a new user entering the system, the system first will place the user into a particular group based on the user's demographic information. Then, the system will recommend products or items to the user based on the buying or rating behavior of the other users in the group.

The purpose of the system is to recommend books to library visitors based on their personal information that is gathered from them through an interactive dialogue. Another recent example of a recommendation systems based on demographic groups is Lifestyle Finder. The system uses demographic groups from marketing research to recommend a range of products and services, and it gathers the data from users through a short survey. The advantage of the demographic approach is: the system does not require maintaining a history of user ratings like in content based and collaborative filtering approaches [8].

5.1 Limitation of demographic approaches

- The demographic approach suffers from is how to identify the group or category that the user belongs to when the user is new to the system.
- The demographic approach how to identify the interests and preferences of users within the same group.
- The demographic approach is the demographic system works well when the demographic data is available to the system.
- The accuracy of recommendation systems based on demographic data is less than those recommendation systems based on content or collaboration filtering.

6 Hybrid recommendation approach

Since all above-mentioned approaches have complementary strengths and weaknesses, so a hybrid recommender system combines two or more recommendation techniques to gain better system performance and mitigate the weaknesses of individual ones.

However, recommendation approaches previously introduced may be combined in hybrid approaches. Many of the studied approaches have some hybrid characteristics. For instance, content-based approach uses global relevance attributes to rank the candidates, or graph methods are used to extend or restrict potential recommendation candidates.

Therefore, hybrid recommendation technique used so-called "feature augmentation". It is a weak form of hybrid recommendation technique, since the primary technique is still dominant. In true hybrids, the combined concepts are similarly important, among the approaches reviewed; only TechLens approaches may be considered true hybrid approaches.

TechLens [31] is one of the most influential research-paper recommender systems. TechLens was developed by the GroupLens31 team. Currently the GroupLens team is still active in the development and research of recommender systems in other fields. Between 2002 and 2010, Konstan, Riedel, McNee, Torres, and several others published six articles related to research-paper recommender systems. Often, McNee et al.'s article from 2002 is considered to be the original TechLens article [34]. However, the 2002 article introduced some algorithms for recommending citations, which was introduced in 2004 by Torres et al. [31]. Two articles about TechLens followed in 2005 and 2007 with respect to recommendations. In 2006, McNee et al. analyzed potential pitfalls of recommender systems [35]. In 2010, Ekstrand et al. published another article on the approaches of TechLens [36].

TechLens' algorithms were adopted from Robin Burke [8] and consisted of three content-based approach variations, two collaborative filtering approach variations, and five hybrid approaches.

Pure-content-based approach served as a baseline in the form of standard content-based approach in which a term-based user model was compared with the recommendation candidates. In the case of TechLens, terms from a single input paper were used. In content-based approach -Separated, for each paper being cited by the input paper, similar papers are determined separately and at the end the different recommendation lists are merged and presented to the user. In combined content-based approach, terms of the input paper and terms of all papers being cited by the input paper are combined in the user model. Then the papers most similar to this user model are recommended. [38, 39]

Pure-collaborative filtering approach served as another baseline and represented the collaborative filtering approach from McNee et al., in which papers were interpreted as users and citations were interpreted as votes [34].

Hybrid: With Pure-CF->CBF Separated, recommendations were first created with Pure- collaborative filtering. These recommendations were then used as input documents for CBF-Separated. Similarly, Pure-CF->CBF Combined, CBF Separated->Pure-CF, and CBF-Combined->Pure-CF were used to generate recommendations. Fusion created recommendations with both CBF and CF independently and then merged the recommendation lists.

The previously discussed filtering techniques can be combined to produce a hybrid filtering [37]. Although any filtering techniques are possible to be combined, we will only focus on combining collaborative filtering approach and content-based approach. There are several ways to combine two filtering techniques [13], as shown in Figure 1:

- Case A: implementing a collaborative filtering approach and a content-based approach separately and combining their recommendations afterwards;

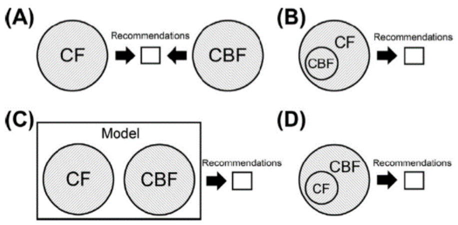

Figure 1: Several models of hybrid filtering, using both collaborative filtering approach and content-based approach [40].

- Case B: incorporating some of the characteristics of the content-based approach into the collaborative filtering approach, e.g. the incorporation of personal information in collaborative filtering approach, to alleviate the problem of introducing a new user to the RS;
- Case C: building a general model that takes into account characteristics from both collaborative filtering approach and content-based approach, therefore combining their results with a machine-learning algorithm (e.g. using Bayes-Networks);
- Case D: incorporating some of the characteristics of the collaborative filtering approach into the content-based approach. For example, using the determined recommendations from the collaborative filtering approach used as an input to the content-based approach algorithm;

7 Discussion and Conclusion

In the 16 years from 1998 to 2013 more than 200 research articles were published in the field of recommender systems. The articles consisted primarily of peer-reviewed conference papers (59%), journal articles (16%), pre-prints (5%), and other documents such as presentations and web pages (15%). The few existing literature surveys in this field cover only a fraction of these articles, which is why we conducted a comprehensive survey of recommender systems. The review revealed the following information [35].

Content-based approach is the predominant recommendation approaches. From 62 reviewed approaches, 34 used content-based approach (55%). From these content-based approach approaches, the majority utilized plain terms contained in the documents. A few approaches also utilized non-textual features, such as citations or authors. [8].

The most popular model to store item representations was the vector space model (VSM). Other approaches modeled their users as graphs, as lists with topics that were assigned through machine learning, or as ACM classification hierarchies. The reviewed approaches extracted text from the title, abstract, header, introduction, foreword, author-provided keywords, bibliography, body text, social tags, and citation context.

According to Yang et al result, it concluded that only eleven approaches applied collaborative filtering approach, and none of them successfully used explicit ratings. Hence, implicit instead of explicit ratings were used. Implicit ratings were inferred from the number of pages the users read, users' interaction with the papers and citations. The main problem of collaborative filtering approach for research papers seems to be scarcity. Vellino compared implicit ratings on Mendeley (research papers) and Netflix (movies), and found that scarcity on Mendeley differs from Netflix by a magnitude of three [30].

As mentioned above, a demographic approach recommends items to the user based on the user's demographic information such as gender, age, and date of birth. Demographic approach puts the users into groups based on their demographic characteristics. Also, the users of ages ranging from 18 to 25 years-old will be in one group. The demographic approaches assume that the users in the same group or category share the same interests and preferences. The demographic approach tracks the buying or rating behavior of the users within the same group or category. The demographic approach first will place the user into a particular group based on the user's demographic information. Then, the system will recommend products or items to the user based on the buying or rating behavior of the other users in the group.

In this study a novel hybrid approach we proposed to prediction of rating, so collaborative filtering approach and content-based approach were used and finally combined. Although there are several hybrid recommendation systems, so in order to combine collaborative filtering approach and content-based approach, rating and content information are integrated to build a hybrid model. The main advantages of this hybrid model are less parameters and more reasonable prediction.

Since content features have a characteristic such as multiplicity, so this hybrid model has flexibility in size, by what the computational effort increased substantially. In order to reduce the runtime in the system, some dimension of hybrid model by means of singular value decomposition decreased. The hybrid model compared with basic collaborative filtering approach, this hybrid approach performed better in prediction accuracy and runtime. So according to result we can conclude that novel hybrid model is practical to real-life applications.

Since, over the last years, recommender systems have made significant progress, accordingly hybrid recommendation model have been proposed and implemented. This proposed hybrid model mainly focuses on providing justifications for the recommendations. This proposed hybrid model is the integration of content and context data with rating data, and also provides accurate justifications for recommendations.

Moreover, this proposed hybrid model provide an explanation interface that shows the recommendations in a group or a category rather than duplicating the same information which reduces the time for decision making of customers. This proposed hybrid model allows the customer to interact with it to provide feedback on the recommendations and justifications. The results have clearly shown that interact with the customer more effectively and boosts the customer's satisfaction on the recommender system. Interacting with the recommender systems allows the customer to achieve their desired product quicker.

This proposed hybrid model is implemented by a prototype web-based application in the JAVA platform. This proposed hybrid prototype is implemented for movies; however, it can be easily implemented for other products. However, all of these advances with accordance with the current generation of recommender systems still require further improvements to make recommendation methods more effective in a broader range of applications. Specifically, there is lot of work needed in the area of providing effective explanations that will increase the customer's trust on the recommender systems and also boosts the business of the organizations.

References

1. Gediminas Adomavicius and YoungOk Kwon (2013). New Recommendation Techniques for Multi-Criteria Rating Systems. Department of Information and Decision Sciences Carlson School of Management University of Minnesota.
2. Alex Cristache (2009). Hybrid recommender system using association rules. School of Computer and Mathematical Sciences. A thesis submitted to Auckland University of Technology in partial fulfillment of the requirements for the degree of Master of Computer and Information Sciences (MCIS)
3. Resnick, P. & Varian, H. R. (1997). Recommender Systems. Communications of the ACM. 40 (3). 56-58
4. Schafer, B., Konstan, J., and Riedl, J. 1999. Recommender systems in e-commerce. In Proceedings of the First ACM Conference on Electronic Commerce. ACM Press, Denver, CO, USA, 158–166.

5. Good, N., Schafer, B., Konstan, J., Borchers, A., Sarwar, B., Herlocker, J., and Riedl, J. 1999. Combining collaborative filtering with personal agents for better recommendations. In Proceedings of the 16th National Conference on Artificial Intelligence and Innovative Applications of Artificial Intelligence. American Association for Artificial Intelligence, Orlando, FL, USA, 439–446.
6. PAZZANI, MICHAEL J. and DANIEL BILLSUS: Content-Based Recommendation Systems. In BRUSILOVSKY, PETER, ALFRED KOBSA and WOLFGANG NEJDL (editors): The Adaptive Web, volume 4321 of Lecture Notes in Computer Science, chapter 10, pages 325–341. Springer-Verlag, Berlin, Germany, May 2007.
7. SCHAFER, J. BEN, DAN FRANKOWSKI, JON HERLOCKER and SHILAD SEN:
Collaborative Filtering Recommender Systems. In BRUSILOVSKY, PETER, ALFRED
KOBSA and WOLFGANG NEJDL (editors): The Adaptive Web, volume 4321 of Lecture Notes in Computer Science, chapter 9, pages 291–324. Springer-Verlag, Berlin, Germany, may 2007.
8. Burke, R. (2002). Hybrid Recommender Systems: Survey anid Experiments. User Modeling and User-Adapted Interaction. 12: 331-370
9. Herlocker, J., Konstan, J., Terveen, L., and Riedl, J. 2004. Evaluating collaborative filtering recommender systems. ACM Transactions on Information Systems 22, 1, 5–53.
10. Demiriz, A. (2004). Enhancing Product Recommender Systems on Sparse Binary Data. Data Mining and Knowledge Discovery. 9. 147–170
11.. Changchien, S. V., & Lu, T. C. (2001). Mining association rules procedure to support on-line recommendation by customers and products fragmentation. Expert Systems with Applications. 20. 325-335
12. Pazzani, M. 1999. A framework for collaborative, content-based and demographic filtering. Artificial Intelligence Review 13, 5-6, 393–408.
13. G. Adomavicius and A. Tuzhilin, “Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions,” Knowledge and Data Engineering, IEEE Transactions on, vol. 17, no. 6, pp. 734–749, 2005.
14. Y. AlMurtadha, M. N. Sulaiman, N. Mustapha, and N. I. Udzir, “Improved web page recommender system based on web usage mining,” in Proceedings of the 3rd International Conference on Computing and Informatics (ICOCI), 2011, pp. 8–9.
15. D. Buttler, “A short survey of document structure similarity algorithms,” in Proceedings of the 5th International Conference on Internet Computing, 2004.
16. S. E. Middleton, D. C. De Roure, and N. R. Shadbolt, “Capturing knowledge of user preferences: ontologies in recommender systems,” in Proceedings of the 1st international conference on Knowledge capture, 2001, pp. 100–107.
17. K. Uchiyama, H. Nanba, A. Aizawa, and T. Sagara, “OSUSUME: cross-lingual recommender system for research papers,” in Proceedings of the 2011 Workshop on Context-awareness in Retrieval and Recommendation, 2011, pp. 39–42.
18. F. Ferrara, N. Pudota, and C. Tasso, “A Keyphrase-Based Paper Recommender System,” in Proceedings of the IRCDL’11, 2011, pp. 14–25.
19. M. Mönnich and M. Spiering, “Adding value to the library catalog by implementing a recommendation system,” D-Lib Magazine, vol. 14, no. 5, pp. 4–11, 2008.
20. S. Bethard and D. Jurafsky, “Who should I cite: learning literature search models from citation behavior,” in Proceedings of the 19th ACM international conference on Information and knowledge management, 2010, pp. 609–618.
21. J. Beel, “Towards Effective Research-Paper Recommender Systems and User Modeling based on Mind Maps,” PhD Thesis. Otto-von-Guericke Universität Magdeburg, 2015.
22. F. Zarrinkalam and M. Kahani, “SemCiR - A citation recommendation system based on a novel semantic distance measure,” Program: electronic library and information systems, vol. 47, no. 1, pp. 92–112, 2013.
23. S. Marinai, “Metadata Extraction from PDF Papers for Digital Library Ingest,” 10th International Conference on Document Analysis and Recognition, 2009.
24. D. Goldberg, D. Nichols, B. M. Oki, and D. Terry, “Using collaborative filtering to weave an information Tapestry,” Communications of the ACM, vol. 35, no. 12, pp. 61–70, 1992.
25. 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, 1994, pp. 175–186.
26. J. L. Herlocker, J. A. Konstan, A. Borchers, and J. Riedl, “An algorithmic framework for performing collaborative filtering,” in Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval, 1999, pp. 230–237.
27. A. Vellino, “A comparison between usage-based and citation-based methods for recommending scholarly research articles,” in Proceedings of the American Society for Information Science and Technology, 2010, vol. 47, no. 1, pp. 1–2.
28. C. Yang, B. Wei, J. Wu, Y. Zhang, and L. Zhang, “CARES: a ranking-oriented CADAL recommender system,” in Proceedings of the 9th ACM/IEEE-CS joint conference on Digital libraries, 2009, pp. 203–212.
29. A. Naak, H. Hage, and E. Aimeur, “A multi-criteria collaborative filtering approach for research paper recommendation in papyres,” in Proceedings of the 4th International Conference MCETECH, 2009, pp. 25–39.
30. A. Vellino, “Usage-based vs. Citation-based Methods for Recommending Scholarly Research Articles,” Arxiv, vol. http://arxiv.org/abs/1303.7149, 2013.
31. R. Torres, S. M. McNee, M. Abel, J. A. Konstan, and J. Riedl, “Enhancing digital libraries with TechLens+,” in Proceedings of the 4th ACM/IEEE-CS joint conference on Digital libraries, 2004, pp. 228–236.
32. S. S. Sundar, A. Oeldorf-Hirsch, and Q. Xu, “The bandwagon effect of collaborative filtering technology,” in CHI’08 Extended Abstracts on Human Factors in Computing Systems, 2008, pp. 3453–3458.
33. P. Lops, M. Gemmis, and G. Semeraro, “Content-based recommender systems: State of the art and trends,” Recommender Systems Handbook, pp. 73–105, 2011.
34. 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 ACM Conference on Computer Supported Cooperative Work, 2002, pp. 116–125.
35. S. M. McNee, N. Kapoor, and J. A. Konstan, “Don’t look stupid: avoiding pitfalls when recommending research papers,” in Proceedings of the 2006 20th anniversary conference on Computer supported cooperative work, 2006, pp. 171–180.
36. M. D. Ekstrand, P. Kannan, J. A. Stemper, J. T. Butler, J. A. Konstan, and J. T. Riedl, “Automatically building research reading lists,” in Proceedings of the fourth ACM conference on Recommender systems, 2010, pp. 159–166.
37. P. C. Vaz, D. M. de Matos, B. Martins, and P. Calado, “Improving a hybrid literary book recommendation system through author ranking,” CoRR,
38. W. Carrer-Neto, M. L. Hern´andez-Alcaraz, R. Valencia-Garc´ıa, and F. Garc´ıa- S´anchez, “Social knowledge-based recommender system. application to the movies domain,” Expert Systems with Applications, vol. 39, no. 12, pp. 10990 – 11000, 2012.
39. W. Carrer-Neto, M. L. Hern´andez-Alcaraz, R. Valencia-Garc´ıa, and F. Garc´ıa- S´anchez, “Social knowledge-based recommender system. application to the movies domain,” Expert Systems with Applications, vol. 39, no. 12, pp. 10990 – 11000, 2012. vol. abs/1203.5324, 2012.
40. J. Bobadilla, F. Ortega, A. Hernando, and A. Guti´errez, “Recommender systems survey,” Knowledge-Based Systems, vol. 46, no. 0, pp. 109 – 132, 2013.

Primary Paper Section: I

Secondary Paper Section: JC, IN, BD