Engineering Applications of Artificial Intelligence 118 (2023) 105641

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Survey paper

An anatomization of research paper recommender system: Overview, approaches and challenges

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ARTICLE INFO

Keywords:
Research paper recommender system
Digital library
Recommendation approaches
User modeling
User preference elicitation
Knowledge acquisition
Evaluation measures
Research challenges

ABSTRACT

The purpose of this study is to present an exhaustive analysis on research paper recommender systems which have become very popular and gained a lot of research attention. Though the major focus is on developing new recommendation algorithms, other research dimensions are left untouched. Renown recommendation classes include content-based approaches, collaborative filtering, link-based algorithms, co-occurrence based approaches, global relevance and hybrid methods. These approaches mainly differ in background knowledge and modes of user behavior analysis. For instance, content-based filtering uses paper descriptions which are mostly word-based features. Collaborative filtering makes predictions based on peers' interests. Link-based algorithms utilize academic associations that exist between different entities in academia. Co-occurrence based techniques incorporate event occurrences to locate related papers. Global relevance adopts a 'one-for-all' policy for recommending popular articles. Hybrid methods combine the above approaches to design efficient algorithms. We have reviewed articles implementing several versions of these classes, however minor customizations make it difficult to categorize the new methods to one of the base classes. We have defined the concept of 'background knowledge and operating principle' for proper classification and to make a clear distinction among the recommendation approaches. We have used a combination of systematic literature review, critical review, and conceptual review to conduct this survey which presents current advancements in the field and discusses popular recommendation approaches. This paper reveals the factors affecting users' behavior and introduces a taxonomy of knowledge acquisition sources. Moreover, various evaluation methods and important performance criteria are explored. Finally, this paper examines the research trends and reports major loopholes in current research to foster the development of efficacious recommender systems.

1. Introduction

Research Paper Recommendation Systems (RPRSs) have become popular due to information overload in digital libraries. With the proliferation of published material, there is a need for an efficient recommender system that produces accurate and useful results. Higher recommendation accuracy is not adequate to provide a good and satisfying user experience. Accuracy means that the system is working as it is supposed to or as expected to, however it does not imply that recommendations are relevant to a user. Usefulness is one of the factors which contributes to user satisfaction. Digital libraries are overloaded with enormously increasing research documents, requiring huge time and effort to find relevant material. Thus, literature search has become a very time-consuming process that necessitates the development of intelligent systems. These systems shall support decision-making and facilitate locating relevant scientific publications. RPRS is intended to deliver personalized recommendations for relevant articles from the available set of million papers. There exist various academic search engines that offer basic recommendation services such as ScienceDirect,[1] ResearchGate,[2] CiteULike,[3] Google Scholar[4] and bX.[5]

We have reviewed more than five hundred papers and their yearly distribution is shown in Fig. 1.

It has been found that most of them have applied different recommendation algorithms with little emphasis on implementation details, which impedes reproducing their results for comparison (Beel et al., 2016a). Also, it is difficult to find the most promising or baseline recommendation approach in this field due to the lack of standard datasets. Only a few standard corpora provide the full text of research

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[1] https://www.sciencedirect.com/.
[2] https://www.researchgate.net/.
[3] http://www.citeulike.org/.
[4] https://scholar.google.com/.
[5] https://www.exlibrisgroup.com/products/bx-recommender/.

https://doi.org/10.1016/j.engappai.2022.105641
Received 13 June 2019; Received in revised form 21 March 2022; Accepted 10 November 2022
Available online 29 November 2022

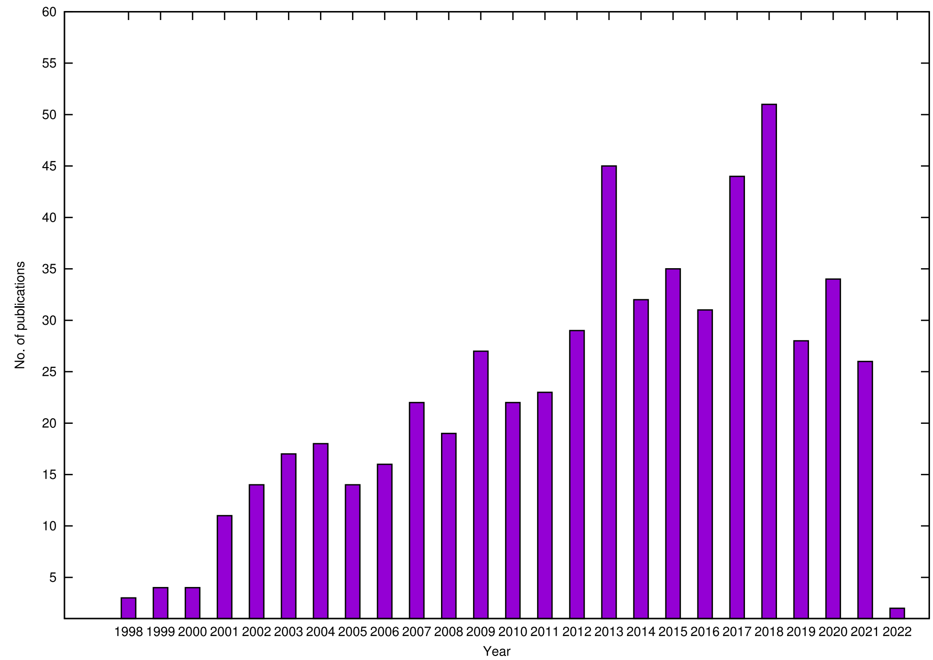


Fig. 1. Year-wise distribution of publications in the area of research paper recommendation system.

papers for conducting research work. A major goal of recommender systems is to scale up to real datasets, which help users navigate the large data collection. With an increase in the size of the dataset, many approaches are either slowed down or need additional resources such as memory or computation power. Many researchers have examined their algorithms on the synthetic dataset consisting of only a few thousand articles. Approaches validated on synthetic datasets may not successfully address the problem of publication overload and may not be deployed in the real world for practical use. As these approaches worked and tested over a small set of papers, it may not cope up with real data comprising millions of documents and probably the system may crash in a real-time environment (Shani and Gunawardana, 2011; Erdt et al., 2015). Some have adopted trivial algorithms as baselines, such as simple content-based filtering, employing bag-of-words or vector space model without any sophisticated adjustments. Furthermore, there are well-established metrics for measuring accuracy, precision, recall, however a lack of standards for assessing novelty, serendipity, coverage, robustness, user satisfaction etc. make it difficult to evaluate the system for multiple dimensions (Herlocker et al., 2004).

The paper recommendation has become a hot research topic and more than five hundred articles have been published in the last two decades. A step-wise process of literature review conducted is shown in Fig. 2. We have searched for the papers using different combination of search terms and downloaded relevant literature available on Google Scholar, ScienceDirect, ACM Digital Library, IEEE Xplore Digital Library and Springer. We have collected 460 articles and included articles from peer-reviewed journals, conferences, arXiv, and other language papers as well which gives us a total of 514 articles. We have not used any exclusion criteria because we want to report every single research or published material in the field of paper recommender systems. Additionally, a bibliographic analysis is performed to find the undiscovered documents of the field which results in 627 articles. This search was extended to patents, newsletters, blogs, dissertations, and other published materials discussing research paper recommendation. We found 23 new articles which gives us a total of around 650 articles. We have removed duplicate articles i.e. different versions of the same paper and consequently, excluded 28 articles from the collection. We then performed a comprehensive study of relevancy and papers related to research paper exploration, search, ranked-list retrieval are discarded. After this pruning, we got a total of 571 articles and a list of yearly-based publications along with the percentage is shown in Table 1. Table 1 only mentions publications on research paper recommendation. We limit our study to paper/citation recommendation and do not cover other related fields such as book, novel, web page, venue, researcher, expert, patent, or citation-context recommendation. We have discussed the research that includes the above-mentioned fields along with paper recommendation. Our study also limits the paper categorization to publication year, recommendation approach, user modeling methods, and evaluation metrics. This study does not classify the available research based on datasets used and implementation platform. In some cases, we are not able to identify the base recommendation approach and correct hybridization techniques due to the method ambiguity, complexity, limited or imprecise approach description.

This paper reviews the available literature and presents an exhaustive analysis of research paper recommendation. This survey was conducted to discuss the important aspects of paper recommendation, which include a detailed description of renowned approaches, user modeling and evaluation measures. This helps us reveal several significant facets that should be explored and incorporated in future research. This study highlights the existing research patterns to focus on limitations and challenges in current research and provides a direction for future possibilities. We have scrutinized the previous work, which helps us better understand the field and enables us to propound the building blocks for the paper recommender system. Contributions of this survey are as follows:

(i) It introduces a new prospect of 'background knowledge' to establish key aspects and develop a clear understanding of the field.

(ii) It examines the existing article recommendation approaches subjected to background features and classifies them based on the proposed knowledge attributes.

(iii) A taxonomy of knowledge acquisition sources is proposed to model user behavioral aspects and various preference elicitation techniques are discussed for effective user modeling.

(iv) Various performance criteria for an efficient recommender system and the leading evaluation approaches are presented.

(v) Short comings of the current research and challenges of the field are discussed to enlighten the scope for future research.

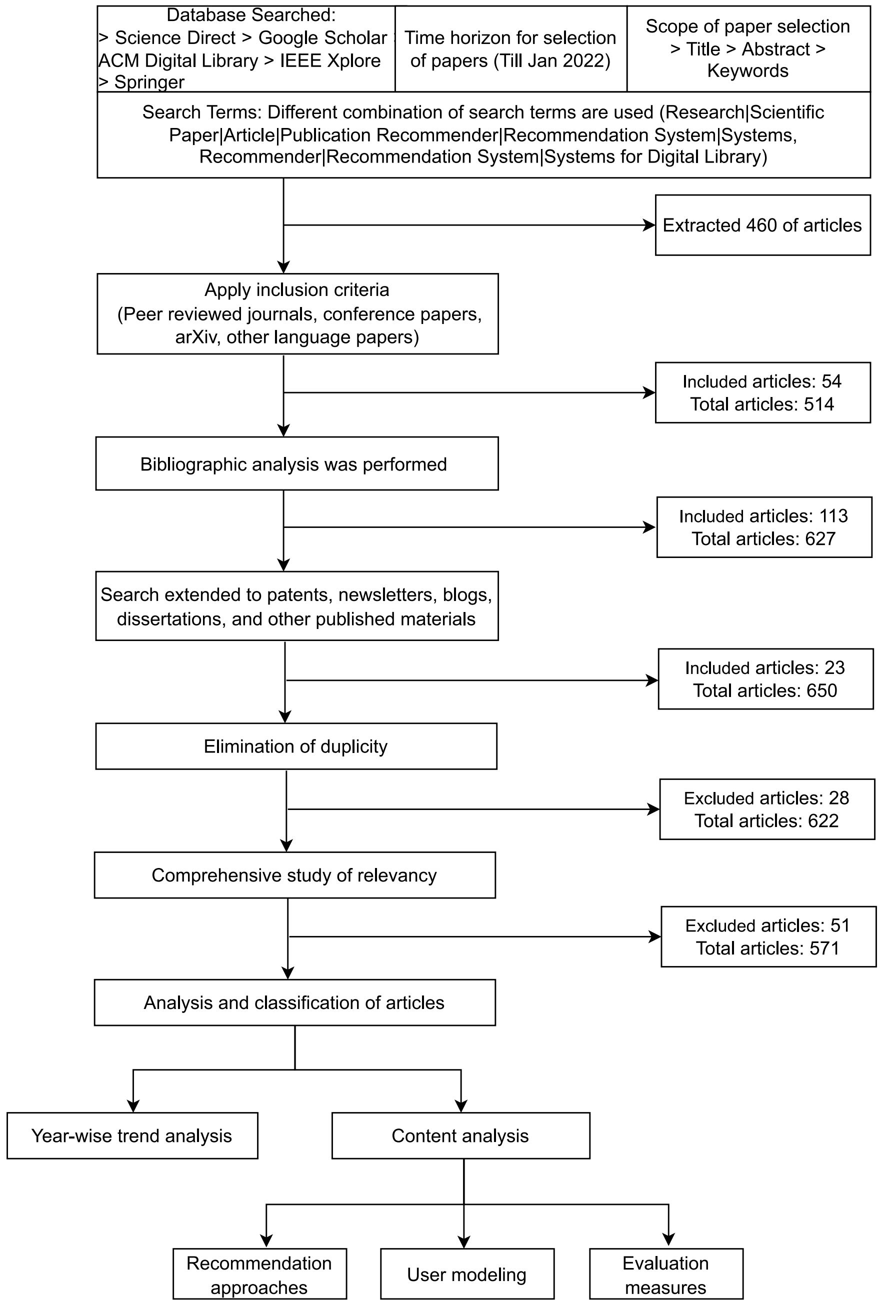


Fig. 2. Literature review flowchart.

Rest of the article is organized in the following way: Section 2 reviews the three main components of a recommendation system, followed by three Sections 2.1–2.3 to acquire deep insights into the individual components. Section 3 discusses the evaluation methods used to validate recommendation systems and algorithms. This section also establishes several performance criteria to be met for developing an efficient system and presents corresponding metrics. Furthermore in Section 4, we examine various limitations of today's research methodologies and discuss key points that are generally ignored, however essential to tweak the system performance. Section 5 concludes this survey and outlines the future possibilities for the development of an efficient recommender system. The terms 'article', 'document', 'publication' and 'paper' are interchangeably used to refer research paper. Also, 'class' and 'algorithm' are alternatively used for recommendation approach.

2. Research Paper Recommendation System

According to our study, Recommender Systems (RSs) can be partitioned into three essential components. To accomplish any task, the very first thing required is domain specific knowledge and how to apply it to perform the assigned task. We denote it as principle or background knowledge and operating theory, principle knowledge is comprised of all the available information about any item that is used to perform the given recommendation task. These are the key attributes used by the system to make recommendations. Operating theory deals with the 'how' part i.e., how to use the given information to achieve defined objective(s). Second is the recommendation approach which discusses step-by-step procedure to address the problem, defines realization methods and deals with the actual implementation of those methods. Third and the most important part is user modeling.

Table 1
Year-wise list of publications.

Year	References	Percentage (%)
1998	Giles et al. (1998), Bollacker et al. (1998) and Joaquin et al. (1998)	0.5253
1999	Bollacker et al. (1999), Lawrence et al. (1999), NEC Research Institute (1999) and Rocha (1999)	0.7005
2000	Woodruff et al. (2000), Fernández et al. (2000), Pennock et al. (2000) and Bollen and Rocha (2000)	0.7005
2001	Geisler et al. (2001), Geyer-Schulz et al. (2001a,b), Middleton et al. (2001), Rocha (2001), Mateus Rocha (2001), Fuhr et al. (2001), Schwab et al. (2001), Geyer-Schulz et al. (2001c), Lawrence et al. (2001) and Di Giacomo et al. (2001)	1.9264
2002	Renda and Straccia (2002), Nakagawa and Ito (2002), McNee et al. (2002), Middleton et al. (2002a), Straccia (2002), Middleton et al. (2002b), Geyer-Schulz and Hahsler (2002a,b), Geyer-Schulz et al. (2002), Pitkow and Pirolli (2002), Ozono et al. (2002), Ozono and Shintani (2002), Fujimaki et al. (2002) and Zeng et al. (2002)	2.4518
2003	Gross (2003), Hwang et al. (2003), Geyer-Schulz et al. (2003b,d), Böhm et al. (2003), Geyer-Schulz et al. (2003c,a), Middleton (2003), Tang et al. (2003), Callan et al. (2003), Neuhold et al. (2003), Tang and McCalla (2003a,b), Brogan (2003), Yao and Yao (2003), Yao (2003) and Luce and Giacomo (2003)	2.9772
2004	Ozono et al. (2004), Petinot et al. (2004b), Straccia and Thanos (2004), Tang and McCalla (2004a), Erosheva et al. (2004), Meyyappan et al. (2004), Petinot et al. (2004a), Vassileva (2004), Middleton et al. (2004b), Huang et al. (2004), Torres et al. (2004), Tang and McCalla (2004b,c), Nelson et al. (2004), Yao (2004), Middleton et al. (2004a), Tonta (2004) and Theobald and Klas (2004)	3.1523
2005	Watanabe et al. (2005), Cazella and Alvares (2005a), Renda and Straccia (2005), Agarwal et al. (2005), Bollen et al. (2005), Du et al. (2005), Cazella and Alvares (2005b), Yao and Yao (2005), Smeaton and Callan (2005), Tang and McCalla (2005), Konstan et al. (2005), LANL (2005), Ferran et al. (2005) and Franke and Geyer-Schulz (2005)	2.4518
2006	Chirawatkul (2006), Kang and Cho (2006), Agarwal et al. (2006), Frias-Martinez et al. (2006), Franke et al. (2006), Ozono and Shintani (2006), McNee et al. (2006), Councill et al. (2006), Hess (2006), Hess et al. (2006), Gori and Pucci (2006), Yao (2006), Bollen and Van de Sompel (2006), Ishikawa et al. (2006), Li et al. (2006) and Giles (2006)	2.8021
2007	Farooq et al. (2007), Vellino and Zeber (2007), Huang (2007), Matsatsinis et al. (2007), Mao et al. (2007), Burns et al. (2007), Bradshaw and Light (2007), Lin and Wilbur (2007), Avancini et al. (2007), Franke and Geyer-Schulz (2007), Shimbo et al. (2007), Ratprasartporn and Ozsoyoglu (2007), Sánchez et al. (2007), Strohman et al. (2007), Yin et al. (2007), Yang et al. (2007), Yang and Allan (2007), Kapoor et al. (2007), Tang and McCalla (2007b,a), Pohl (2007) and Liu and Hu (2007)	3.8529
2008	Chandrasekaran et al. (2008), Farooq et al. (2008), Henning and Reichelt (2008), Zhang et al. (2008), Lopes et al. (2008), Mönnich and Spiering (2008a), Yao (2008), Bogers and Van den Bosch (2008), Popa et al. (2008), Lakkaraju et al. (2008), Zhou et al. (2008), Nallapati et al. (2008), Mönnich and Spiering (2008b), Naak et al. (2008), Franke et al. (2008), Neumann (2008), Heß (2008), Weng and Chang (2008) and Ritchie et al. (2008)	3.3275
2009	Kodakateri Pudhiyaveetil et al. (2009), Beel et al. (2009), Naak (2009), Tang and Zhang (2009), Morales-del-Castillo et al. (2009), Tang and McCalla (2009a), Breeding (2009), Vellino (2009), Sun et al. (2009), Yang et al. (2009), Gipp and Beel (2009a), Stock et al. (2009), Gipp and Beel (2009b), Arnold and Cohen (2009), Will et al. (2009), Porcel et al. (2009), Gipp et al. (2009), Dong et al. (2009), Vivacqua et al. (2009), Naak et al. (2009), Du et al. (2009), Neumann (2009), Daud et al. (2009), Dattolo et al. (2009), Söldner et al. (2009), Tang and McCalla (2009b) and Parra and Brusilovsky (2009)	4.7285
2010	Ekstrand et al. (2010), Porcel and Herrera-Viedma (2010), Hwang et al. (2010), Choochaiwattana (2010), Bethard and Jurafsky (2010), Vellino (2010), Jomsri et al. (2010), Zhang and Li (2010), Morales-del-Castillo et al. (2010), Shaoping (2010), Logvynovskiy and Dastbaz (2010), Sugiyama and Kan (2010), Cui et al. (2010), Wang et al. (2010), Guan et al. (2010), Lao and Cohen (2010), He et al. (2010), Kataria et al. (2010), Beel and Gipp (2010), Martín et al. (2010), Pan and Li (2010) and Zhang and Koppaka (2010)	3.8529
2011	Wang and Blei (2011), Sugiyama and Kan (2011), He et al. (2011), Pitigala et al. (2011), Pera and Ng (2011), Liang et al. (2011b), Nascimento et al. (2011), Ferrara et al. (2011), Lao and Cohen (2011), Beel et al. (2011), Vaughan (2011), Liang et al. (2011a), Baez et al. (2011), Liu and Belkin (2011), Thomas et al. (2011), Zhou et al. (2011), Chen et al. (2011), Uchiyama et al. (2011), Gottwald (2011), Lu et al. (2011), Ohta et al. (2011), Amini et al. (2011) and Nagori and Aghila (2011)	4.0280
2012	Jain (2012), Zarrinkalam and Kahani (2012a,b), Küçüktunç et al. (2012c), Zhou et al. (2012a), Gautam and Kumar (2012), Hong et al. (2012), Jiang et al. (2012a), Mishra (2012), Winoto et al. (2012), Akbar et al. (2012), Patton et al. (2012), Lao (2012), Wu et al. (2012), Küçüktunç et al. (2012), Jiang et al. (2012b), Küçüktunç et al. (2012b), Huynh et al. (2012), Soulier et al. (2012), Bancu et al. (2012), Tang and Zeng (2012), Kuberek and Mönnich (2012), Doerfel et al. (2012), Lao and Cohen (2012), Xia et al. (2012), He et al. (2012), Yu et al. (2012), Huang et al. (2012) and Bollen and Van De Sompel (2012)	5.0788
2013	Sugiyama and Kan (2013), Beel et al. (2013f), Chen et al. (2013), Vellino (2013), Beel et al. (2013b), Caragea et al. (2013), Zarrinkalam and Kahani (2013a), Lai and Zeng (2013), Yang et al. (2013), Sun et al. (2013), Rokach et al. (2013), Yang and Lin (2013), Meng et al. (2013), Beel et al. (2013e), Hong et al. (2013a), Lee et al. (2013), Nunes et al. (2013), Guo and Chen (2013), Oh et al. (2013), Küçüktunç et al. (2013a), Stock et al. (2013), Yan et al. (2013), Kim (2013), Manouselis and Verbert (2013), Chakraborty and Chakraborty (2013), De Nart et al. (2013), Yao et al. (2013), Hong et al. (2013b), Wang et al. (2013), Tian and Jing (2013), Beel et al. (2013c), Tao et al. (2013), Küçüktunç et al. (2013b), Kucuktunc (2013), Li et al. (2013), Sitthisarn and Rattanabundan (2013), Küçüktunç et al. (2013c,d), Alotaibi and Vassileva (2013), Zarrinkalam and Kahani (2013b), Li and Xiao (2013), Yan (2013), Amini et al. (2013), Jin et al. (2013) and Zhang et al. (2013)	7.8809
2014	Le Anh et al. (2014), Livne et al. (2014), Beel et al. (2014a), Pera and Ng (2014), Sun et al. (2014), Huang et al. (2014), De Nart and Tasso (2014), Tejeda-Lorente et al. (2014b), Philip et al. (2014), Zhou et al. (2014), Amjad et al. (2014), Amini et al. (2014), Ren et al. (2014), Tantanasiriwong and Haruechaiyasak (2014), Guo and Chen (2014), Tang et al. (2014), Kurtz and Henneken (2014), Xia et al. (2014), Liu et al. (2014b,a), Shirude and Kolhe (2014), Tejeda-Lorente et al. (2014a), Beel et al. (2014b), Xue et al. (2014), Akbar et al. (2014), Yang et al. (2014), Ha et al. (2014), Hajra et al. (2014), Jardine and Teufel (2014), Duma and Klein (2014), Omisore and Samuel (2014) and Omisore (2014)	5.6042
2015	Liu and Yang (2015), Tran et al. (2015), Sugiyama and Kan (2015b), Chakraborty et al. (2015), Amini et al. (2015), Kim and Chen (2015), Champiri et al. (2015), Meilian et al. (2015), Sinha et al. (2015), Hanyurwimfura et al. (2015), Liu et al. (2015b), Lee et al. (2015), Liu et al. (2015a), Verma and Dey (2015), Sesagiri Raamkumar et al. (2015), Alotaibi and Vassileva (2015), Fu et al. (2015), Vellino (2015), Tejeda-Lorente et al. (2015), Asabere et al. (2015), Patil and Ansari (2015), Steinert et al. (2015), Beel et al. (2015a,b), Beel (2015), Küçüktunç et al. (2015), Lu et al. (2015), Hsiao et al. (2015), Alzoghbi et al. (2015), Gao (2015), Sugiyama and Kan (2015a), Jiang et al. (2015), Ha et al. (2015), Beel and Langer (2015) and Huang et al. (2015)	6.1296

(continued on next page)

Table 1 (*continued*).

Year	References	Percentage (%)
2016	Beel et al. (2016a), Zhao et al. (2016), Steinert and Hoppe (2016), Bean (2016), Raamkumar et al. (2016), Paraschiv et al. (2016), Totti et al. (2016), West et al. (2016), Jadhav and Wankhade (2016), Wang et al. (2016), Alotaibi (2016), Amami et al. (2016), Wolfram (2016), Liu et al. (2016), Shirude and Kolhe (2016), Alotaibi and Vassileva (2016), Rúbio and Gulo (2016), Igbe and Ojokoh (2016), Vargas et al. (2016), Nishioka and Scherp (2016), Allen et al. (2016), Lee et al. (2016), Dhanda and Verma (2016), Tsolakidis et al. (2016), Xia et al. (2016), Chakraborty and Narayanam (2016), Alzoghbi et al. (2016), Duma et al. (2016b), Chakraborty et al. (2016), Duma et al. (2016a) and Beel et al. (2016b)	5.4291
2017	Beel (2017a), Sharma et al. (2017b), Haruna et al. (2017), Kazemi and Abhari (2017), Amami et al. (2017), Wang et al. (2017b), Langer and Beel (2017), Liu and Chien (2017), Xia et al. (2017), Hristakeva et al. (2017), Guo et al. (2017b), Ravi et al. (2017), Sharda and Dawgotra (2017), Guo et al. (2017a), Hassan (2017), Feyer et al. (2017), AlShebli et al. (2017), Tsolakidis et al. (2017), Beel et al. (2017a), Neethukrishnan and Swaraj (2017), Habib and Afzal (2017), Yin and Li (2017), Beel and Dinesh (2017), Chaitanya and Singh (2017), Guseva et al. (2017), Gupta and Varma (2017), Al-Natsheh et al. (2017), Wang et al. (2017a), Beel et al. (2017c), Hwang et al. (2017), Magara et al. (2017), Sahijwani and Dasgupta (2017), Raamkumar et al. (2017), Beel (2017b), Beierle et al. (2017), Jia and Saule (2017), Roy (2017), Anand et al. (2017), Ebesu and Fang (2017), Beel et al. (2017b), Al Alshaikh et al. (2017c,a,b) and Ahmad and Afzal (2017)	7.7058
2018	Kaya (2018), Yang et al. (2018), Collins et al. (2018), White (2018), Li et al. (2018a), Dai et al. (2018b,a), Liang et al. (2018), Mu et al. (2018), Wenige and Ruhland (2018), Cai et al. (2018b), Zhang et al. (2018b), Bulut et al. (2018), Cai et al. (2018a), Fernández-Isabel et al. (2018), Haruna et al. (2018), Son and Kim (2018), Zhao et al. (2018), Jiang et al. (2018), dos Santos and Machado (2018), Ayala-Gómez et al. (2018), Jia and Saule (2018), Wang et al. (2018a), Supriyanto et al. (2018), Mayr et al. (2018), Ollagnier et al. (2018b), Beel et al. (2018b), Sesagiri Raamkumar and Foo (2018), Chughtai et al. (2018), Ziegler and Shrake (2018), Lu et al. (2018), Bertin and Atanassova (2018), Haruna and Ismail (2018), Nishioka and Ogata (2018), Porcel et al. (2018), Zhang et al. (2018a), Beel et al. (2018a), Magara et al. (2018), Ollagnier et al. (2018a), Kong et al. (2018), Beel et al. (2018d), Kobayashi et al. (2018), Bhagavatula et al. (2018), Dinesh (2018), Beel et al. (2018c), Wang et al. (2018b), Raamkumar et al. (2018), Ullah (2018), Al Alshaikh (2018), Färber et al. (2018) and Li et al. (2018b)	8.9317
2019	Dai et al. (2019), Li et al. (2019a), Waheed et al. (2019), Bai et al. (2019), Cai et al. (2019), Yang et al. (2019c), Beel et al. (2019), Li et al. (2019b), Rahdari and Brusilovsky (2019), Yang et al. (2019b), Samad (2019), Alshareef (2019), Collins and Beel (2019), Hassan et al. (2019), Maake et al. (2019a), Murali et al. (2019), Kanakia et al. (2019), Habib and Afzal (2019), Ma et al. (2019), Ma and Wang (2019), Li and Zou (2019), Chen et al. (2019b), Maake et al. (2019b), Chen et al. (2019a), Zhao et al. (2019), Yang et al. (2019a), Duma (2019) and Nishioka et al. (2019)	4.9036
2020	Ali et al. (2020b), Färber and Jatowt (2020), Färber and Sampath (2020), Färber et al. (2020), Haruna et al. (2020), Liu et al. (2020), Alfarhood and Cheng (2020), Jeong et al. (2020), Cohan et al. (2020), Ma et al. (2020), Wang et al. (2020a), Nogueira et al. (2020b), Ostendorff (2020), Ali et al. (2020a,c), Guo et al. (2020), Bulut et al. (2020), Sakib et al. (2020), Du et al. (2020), Khadka (2020), Medić and Šnajder (2020), Nair et al. (2020), Nishioka et al. (2020), Li et al. (2020), Medić and Snajder (2020), Saier and Färber (2020), Nogueira et al. (2020c), Tao et al. (2020), Nogueira et al. (2020a), Khadka et al. (2020), Alkhatib and Rensing (2020), Dai et al. (2020), Wang et al. (2020b) and Choi et al. (2020)	5.9545
2021	Zhu et al. (2021), Ali et al. (2021b), Qiu et al. (2021), Ali et al. (2021a), Tang et al. (2021), Wang et al. (2021), Dai et al. (2021), Kang et al. (2021), Chaudhuri et al. (2021), Ali et al. (2021d), Kieu et al. (2021a), Xie et al. (2021), Kieu et al. (2021b), Boudin (2021), Zhang et al. (2021a), Portenoy (2021), Ali et al. (2021c), Sakib et al. (2021), Nair et al. (2021), Hao et al. (2021), Shyani (2021), Meyer et al. (2021), Chen (2021), Zhang et al. (2021b), Ma et al. (2021) and Bhowmick et al. (2021)	4.5534
2022	Zhang and Zhu (2022) and Nair et al. (2022)	0.3502

Behavior analysis from various means to identify user needs, triggers a recommender system to make predictions for the target user. To make it more clear, all the components along with recommendation process are illustrated in Fig. 3. The three aspects are discussed in detail in the following sections.

2.1. Principle knowledge and operating theory

Before discussing the recommendation approaches, first we would explain the background knowledge and operating principle behind various recommendation approaches. Principle knowledge is defined as the set of features or the piece of information about an item. Operating principle defines how the knowledge is employed i.e., how to use the principle features for generating recommendations. Background knowledge and operating principle together define a recommendation algorithm. These two concepts reside at the back of a recommender system and differentiate between various classes. The principle features discussed in this section are considered in the context of recommendation approach. Some of these features may be used in modeling user interest, however the context differs. The following section describes the background knowledge along with the operating principle used in recommendations.

2.1.1. Attributes of research document

Research paper can be represented in terms of word-based features, a single or group of words. Word features can be extracted from various document fields such as paper header (which includes title & author block), abstract, keywords, conclusion, bibliography, or whole text (body) of the document. These features can be used to find similarity among various documents.

2.1.2. Author profile

Experts publish more and more information related to a specific area and there is a close association between their publications. This provides an opportunity to use author's name, affiliation, ORCID, research interests, their publications, personal document collection, total citations and other details for recommendation. Author details can be used in following three ways:

1. Authors' profile include their research areas, publications, topics, concepts and other interest details which can be used to recommend other relevant documents based on the textual similarity.
2. Author profile can be used to find researchers with overlapping research interest. Recommending published material liked by the like-minded researchers can help users to develop a better understanding of the field.
3. Author information can also be used to determine how often researchers cite the publications from a specific author. Citation counts can also be used to determine authors' reputation or popularity. Citation to a particular author shows that the user is interested in his research and other publications from the cited author can be recommended.

2.1.3. Cite information

References cited in document text are used to describe related work or to justify an argument with the help of previous explanations. The citation text can be used in following ways:

1. Citation Context- In a research paper, text surrounding a specific citation summarizes its work. Determining the context in which

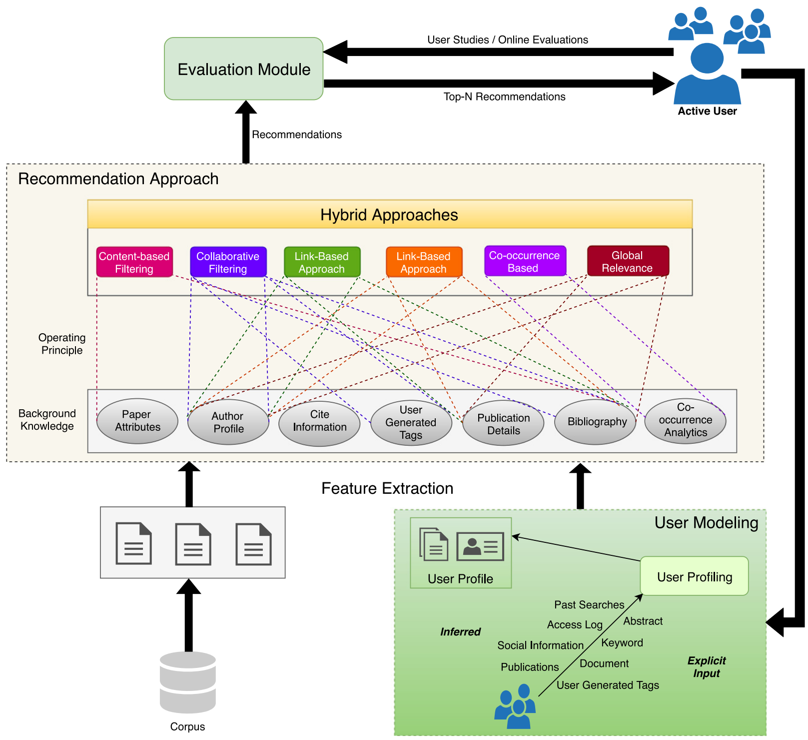


Fig. 3. General architecture of Research Paper Recommendation System.

a particular reference is used, helps in discovering the topic of interest. Papers discussing the related topics or used in similar context can be recommended to the user.

2. Citation Proximity- It determines how close the two citations appeared in the current article. Papers cited in close proximity shows the higher degree of relatedness which eventually decreases when the two move farther. Also, multiple citations to the same paper in document text shows the influence of cited paper. Important articles are cited at many places to indicate the close connection between the cited paper and the current work. It creates a pack of closely related cited documents with their influence factor. This information can be used to rank recommendations or to suggest other relevant papers based on the users choice of citation.
3. Citation Order- When two or more articles are cited together, thus analyzing their order of citation in citing papers helps us to discover related documents. Citing articles following the similar citation order may appear relevant to user.

2.1.4. *User generated tags*

When researchers find any relevant article, they may annotate the document using labels, ratings, adding comments, by recommending that article or providing reviews. These tags given by user to various articles are strong indication of their interest. This explicit information can be used to determine their preference with respect to various research areas. If explicit interest is not known, it can be inferred through user actions such as paper browsing, reading, downloading etc. A user profile can be created using the generated tags and this knowledge can be used in three ways:

1. User Information-Tags given by researcher are useful in identifying the users' area of interest thus, other articles belonging to the related category or associated with similar tags can be recommended.
2. Peer Information- Opinion of similar users (in terms of explicit or implicit ratings) can be used to predict one's preference for an article. Similarity can be determined by analyzing user generated tags specifically the ratings stored in rating database. Here, the recommendations are given on the basis of peers' interest rather than oneself.
3. Popularity- Ratings provided by users to various papers can be used to assess overall popularity of a paper which further can be considered to make generalized recommendations.

2.1.5. *Publication details*

Publication details include its name, sponsors, publisher, venue name, type of venue, year of publication etc. This information can be used as follows:

1. One can use the publication details to recommend other relevant articles from the same publisher/conference as it includes papers from related scope. A graph can be build comprising of papers and their publication information to determine similar articles.
2. Conference raking, journal impact factor, mean citation counts of venue can be used to identify good and popular papers for recommendation.

2.1.6. *Bibliography*

Bibliography or references are very significant features that can be used in multiple ways.

1. Determining common bibliography- When two articles share reasonable number of cited papers, they appeared to be similar. Common citations show that the two papers discuss related topic. This is referred as co-coupling or biographic coupling which means two or more papers have common citation(s). Significant number of overlapping citations shows the strength of association between the two.
2. Citations- Papers cited by researchers are strong indicator of their preferences thus, finding and recommending articles similar to the cited publications may appear useful to the current researcher.
3. Forming citation network- A graph can be build whose nodes represent research documents and presence of link between the two nodes shows a citation relationship. This citation graph can be analyzed in following ways:

- When a user is searching for a specific research paper (input paper) then, the related work cited by the input paper may also be relevant to the active user.
- Current user might be interested in articles that cites the input paper.
- Recommending papers that are cited along with the input paper (co-cited) in many publications may prove useful to the target user. This is known as co-citation which means two papers that are cited together in two or more articles. Co-citation strength is determined by the number of common citations i.e., number of papers citing the two documents.

4. Popularity of research document- Number of citations to a paper is regarded as one of the principle measures for determining its popularity. Recommending top-cited articles of the area to which the input paper belongs, is expected to be liked by the user.

The citation network may include other entities such as authors, venues etc. instead of (or along with) research papers. Depending upon the type of entity, the graph exhibits different kinds of association between the nodes.

2.1.7. Occurrence analytics

A sequence of transactions or sessions is analyzed to mine users' purchase behavior or usage history. When two or more papers occur together in a number of transactions, they are assumed to be highly related. Papers that are collectively viewed, browsed or downloaded in most of the browsing sessions form a cluster and are said to be co-occurred. When user actions include a paper from this co-occurrence set, other paper(s) from the set can be recommended to the user. This records the user session histories without looking into the specific user and paper details.

2.1.8. Consolidated information

Principle features can be combined in numerous ways to overcome the limitations of using a single feature and to serve for a better recommendation algorithm. A feature combination is wisely chosen that is appropriate to solve the target problem.

2.2. Recommendation approaches

Recommendation approach explains the use of background knowledge applying one of the operating principles to obtain recommendations. A typical combination of background knowledge and operating theory defines a unique recommendation approach. Based on the different combinations, renown approaches in the domain of paper recommendation are Content-Based Filtering (CBF), Collaborative Filtering (CF), Link-Based Approach (LBA), Co-occurrence Based Approach (CBA), Global Relevance (GR) and Hybrid Approaches. Table 2 shows the principle features associated with different recommendation algorithms, also summarizes the related work based on the recommender approach and feature-set. Papers applying more than one algorithm to compare their performances are referenced at multiple blocks in Table 2 and those which combine two or more approaches are presented in hybrid approach. Global relevance is rarely used as a standalone algorithm and is generally employed to fine-tune or to rank the recommendation results. However, it is used by some researchers to make a good start when no other user information is available. Papers using a combination of GR with other algorithms to produce a hybrid version are also referenced at global relevance section to show the global relevance features used by the approach. This section covers the well-known recommendation approaches and advancements so far in this direction.

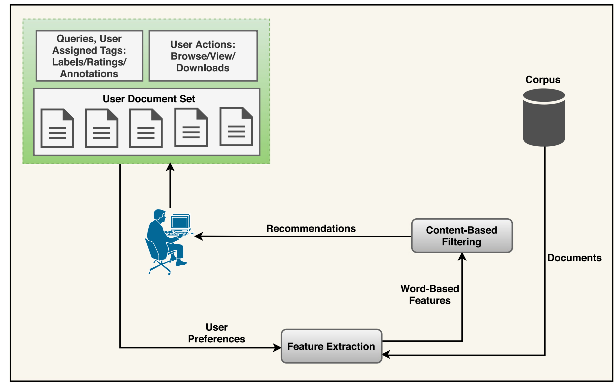


Fig. 4. Design and work flow of content-based filtering systems.

2.2.1. Content-based Filtering

According to our study, Content-based Filtering (CBF) is the most widely explored technique in the field of paper recommendation. CBF maps user interests and candidate papers to feature vectors for determining similarity between the user profile and the candidate documents as shown in Fig. 4. Documents similar to user's previous choices are produced as recommendations.

The idea of recommending scientific publication came into existence in 1998 with the development of CiteSeer autonomous indexing system (Giles et al., 1998) which helps in developing users' knowledge by providing citations along with the citation context. It accepts input as user query and performs a keyword search to display a list of citations which are ranked by their total number of citations. After this initial search, user can browse for other relevant publications following the citation links i.e. papers citing a particular document and papers cited by that particular document, including the citation context. Further, the citeseer system was upgraded by incorporating heterogeneous user profile and user–system interactions to capture user interests (Bollacker et al., 1999).

A probabilistic topic model called 'PMRA' was proposed to determine content similarity and enable related document search in PubMed (Lin and Wilbur, 2007). It estimates the probability that user will find a particular paper interesting, given another document in which user has shown interest. Documents are ranked based on the degree of relatedness which can be expressed using the topic distribution and prior topic probability. Some have measured semantic correlations via latent topics to recommend citations for a given paper (Daud et al., 2009). Each document is represented as probabilistic distribution over latent topics and each topic as distribution over document terms, the latent topics are then used to find relevant literature. Some authors have used Latent Semantic Analysis (LSA) and Latent Dirichlet Allocation (LDA) to determine semantic vectors for user query and documents (Paraschiv et al., 2016). Semantic distance is computed between them to recommend relevant papers based on cohesion scores. Some have enhanced the use of topic modeling by integrating citations along with words in LDA (Xia et al., 2012). Some have applied a clustering technique to partition documents into various topic-coherent clusters (Liang et al., 2011b). PLSA (Probabilistic Latent Semantic Analysis) is used to infer document topic and generate topic-coherent clusters. Topic of each cluster is compared to the user's interest topic and most relevant subset is obtained. Recommendations are filtered based on the user's personalized preference.

Some have used concepts from ACM's Computing Classification System (CCS) to represent user profile and corpus documents. And concept similarity is determined using cosine measure (Chandrasekaran et al., 2008) and weighted concepts (Kodakateri Pudhiyaveetil et al., 2009) to recommend conceptually related articles. Some authors have represented user profile and paper content using a context graph which

Table 2
Classification of available literature based on the recommendation approaches and applied background knowledge.

Recommendation approach	Background knowledge	References
Content-based filtering	Attributes of research document	Bollacker et al. (1998), Giles et al. (1998), Renda and Straccia (2002), Gross (2003), Tang and McCalla (2003b), Erosheva et al. (2004), Theobald and Klas (2004), Renda and Straccia (2005), Watanabe et al. (2005), Lin and Wilbur (2007), Avancini et al. (2007), Ratprasartporn and Ozsoyoglu (2007), Chandrasekaran et al. (2008), Lopes et al. (2008), Kodakateri Pudhiyaveetil et al. (2009), Morales-del-Castillo et al. (2009), Sun et al. (2009), Daud et al. (2009), Sugiyama and Kan (2010), Morales-del-Castillo et al. (2010), Paraschiv et al. (2016), Liang et al. (2011b), Nascimento et al. (2011), He et al. (2011), Nagori and Aghila (2011), Ferrara et al. (2011), Patton et al. (2012), Xia et al. (2012), He et al. (2012), Yang et al. (2013), Hong et al. (2013a), Lee et al. (2013), Nunes et al. (2013), De Nart et al. (2013), Hong et al. (2013b), Jin et al. (2013), Huang et al. (2014), Philip et al. (2014), Xue et al. (2014), De Nart and Tasso (2014), Hajra et al. (2014), Hanyurwimfura et al. (2015), Verma and Dey (2015), Patil and Ansari (2015), Alzoghbi et al. (2015), Gao (2015), Zhao et al. (2016), Amami et al. (2016), Alzoghbi et al. (2016), Igbe and Ojokoh (2016), Sharma et al. (2017b), Hassan (2017), Hristakeva et al. (2017), Chaitanya and Singh (2017), Wang et al. (2017b), Ahmad and Afzal (2017), Al-Natsheh et al. (2017), Ravi et al. (2017), Yin and Li (2017), Hwang et al. (2017), Raamkumar et al. (2017), Ebesu and Fang (2017), Kaya (2018), Yang et al. (2018), Bulut et al. (2018), Bhagavatula et al. (2018), Chughtai et al. (2018), Yang et al. (2019c), Färber and Sampath (2020), Hassan et al. (2019), Guo et al. (2020), Nair et al. (2020), Wang et al. (2020b), Choi et al. (2020), Zhu et al. (2021), Wang et al. (2021), Kieu et al. (2021b), Hao et al. (2021), Meyer et al. (2021), Chen (2021) and Ma et al. (2021)
	Author profile	Middleton et al. (2004a), Morales-del-Castillo et al. (2009), Porcel and Herrera-Viedma (2010), Morales-del-Castillo et al. (2010), Sugiyama and Kan (2010), Hong et al. (2012), Winoto et al. (2012), Tang and Zeng (2012), Beel et al. (2013e), Yan et al. (2013), Sitthisarn and Rattanabundan (2013), Hong et al. (2013b), Xue et al. (2014), Patil and Ansari (2015), Lee et al. (2015), Zhao et al. (2016), Amami et al. (2016), Igbe and Ojokoh (2016), Yin and Li (2017), Hassan (2017), Raamkumar et al. (2017), Hwang et al. (2017), Ebesu and Fang (2017), Yang et al. (2018), Bulut et al. (2018), Wang et al. (2020b) and Hao et al. (2021)
	Cite information	Tang and Zhang (2009), Gipp and Beel (2009a,b), Lu et al. (2011), He et al. (2011), Huang et al. (2012), Xia et al. (2012), Yan et al. (2013), Huang et al. (2014), Xue et al. (2014), Yin and Li (2017), Ebesu and Fang (2017), Ollagnier et al. (2018a), Yang et al. (2018, 2019c), Färber and Sampath (2020), Habib and Afzal (2019) and Wang et al. (2020b)
	User generated tags	Choochaiwattana (2010), Jomsri et al. (2010), Guan et al. (2010), Gautam and Kumar (2012) and Ha et al. (2015)
	Publication details	Bollacker et al. (1998), Sugiyama and Kan (2010), Xue et al. (2014), Gao (2015), Igbe and Ojokoh (2016), Yang et al. (2018), Bulut et al. (2018), Yang et al. (2019c), Wang et al. (2021) and Hao et al. (2021)
	Bibliography	Bollacker et al. (1998), Giles et al. (1998), Ratprasartporn and Ozsoyoglu (2007), Tang and Zhang (2009), Sugiyama and Kan (2010), Huang et al. (2012), Xia et al. (2012), Yan et al. (2013), Xue et al. (2014), Lee et al. (2015), Ha et al. (2015), Ahmad and Afzal (2017), Raamkumar et al. (2017), Ollagnier et al. (2018a), Habib and Afzal (2019), Wang et al. (2020b, 2021) and Ma et al. (2021)
Collaborative filtering	Author profile	Fuhr et al. (2001), Nakagawa and Ito (2002), Ferran et al. (2005), Popa et al. (2008), Morales-del-Castillo et al. (2009, 2010), Winoto et al. (2012), Meilian et al. (2015), Hristakeva et al. (2017) and Neethukrishnan and Swaraj (2017)
	User generated tags	Pennock et al. (2000), Renda and Straccia (2002, 2005), Agarwal et al. (2005), Avancini et al. (2007), Tang and McCalla (2009a), Dattolo et al. (2009), Tang and McCalla (2009b), Parra and Brusilovsky (2009), Mishra (2012), Jain (2012), Winoto et al. (2012), Jiang et al. (2012b), Yu et al. (2012), Manouselis and Verbert (2013), Asabere et al. (2015) and Murali et al. (2019)
	Bibliography	McNee et al. (2002), Erosheva et al. (2004), Haruna et al. (2017), Liu et al. (2015a) and Sakib et al. (2020)
	Cite information	Liu et al. (2015a)
Link-based approach	Author profile	Zhou et al. (2008), Arnold and Cohen (2009), Lao and Cohen (2010), Baez et al. (2011), Lao and Cohen (2011), Küçüktunç et al. (2012c), Lao and Cohen (2012), Guo and Chen (2013), Cai et al. (2018a) and Du et al. (2020)
	Publication details	Zhou et al. (2008), Lao and Cohen (2010, 2011), Küçüktunç et al. (2012c), Lao and Cohen (2012) and Cai et al. (2018a)
	Bibliography	Pitkow and Pirolli (2002), Zhou et al. (2008), Arnold and Cohen (2009), Lao and Cohen (2010), Baez et al. (2011), Liang et al. (2011a), Lao and Cohen (2011), Küçüktunç et al. (2012c,b), Huynh et al. (2012), Lao and Cohen (2012), Guo and Chen (2013), Caragea et al. (2013), Ha et al. (2014), Liu et al. (2015b), West et al. (2016), Cai et al. (2018a), Haruna et al. (2018), Son and Kim (2018) and Du et al. (2020)
Co-occurrence based technique	Occurrence analytics	Geyer-Schulz et al. (2001b), Geyer-Schulz and Hahsler (2002b), Geyer-Schulz et al. (2002), Geyer-Schulz and Hahsler (2002a), Geyer-Schulz et al. (2003b,d), Böhm et al. (2003), Geyer-Schulz et al. (2003c,a), Franke et al. (2006), Franke and Geyer-Schulz (2007) and Mönnich and Spiering (2008a)
Global relevance	User generated tags	Winoto et al. (2012)
	Bibliography	Bethard and Jurafsky (2010) and Rokach et al. (2013)
	Author profile	Bethard and Jurafsky (2010), Rokach et al. (2013) and Hristakeva et al. (2017)
	Publication details	Bethard and Jurafsky (2010) and Rokach et al. (2013)

(*continued on next page*)

is constructed by processing weighted terms of key-phrases. Recommendations are generated by scoring and finding the overlap between two context graphs (De Nart and Tasso, 2014). Some researchers have modeled domain knowledge by constructing concept map based on LDA, each node defines a topic and an edge between them represents correlation. User's knowledge gap is analyzed by taking a path of concepts in concept map and a score is used to find a match between papers and a concept path. Recommendations include those documents which bridge this gap by providing the knowledge the user lacks (Zhao et al., 2016). While others have considered the task of recommendation as a ranking optimization problem, formulating objective function in terms of ranking SVM (Support Vector Machine) to generate recommendations (Xue et al., 2014).

Content-based filtering extracts key-terms (Kaya, 2018), key-phrases (De Nart and Tasso, 2014), keyword relationship (Le Anh et al., 2014), topics (Amami et al., 2016) or concepts (Sharma et al., 2017b; Hassan et al., 2019) from research articles to match them against user profile. Typically, a research document is comprised of many attributes, already

Table 2 (*continued*).

Recommendation approach	Background knowledge	References
Hybrid approach	Consolidated information	Joaquin et al. (1998), Fernández et al. (2000), Woodruff et al. (2000), Bollen and Rocha (2000), Rocha (2001), Schwab et al. (2001), Middleton et al. (2002a), Renda and Straccia (2002), Tang and McCalla (2003a, 2004a,b,c), Middleton et al. (2004b), Huang et al. (2004), Torres et al. (2004), Middleton et al. (2004a), Cazella and Alvares (2005a), Renda and Straccia (2005), Cazella and Alvares (2005b), Tang and McCalla (2005), Bollen and Van de Sompel (2006), Gori and Pucci (2006), Agarwal et al. (2006), Vellino and Zeber (2007), Avancini et al. (2007), Strohman et al. (2007), Yin et al. (2007), Matsatsinis et al. (2007), Zhang et al. (2008), Popa et al. (2008), Naak et al. (2008, 2009), Yang et al. (2009), Gipp et al. (2009), Will et al. (2009), Porcel et al. (2009), Dong et al. (2009), Du et al. (2009), Vellino (2009), Bethard and Jurafsky (2010), Ekstrand et al. (2010), Zhang and Li (2010), He et al. (2010), Kataria et al. (2010), Porcel and Herrera-Viedma (2010), Pan and Li (2010), Pera and Ng (2011), Wang and Blei (2011), Sugiyama and Kan (2011), Uchiyama et al. (2011), Chen et al. (2011), Ohta et al. (2011), Zarrinkalam and Kahani (2012a,b), Zhou et al. (2012a), Chen et al. (2013), Soulier et al. (2012), Jiang et al. (2012a), Winoto et al. (2012), Bancu et al. (2012), Doerfel et al. (2012), Sun et al. (2013), Zarrinkalam and Kahani (2013a), Meng et al. (2013), Zhang et al. (2013), Rokach et al. (2013), Oh et al. (2013), Yang and Lin (2013), Alotaibi and Vassileva (2013), Sugiyama and Kan (2013), Wang et al. (2013), Küçüktunç et al. (2013a,d), Le Anh et al. (2014), Tejeda-Lorente et al. (2014b), Zhou et al. (2014), Ren et al. (2014), Pera and Ng (2014), Liu et al. (2014b,a), Shirude and Kolhe (2014), Sun et al. (2014), Livne et al. (2014), Tejeda-Lorente et al. (2014a), Jardine and Teufel (2014), Chakraborty et al. (2015), Sugiyama and Kan (2015b), Steinert et al. (2015), Tejeda-Lorente et al. (2015), Sesagiri Raamkumar et al. (2015), Hsiao et al. (2015), Jiang et al. (2015), Totti et al. (2016), Liu et al. (2016), Wang et al. (2016), Shirude and Kolhe (2016), Lee et al. (2016), Tsolakidis et al. (2016), Amami et al. (2017), Liu and Chien (2017), Guo et al. (2017b), Anand et al. (2017), Sharda and Dawgotra (2017), Habib and Afzal (2017), Mu et al. (2018), Dai et al. (2018b), Li et al. (2018a), Cai et al. (2018b), Wang et al. (2018a), Lu et al. (2018), Kong et al. (2018), Kobayashi et al. (2018), Dai et al. (2019), Waheed et al. (2019), Cai et al. (2019), Yang et al. (2019c), Li et al. (2019a), Kanakia et al. (2019), Ma and Wang (2019), Chen et al. (2019a), Yang et al. (2019a), Haruna et al. (2020), Liu et al. (2020), Alfarhood and Cheng (2020), Jeong et al. (2020), Wang et al. (2020a), Nogueira et al. (2020b), Ostendorff (2020), Medić and Snajder (2020), Khadka et al. (2020), Alkhatib and Rensing (2020), Ali et al. (2021b), Qiu et al. (2021), Ali et al. (2021a), Kang et al. (2021), Zhang et al. (2021a), Ali et al. (2021c), Sakib et al. (2021), Nair et al. (2021) and Bhowmick et al. (2021)

discussed in Section 2.1 and researchers have used these fields as principle features. Many authors featured title (Hassan, 2017) as it is the most appropriate shorthand representation of a document. Abstract is the most important part and precise description of author's work, predominantly used by researchers (Al-Natsheh et al., 2017) to mark up significant features. Others have used author profile (Lee et al., 2015), user assigned tags (Choochaiwattana, 2010), publication details (Wang et al., 2021), header block (Bancu et al., 2012), author specified keywords (Hong et al., 2013a), citation context (Huang et al., 2012), citation proximity (Gipp and Beel, 2009b; Habib and Afzal, 2019), citation order (Gipp and Beel, 2009b), document text (Ollagnier et al., 2018a) and bibliography (Tang and Zhang, 2009; Wang et al., 2021) for generating feature vectors or to improve recommendation list. Some researchers have used only one document field, others have used the combination of above-mentioned fields (Erosheva et al., 2004; He et al., 2011) and a few have used weighted mechanism for fields i.e. higher weight is assigned to prominent features (Nascimento et al., 2011).

Content-based filtering mostly employs Bag-of-Words (BoW) model (Lee et al., 2013) or its variant like Bag-of-n-Grams (BoG) (Ferrara et al., 2011) to derive feature set for candidate papers and user preferences. Vector Space Model (VSM) is another most popular approach used to generate feature vector for documents, where each term (word) represents a unique feature and term weight denotes its value (Watanabe et al., 2005). Term weight can be expressed in the form of binary value or term frequency (Sugiyama and Kan, 2010) or Term Frequency-Inverse Document Frequency (TF-IDF) (Chaitanya and Singh, 2017; Zhu et al., 2021). Document representation techniques specified above are not able to capture the word or document semantics and suffer with language ambiguity problems. To overcome this limitation, very few researchers have applied the concept of distributed representations or deep learning in paper recommendation (Sharma et al., 2017b; Hassan, 2017). Some authors have proved that distributed representation method 'doc2vec' outperforms the other text representation techniques (Zhang and Zhu, 2022).

CBF provides highly personalized recommendations exclusively based on users' past interest, thus suffers with the problem of overspecialization. Furthermore, it provides recommendations that are highly predictable and less serendipitous (Lops et al., 2011). On the other side, it requires high computation power for performing background tasks such as text analytics of high volume data, user modeling and similarity calculations.

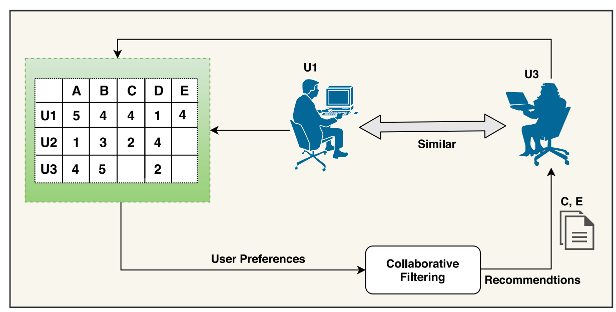


Fig. 5. Recommendation process in collaborative filtering-based systems.

2.2.2. Collaborative filtering

Collaborative filtering is often used for research paper recommendation, which predicts user interests by observing the preference pattern of other similar users. Researchers are considered like-minded when their likings and dis-likings match with respect to several papers. A collaborative filtering system collects user preferences generally in terms of ratings given to papers by various users. The whole process of recommendation is illustrated in Fig. 5.

There developed many systems that facilitate research management along with the recommendation services. CYCLADES provides a collaborative work environment and represents users' interests by their personal folders (Renda and Straccia, 2002, 2005; Avancini et al., 2007). Recommendations were given for data items, collections, users and communities based on implicit or explicit ratings of other users. Rating similarity was determined using Pearson correlation coefficient between user folders to find similar users for recommendation. Some have applied three variants of user-based collaborative filtering (Parra and Brusilovsky, 2009). The first algorithm predicted the ranking score using ratings given by similar users. Second method estimated the prediction score by considering number of raters and keeping those papers at the top which were rated by maximum number of neighbors. Third algorithm measured similarity between user query and set of user-assigned tags to find similar users, then predicted the rating score based on the tags assigned by neighbors.

Ratings given to papers may not be sufficient to assess user needs from multiple perspectives. A new dimension to collaborative filtering is presented by offering multi-criteria ratings to model user needs from different perspectives. Some authors have applied unidimensional and multidimensional collaborative filtering to research paper recommendation (Tang and McCalla, 2009a,b; Winoto et al., 2012). Unidimensional CF relies solely on ratings given to various papers, while multidimensional CF incorporates several other factors to determine correlation between users. Specifically, the authors have considered paper's overall ratings, value-added and user's pedagogical features for multidimensional CF. Similarity between users was derived by applying Pearson correlation coefficient on ratings given by various users. However in the absence of ratings for a given user, the authors have used user's interest and background knowledge in Pearson correlation to find similar users. Some have considered other dimensions such as presence of an article in user library, whether an article was read and presence of a vote/star for an article, which can be used to acquire users' preferences over a document (Manouselis and Verbert, 2013).

Collaborative filtering can be easily applied when external rating database is available. In the absence of explicit ratings, some authors have inferred implicit ratings via user actions and assigned different weights to each user action (Pennock et al., 2000). These actions include viewing, downloading and adding a paper to user profile. Rating for a document is computed by adding the respective weights for all actions performed by a user on the document. Given user ratings, authors have applied Bayes theorem to determine the probability that active user possess same personality as any other user. Probability distribution of user ratings on unseen documents was estimated and most probable ratings were returned as prediction. Some have developed user preference model by monitoring user behavior which includes reading, sharing, downloading, collecting and scoring of research papers (Meilian et al., 2015). Authors employed LDA to extract topics from title, abstract and keywords for all corpus papers as well as user preferred documents, feature vectors are then constructed for respective topics. Cosine measure was used to determine similarity between users and active user's interest was predicted over topics liked by the similar users. Based on the predicted score, topics with highest scores were selected for recommendation. Some authors have build users' navigational profile by considering search and browse operations in digital library and its semantic description given by an ontology. These profiles were then used to make recommendations by finding users with similar interest profiles (Ferran et al., 2005). Some have used ontological similarities to find similar users (Neethukrishnan and Swaraj, 2017) and unseen papers were recommended based on the predicted value.

Some authors have discussed the implementation of Mendeley Suggest recommender system which finds similar users by employing K nearest neighbors (K-NN) on their document libraries (Hristakeva et al., 2017). Users were represented by a vector of their libraries, 1 indicating the presence of document in user library. For a given user, it predicted a rating score of document by adding the cosine score across the user's neighborhood. Documents with higher predicted values were recommended as user would be more likely to read those documents. Some have used the citation web to populate the rating matrix, 1 indicates that author has made a citation to the paper (McNee et al., 2002). The authors then employed user-based and item-based CF to build neighborhoods among users and items respectively. Others have incorporated the social relations of conference participants while determining the similarity in their research interests (Asabere et al., 2015).

Collaborative filtering mainly relies on rating database and recommend papers that are rated high by similar users. A major drawback of CF in paper recommendation research is lack of rating data. To rate an article, one should carefully read and understand it, which is a time-consuming process. Subsequently, it decreases the number of ratings due to the slow user response (Yang et al., 2009). High dependence on user participation gives rise to the problem of cold-start which can be further divided into user and item cold-start (Sharma et al., 2017a). When a new researcher enters a system with no or very less ratings, then it becomes very difficult to find similar users and generate recommendations for the new user. Similarly, when a new article is published, very few users have read and rated that article, thus, the paper cannot be recommended until enough ratings are available. Due to the information overload, the amount of publications increases exponentially, though the users are limited. Therefore, the user–item matrix created is extremely sparse which consequently leads to the problem of data sparsity (Vellino, 2013).

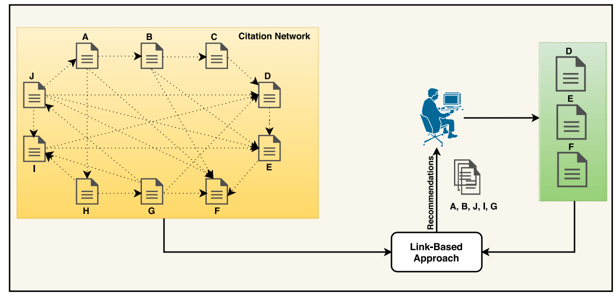


Fig. 6. An illustration of recommendation process using link-based approach.

To reduce the dependency on explicit ratings, implicit ratings can be inferred through user actions (Pennock et al., 2000) such as browsing, downloading (Guo et al., 2017b), adding paper to his/her collection (Alotaibi and Vassileva, 2013), commenting (Guo et al., 2017b), purchasing, citing a paper (Sakib et al., 2020; Haruna et al., 2017), number of pages read by the users (Yang et al., 2009), based on interest areas (Cazella and Alvares, 2005a) and trust relationships (Alotaibi and Vassileva, 2013). However these assumptions were criticized by some authors, they argue that implicit ratings may not be able to model the real-world requirements (MacRoberts and MacRoberts, 1989; Liu, 1993). Apart from these, various issues such as gray sheep, ramp-up problem, shilling attacks etc. have been associated with a collaborative-filtering based system (Ricci et al., 2011; Sharma et al., 2017a).

2.2.3. Link-based approach

Link-based approaches create a network establishing the relationship that exist between various academic entities. The graph comprises different types of entities and captures association between them. Generally, the network contains one type of entity as a research document or an author. Research document can be represented by its title, unique paper id etc., likewise, author name (Zhou et al., 2008), ORCID or any unique identifier can be used for author entity. The graph may contain other entities which includes researcher's profile (name, affiliation, publications, research interests etc.) (Sinha et al., 2015; Ma et al., 2019), publication details like year (Strohman et al., 2007), type/venue (Safa et al., 2018; Bethard and Jurafsky, 2010), publisher (Liu and Chien, 2017) or it can be genes (Arnold and Cohen, 2009), customer and so on. Researchers have used the citation network for the task of venue, references, expert/reviewer, peer or gene recommendation. Link-based methods capture academic associations to generate paper recommendations as depicted in Fig. 6.

Some authors have utilized the researchers' profile and their social network to create co-authorship, venue and topic graph (Ali et al., 2020c; Baez et al., 2011). Based on the user's goal and context, appropriate network was selected for recommendation and similarities among various entities were computed. Some have enhanced the citation network by incorporating gene information for the novel task of gene prediction i.e. to predict user's future interest for writing publications based on the past publications (Arnold and Cohen, 2009). The graph consists of authors, papers and genes with connecting edges between them. Starting with the query node, a random walk was performed to cover the adjacent nodes with a probability following the inverse of total number of adjoining nodes. This process was repeated to get a probability distribution for ranking and predicting the most probable nodes that appear in the walk, given a query. Some authors have used the probabilistic inference model to predict the likelihood of user's interest towards a paper (Ha et al., 2014). Others have modeled co-authorship and co-citation relationships, then random walk with restart algorithm was applied to determine and rank the scientific collaborators for recommendation (Guo and Chen, 2013). Some authors have proposed recommendation algorithm based on heterogeneous information networks consisting of citation relationship, author collaboration relationship, and research area information (Du et al., 2020).

Some authors have defined a time variant network where each edge is associated with a time stamp and label (Lao and Cohen, 2010, 2011, 2012). They considered the task of venue recommendation to suggest relevant venue to publish a new paper, citation recommendation to generate references for a given paper, expert recommendation to find an expert for a particular domain or topic and gene recommendation to predict users' future interest in which they are likely to publish new research papers. Path ranking algorithm with random walk was used to determine the most optimize path for the given query. Some authors have considered the task of paper, expert and venue recommendation using direction aware citation analysis to tune the search for traditional or recent papers (Küçüktunç et al., 2012c). A direction awareness parameter is introduced in random walk with restart algorithm to suggest traditional or recent documents based on user's need. Few have utilized citation contextual information to improve link-prediction tasks (Kataria et al., 2010; Zarrinkalam and Kahani, 2013a). Multi-layer network was introduced to enhance the capabilities of citation graph by embedding a layer of trust network over the citation graph (Hess, 2006; Hess et al., 2006).

Graph-based approaches involve computation overhead of extracting citations, authorship, co-authors etc., this complicates the overall process and increases computational complexity. Once the graph is built, it is easy to discover suitable candidates for recommendation using random walk (Chakraborty et al., 2015) or other matrix operations like correlation (Gori and Pucci, 2006), co-citation (Woodruff et al., 2000). To reduce computation overhead, some authors have applied interactive clustering approach which clusters related nodes in the three layered graph (Cai et al., 2018a). Then, personalized citations were recommended based on the subgraph, produced by the clusters. Some authors have addressed the scalability issues and proposed an incremental approach to avoid the re-computation of known documents in a batch process (Zhou et al., 2008). A low dimensional approximate embedding was computed only for the new documents and semi-supervised learning was employed on multiple graphs to generate recommendations.

Depending upon the type of entities used in graph, connections can be expressed as document citations (Gori and Pucci, 2006), author citations (Soulier et al., 2012), Refs. He et al. (2011), authorship (Zhou et al., 2008), related-to (refers to genes relatedness) (Lao and Cohen, 2010), mentions (associated gene or topic, field-of-study, covers paper–topic relation) (Arnold and Cohen, 2009), published-in relationship (Wang et al., 2013) and purchases. This graph helps us to predict and use other relevant information such as co-authorship (Sugiyama and Kan, 2015b), co-cited (Livne et al., 2014), co-venue (Sinha et al., 2015), co-citation strength (Huynh et al., 2012) and co-coupling strength (Zarrinkalam and Kahani, 2013a) for effective recommendations. Some authors have used the combination of co-reference and co-citation to improve the effectiveness of link-based algorithms (Huynh et al., 2012).

2.2.4. *Co-occurrence based approach*

Research papers are said to be co-occurred when two or more papers occur together in events such as browsing, viewing, downloading etc. Co-occurrence based approaches capture regularities that exist in academia by keeping track of the co-occurred academic entities as shown in Fig. 7. Generally, these approaches employ association rule mining, Ehrenberg's repeat buying theory or any other method for user purchase behavior analysis. Association rule mining discovers co-related papers by studying frequent patterns from transactional database (Geyer-Schulz and Hahsler, 2002b). Repeat buying theory analyzes the factors that affect customer buying behavior by modeling the regularities in consumption patterns and market behavior (Geyer-Schulz and Hahsler, 2002b). The two concepts are widely used to monitor the user purchase pattern through a series of transactions, this analysis can be further used to make recommendations for related information products (Geyer-Schulz et al., 2001a).

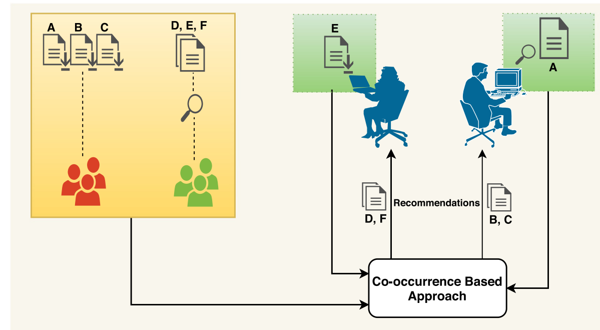


Fig. 7. Co-occurrence based model for research paper recommendation.

Some authors have computed the co-occurrence frequency distribution for items in market basket and frequency distributions less than a threshold were discarded (Böhm et al., 2003). Then, logarithmic series distribution (LSD) was used to generate significant distributions by separating non-random co-occurrences from that of random ones. Finally, recommendations for information products were given based on the qualifying distributions. By keeping the record of articles bought or visited, the conditional probability distribution of purchasing other article during the same session can be computed for recommending correlated items (Geyer-Schulz et al., 2001b). Some authors have used the graphical representation to model the co-occurrences of documents with a purchase history in Online Public Access Catalog (OPAC) (Franke et al., 2006; Franke and Geyer-Schulz, 2007). Vertices represent the set of articles, an edge between two vertices shows that the documents were co-viewed in a session with edge weight representing the number of co-occurrences. Restricted random walks were performed with clustering to generate a cluster hierarchy which helps in constructing the recommendation lists by selecting the higher order members. Some have presented the use of BibTip recommender system which analyzes user behavioral patterns during their interaction with the library catalog and statistically evaluates the usage data (Mönnich and Spiering, 2008a). Given the session histories, it counted the number of co-occurrences if two articles were viewed together in one or more session(s). These counts were represented using a co-occurrence matrix and repeat buying theory with LSD model was applied to generate recommendations.

Co-occurrence based approaches analyze the customer purchase history and market behavior. It keeps record of the papers that are accessed together by a large number of users. This counts for the papers that are co-browsed, co-downloaded, co-viewed or co-clicked in a number of browsing sessions. If co-occurrence frequency of a set of documents exceeds a certain confidence level or threshold limit, then other related documents from this set can be recommended. Elsevier's academic search engine is a real example of this approach, for instance when a paper is downloaded, it shows "Other users also viewed these articles". This concept is same as amazon's "Customers Who Bought This Item Also Bought…".

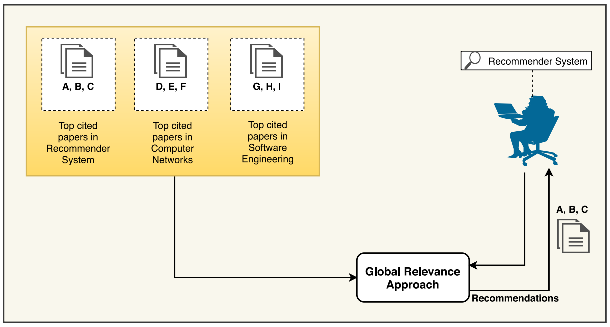


Fig. 8. Global relevance based approach for research paper recommendation.

Co-occurred articles are assumed to be tightly coupled, possessing high degree of relatedness. It does not recommend similar items, instead provides useful recommendations based on relatedness. Two papers accessed together in many transactions may not appear similar, however they are highly related or inter-dependent. For example, handset and sim card both are essential for a fully operating mobile phone, they are correlated not similar. This approach provides generalized recommendations that are relevant and serendipitous. It prepares a collection of qualifying co-occurred documents by observing user access patterns. When any action (view, download, browse) is performed by a user on one of the papers from this set, other related documents from the cluster are recommended. To some readers, a question may arise that why this approach does not include the knowledge of co-cited, co-author, co-venue etc. as part of co-occurrence information. There are two possible reasons behind it, firstly, given the fact that co-occurrence based approaches do not look into the specific user or paper details and above mentioned features can only be extracted by accessing meta-data, full paper or any other publication related details. Secondly, these features can be better derived using citation analysis which examines the paper/author network, published-in relations and so on, therefore this information is incorporated in link-based algorithms.

2.2.5. Global relevance

Global relevance based approaches consider popularity factors and recommend articles with high global importance as shown in Fig. 8. Algorithms employing global relevance measures do not incorporate user and paper's internal details, thus these approaches are unable to generate user-specific recommendations. However for a system with new users, global relevance is used as a fallback approach which can provide a good start when no other user information is available. Global relevance is measured based on the interest of major population i.e. the overall popularity of the paper. There are various measures available that define the importance or popularity of research documents. These measures are paper citation counts (Le Anh et al., 2014), author impact (Bethard and Jurafsky, 2010), affiliation citation counts (Rokach et al., 2013), venue citation frequency (Rokach et al., 2013), PageRank (Guo et al., 2017b), h-index (Alotaibi and Vassileva, 2013), journal impact factor (Bollen and Van de Sompel, 2006), Katz metric (Strohman et al., 2007), HITS (Ekstrand et al., 2010) etc. The given factors are embedded into other recommendation algorithms to fine-tune or deliver quality recommendations (Soulier et al., 2012; Livne et al., 2014).

Some authors have considered document popularity in terms of its average ratings to initiate the recommendation process in the absence of user ratings (Winoto et al., 2012). This algorithm was considered to be non-personalized and used as an alternative method until the user preferences were learned. Others have proposed discipline-based approach which recommends popular articles from user's discipline (Hristakeva et al., 2017). Paper popularity was determined by the total number of users who have the paper stored in their libraries. The recommendations were very broad and consist only a small amount of popular articles.

Based on the simple metrics, global relevance evaluates the overall popularity of papers and recommend articles with high global importance. The recommendation principle follows the assumption that popular items are liked by most of the users. It does not consider the preference of individual user while recommending research papers. Recommendations produced using this approach are very generic, thus it barely used as a standalone algorithm. To generate personalized and effective recommendations, it is used in combination with other approaches (Guo et al., 2017b; Ekstrand et al., 2010). Most of the references shown in Table 2 for global relevance employ hybrid approaches that integrate global relevance features with other recommendation algorithms.

Fig. 9 shows the distribution of articles based on the recommendation approach and applied background knowledge. It is clear from Figs. 9(a) and 9(b) that CBF predominantly uses paper attributes for recommendation, other commonly used features are bibliography, researcher's profile, publication details cite information and user-generated tags. Collaborative filtering make use of user-generated tags which includes explicit and implicit ratings. It utilizes bibliography, author profile and cite information to some extent for recommendation. Link-based approach mostly uses bibliography for link predictions in academia, it also employs author profile and publication details to capture relationship between various authors, venues, author–venue and so on. Co-occurrence based approach solely applies occurrence analytics for generating recommendations. We have not considered global relevance because it barely used as an independent algorithm.

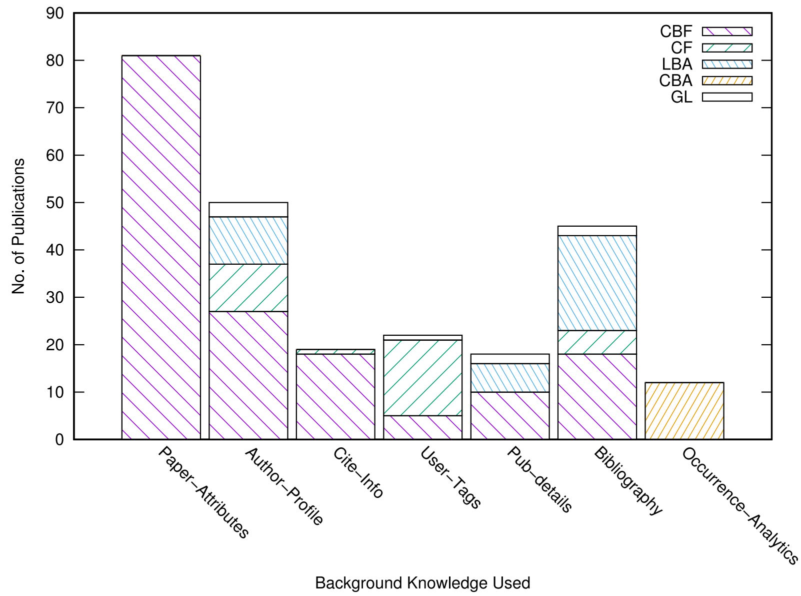
2.2.6. Hybrid approaches

Hybrid methods improve recommendations by combining principle features from two or more algorithms as shown in Fig. 10. It incorporates the advantages of different recommendation approaches to overcome the limitations of individual algorithms.

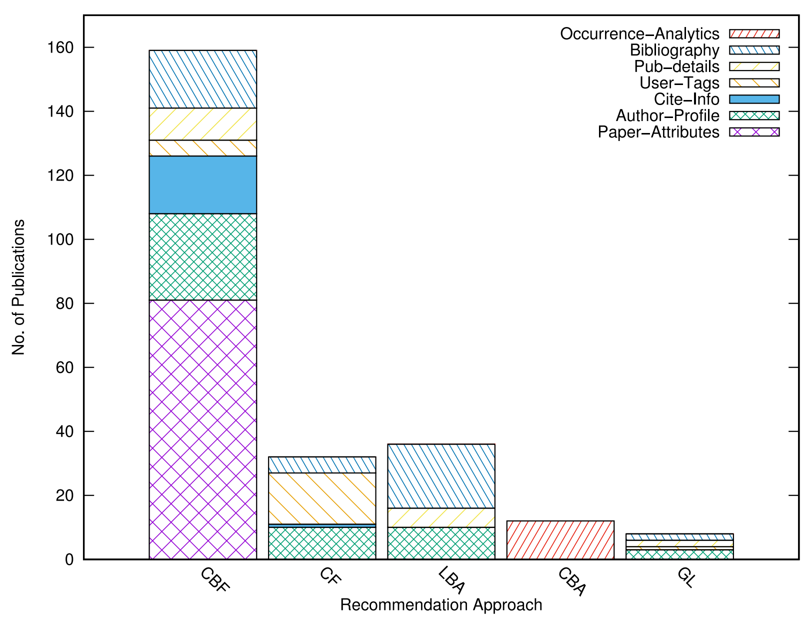
Table 3 defines available techniques for hybridization along with the citations for respective methods. Researchers may choose a typical mode of combination depending on the problems to be focused and data availability.

A hybrid paper recommendation system 'Scienstein' was developed by amalgamating the features of content-based technique, collaborative filtering, link-based approach and global relevance (Gipp et al., 2009). Scienstein combines text analysis, implicit ratings, explicit ratings, citation analysis, source analysis and author reputation to recommend relevant papers. For effective recommendations, some authors have combined content, collaborative and link features to propose a probabilistic topic model which extends LDA by incorporating link information of documents and researchers in bipartite citation network (Dai et al., 2018b). Matrix factorization was used to detect author communities with similar interest. Relevant documents were recommended that are highly correlated with the given query, correlation was modeled based on the content and author similarities. Some authors have combined content-based and link approaches by spreading activation over content as well as citation data to recommend useful documents (Woodruff et al., 2000). Further, a weighted combination of hybrid algorithms was used to generate final recommendations. Some authors have combined content-based filtering with co-occurrence based approach to find frequently occurring documents (Nair et al., 2021).

Collaborative filtering can be fused with content-based approaches to produce better results in sparse situations (Alfarhood and Cheng, 2020; Khadka et al., 2020). Some have used the content-based technique for preparing initial recommendation list which was further used to populate collaborative filtering matrices for identifying potential papers (Sesagiri Raamkumar et al., 2015). The results from CF matrices were consolidated into the final recommendation list, ranked based on the decreasing order of textual similarity. Content-based algorithms and collaborative filtering complement each other in many ways. For instance, CBF does not face the issues of cold-start and sparsity since rich content in terms of paper meta-data is



(a)



(b)

Fig. 9. Distribution of research papers based on the background knowledge and recommendation approach.

available which can be used to find similar users. Some researchers have extracted the keywords from paper abstract to represent author's profile (Chen et al., 2013). The extracted keywords were used to built person-word co-occurrence matrix, then CF was employed to generate recommendations based on similar users. On the other side, CF pulverizes the problem of over-specialization by delivering serendipitous recommendations. Some authors have used feature augmentation and mixed hybrid versions to implement various combinations of CBF and CF to overcome respective weaknesses (Torres et al., 2004). Some authors have described Papyres, a hybrid recommender system employing the two approaches in cascade mode (Naak et al., 2009). Recommendation results produced by content-based techniques were refined for quality parameters using multi-criteria collaborative filtering. Some authors have applied three hybridization algorithms, two of which used feature augmentation and one used fusion of CBF and CF (Ekstrand et al., 2010). CBF–CF and CF–CBF were used to fed output of first algorithm into the second one while fusion merged the results of two independently executed algorithms. In all the three cases, CBF and CF used link-based as well as global relevance features in cascade mode to rank the recommendation list. Recommendations based on citation analysis may suffer with the problem of topic drift or low coverage, which can be removed by combining it with content-based features (Soulier et al., 2012; Kanakia et al., 2019; Ostendorff, 2020). Text-based representations are combined with network representations to improve recommendation performance (Qiu et al., 2021).

Some authors have used the feature combination of content-based filtering and global relevance to determine if a candidate document is relevant to the given query (Rokach et al., 2013). A recommendation approach 'PaperRank' was designed which employed link-based approach, performing random walk on citation graph to develop a model

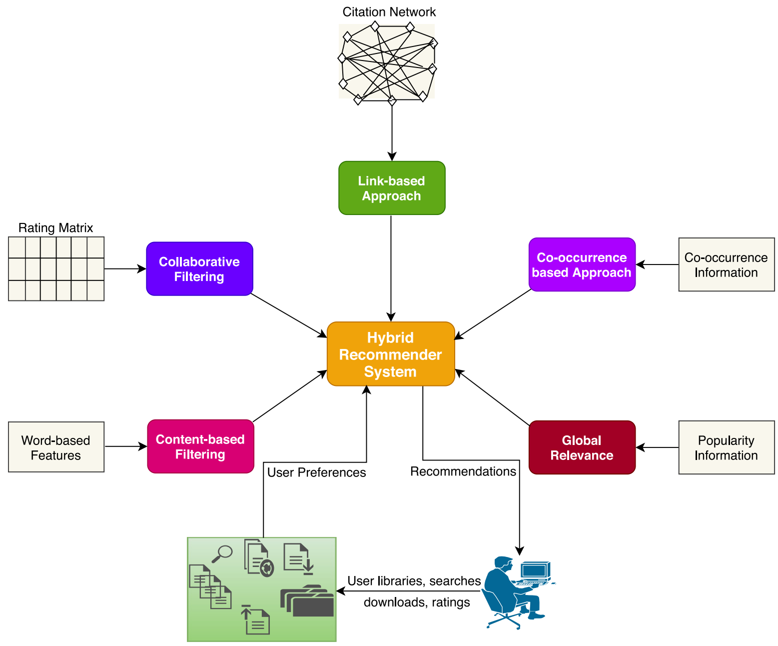


Fig. 10. An illustration of hybrid Approach for research paper recommendation.

Table 3
Hybridization techniques used for combining recommendation algorithms.

Method	Description	References
Weighted	Weights can be assigned to recommendation algorithm based on their performance. Preference score for an item is computed using the weighted results from the applied recommendation techniques	Woodruff et al. (2000), Lee et al. (2016), Wang et al. (2018a), Haruna et al. (2020), Medić and Snajder (2020) and Sakib et al. (2021)
Switching	In this mode, one algorithm works at a time but there is switching between these algorithms depending upon some conditions or criteria	Agarwal et al. (2006), Porcel et al. (2009), Uchiyama et al. (2011), Tejeda-Lorente et al. (2014b,a), Hsiao et al. (2015) and Kanakia et al. (2019)
Mixed/Fusion	Every algorithm works separately and produces independent outcome. Final recommendation list is comprised of the results from various algorithms	Torres et al. (2004), Will et al. (2009), Dong et al. (2009), Ekstrand et al. (2010), Winoto et al. (2012), Shirude and Kolhe (2014, 2016), Sharda and Dawgotra (2017) and Kang et al. (2021)
Feature combination	This integrates specific features from multiple approaches to form an effective recommendation algorithm	Huang et al. (2004), Tang and McCalla (2004a,b,c), Cazella and Alvares (2005a,b), Tang and McCalla (2005), Matsatsinis et al. (2007), Vellino (2009), Gipp et al. (2009), Bethard and Jurafsky (2010), He et al. (2010), Sugiyama and Kan (2011), Rokach et al. (2013), Zarrinkalam and Kahani (2012a), Zhou et al. (2012a), Soulier et al. (2012), Wang et al. (2013), Zarrinkalam and Kahani (2013a), Küçüktunç et al. (2013a), Meng et al. (2013), Yang and Lin (2013), Sugiyama and Kan (2013), Tian and Jing (2013), Livne et al. (2014), Ren et al. (2014), Jardine and Teufel (2014), Sugiyama and Kan (2015b), Jiang et al. (2015), Totti et al. (2016), Liu et al. (2016), Liu and Chien (2017), Mu et al. (2018), Guo et al. (2017b), Li et al. (2018a), Cai et al. (2018b), Dai et al. (2019), Cai et al. (2019), Yang et al. (2019c), Li et al. (2019a), Ostendorff (2020), Khadka et al. (2020), Ali et al. (2021b), Qiu et al. (2021), Ali et al. (2021a,c) and Bhowmick et al. (2021)
Cascade	Here, first algorithm is used to generate a candidate set of recommendations and other is used to fine-tune the resultant set	Middleton et al. (2004b), Naak et al. (2008, 2009), Yang et al. (2009), Dong et al. (2009), Du et al. (2009), Ekstrand et al. (2010), Pera and Ng (2011), Ohta et al. (2011), Jiang et al. (2012a), Zarrinkalam and Kahani (2012b), Bancu et al. (2012), Küçüktunç et al. (2013d), Doerfel et al. (2012), Sun et al. (2013), Oh et al. (2013), Le Anh et al. (2014), Zhou et al. (2014), Pera and Ng (2014), Sun et al. (2014), Chakraborty et al. (2015), Sesagiri Raamkumar et al. (2015), Sinha et al. (2015), Wang et al. (2016), Habib and Afzal (2017) and Wang et al. (2020a)
Feature augmentation	One algorithm is used to produce preference score or to classify an item. This information or output from the first algorithm is used in the processing of other approach. Here, a learned model by previous algorithm is used to generate features for input to a second algorithm	Tang and McCalla (2003a), Torres et al. (2004), Bollen and Van de Sompel (2006), Gori and Pucci (2006), Yin et al. (2007), Zhang et al. (2008), Porcel and Herrera-Viedma (2010), Pan and Li (2010), Ekstrand et al. (2010), Wang and Blei (2011), Chen et al. (2013), Sesagiri Raamkumar et al. (2015) and Nair et al. (2021)
Meta-level	First technique is used to generate the model, which is given as input to the second one to produce recommendations	Schwab et al. (2001)

represented by correlation graph (Gori and Pucci, 2006). Collaborative filtering was combined with link-based and global relevance features to yield preference matrix (Vellino, 2009). Weighted PageRank was employed on citation graph to generate preference scores which was used to compute item-based recommendations. Some authors have used the textual features to produce an initial set of candidate documents, other relational features such as venues, authors, reference list were used further to extent the initial candidate set (Zarrinkalam and Kahani, 2013a). The final recommendations were ranked based on their semantic distance with the input text.

Thus, the need for development of effective algorithms is based on the current problems and research challenges. The development can combine various recommendation approaches or various features from different algorithms to overcome the current issues or drawbacks of individual approaches. Limitations of one algorithm can be resolved by merging the features of other algorithms that complement it.

2.3. User modeling

2.3.1. Acquisition of user data

User Modeling is the process of learning user attributes by either observing their behavior or analyzing the data elicited from user. Modeling process follows some statistics to extract key features from direct and indirect user information. Knowledge is inferred by interpreting users' action during their interaction with the system. User profiling techniques are either behavior-based or knowledge-based. Behavior-based methods analyze useful patterns by employing machine learning techniques and using this behavioral aspect as a model. Knowledge-based approaches use some already defined static user models and dynamically map user to the closest standard based on the information available in questionnaires and interviews. There are certain characteristics that must be taken into account while modeling user preference, they are as follows:

- *Personal and Demographic Details:* Initially, this information may provide a rough idea about the user attributes. Further, it can be used to revise preferences obtained from user specific examination of the needs.
- *Current Goals and Tasks:* Considering user's immediate requirement and present task scenario helps in effective modeling of user interests, consequently increases the level of user satisfaction.
- *User Background Knowledge:* To know user's comfort level for already known concepts and topics which require additional explanation augments the modeling technique by incorporating user's cognitive process.
- *User interests:* It is necessary to acquire users' interest and preference towards various products and services.
- *Skills and Capabilities:* User's practical knowledge varies depending upon the type of users, novice or expert. Determining the target population and their competencies over subjects like how to use and interact with the system could help in developing better a system.
- *User's Mood:* Users' task and performance are largely affected by their mood. For instance, users' may choose different tracks to listen and books to read, movies to watch depending upon their current state of mind i.e. happy, tensed, relaxed, motivated, bored etc.
- *User traits:* Other attributes that influence user behavior are personality, living standard, learning styles, ethics, environment etc.
- *Social Network:* A fair amount of information can be predicted from user's social behavior. People are greatly influenced by their friends and share similar choices therefore, inference about users' behavior can be made by examining their social network and friends' taste.

In research paper recommendation, two prominent entities are user and research paper. For personalized recommendations, a system must know its users and their interests. Also, it must possess the knowledge of article's principle features to serve the purpose of recommendation. We have proposed a taxonomy of knowledge sources for the two entities in paper recommender system as shown in Fig. 11.

2.3.2. Types of user model

There are various sources from where the information about user choices can be elicited as shown in Fig. 11. The user models described in this section make use of this information and differ based on the sources used to acquire the user knowledge.

1. *Explicit User Model*
   These models obtain user information from explicit knowledge sources to model their requirements. It captures data that is explicitly stated by user in terms of requirement, opinion or profile (Ricci et al., 2011). A brief of the three knowledge sources is given as follows:
   - *User opinion-* Here, users express their viewpoint with respect to a particular item in the form of ratings (Gipp et al., 2009; Alotaibi and Vassileva, 2013; Guo et al., 2017b) reviews or tags. It is used to record a person's relevance feedback towards a topic (Küçüktunç et al., 2012c).
   - *User Profile-* Users explicitly input their personal and demographic details, qualification, area of interest, location and other details. This information can be gathered by filling up a form or questionnaire at the time of registration (Hassan, 2017). It creates and saves user profile for further use.
   - *Requirement-* When users specify their needs in terms of query entered in the search box (Philip et al., 2014; Yang et al., 2019a). Users may define preferences by ticking the check box or apply a set of constraints to filter the search results.
2. *Analytical Models*
   This incorporate user's cognitive processes during their interaction with the system. It gathers data through the series of actions performed by user during a session. Here, users do not state their requirements and are unaware of the information captured by the system. Implicit sources help in analyzing user behavior by keeping track of user actions (Mönnich and Spiering, 2008a), their publications (Chandrasekaran et al., 2008; Amami et al., 2016; Kaya, 2018), usage logs (Bollen and Van de Sompel, 2006), purchase history (Geyer-Schulz et al., 2002), social information (Dong et al., 2009), mind-maps (Beel and Langer, 2011; Beel et al., 2014b). Log maintains record for all the events and transactions that occur during a session which includes past searches (Middleton et al., 2004b), cookies etc. User actions comprise of the tasks such as viewing a document (Gipp et al., 2009), file downloading (Pennock et al., 2000; Guo et al., 2017b), reading (Gipp et al., 2009), commenting (Guo et al., 2017b), adding a document (Alotaibi and Vassileva, 2013), citing (Ekstrand et al., 2010), sharing an article, visiting a file link/viewing (Guo et al., 2017b; Kodakateri Pudhiyaveetil et al., 2009; Hassan, 2017), bookmarks (Gipp et al., 2009; Alotaibi and Vassileva, 2013; Li et al., 2018a), highlighted text and so on. Sometimes, specific system is designed to assist user in literature development (Ozono and Shintani, 2006; Beel et al., 2011), reference management (Naak et al., 2008), providing storage space (Gross, 2003) and facilitate sharing of resources (Gross, 2003). These systems record all the steps that takes place during interaction between the two and additionally provide recommendation services.
3. *Empirical Model*
   This type of model makes empirical observations to predict the user behavior. It does not develop an understanding of the cognitive process a user has to undergo while performing any task. This incorporates the use of stereotypes which was first introduced by E. Rich in a stereotype based system named 'Grundy' (Rich, 1979b). Stereotypes represent a set of characteristics that often found in group of people. These are the popular beliefs

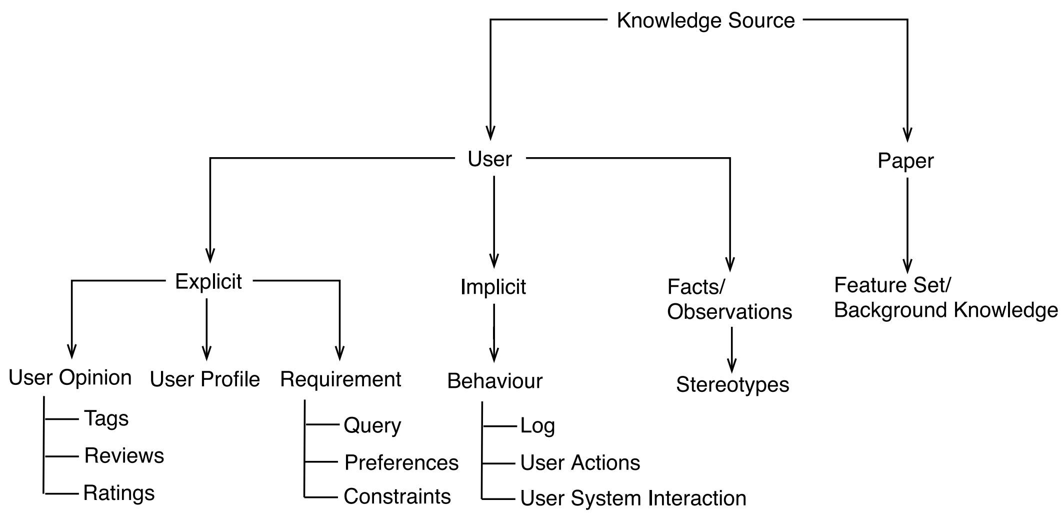


Fig. 11. Knowledge Sources in paper recommender system.

about specific community based on prior assumptions. Stereotypes can be revised over time with follow-up query procedure. When a new user enters the system, predefined stereotype is assigned based on user's behavioral pattern. This initializes a set of default preferences for once which may fine-tuned over time. It treats a group of users in a similar manner and enables a system to make numerous inferences based on the observations from a relatively small subset of population (Rich, 1989, 1979). However, these inferences are generic and can be superseded by specific observations. This is simple and quite successful method, later adopted by others for modeling user interest at initial stage. When there is lack of user information to begin with specific recommendations, Docear system recommends papers on academic writing based on the assumption that these documents will be useful for all researchers (Beel et al., 2015b). Some authors have used the stereotypic profiles based on user's knowledge to provide additional level of recommendation filtering (Morales-del-Castillo et al., 2010).

4. *Hybrid User Model*
It acquires user preferences from various sources and integrates features from above models for thorough understanding of the user requirements. Consideration of multiple dimensions allow a system to visualize user behavior from various perspectives. It models user needs more effectively and enhances the system capabilities by combining several user modeling techniques (Gipp et al., 2009). Hybrid methods may use analytical model to infer user behavior and explicit model to provide feedback or preference score for updating user preferences (Guo et al., 2017b). Hybrid model may develop user profile during the registration process which can be improved by capturing implicit actions (Hassan, 2017). Preference models can be combined in many ways depending upon the situations like available information source, data validity, system requirements and so on. Table 4 classifies papers based on the sources used to acquire user preferences. Papers that use author's publication, their research interests, social or academic profile to model user requirements are cites under implicit measure i.e. behavior.

3. Evaluation measures

A system is designed to fulfill a variety of purposes, it exhibits various features that are responsible for better user experience. It is necessary to validate the system performance from different perspectives such as accuracy, novelty, diversity, scalability, robustness and so on. For this, three evaluation measures are available namely offline methods, user study and online evaluations (Ricci et al., 2011). This section presents a comparative analysis of the reviewed evaluation methods and discusses metrics used to measure various performance aspects.

3.0.1. *Offline methods*

Offline methods are traditional means to measure accuracy and most commonly used in literature to evaluate recommendation system (Jannach et al., 2013). These methods use offline datasets for which user preference is already known. Some piece of information was removed from the available set and designed approach is made to predict the same. Algorithms are then validated based on their potential to correctly recommend the missing items. More accurate are the predictions, so is the recommendation approach. It is believed that if the missing information is predicted correctly, the algorithm will be able to anticipate the true ratings on unseen items. Offline evaluations perform well for selecting the most promising recommendation algorithm from a pool of algorithms. However, these methods must be supported by other evaluation approaches for producing significant results in real-world. Offline evaluations are very popular and widely adopted due to its simplicity and availability of offline datasets. Three kinds of offline datasets used for the purpose are true-offline datasets, user-offline dataset and expert-offline datasets (Beel et al., 2013a).

1. *True-offline datasets*
This consists of users, items and ratings or preferences given to various items. Some ratings are removed and recommendation algorithm uses rest of the ratings to predict a relevance score for the removed set. Several approaches may be compared to find the most promising one, recommendation algorithm that minimizes the difference between estimated and actual ratings is adopted as an optimal approach. More closer the predictions are, better is the recommendation algorithm. In case of research paper recommendation, it is difficult to obtain explicit user ratings for research articles. An alternative must be used to infer implicit ratings through user actions such as downloading, browsing, citing an article. Every user action contributes to some positive votes, that can be assigned depending upon the type of action. For example, when users cite other researchers in their paper, positive votes are counted for the bibliography included in their authored documents (McNee et al., 2002). Citation implies the usefulness of cited paper for the citing article, this way rating matrix can be populated by counting positive votes for all the documents referenced in citing paper.

Table 4
User modeling methods used by various papers to model user behavior.

References	Explicit			Implicit	F/Os
	User opinion	User profile	Requirement	Behavior	Stereotypes
Bollacker et al. (1998), Giles et al. (1998), Lawrence et al. (1999), Gori and Pucci (2006), Lao and Cohen (2010), Liang et al. (2011b,a), He et al. (2011), Huynh et al. (2012), Soulier et al. (2012), Caragea et al. (2013), Philip et al. (2014), Liu et al. (2014a), Hsiao et al. (2015), Jiang et al. (2015), Anand et al. (2017), Ebesu and Fang (2017), Kobayashi et al. (2018), Bhagavatula et al. (2018), Hassan et al. (2019), Zhao et al. (2019), Yang et al. (2019a), Haruna et al. (2020) and Sakib et al. (2020)			✓		
Bollacker et al. (1999) and Ekstrand et al. (2010)			✓	✓	
Geisler et al. (2001) and De Nart and Tasso (2014)	✓	✓	✓	✓	
Pennock et al. (2000), Woodruff et al. (2000), Geyer-Schulz et al. (2001a,b), McNee et al. (2002), Geyer-Schulz and Hahsler (2002a,b), Geyer-Schulz et al. (2002, 2003c,b), Hwang et al. (2003), Böhm et al. (2003), Gross (2003), Watanabe et al. (2005), Agarwal et al. (2005), Franke et al. (2006), Franke and Geyer-Schulz (2007), Chandrasekaran et al. (2008), Mönnich and Spiering (2008a), Kodakateri Pudhiyaveetil et al. (2009), Dattolo et al. (2009), Baez et al. (2011), Ferrara et al. (2011), Lao and Cohen (2011), Patton et al. (2012), Lao and Cohen (2012), Ha et al. (2014), Meilian et al. (2015), Liu et al. (2015a), Sesagiri Raamkumar et al. (2015), Alzoghbi et al. (2015), Gao (2015), Alzoghbi et al. (2016) and Li et al. (2019a)				✓	
Tang and McCalla (2003b) and Hristakeva et al. (2017)		✓		✓	
Theobald and Klas (2004), Morales-del-Castillo et al. (2009), Naak et al. (2009), Jiang et al. (2012b), Küçüktunç et al. (2012c) and Yang et al. (2013)	✓		✓		
Lopes et al. (2008), Nagori and Aghila (2011) and Murali et al. (2019)	✓				
Gipp et al. (2009)	✓		✓	✓	
Tang and McCalla (2009a,b) and Winoto et al. (2012)	✓	✓			
Morales-del-Castillo et al. (2010)	✓		✓		✓
Manouselis and Verbert (2013)	✓	✓		✓	
Xue et al. (2014)	✓			✓	
Beel et al. (2015b)				✓	✓

An algorithm may be evaluated using bibliography or text of the paper. Some of the citations are removed from the current article and the algorithm is used to recommend citations based on the supplied document text or remaining bibliography (Ekstrand et al., 2010). Recommendations are compared with the missing references of input paper (Lao and Cohen, 2010) and accuracy is measured by the number of recommendations matching the removed citations. Greater overlap between the two, leads to higher system accuracy.

2. *User-offline dataset*
There are various literature management softwares publicly available such as Mendeley,[6] RefWorks,[7] zotero,[8] mendeley,[9] docear,[10] JabRef[11] etc. which help users to share, annotate and organize literature. Personal space is provided to store and manage research documents, this user's collection of articles is termed as user-offline dataset. To evaluate a recommendation approach, some articles from the user collection are removed, further recommendations are made and compared based on the remaining documents.
3. *Expert-offline datasets*
These datasets are created by experts such as TREC,[12] CORA[13] etc. to meet users' information needs. In CORA, research papers are classified based on pre-defined categories with the help of experienced people. Each article is assigned one or more topics and this labeled dataset is used to evaluate the algorithm. User preferences are inferred and recommendations are made depending on their research interests. Recommendation list is evaluated by comparing topic relatedness between the user preferences and recommended items. Recommendation algorithm is considered accurate when documents from preferred areas or discussing relevant topics are recommended.

Generally, offline evaluations are used to measure system accuracy, however other aspects such as coverage, serendipity, diversity, novelty should also be covered. These are well suited methods for identifying favorable approaches at initial phase for a good start in the field of recommender system. Offline evaluations should be followed by a proper validation to find out the most efficient algorithms. User studies and online methods used to validate results produced by offline evaluations may not necessarily yield optimal algorithm (Turpin and Hersh, 2001). Offline evaluations are highly criticized by many researchers for not capturing the real-world scenarios and problems occurring in real time. Several authors have reported that the differences in results from offline evaluations and user-studies/online evaluations (McNee et al., 2002; Cremonesi et al., 2011). The main reason for criticism is it's focuses mainly on accuracy, other factors such as usefulness, relevance, user satisfaction are not taken into account (McNee et al., 2006). Despite all the criticism, these are most widely used methods for evaluating recommender system.

3.0.2. User study

It is used to assess the user behavior and experience towards the developed system. A number of participants are asked to take part

6 https://www.mendeley.com/homepage8/?switchedFrom=.
7 https://www.refworks.com.
8 https://www.zotero.org/.
9 https://www.mendeley.com/.
10 http://www.docear.org/.
11 http://www.jabref.org/.
12 https://trec.nist.gov/data.html.
13 https://relational.fit.cvut.cz/dataset/CORA.

in user study and perform a set of actions during their interaction with the system. This typically includes question answering about their choice, experience etc. While interacting with the system, user behavior is observed subjected to statistical methods for identifying latent characteristics. By using some quantitative measures, knowledge about hidden features which are difficult to observe, can be drawn. Based on the inferred user information, personalized recommendations are generated. Further, various explicit and implicit methods are employed to validate the correctness of algorithm. Questionnaires are frequently used in user studies to collect user opinion, expressed in terms of reviews, ratings (Mönnich and Spiering, 2008a) etc. Following the recommendations, a user is asked to answer various questions about the recommended articles (Ekstrand et al., 2010). Questionnaire should be designed in such a way that it considers user opinion on different aspects such as accuracy, novelty, diversity, usefulness, serendipity etc. Implicit methods such as click-through rate may also be used to measure relevance, usefulness, satisfaction and so on.

User studies are of two types: lab (Kodakateri Pudhiyaveetil et al., 2009) and real-world user studies (Beel and Langer, 2015). In lab studies, users are well informed of the experiments conducted. Participants own prior understanding of the system and know that they are taking part in a user study. They are aware that their interaction with the system and actions performed are recorded, which knowingly or unknowingly affect their response. The user behavior observed may not be genuine or include some biases, therefore the evaluation results are not as expected (Gorrell et al., 2011; Leroy, 2011). In real-world studies, real users participate in the evaluation process. They do not have any prior knowledge about the system and a genuine interaction takes place during the user session. They are unaware of the experiments conducted and explore the system features for their own benefit. In these studies, users provide what they actually feel about the system in terms of ratings, reviews, tags and so on. Their feedback helps in fine-tuning the system for real users and improves the efficiency of recommendation system. With true user opinion, the system generates useful recommendations by adapting to the new circumstances and user's current requirements.

3.0.3. Online evaluations

Online experiments also known as real-life testing, are used to test the performance of recommendation approach on large scale consisting of real users. System is deployed in real world to check the user response and acceptance of the system. The recommender system of Amazon and Flipkart are the examples of online evaluations. These systems are deployed in real world for commercial use and recommendations are displayed to the real users during their interaction with the system. In online evaluations, users are unaware of the ongoing experiments and therefore, do not explicitly confirm their fascination towards the recommender system. Thus, user response has to be observed by determining how often a user welcomes or appreciates the given suggestions. Click-Through Rate (CTR) is widely used to measure the user acceptance in online systems. CTR defines the proportion of clicked recommendations i.e. the number of recommendations clicked out of the total recommendations given. Different algorithms and recommendation systems are compared by measuring the corresponding CTRs. There are various factors that influence the user behavior and thus, responsible for the recommendation quality. The most significant aspect is the knowledge of user characteristics that we have discussed in Section 2.3.1. Online evaluation is the most reliable measure which is used to evaluate many real world systems, it tests all the functional and non-functional aspects of a system. It evaluates a recommender system under real-world situations covering real facets such as user satisfaction, robustness, scalability, latency, performance in terms of stress and load testing.

3.0.4. Evaluation metrics

Evaluation of a recommendation system is differentiated into two: first is evaluating the whole recommender system and other is the recommendation algorithm. When a system is evaluated as a whole, it has to be tested for parameters such as robustness, resource usage, user interface, etc. along with the factors used to evaluate recommendation algorithms.

Recommender systems are developed for a variety of purposes; e-commerce, entertainment, healthcare, e-learning etc. The e-commerce recommender systems are developed to satisfy users with the right purchase options and make profits at the same time. Other systems provide free recommendations to improve their services and user experience. Generally, these systems are intended to satisfy user specific information needs that assist in accomplishing the user goals. Prior to the actual development of the system, its targets and performance goals have to be clarified in detail. To achieve system objectives, there are multiple criteria and conditions to be fulfilled. Thereby, the specified criteria should be met and evaluated for the development of an efficient system. The performance criteria stipulate certain guidelines to evaluate a system, moreover enable us to choose the appropriate evaluation measures and metrics that best suited for the stated purpose. The factors responsible for quality deliverable must be tested from multiple perspectives. Small-scale initiatives have taken in literature from evaluation point of view.

The evaluation parameters differ while assessing a system from user's perspective to that of developer's and administrator's viewpoint. A user is concerned only about the factors that affect their use and benefit. A developer is much concerned about the technical aspects along with the resource usage and optimization. However a system administrator has to take several other factors into account with prime importance given to user satisfaction. This section will discuss the important aspects for an efficient recommendation system and metrics to evaluate them. Evaluation aspects given in subsequent section cover all the three perspectives- user, developer and administrator.

1. *Accuracy*
   It is the most widely used criteria, when it comes to the evaluation of recommendation systems. Majority of the developed algorithms are validated for correctness. Accuracy means that the system is working as it is expected to do. Before developing an application, targets are defined that specifies its purpose, inputs, expected outcomes and so on. An accurate system achieves the specified targets and produced the desired output. Correctness of a recommender system is measured if it is able to produce accurate recommendations. Moreover, accuracy measures system performance based on the average performance over a large set of users. Predictions seem good as long as they overlap with the user's interests, other prediction qualities are not captured by accuracy metrics. The evaluation strategy withholds a number of papers that are relevant to a user and assess the system's ability to recommend these papers. It can further be classified into two, decision support and statistical accuracy measures. Accuracy metrics popularly used in the field of paper recommender systems are defined as follows.

   (a) Decision Support metrics- We explain decision support accuracy metrics with the help of confusion matrix which is shown in Fig. 12.

      - Precision- It measures the percentage of actual relevant papers among those that were predicted relevant by the system. It determines the proportion of relevant articles over the retrieved set of articles. With reference to the confusion matrix, True Positive (TP) denotes the relevant documents (*REL*) that are retrieved (*RET*) and False Positive (FP) shows the retrieval of documents that are not relevant.

	Relevant	Not Relevant
Retrieved	True Positive	False Positive
Not Retrieved	False Negative	True Negative

Fig. 12. Confusion matrix for item retrieval.

Precision is the ratio of true positives to the total number of papers in the recommendation list as given in Eq. (1).

$$Precision(P) = \frac{REL \cap RET}{RET} \tag{1}$$

- Recall- It determines the percentage of correctly predicted relevant documents among those that were known to be relevant. It measures the count of relevant papers that are retrieved out of the total number of relevant documents. In other words, recall can be defined as the number of successful retrievals from the total relevant papers or ratio of true positives to the total number of relevant candidates as shown in (2).

$$Recall(R) = \frac{REL \bigcap RET}{REL} \tag{2}$$

- F-measure- There are various measures that consider both precision and recall to design a new metric. However, F-measure is most popular that combines precision and recall into a single accuracy metric. It is the harmonic mean of two measures, calculated using Eq. (3).

$$F - measure = 2\frac{P.R}{P+R} \tag{3}$$

- Accuracy- Prediction accuracy of a system can be determined in terms of relevant papers that are retrieved and irrelevant articles that are not retrieved. It is the ratio of true positives and negatives to the total number of corpus documents as given in (4).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{4}$$

(b) Statistical accuracy metrics- These metrics determine the ability of a system to correctly predict the user rating score for a research document. More close the predictions are, higher is the system accuracy.

- Root Mean Squared Error (RMSE)- It is among the most popular metrics used to evaluate the correctness of predicted ratings. RMSE measures how well a system can estimate the actual rating score. Recommender system predicts a user preference score for papers in test set. Test set (T) consists of user–item (u-i) pairs for which true ratings are already known. Then, deviation from absolute/true rating or RMSE between the predicted score (p_{ui}) and the actual rating (r_{ui}) is computed using (5).

$$RMSE = \sqrt{\frac{1}{|T|}\sum_{(u,i)\epsilon T}(p_{ui} - r_{ui})^2} \tag{5}$$

Other commonly used variation of RMSE is Mean Square Error (MSE).

- Mean Absolute Error (MAE)- It is another renown predictive metric that measures the closeness of predicted results to user's actual preferences. The system accuracy or prediction error can be determined using Eq. (6).

$$MAE = \frac{1}{|T|}\sum_{(u,i)\epsilon T}\left|p_{ui} - a_{ui}\right| \tag{6}$$

Other version widely employed is Normalized MAE (NMAE).

2. *Relevancy and Usefulness*
Usefulness can be defined as user perceived relevance or fitness of the generated recommendations. It can only be measured unless and until user provides the explicit feedback. Through surveys and questionnaire, user is asked to evaluate or rate the recommended items on their usefulness (Woodruff et al., 2000), relevance to the topic of their interest (Ekstrand et al., 2010) and acquaintance with the paper. Few attempts have been made to predict relevance with implicit user feedback (AlJadda et al., 2018). A case study shows that Lucene's relevance score is useful in predicting the degree of relevancy for given recommendations in context to a particular user (Langer and Beel, 2017). Recommendations are considered relevant or useful if they are able to satisfy the user information needs or can increase the level of user satisfaction.

- Normalized Discounted Cumulative Gain (NDCG)- It is a standard evaluation metric which can be used to measure relevancy when graded relevance scores are known. NDCG assigns more weight to the documents appearing at top positions, considering two relevance values as 0 and 1. It finds the usefulness of recommendation approach as given in Eq. (7).

$$NDCG = \frac{DCG}{IDCG} \tag{7}$$

Discounted Cumulative Gain (DCG) can be calculated using Eq. (8).

$$DCG = \sum_{p=1}^{N} rel(p) \times disc(p) \tag{8}$$

where, p shows the document position in recommendation list. Document relevance value *rel(p)* is set to 1 for relevant article or 0 otherwise. Discount function disc(p) is defined using Eq. (9)

$$disc(p) = \frac{1}{log(1+p)} \tag{9}$$

Ideal Discounted Cumulative Gain (IDCG) is calculated in similar way as DCG with a difference that p specifies the ideal position of documents i.e. organized by their order of relevance in corpus.

3. *Efficiency*
User Perspective- Evaluating only prediction accuracy of a system is not enough, considering its efficiency to help users in making appropriate choices about the recommendation quality is important. Thus, following metric can be employed to measure system efficiency from user's point of view.

- Mean User Gain (MUG)- It is a user-centric metric which can be used to evaluate a system's capability to direct its user towards interesting and qualitative papers (Carenini, 2005). This metric considers the criterion used by researchers in deciding whether to accept the recommendations or not. When the recommendation is given in terms of predictions, a user specific threshold between the value of true ratings could be used as plausible criterion. For a given user u, r_{ud} provides true rating score for document d and p_{ud} is the predicted score on d. Then, MUG for user u can be evaluated using Eq. (10).

$$MUG = \frac{1}{|D_u|} \sum_{d \epsilon D_u} UG(p_{ud}) \tag{10}$$

User Gain $UG(p_{ud})$ is given as follows:

$$UG(p_{ud}) = \begin{cases} r_{ud} - \Theta_u & \text{if } p_{ud} \geq \Theta_u \\ \Theta_u - r_{ud} & \text{otherwise} \end{cases}$$

where, Θ_u denotes user-specific threshold to measure quality of given recommendation and D_u is the set of documents rated by user u. The first condition states that researcher will decide to read the paper and appreciate it to the extent the absolute score is greater than the threshold. The second condition refers to the case when researcher does not welcome the suggestion and decides not to read the paper.

Developer Perspective- Efficiency is highly dependent on how well a system allocates resources to the given task. An efficient system maximizes productivity by optimizing the resource utilization, most prominent resources are CPU, network and memory. Algorithm should be designed in such a way that it fully utilize all the available resources. It should minimize the CPU idle time, efficiently use the allocated memory and network. To maximize CPU utilization for the available time, CPU can be used to perform background tasks and processing while waiting for I/O operations. Primary memory is a limited resource that should be properly utilized for running large applications and dealing with voluminous data. Similarly, disc and network usage should be properly monitored and utilized.

4. *Diversity*
Diversity is an important user-centric aspect which allow users to explore a wide range of possibilities. It basically applies to a set of papers in recommendation list that how different these papers are with respect to each other. Highly accurate recommendation approaches have criticized for providing a narrow set of choices which is popularly known as the problem of over-specialization. Diversity is one of the factors that captures uncertainty in user interests and considers variety of preferences within the individual profile. It provides an opportunity to discover a variety of papers which consequently, improves the user experience and appreciation for the given recommendations. There is always a trade-off between accuracy and diversity. High diversity between the items subsequently decreases the accuracy of recommendations. Several attempts have been made to avoid the explicit trade-off between the two (Puthiya Parambath et al., 2016) and maintain a satisfactory ratio of quality and diversity (Küçüktunç et al., 2015). Metrics are given below to measure implicit and explicit diversity.

(a) Implicit Diversity- It is defined based on the dissimilarity of papers in recommendation list and can be measured using Intra-List Diversity (Ziegler et al., 2005).

- Intra-List Diversity (ILD)- It measures the pairwise distance between the papers (say x and y) in recommendation list R as shown in Eq. (11).

$$ILD(R) = \frac{\sum_{x \epsilon R} \sum_{y \epsilon R, x \neq y} dist(x, y)}{|R| . (|R| - 1)} \tag{11}$$

what often differs in Eq. (11) is the distance function which may be computed using complement of similarity measure as shown in Eq. (12).

$$dist(x, y) = 1 - sim(x, y) \tag{12}$$

where sim(x,y) can refer to any similarity metric such as Pearson correlation coefficient, cosine or Jaccard similarity based on the type of arguments. Cosine similarity between two vector inputs (X and Y) is given in Eq. (13).

$$sim(X, Y) = \frac{\sum_{i=1}^{n} X_i Y_i}{\sqrt{\sum_{i=1}^{n} X_i^2} \sqrt{\sum_{i=1}^{n} Y_i^2}} \tag{13}$$

(b) Explicit Diversity- It is used to measure topical difference between the documents in recommendation list which can be determined using α-NDCG (Clarke et al., 2008).

- α-NDCG- It is an aspect and redundancy-aware version of NDCG, used to measure diversity as shown in Eq. (14).

$$\alpha - DCG = \frac{1}{\alpha - IDCG} \sum_{p=1}^{N} disc(p) \times \sum_{f \epsilon F} rel(p \mid u, f)(1 - \alpha)^{r(p,u,f)} \tag{14}$$

where $disc(p)$ is the same discount function used in calculation of NDCG which is given by (9). F is the document feature set and $rel(p \mid u, f)$ is 1 if pth document is relevant to user u and contains feature f, or 0 otherwise. α-IDCG defines the highest possible value considering ideal position of documents in α-NDCG. Parameter α is used to control penalty for redundant recommendations and function $r(p, u, f)$ is computed using Eq. (15).

$$r(p, u, f) = \sum_{k=1}^{p-1} rel(k \mid u, f) \tag{15}$$

5. *Coverage*
Algorithms providing useful recommendations may include only a small subset of large item space. A higher coverage implies that recommendations cover a maximum proportion of items/users space and assists in decision making in more number of situations (Herlocker et al., 2004). Users are exposed to a wide variety of items which may enhance their satisfaction. Two aspects are considered, catalog and prediction coverage. First refers to the percentage of total available items that are ever recommended to a user. While other estimates the fraction of items for which predictions can be made. It can be measured by soliciting recommendations for a subset of users and then estimating the percentage of items that are recommended and number of users for which effective predictions can be made (Wit, 2008).

- Catalog Coverage- It covers the number of items that effectively occur in recommendations presented to system users. If R_u is used to denote recommendations generated for user u, U is the set of all users and I is the set of available items, then catalog coverage can be given by (16).

$$Cat\_Cov = \frac{|\cup_{u \epsilon U} R_u|}{|I|} \tag{16}$$

- Prediction Coverage- It covers a set of items for which recommendation approach is able to make predictions. If I denotes the item catalog and I_p denotes the subset of items in I for which predictions can be made, then prediction coverage is measured using Eq. (17).

$$Pred\_Cov = \frac{|I_p|}{|I|} \tag{17}$$

6. *Serendipity*
Serendipitous recommender system aims to provide recommendations for the items that are difficult to predict and pleasantly surprise users with their service. It is used to measure non-obviousness as a user may feel bored or frustrated by receiving obvious recommendations. Surprise and relevance are two components of serendipity i.e. discovery of unexpected and relevant items leads to serendipity (Herlocker et al., 2004). It can be measured in terms of co-occurrence-based surprise and content-based surprise (Kaminskas and Bridge, 2014). Serendipity can be determined by using (18).

$$Serendipity(R,u) = \frac{\left|R_{rel} \cap R_{unexp}\right|}{|R|} \tag{18}$$

where R is the set of recommendations given to user u, R_{rel} is the set of relevant items in R and R_{unexp} is the set of unexpected items in R which is given by (19).

$$R_{unexp} = RS \setminus PM \tag{19}$$

where PM represents the set of items recommended by a primitive prediction model and RS is the set of recommendations delivered by a recommender system. An item is considered unexpected if it belongs to RS but does not occur in PM.

7. *Novelty*
Novelty means how different the recommendations are with respect to the items that a user has previously seen. It can be determined based on the number of users who are familiar with the recommended items. Novelty aims at recommending items that are relevant and unknown to users. Recommendation novelty can be defined with respect to the ratio of seen and unseen relevant items in the list. One basic approach to present novel recommendations is to prune already seen or rated items however, it is inefficient as user may not report all items used or observed (Ricci et al., 2011). P. Castells et al. proposed two models for item novelty, one is popularity-based item novelty and other is distance-based novelty (Castells et al., 2011).

   (a) Popularity-based novelty- It is defined based on the amount of information conveyed by the observation of an item. If $p(i)$ denotes the probability that item i is observed, then item novelty can be expressed by using Eq. (20).

   $$novelty(i) = I(i) = -log_2 p(i) \tag{20}$$

   (b) Distance-based novelty- It is measured based on the Euclidean view of recommended items. It can be defined as the minimum or average distance between the target item and other items in recommendation list R as shown in Eq. (21).

   $$novelty(x \mid R) = \min_{y \epsilon R} dist(x,y) \tag{21}$$

   where $dist$ is the distance measure, defined using Eq. (12).

8. *Trust, Transparency and Explainability*
It is very important to gain user's trust and confidence in recommendations generated by the system. A typical recommender system cannot be fully transparent however can achieve a sufficient level by including explanations with the recommendations given. It explains the reason that why a particular item is recommended to a user. Explanations help users to draw out a conclusion over the quality of recommendations. When a users discover relevant items and understands the notion behind it, eventually increases the users' trust and confidence in system's capability. Many solutions have been developed for building trust in recommender system by explaining recommendations to user (Pu and Chen, 2007). For a better system, recommendation-by-explanation is introduced and best possible explanation is generated for recommendations using explanation chain generation and selection (Rana and Bridge, 2018). Explainability plays an important role in developing user's trust and confidence, consequently enables the system to retain its users with increased level of satisfaction (Herlocker et al., 2000; Sinha and Swearingen, 2002). Retain-ability can be used as one of the factors to predict user's trust and loyalty towards the system.

9. *Privacy and Security*
To retrieve useful recommendations, a user reveals his personal information, shares his preferences over items, provides review and feedback. Privacy is a topic of major concern for users that how the data are collected, stored and shared. It should be kept safe and protected from any kind of security breach. For an efficient recommender system, prime importance is given to preserve data integrity and user privacy. Proper security mechanism should be deployed to restrict third party or unauthorized access and prevent misuse of user data. A simple way to protect privacy leak is the anonymization of collected data (Mönnich and Spiering, 2008a). A system must also address other issues such as denial-of-service, shillings attacks etc. (Yilmazel and Kaleli, 2016) and should be tested thoroughly against all types of vulnerability. Complete privacy may not be guaranteed by a system, however one must settle down on minimal security risk.

10. *Throughput and Latency*
Sometimes, reactivity of the system is more important than accuracy and latency to deliver predictions should be minimized. In real-time applications, a system with quick response is preferred as the awaited action should occur immediately. Latency can be improved at two levels, the model level and the serving level. At model level, we reduce the time taken by the model to generate recommendations when the request is received. At serving level, we minimize the time required by the system to serve recommendations once the input is provided. An empirical analysis was presented for selection of appropriate design choices to reduce response time (Herlocker et al., 2002). Throughput measures the number of recommendations generated per unit time. An algorithm is considered ideal if it achieves maximum throughput with minimum latency. Few have discussed the impact of various parameters on throughput and response time (Sarwar et al., 2001).

11. *Robustness*
It refers to the stability or tolerance of a system during unfavorable circumstances and its sensitivity to certain kind of attacks (Ricci et al., 2011). When a recommender system is to be deployed in real world for commercial use, it must sustain various kinds of attack and hardware/software failure. RS must be robust enough to recover from system failure or any other external attack without deviating from its normal functioning. For instance, a collaborative recommender system is susceptible to different types of shilling attacks (Yilmazel and Kaleli, 2016) which can be detected by monitoring user ratings and prevented by removing attacker's profile (Chirita et al., 2005).

12. *User Satisfaction*
The primary objective of a recommendation system is to satisfy its users by generating high quality recommendations. Explicit or implicit measures can be used to evaluate user satisfaction. Former methods explicitly asks users in terms of ratings, reviews, feedback to express their satisfaction. Later method observes it in some way and need assumptions to transform the observations into an evaluation for user satisfaction. For example, increase in number of active users, retain-ability etc. imply greater user satisfaction. Relevancy and useful recommendations leads to high user satisfaction. Not only usefulness but there are several other factors too that contribute towards user satisfaction. These include serendipity (Ge et al., 2010), coverage (Ge et al., 2010), quick response time (Herlocker et al., 2004), fascinating design

and layout (Ricci et al., 2011), personalized recommendations, explanations may also be helpful (Herlocker et al., 2000; Sinha and Swearingen, 2002) and so on.

13. *Scalability*
The foremost responsibility while designing a recommender system is to address the problem of data explosion and locate desired information from the massive amount of publications. A real-time system is overburdened with many users and with high amount of publications during the course of time. Number of users is very less as compared to the voluminous document set which is growing at an exponential rate. Many algorithms fail to perform as expected under the stress and systems may slow down or crash. Therefore, to meet user expectations and proceed with normal functioning in such adverse conditions, a system must scale up to the real-time growing needs. It must be equipped with additional resources such as computation power or memory to cope up with scalability issues. Time is very crucial in real time applications, quick response is essential for user satisfaction without compromising on other performance aspects. Scalability can be measured by examining the algorithm behavior with growing data and analyzing its effect on various parameters such as resource utilization, processing time and speed (George and Merugu, 2005). Thus, monitoring resource consumption over huge data helps us to understand and predict future scalability patterns. One standard method is to determine computational complexity i.e space and time requirements for an algorithm (Boutilier and Zemel, 2003; Karypis, 2001).
14. *Development Time and Cost-effective Development*
Time is a critical factor, associated with every phase of development as all the tasks and processes are time-bound. Training a model is long running and time consuming process, it is even worse when a model has to be trained with enormous research documents. It consumes most of the development time and thus, efficient methods should be employed for fast processing. One of the possibilities is to equip the system with parallel processing components to reduce training and development time. Cost-effective development is making optimum use of the available resources which minimizes the development cost and maximizes the overall profit.

Table 5 shows the evaluation metrics used by various researchers to justify their experimental results. We have examined the evaluation methods used in the domain of paper recommendation research, it is observed that more than 90% of researchers have used offline measures to validate their work. Most of them have evaluated the system performance in terms of accuracy while some authors have considered other aspects as well. Only few researchers evaluated their approach by conducting user studies which involve real users. However, the number of participants involved in experiments is quite less and insufficient to analyze the effectiveness of recommendation algorithm.

4. Research challenges and limitations

This section refers to the drawbacks in current trends of recommendation research. We have read several articles on paper recommender system and analyzed various loop holes in today's research conduct. Some of the short comings are from researcher's side i.e. the way methods and algorithms are engineered, on the other side there is a lack of resources available for research which includes dataset, evaluation framework etc. This section describes the current limitations and provides a platform for other researchers to take constructive measures in the directions presented as follows.

- *Standardization of evaluation framework*
Assessing the quality of various recommendation algorithms is difficult in the absence of standard evaluation framework. Researchers propose algorithms focusing on different aspects, using different datasets and evaluated using distinct methodologies. There are many possible combinations available at each phase and can be chosen alternatively for developing a recommender system. The choice of user modeling technique, dataset, evaluation method and metrics leads to the variation in results and system performance. This gives rise to imprecise comparison of the recommendation techniques, therefore there is a need for common evaluation platform. This framework will be used to compare different recommendation algorithms from various domains (movies, news, research documents etc.) using standard datasets conditioned on same evaluation settings. Few evaluation tools are publicly available for other domains such as WrapRec,[14] ranksys,[15] recommenderlab.[16]
- *Lack of standard datasets*
Citation databases are easily available to assist link prediction and recommendation tasks. These repositories exhibit associations between different academic entities such as papers, authors, venues etc. Some databases also capture paper meta-data, author's demographic details and relationships with other authors. Unfortunately, only few standard datasets are available for content-based and collaborative filtering in paper recommendation. Researchers have limited access to the full text of research articles which binds them to use meta-data for employing content-based techniques. The content in these corpora is organized in a different format and is not readily available for use which involves the overhead of text extraction and processing.
- *Dependency on text-processing techniques*
In paper recommendation system, majority of researchers have employed content-based filtering. The quality of CBF system is largely depend on item's features accessed by the system. We have already discussed paper features used in research paper recommendations which are basically word-based features. In digital libraries, research documents are available in PDF which must be parsed and transformed to plain text before use. Efficient methods should be employed to identify document fields and to extract features (Marinai, 2009). These non-trivial tasks of language processing adversely affect the quality of recommendations. Even the efficient techniques for text processing may not yield optimum results. Unfortunately, the errors of text processing as well as their effects are cascaded to further stages of recommendation. Processing error therefore lowers the accuracy and efficiency of recommender algorithms (Beel et al., 2013d).
- *Difficult to determine baseline algorithms*
With huge number of published articles, many apply minor customizations to base recommendation approaches and it becomes difficult to find the most promising algorithm. Root cause is the inadequate algorithmic and implementation details in research papers, hinders the reproducibility of evaluation results (Beel et al., 2016a). Most of the papers do not provide implementation details of their algorithms as one algorithm may be implemented in multiple ways. Implementation details include low-level system, model and parameter related information which enable users to generate an algorithm replica for comparison. Many researchers have examined their approaches based on the synthetic dataset which is prepared manually. It consists of few hundreds articles and is not publicly available which further obstructs reproducibility in paper recommendation research.
- *Less novelty and major focus on recommendation tool/framework*
Current research mainly focuses on system development and overall functionality offered by the recommender system. Very few discuss the new research or development of novice algorithms for recommendation. We have studied various papers and found that

[14] http://babakx.github.io/WrapRec/.
[15] http://ranksys.org/.
[16] http://s2.smu.edu/IDA/recommenderlab/.

Table 5
Evaluation measures used in literature to evaluate research document recommender system.

References	Performance criteria							
	Precision	Recall	NDCG	MRR	MAP	F-measure	MAE	User evaluation
Wang et al. (2020b), Dai et al. (2020), Tao et al. (2020), Färber and Sampath (2020), Ebesu and Fang (2017) and Gao (2015)		✓	✓	✓	✓			
Ali et al. (2021c,a,b), Yang et al. (2019c) and Yang et al. (2019b)		✓	✓		✓			
Kieu et al. (2021b,a) and Bhagavatula et al. (2018)				✓		✓		
Alfarhood and Cheng (2020) and Kong et al. (2018)	✓	✓	✓			✓		
Li et al. (2018a)	✓	✓			✓	✓		
Alkhatib and Rensing (2020), Ali et al. (2020c), Jeong et al. (2020), Cai et al. (2019), Yang et al. (2018), Cai et al. (2018b) and Cai et al. (2018a)		✓		✓	✓			
Kaya (2018)	✓	✓						✓
Kobayashi et al. (2018), Sharma et al. (2017b), Livne et al. (2014), Jiang et al. (2012b) and Soulier et al. (2012)			✓					
Sakib et al. (2021, 2020), Haruna et al. (2020, 2018) and Haruna et al. (2017)	✓	✓		✓	✓	✓		
Yang et al. (2019a), Wang et al. (2018a), Liu and Chien (2017), Guo et al. (2017b), Lee et al. (2016), Hsiao et al. (2015), Ha et al. (2015), Yang and Lin (2013), Baez et al. (2011), Choochaiwattana (2010) and Lopes et al. (2008)	✓	✓						
Anand et al. (2017)		✓			✓			✓
Ostendorff (2020), Hassan (2017), Al-Natsheh et al. (2017), Lee et al. (2015), Sitthisarn and Rattanabundan (2013), Winoto et al. (2012) and Mönnich and Spiering (2008a)								✓
Chaitanya and Singh (2017), Liu et al. (2016), Jiang et al. (2015), Liu et al. (2014a) and Jiang et al. (2012a)			✓		✓			
Alzoghbi et al. (2016)		✓	✓	✓				
Tejeda-Lorente et al. (2014b)	✓	✓				✓	✓	
Dai et al. (2019, 2018b) and Ren et al. (2014)	✓	✓		✓				
Du et al. (2020) and Sun et al. (2014)	✓			✓	✓			
Li et al. (2019a) and Sun et al. (2013)	✓				✓			
Yan et al. (2013)		✓			✓			
Amami et al. (2016) and Tian and Jing (2013)		✓						
Hassan et al. (2019) and Oh et al. (2013)	✓	✓			✓			
Nogueira et al. (2020b) and Caragea et al. (2013)		✓		✓		✓		
Chen et al. (2013) and Middleton et al. (2004a)	✓							✓
Chen et al. (2019a), Hanyurwimfura et al. (2015), Zarrinkalam and Kahani (2013a), Guo et al. (2017a), Nascimento et al. (2011), Mu et al. (2018), He et al. (2011, 2010), Zarrinkalam and Kahani (2012b) and Zarrinkalam and Kahani (2012a)		✓	✓					
Ma et al. (2021)	✓	✓	✓	✓	✓			
Choi et al. (2020) and Huang et al. (2012)	✓	✓		✓		✓		
Guo et al. (2020), Pera and Ng (2014), Wu et al. (2012) and Pera and Ng (2011)	✓		✓	✓				
Son and Kim (2018), Alzoghbi et al. (2015), Sugiyama and Kan (2013) and Sugiyama and Kan (2010)			✓	✓				
Wang et al. (2017b) and Guan et al. (2010)	✓		✓		✓			
Liang et al. (2011a)	✓	✓	✓	✓				
Jin et al. (2013)		✓				✓		
Lao and Cohen (2012) and Tang and Zhang (2009)				✓	✓			
Naak et al. (2009) and Murali et al. (2019)							✓	
Parra and Brusilovsky (2009)	✓		✓					
Zhou et al. (2008)						✓		
Zhang et al. (2021b), Chen (2021), Liu et al. (2020), Ma and Wang (2019), Hristakeva et al. (2017), Xia et al. (2016), Shirude and Kolhe (2016), Liu et al. (2015b), Asabere et al. (2015), Liu et al. (2015a), Shirude and Kolhe (2014), Ha et al. (2014), Zhang et al. (2013), Rokach et al. (2013), Porcel and Herrera-Viedma (2010), Morales-del-Castillo et al. (2010, 2009), Porcel et al. (2009), Weng and Chang (2008) and Avancini et al. (2007)	✓	✓				✓		
He et al. (2012), Lu et al. (2011) and Pohl et al. (2007)					✓			
Kanakia et al. (2019)	✓		✓					✓
Chen et al. (2019b)	✓	✓	✓					
Kang et al. (2021), Dai et al. (2021), Zhu et al. (2021) and Wang et al. (2020a)	✓	✓		✓	✓			
Khadka et al. (2020)	✓	✓	✓		✓	✓		

the basic algorithms with slight modifications are employed in most of the papers or systems. Functionality and system services are of prime importance as opposed to the system technicality, techniques and methodologies used for recommendation. Many papers explain the variety of functionality and features exhibited by the system, they mention limited technical details about the recommendation module (Livne et al., 2014; Beel et al., 2018c). In this scenario, it becomes very difficult to understand and trace the approach followed by the authors to generate recommendations.

- *A few systems are available for practical use*
  Researchers implement new algorithms, validate them, publish articles and the process come to an end. Sometimes, not even the enhancements are made in the developed system. Unfortunately, the research product is not available for public use as most of the research work do not benefit the society. According to a study, only 24 paper recommender systems are currently available for practical use (Beel et al., 2016b). Each of these system is categorized into two classes based on the maturity, prototype or real system and associated with one of the three statuses- Active, Idle or Offline. The study reveals that many systems are in their prototyping stage and some of the real systems became inactive with time. This shows lack of pragmatic aspects and limited research work that actually transforms theory into practice considering real circumstances.
- *Neglected user modeling*
  User modeling is an important and core aspect of recommender systems, it differentiates RSs with search engines. In most of the papers, process of preference acquisition is simply neglected and others barely discuss new methods for modeling user behavior. In many systems, user has to explicitly provide their information needs in terms of search query by providing abstract (Bethard and Jurafsky, 2010; Zarrinkalam and Kahani, 2013a), key terms (Heß, 2008; Liu and Chien, 2017), single paper (Strohman et al., 2007; Lao and Cohen, 2010) or set of articles (Ekstrand et al., 2010; Küçüktunç et al., 2012c). Explicit methods do not serve the real purpose of recommender systems as it ignores the process of user modeling.
- *Problem of big data*
  Digital libraries are exploded with voluminous publications which necessitates the need for an efficient system. While developing a service that can ease in locating the useful information, it has to deal with the challenges of enormous and continuously increasing research data. Powerful systems with advance computational infrastructure should be devised to efficiently handle the vast amount of data. The systems must be versatile and scalable to overwhelming research documents. The systems which are inflexible to the growing needs, may not be able to solve the problem of information overload and cannot be deployed in real world for practical use. In literature, adaptivity and scalability issues with respect to big data are hardly discussed. Mendeley Suggest presented the implementation of recommender system at scale with big data technologies and considerations for serving timely recommendations (Hristakeva et al., 2017).
- *Accuracy as main performance aspect*
  Accuracy is the most common measure to assess the performance of a system. Beyond accuracy, there are numerous other criteria that are as important or sometimes, even more important than accuracy. In literature, accuracy is considered the most prominent aspect and is dominantly used to determine the system efficiency. Other measures such as diversity, novelty, serendipity, user satisfaction etc. are less perceived in the domain of paper recommendation. Also, no single ideal metrics are available to evaluate features other than accuracy. Initiatives have been taken for designing new methods for measuring surprise, novelty, diversity, user satisfaction and so on. Thereby in the absence of benchmark, the strengths of several algorithmic aspects are difficult to compare. No one focused on the degree of diversification which should be properly analyzed and may varies for different users. System must be flexible enough to present the diversified list of recommendations with appropriate degree while maintaining a balance between accuracy and diversity (Kunaver and Požrl, 2017). Very few have derived new methods for serendipity, novelty and some have measured diversity in terms of the number of journals from which articles were recommended (Vellino, 2013). In addition to accuracy, other performance aspects are also important and must be used to evaluate research in paper recommendation system.
- *Undervalued technical quality*
  The purpose of recommender systems is not just to provide accurate recommendations, also to consider its quality standards. In literature, many authors have determined article quality in terms of accuracy, relevancy or usefulness (Ekstrand et al., 2010), very few have discussed about the technicality of recommendations (Bollen and Van de Sompel, 2006). There are various factors that can be taken into account for technical quality considerations such as journal impact factor, conference ranking, venue citation frequency, author impact or expert review. Authors have used some of these features for suggesting and ranking relevant papers (Meilian et al., 2015), however none has focused on technical quality assessment of recommendations. In case of research paper recommender system, suggestions for technically sound papers are preferably valuable and appreciated by many users. Thus, technical quality should be considered as one of the important aspects and new measures should be designed for quality evaluation.
- *Overlooked user's background knowledge and capabilities*
  Recommender system seems to work in similar fashion for novice and experienced users without considering their learning skills and cognitive patterns which differ for each user. Same approach is used to recommend articles without considering users' knowledge level or command over the research area. For instance, advance papers recommended to naive users, will be difficult to comprehend until and unless they gain a thorough understanding of the field. Similarly, presenting trivial research to experts may not help them to explore recent developments and not considered as valuable recommendations. In both the cases, users will be annoyed and system has to strive for retaining them. Some authors have considered that multiple user–system interactions play a vital role in gaining a deeper insight of their knowledge level and skills to encourage recommendations (Tang and McCalla, 2003b). Few efforts have been made by considering user expertize such as novice or expert to generate recommendations (Sugiyama and Kan, 2010; Winoto et al., 2012). Some have embedded scholar's background knowledge in terms of ontological concepts into researcher profiles (Amini et al., 2011) while others have considered user expertize based on their background studies and education level i.e. masters, doctorate or full researcher (Amini et al., 2014). Some authors have tried to identify the knowledge gap between researcher's knowledge and target knowledge, then make recommendations based on the user cognition patterns to acquire the target knowledge (Zhao et al., 2016).
  As pointed out above, majority of researchers have neglected user pedagogical features, cognition patterns, background knowledge, skills and capabilities in the process of recommendation. These factors are very much important to deliver fruitful recommendations, consequently improve user experience and satisfaction. While making recommendations, it must be ensured that the papers are recommended based on the user's understanding and cognitive abilities.

5. Conclusion

The idea of recommender system was explored in the early 90s to perform the basic tasks of mail filtering, while the term 'recommender system' was coined later. A tremendous increase in the number of publications and a need to find relevant papers with ease, directed the research towards the development of paper recommender system. Few research aspects are well explored, however some are left untouched or less emphasized. This study makes an effort to bring those facets into one's consciousness for developing better systems.

This survey has aspired to cover all the important aspects of research paper recommendation and scrutinizes available literature for analyzing the current trends of recommendation research. Our primary goal is to provide a better understanding of this field with the help of fundamental knowledge features which serve as a basis for developing a clear insight into the existing approaches. We have discussed the three significant aspects of the recommender system, namely 'background knowledge and operating theory', 'recommendation approaches' and 'user modeling'. Background knowledge helps us differentiate between various recommendation approaches and is concerned with the set of available features that can be used for recommendation. Operating theory deals with the mechanism of using those background features for recommendation purposes. Further, the recommendation approaches with their advantages and disadvantages are discussed. The most widely used approach is content-based filtering which uses word features to generate personalized recommendations. On the other side, collaborative filtering utilizes users' social network to mine their preferences. Link-based approaches use relations that exist in academic networks and analyze the association between various entities to recommend an article. Co-occurrence based techniques capture the events that occur together to recommend related papers. Global relevance works on 'one-for-all' strategy which suggests the documents of global importance. Hybrid techniques combine two or more approaches using different methods of hybridization for developing an effective algorithm. User modeling is one of the main aspects of recommender system, many user traits and knowledge acquisition methods are discussed that must be considered while designing new user modeling techniques. More attention is given to the evaluation methods, applicability and limitations of the current strategies. Various performance criteria are listed to encourage multi-dimensional research involving factors other than accuracy. Moreover, we have outlined various drawbacks in existing research methodologies and the challenges one faces while exploring the extent of the paper recommender system.

CRediT authorship contribution statement

Ritu Sharma: Conceptualization, Data curation, Investigation, Writing – original draft. **Dinesh Gopalani:** Writing – review & editing, Supervision. **Yogesh Meena:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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