RESEARCH REVIEW JOURNALS
Volume-03
Issue-09
September -2018

ISSN: 2455-3085 (Online)
RESEARCH REVIEW International Journal of Multidisciplinary
www.rrjournals.com [UGC Listed Journal]

Recommender systems: a literature survey on Recommender System

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ARTICLE DETAILS

Article History
Published Online: 07 September 2018

Keywords
recommender systems, evaluation, comparative study, recommender systems, survey

ABSTRACT

There are number of methods to recommend different items available today. Mostly people connected with social media because of availability of internet. But nowadays shortage of timing recommender system helps to the people to choose the items easily on the behalf of ratings. We reviewed these methods and found many analyzes that contain significant shortcomings. To work with recommender system we reviewed number of research articles and research papers. We found that more than half of the recommendations were used Content-based filtering. Collaborative filtering is also used to collect the recommendations. Other complimentary concepts include stereotyping, compound-based recommendations, and mixed recommendations. Content-based filter is most widely used methods in recommendation systems.

1. Introduction

Recommender systems are great need of today's people to select items online. In the past 16 years, more than 180 research and review papers etc. were published in this field. Introduce from the numbers of published articles during this year, we estimate 42 new publications to appear in 2013 (Figure 1). Recommender systems for research articles are useful applications, which as an example help researchers keep track of their research field. With the increase in the development of recommended system, it is important to find out the various advantages and disadvantages of all the approaches that were used to recommend the system.

Evaluating recommendation plans requires an explanation of what constitutes a reliable recommendation program, and how this can be measured. There is a strong consensus on what constitutes a reliable recommendation system and how to look at recommendation systems [1,11,62]. However, at least in the related research fields, in the related research fields, In another part of this paper, we describe many factors, which have a 'good' effect, namely high quality, recommendation system, so common methods check the recommendation systems. Quality is a key feature of the Recommender System.

"The first factor that contributes to a reliable recommendation is its accuracy, meaning that it will satisfy the needs of each user [62]. Information needs vary between users due to background and different information [3], preferences and goals [4], and contexts [108]. One user may also be curious about the most recent research papers on a mind map, while another may also be curious about the main publication introducing recommended programs, or popular medical research for carcinoma, but only during a particular language, etc. Things that satisfy the information needs are "important" to the user [62]. Therefore, a reliable compliment program is one that recommends (most) the right things. To do so, the recommendation system must first identify the information needs of its users and then identify the items that satisfy those needs. The efficiency of the recommendation system is reflected in its accuracy: the more appropriate it is, and therefore the less important the things it recommends, the more accurate it is.

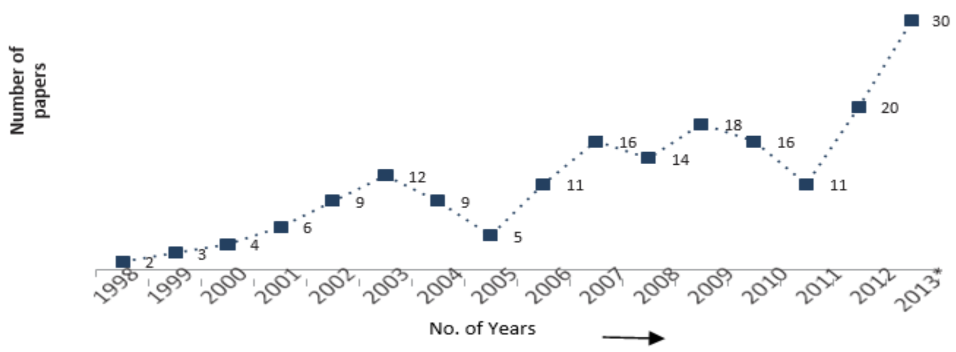

Figure 1: No. of Published Papers per years

A condition to realize high accuracy is high range of the available items [5]. Range describes what percentage papers of these within the recommender's database could also be recommended with the advice approach. For text-based approaches, range is typically 100%. For several citation-based approaches, scope is typically significantly lower, because only a fraction of all documents is cited, and may hence be recommended [58]."

We conjecture that minor variations in datasets, algorithms, or user populations inevitably lead to strong variations in the performance of the approaches. Hence, finding the most promising approaches is a challenge. As a second limitation, we noted that many authors neglected to take into account factors other than accuracy, for example overall user satisfaction. If the milk was recommended to the customer during the supermarket, this may be a very accurate, but not satisfactory recommendation [60]. "Milk is a clear product that you can buy at the supermarket. Therefore, many customers can be very satisfied with a variety of recommendations (which are still to some degree accurate). Users may also be dissatisfied with the correct recommendation plans, if they need to wait longer to receive recommendations [62], the presentation is not attractive [11], the appropriate method and marketing reasons are used to label the recommendation program [7]. User satisfaction can also vary by demographics - older users tend to be more satisfied with recommendations than younger users [8]. Additionally, costs can play a role. Generally, recommendation systems are free but some systems charge users or are only available as part of subscription packages. One example is the reference manager Mendeley, who offers its Mendeley Recommend program only to its premium users. The time a user has to invest before receiving recommendations can affect user satisfaction. Some systems are based on personal user preferences. In some systems, users' interests are automatically redirected, which greatly reduces the user's commitment of time. The things mentioned are a small selection. There are many factors that influence whether a user is satisfied with a recommendation system [9,11].

The third factor contributing to an honest recommender system is its ability to satisfy the advice provider. Typically, it's assumed that providers of recommender systems are satisfied when their users are satisfied, but this is often not always the case. One interest of the providers is keeping costs low, where costs could also be measured in terms of labor, disk storage, memory, CPU power, and traffic [11]. As such, an honest recommender system can also be defined together which will be developed, operated, and maintained at a coffee cost. Other providers, e.g. publishers, may have the goal of generating a take advantage of the recommender system [61]. With this goal, a publisher would like to recommend items with higher profit margins albeit user satisfaction wasn't that prime. A news-website may need the goal of keeping their readers as long as possible on their website [61]; during which case, a recommender would preferably suggest longer articles albeit shorter articles might end in higher user satisfaction. In most situations, there'll be a tradeoff between the three factors." as an example, clustering strongly reduce runtimes, and hence costs, but also decreases accuracy [10]; and when the first goal is to get revenue, user satisfaction may suffer.

Satisfaction of the recommendation provides the third factor contributing to an honest recommender system is its ability to satisfy the recommendation provider. "Typically, it's assumed that providers of recommender systems are satisfied when their users are satisfied, but this is often often not always the case. One interest of the providers is keeping costs low, where costs could even be measured in terms of labor, disk storage, memory, CPU power, and traffic [11]. As such, an honest recommender system also can be defined together which can be developed, operated, and maintained at a coffee cost. Other providers, e.g. publishers, may have the goal of generating a cash in of the recommender system [61]. With this goal, a publisher would really like to recommend items with higher profit margins albeit user satisfaction wasn't that prime. A news-website may have the goal of keeping their readers as long as possible on their website [61]; during which case, a recommender would preferably suggest longer articles albeit shorter articles might end in higher user satisfaction. In most situations, there will be a trade off between the three factors. Taking an example of clustering which reduce the costs and runtimes, but affects the accuracy of the system by decreasing it [10]; and the user will suffer if its primary goal is to provide revenue."

Another important consideration regarding the evaluation of recommended systems is the basis on which the algorithm is compared. Knowing that CTR during a particular algorithm e.g. 9% are invalid if the CTR of other methods is unknown. Therefore, high-quality methods should be compared with the basic representative of the cutting art. Only then can it be possible to determine if a completely different approach is superior and what is best. In addition, a statistically significant number of participants is important for user validation studies, and as a sufficient knowledge of the complexity of the algorithm and order, the use of representative data sets, and various other factors [11]. as long as these factors are taken into account, the evaluation will produce valid results that allow for the identification of simple recommendations. Of course, it is also important for researchers to publish all the relevant information about their experiments and to allow others to verify the validity of the experiments performed and to use the methods."

2. Purpose of Research and Methods

The purpose of the research we pursued was to verify the validity of the experiments performed on existing research recommendation programs." In reviewing the literature, we explore how well the existing experiments are to identify the most promising programs for recommending research papers. To achieve this goal, we performed a chemical analysis of the quantity of the order. We want to answer the following questions in sequence.

1. How do the authors perform online and offline evaluations, user studies?
2. What percentage participants do user studies have?
3. Against which baselines are approaches compared?
4. Will the authors give the information about their computational complexity and algorithm's runtime?
5. What kinds of metrics are required for evaluating an algorithm, and will they give same ranking to all algorithms?
6. What kinds of datasets are required for evaluating the system in offline mode?
7. Are results comparable among different evaluations supported different datasets?

8. How consistent are online and offline evaluations? Do they supply an equivalent, or a minimum of similar, rankings of the evaluated approaches?
9. Will the authors give sufficient information about how to re- implement and replicate their algorithms and experiments?

"To identify the established order, we reviewed 178 papers, including a couple of patents, presentations, blogs, and websites on 98 research paper recommendation approaches. We differentiate the various approaches and papers and we find most of the system uses same approaches. As an example, there are three papers on the recommender system Papers and every one above different aspects of an equivalent system. Therefore, we count Papers together recommendation approach. To cite an approach, that quite one paper exists, we subjectively selected the foremost representative paper. For our analysis, we also 'combined' the content of all papers concerning one approach. If an approach was once evaluated using a we evaluation, and in another paper using an offline evaluation, we are saying that the approach was evaluated with both online and offline evaluations. Space restrictions keep us from providing an exhaustive bibliography of the 178 papers reviewed, in order that we only cite the 89 approaches, i.e. one representative paper for every approach. During a second step, the bibliography of every article was examined. When an entry within the bibliography pointed to a piece of writing not yet downloaded, the cited article was also downloaded and inspected for relevant entries in its bibliography.

3. Results

There are19 approaches (21%) weren't evaluated [14–26], or were evaluated using system-unique or uncommon and convoluted methods [27– 31,93]. within the remaining analysis, these 19 approaches are ignored. There are mainly 70 approaches, out of which 48 approaches (69%), were analyzed with the help of an offline evaluation [32–52,54,58,59,74,78,80,83,86,88–92,94–100,102–107,109], and 24 approaches (34%) uses user study for their analysis [66–74,76,77,79,81,82,87,102– 108,110], five approaches (7%) were evaluated in real-world systems with a web evaluation [53–56,68] and two approaches (3%) were evaluated employing a qualitative user study [84,85] (Table 1)7. Interesting during this context is that the low number of online evaluations (7%) and therefore the prevalence of offline evaluations (69%). Despite active experimentation within the field of research papers recommender systems, we observed that a lot of researchers haven't any access to real-world systems to guage their approaches and researchers who do, often don't use them. as an example, C. Lee Giles and his co- authors, who are a number of the most important contributors within the field [57– 59,94,96,99,100], could have conducted online experiments with their academic program CiteSeer. However, they chose primarily to use offline evaluations. the rationale for this might be that offline evaluations are more convenient than conducting online evaluations or user studies. Results are available within minutes or hours and not within days or weeks as is that the case for online evaluations and user studies. However, as stated, offline-evaluations are subject to varied criticisms [60–65,106,111].

Table 1: Evaluation methods[7]

Offline	User Study	Online	Qualitative
50	38	7	3
70%	35%	8%	7%

Four of the 24 user-studies (17%) were conducted with but five participants [66,67,102,104]. Another four studies had five to 10 participants [77,79,103,110]. In this, studies on three parameters have nearly 15 participants [68,81,87], and another four studies have approximately 20 participants [69–71,105]. Only six studies (25%), were conducted with quite 50 participants [72–74,106–108]. Three studies did not mention the amount of participants [75,76,82] (Table 2). Given these findings, we conclude that the majority user studies weren't large enough to reach meaningful conclusions on algorithm quality.

Table 2: Number of participants in user studies

	Number of Participants					
	n/a	**<5**	**5-10**	**11-15**	**16-50**	**>50**
Absolute	2	3	6	4	5	8
Relative	14%	18%	16%	17%	18%	28%

Thirteen of the evaluated approaches (20%) weren't evaluated against a baseline (Table 3) [77–88,102]. The evaluations' usefulness is low because knowing that in certain circumstances an algorithm features a certain CTR allows no conclusion on how it compares against other algorithms. Another 50 approaches (73%) were evaluated against trivial baselines, like simple content- based filtering with none sophisticated adjustments. These trivial baselines don't represent the state-of-the-art and aren't helpful for deciding which of the 89 approaches are most promising. this is often especially true, since different approaches weren't evaluated against an equivalent simple baselines. Even for an easy content-based approach, there are many variables like whether stop-words are filtered, if and which stemmer is applied, from which document section (title, abstract, etc.) the text is extracted, etc. this suggests, most approaches were compared against different baselines. Only seven authors (10%) evaluated their approaches against state- of-the-art approaches proposed by other researchers within the field. It remains unclear how they might have performed against the remaining state-of-the-art approaches [8].

Table 3: Baselines

	No Baseline	Simple Baseline	St.of the Art Bsln.
Absolute	14	52	8
Relative	29%	76%	11%

Only eight approaches (11%) provided information on runtime. Runtime information, however, is crucial. In one comparison, the runtimes of two approaches differed by factor 600 [100]. for several developers, an algorithm requiring 600 times more CPU power than another would probably not be an option. While this instance is extreme, it frequently occurred that runtimes differed by factor five or more, which may also affect the choices on algorithm selection. Computational complexity was reported by even fewer evaluations. Computational complexity could also be less relevant for researchers but highly relevant for providers of recommender systems. it's important for estimating the long-term suitability of an algorithm. An algorithm may perform well for a couple of users but it'd not scale well. Hence, algorithms with, for instance, exponentially increasing complexity presumably won't be applicable in practice.

Out of the 48 offline evaluations, 33 approaches (69%) were evaluated with *precision* (Table 4). Recall was used for eleven approaches (23%), F-Score for six approaches. Seven approaches (15%) were evaluated using other measures Above all, results of the various measures highly correlated – that's algorithms, which performed well using precision."

Table 4: Evaluation measures[7]

	Precision	Recall	F-Score	Other
Absolute	33	11	6	7
Relative	69%	23%	13%	15%

The different techniques having different datasets are used for conducting the offline evaluations (Table 5). The Cite Seer data is used for evaluating 14 techniques (29%) and data from papers are used for evaluating five approaches (10%) from ACM. Other data sources included Cite ULike (10%), DBLP (8%) and a spread of others, many not publicly available (52%). Even when data originated from equivalent sources, this didn't guarantee that an equivalent datasets were used. as an example, fourteen approaches used data from CiteSeer but no single 'CiteSeer dataset' exists. Some authors removed documents with but two citations from the corpus [92], others with but three citations [107], et al. with but four citations [93]. One study removed all papers with but ten and quite 100 citations and every one papers citing but 15 and quite 50 papers [94]. Of the first dataset of 1,345,249 papers, only 81,508 remained, about 6%. The question arises how representative results are often supported such a pruned dataset.

Table 5: Data sources

	Cite Seer	ACM	CiteULike	DBLP	Others
Absolute	14	5	5	4	25
Relative	29%	10%	10%	8%	52%

In conclusion, it's safe to mention that no two studies performed by different authors, used an equivalent dataset. This raises the question to what extent results based of various datasets are comparable?

4. Universality for offline datasets

There are mainly seven techniques that were conducted on different offline datasets [95– 100,110]. The analysis of those seven evaluations confirms a well known finding: results from one dataset don't allow any conclusions on absolutely the performance achievable in another dataset. as an example, an algorithm, which achieved a recall of 4% on an IEEE dataset, achieved a recall of 12% on an ACM dataset [110]. However, the analysis also showed that the relative performance among different algorithms remained quite stable above different datasets. Algorithms performing well on one dataset (compared to some baselines) also performed well on other datasets (compared to an equivalentbaselines). Dataset combinations included CiteSeer and a few posts from various blogs [97], CiteSeer and Web-kd [98], CiteSeer and CiteULike [100], CiteSeer and Eachmovie [99], and IEEE, ACM and ScienceDirect [110]. Only in one study results differed notably, however, absolutely the ranking of the algorithm remained stable [100] (see Table 6). during this paper, the proposed approach (CTM) performed best on two datasets with a MRR of

0.529 and 0.467 respectively. Three of the four baselines performed similarly on the CiteSeer dataset (all with a MRR between 0.238 and 0.288). However, for the CiteULike dataset the TM approach performed fourfold also as CRM. this suggests, if TM had been compared with CRM, rankings would have been similar on the CiteSeer dataset but different on the CiteULike dataset. As mentioned, for all other reviewed evaluations no such variations in the rankings were observed.

Table 6: MRR of different recommendation approaches on CiteSeer and CiteULike datasets

		Dataset	
Rank	Approach	CiteSeer	CiteULike
1	CTM	0.529	0.467
2	TM	0.288	0.285
3	cite-LDA	0.285	0.143
4	CRM	0.238	0.072
5	link-LDA	0.028	0.013

Above all, a sample size of seven is small, but it gives at least some indication that the impact of the chosen dataset is rather low. It may happens that different approaches provide different results [101].

Six approaches were evaluated using an offline evaluation additionally to a user study [102–107]. of those six evaluations, one didn't compare its approach against any baseline [102]. The remaining five evaluations reported non-uniform results. In two cases, results from the offline evaluations were almost like results of the user studies [103,105]. In this five user studies, it has 19 participants. As such, results should be interpreted with some skepticism. When studied on three another reported the results of the user studies do not match with the results of offline evaluations studies [104,106,107]. Two of those studies had quite 100 participants; the opposite study only had two participants. The findings indicate that results from user studies and offline evaluation don't necessarily correlate, which could question the validity of offline evaluations generally [111].

Many authors provided sparse information on the exact workings of their proposed approaches. Hence, replication of their evaluations, or re-implementing their approaches, for example, to use them as a baseline, is hardly possible. To exemplify, some of the authors point out that they draw content-based models which works with the help of user's documents. From which document section (title, abstract, keywords, body, etc.) the text was taken was not explained. However, taking text from titles, abstracts or the body makes a significant difference [109,110].

5. Summary and Outlook

A review of 176 publications has shown that there is no consensus in the method of evaluating and comparing methods to recommend a research paper. This results in the unsatisfactory state that despite various tests, the individual strengths and weaknesses of the proposed methods remain largely unknown. Of the 89 revised routes, 21% were not tested. Of the tested methods, 19% were not tested compared to baseline. More tests compared to foundation, compared to lesser bases. Only 10% of the updated methods are compared to the minimum number of modern one methods. Only 11% of the information is provided during operation, this information is used to test algorithm performance. Only five methods (7%) have been tested using online analytics. the majority of authors conducted offline surveys (69%). The leading sources for retrieving offline databases were CiteSeer (29%), ACM (10%), and CiteULike (10%). However, most (52%) tests were performed using other data sets and even data sets from CiteSeer, ACM, and CiteULke are different, as they are downloaded at different times and cut differently. Due to the various databases used, the results of each study are not comparable. Of the user-survey methods (34%), the majority (58%) of those studies had only 16 participants. Additionally, user studies have sometimes contradicted the results of offline testing. Awareness helps to provide information for offline testing which will also help in further research. Given the circumstances, the identification of the most promising ways to recommend research papers is not possible, and may be a repeat of many experiments. We see this as a major problem in the development of programs to recommend research papers. Similarly, education service providers, who wish to use the recommendation system, do not have the opportunity to know which 89 methods to use. We propose the following three action points to ensure that simple ways to recommend a research paper are often determined:

1. The suitability of offline testing is discussed in order to analyze the recommendation systems for research papers [111].
2. Existing strategies are reviewed with the help of real-world systems with appropriate frameworks that provide information about participants with information related to computer complexity and operating times.
3. Create a framework that combines promising best practices, so that other researchers can easily compare their novel approaches against modernity."

If these actions are not done, researchers will still test their methods without comparable results, and although there may be many alternatives, it may not be known which ones are the most promising, or which should be compared with new method."

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