Expert Systems With Applications 97 (2018) 205–227

Contents lists available at ScienceDirect

Expert Systems With Applications

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

Review

The use of machine learning algorithms in recommender systems: A systematic review

Ivens Portugal*, Paulo Alencar, Donald Cowan

David R. Cheriton School of Computer Science, University of Waterloo, 200 University Avenue West Waterloo, N2L 3G1, Canada

ARTICLE INFO

Article history:
Received 27 May 2016
Revised 7 December 2017
Accepted 8 December 2017
Available online 9 December 2017

Keywords:
Systematic review of the literature
Recommender systems
Machine learning
Machine learning algorithms
Application domains
Performance metrics

ABSTRACT

Recommender systems use algorithms to provide users with product or service recommendations. Recently, these systems have been using machine learning algorithms from the field of artificial intelligence. However, choosing a suitable machine learning algorithm for a recommender system is difficult because of the number of algorithms described in the literature. Researchers and practitioners developing recommender systems are left with little information about the current approaches in algorithm usage. Moreover, the development of recommender systems using machine learning algorithms often faces problems and raises questions that must be resolved. This paper presents a systematic review of the literature that analyzes the use of machine learning algorithms in recommender systems and identifies new research opportunities. The goals of this study are to (i) identify trends in the use or research of machine learning algorithms in recommender systems; (ii) identify open questions in the use or research of machine learning algorithms; and (iii) assist new researchers to position new research activity in this domain appropriately. The results of this study identify existing classes of recommender systems, characterize adopted machine learning approaches, discuss the use of big data technologies, identify types of machine learning algorithms and their application domains, and analyzes both main and alternative performance metrics.

1. Introduction

Recommender systems (RSs) are used to help users find new items or services, such as books, music, transportation or even people, based on information about the user, or the recommended item (Adomavicius & Tuzhilin, 2005). These systems also play an important role in decision-making, helping users to maximize profits (Chen, Hsu, Chen, & Hsu, 2008) or minimize risks (Bouneffouf, Bouzeghoub, & Gancarski, 2013). Today, RSs are used in many information-based companies such as Google (Liu, Dolan, & Pedersen, 2010), Twitter (Ahmed et al., 2013), LinkedIn (Rodriguez, Posse, & Zhang, 2012), and Netflix (Steck, 2013). The field of RS has its origins in the mid-1990s with the introduction of Tapestry (Goldberg, Nichols, Oki, & Terry, 1992), the first RS.

As the RS field evolved, researchers studied the use of algorithms from machine learning (ML), an area of artificial intelligence (AI). ML has been studied since the late 1950s (Martens, 1959), with the emergence of the field of AI. Today, there is a plethora of ML algorithms (k-nearest neighbor (Patrick & Fischer III, 1970), clustering (Jain, Murty, & Flynn, 1999), Bayes network (Friedman, Geiger, & Goldszmidt, 1997), to name a few types), which are used in applications that range from vacuum cleaner robots (Burhans & Kandefer, 2004) and assistance for disabled people (Karimanzira, Otto, & Wernstedt, 2006) to pattern recognition in images (Torralba, Fergus, & Weiss, 2008), or self-driving vehicles (Thrun, 2007). The potential application of ML algorithms is vast and the field looks very promising.

ML algorithms are being used in RSs to provide users with better recommendations. However, the ML field does not have a clear classification scheme for its algorithms, mainly because of the number of approaches and the variations proposed in the literature (Lv & Tang, 2011). As a consequence, it becomes difficult and confusing to choose an ML algorithm that fits one's need when developing an RS. In addition, researchers may find it challenging to track the use and the trends of ML algorithms in RSs.

One way to assist researchers and practitioners (e.g. software engineers and developers (Isazadeh, 2004; Pressman, 2015)) in choosing which ML algorithm to use in an RS is the study of the RS and ML fields. Research about RSs containing ML algorithms implemented in the literature can help show trends and provide a direction for future studies.

* Corresponding author.
E-mail addresses: iportugal@uwaterloo.ca (I. Portugal), palencar@cs.uwaterloo.ca (P. Alencar), dcowan@csg.uwaterloo.ca (D. Cowan).

https://doi.org/10.1016/j.eswa.2017.12.020
0957-4174/

This paper provides a systematic review to investigate how ML algorithms used in RSs are studied and used; and what are the trends in ML algorithm research and development. It is expected that, with this systematic review, researchers and practitioners can obtain more information about the RS field, and make better implementation or research decisions. The goals of this study are to (i) identify trends in the use or research of machine learning algorithms in recommender systems; (ii) identify open questions in the use or research of machine learning algorithms; and (iii) assist new researchers to position new research activity in this domain appropriately. The results of this study identify existing classes of recommender systems, characterize adopted machine learning approaches, discuss the use of big data technologies, identify types of machine learning algorithms and their application domains, and analyze main and alternative performance metrics.

This paper is organized as follows: Section 2 describes the theoretical background needed; Section 3 explains the systematic review protocol, and Section 4 explains the results of this study. Section 5 presents conclusions and future work.

2. Theoretical background

This section gives an overview of the two main research fields related to this article, namely recommender systems and machine learning.

2.1. Recommender systems

Recommender systems (RSs) use artificial intelligence (AI) methods to provide users with item recommendations. For example, an online bookshop may use a machine learning (ML) algorithm to classify books by genre and then recommend other books to a user buying a specific book. RSs were introduced in 1992 when Tapestry, the first RS, appeared. Its authors used the term collaborative filtering to refer to the recommendation activity. This term is still used to classify RSs. RSs are divided into three main categories to drive the recommendations: collaborative, content-based, and hybrid filtering (Adomavicius & Tuzhilin, 2005).

First, RSs using a collaborative approach consider the user data when processing information for recommendation. For instance, by accessing user profiles in an online music store, the RS has access to all the user data, such as the age, country, city, and songs purchased. With this information, the system can identify users that share the same music preference, and then suggest songs bought by similar users.

Second, RSs with a content-based filtering approach base their recommendations on the item data they can access. As an example, consider a user who is looking for a new computer using an online store. When the user browses a particular computer (item), the RS gathers information about that computer and searchers in a database for computers that have similar attributes, such as price, CPU speed, and memory capacity. The result of this search is then returned to the user as recommendations.

The third category describes RSs that combine the two previous categories into a hybrid filtering approach, recommending items based on the user and the item data. For example, on a social network, an RS may recommend profiles that are similar to the user (collaborative filtering), by comparing their interests. In a second step, the system may consider the recommended profiles as items and thus access their data to search for new similar profiles (content-based filtering). In the end, both sets of profiles are returned as recommendations.

When using a collaborative or a hybrid filtering approach, RSs must gather information about the user in order to develop recommendations. This activity can be done explicitly or implicitly. Explicit user data gathering (Sutton & Barto, 1998) happens when users are aware they are providing their information. For instance, when registering for a new online service, users usually fill in a form that asks their name, age, and email. Other forms of explicit user data gathering (Gemmis et al., 2011; Longo, Barrett, & Dondio, 2009) are when users express their preferences by rating items using a numerical value or a preference such as a Facebook “like.” Implicit user data gathering accesses information about the user indirectly. For example, when visiting an online store, the server at the online store exchanges messages with the user’s computer, and based on that, the store’s RS may know the browser the user is using, as well as the user’s country. More advanced applications monitor user clicks and keystroke logs.

Besides the common recommendation process, in which users are presented with items that might be of interest, recommendations can be provided in other ways. Trust-based recommendations (O’Donovan & Smyth, 2005) take into consideration the trust relationship that users have between them. A trust relationship is a link in a social network to a friend or a related connection. Recommendations based on trust are worth more than those that do not have trust links. Context-aware recommendations (Adomavicius, Mobasher, Ricci, & Tuzhilin, 2011) are based on the context of the user. A context is a set of information about the current state of the user, such as the time at the user location (morning, afternoon, evening), or their activity (idle, running, sleeping). The amount of context information to be processed is high, making context-aware recommendations a challenging research field. Risk-aware recommendations (Bouneffouf et al., 2013) are a subset of context-aware recommendations and take into consideration a context in which critical information is available, such as user vital signs. It is risk-aware because a wrong decision may threaten a user’s life or cause damage. Some examples are recommending pills to be taken or stocks the user should buy or, sell.

2.2. Machine learning

Machine Learning (ML) uses computers to simulate human learning and allows computers to identify and acquire knowledge from the real world, and improve performance of some tasks based on this new knowledge. More formally, ML is defined as follows: “A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E” (Michalski, Carbonell, & Mitchell, 1985). Although the first concepts of ML originated in the 1950s, ML was studied as a separate field in the 1990s (Michalski, Carbonell, & Mitchell, 2013). Today, ML algorithms are used in several areas besides computer science, including business (Apte, 2010), advertising (Cui, Bai, Gao, & Liu, 2015) and medicine (Kononenko, 2001).

Learning is the process of knowledge acquisition. Humans naturally learn from experience because of their ability to reason. In contrast, computers do not learn by reasoning, but learn with algorithms. Today, there are a large number of ML algorithms proposed in the literature. They can be classified based on the approach used for the learning process. There are four main classifications: supervised, unsupervised, semi-supervised, and reinforcement learning.

Supervised learning (Kotsiantis, 2007; Zhang & Tsai, 2006) happens when algorithms are provided with training data and correct answers. The task of the ML algorithm is to learn based on the training data, and to apply the knowledge that was gained using real data. As an example consider an ML learning algorithm being used for book classification in a bookstore. A training set (training data + answers) can be a table relating information about each book to a correct classification. Here, information about each book may be title, author, or even every word a book contains. The ML algorithm learns with the training set. When a new book arrives at the bookstore, the algorithm can classify it based on the knowledge about book classification it has acquired.

In unsupervised learning (Celebi & Aydin, 2016), ML algorithms do not have a training set. They are presented with some data about the real world and have to learn from that data on their own. Unsupervised learning algorithms are mostly focused on finding hidden patterns in data. For example, suppose that an ML algorithm has access to user profile information in a social network. By using an unsupervised learning approach, the algorithm can separate users into personality categories, such as outgoing and reserved, allowing the social network company to target advertising more directly at specific groups of users.

ML algorithms can also be classified as semi-supervised. Semi-supervised learning (Chapelle, Schölkopf, & Zien, 2006; Xu, Mo, & King, 2012) occurs when algorithms work with a training set with missing information, and still need to learn from it. An example is when an ML algorithm is provided with movie ratings. Not every user rated every movie and so, there is some missing information. Semi-supervised learning algorithms are able to learn and draw conclusions even with incomplete data.

Lastly, ML algorithms might have a reinforcement learning approach. Reinforcement learning (Sutton & Barto, 1998) occurs when algorithms learn based on external feedback given either by a thinking entity, or the environment. This approach is analogous to teaching dogs to sit or jump. When the dog performs the action correctly, the dog receives a small treat (positive feedback). It does not receive any treat (negative feedback) if it performs the wrong action. As an example in the computer science field, consider an ML algorithm that plays games against an opponent. Moves that lead to victories (positive feedback) in the game should be learned and repeated, whereas moves that lead to losses (negative feedback) are avoided.

ML has become quite popular recently with the increase in processor speed and memory size. As a consequence, the field now has a large number of algorithms that use mathematical or statistical analysis to learn, draw conclusions or infer data. This number continues to increase as evidenced by the number of scientific publications that propose variations or combinations of ML algorithms. For that reason, ML algorithms have been categorized based on the purpose for which they are designed. Some examples of classification can be found in (Shalev-Shwartz & Ben-David, 2013) and (Kulkarni, 2012), although the field still does not have any standard classification.

3. Systematic review

When developing RSs, software engineers must decide on the specific recommender algorithm of all those available. This choice has significant effect on the rationale of the RS, on the data that will be needed from users and recommendation items, and on performance issues. The number of algorithm variations and combinations in the literature makes this choice a challenging task.

This large number of recommender algorithms, which appears to be constantly growing and changing, makes software engineering for RSs a continuing challenge. Trying to develop tools to make RS development easier is a moving target, as new studies must be done to observe new open problems and trends, and further enrich the knowledge base.

For these reasons the authors conducted a systematic review to analyze the development of RSs containing ML algorithms. This systematic review follows the procedures of (Kitchenham, 2004) and has, as goals, to:

1. identify trends in the use or research of ML algorithms in RSs,
2. identify open questions in the use or research of ML algorithms,
3. assist new researchers to position new research activity in this domain appropriately.

This systematic review has one restriction. The authors decided to limit the set of studies investigated to those describing an experiment or a validation study. The main reason for this restriction is that several publications in the literature propose new algorithms that are never tested or validated. Thus, by including this restriction, this systematic review is able to analyze the performance metrics of the ML algorithms, such as precision, recall, and f-measure.

This review examines the following three research questions (RQ):

- RQ1. What are the trends in recommender system use and research when implementing a machine learning algorithm?
- RQ2. What are the trends in machine learning algorithm use and research when developing a recommender system?
- RQ3. What are the main sources of articles of machine learning algorithms research when embedded in recommender systems?

The protocol for this systematic review has three main steps. The first step is to gather as many publications as possible using scientific search engines. The authors then analyze the studies that were retrieved and apply an initial exclusion criteria. The second step is to read the abstract of the remaining papers and apply an additional exclusion criteria. The third and last step is to read the entire study and gather data from it, or apply a third set of exclusion criteria. All the data is then compiled and is used to answer the research questions discussed earlier.

To answer the first research question, the authors investigated the type of filtering strategy used in the recommender system being described in a study. The approach to answering the second question involved more data. The publication proposed in the publications had its classification (supervised, unsupervised, etc), their type (clustering, decision tree, etc) investigated, as well as its support for distributed technologies (Hadoop, MapReduce). The performance metrics that describe each ML algorithm inspected in this systematic review were analyzed. The third question is answered by inspecting the conferences and journals in which the studies were published, and the surveys that were returned by the search query.

To strengthen the validity of the review the authors applied certain exclusion criteria (EC) to the studies that were included in this systematic review. These criteria and the rationale are presented next.

- EC1. Studies must be peer-reviewed articles, published in a conference, journal, press, etc. For example, conference entries are not considered for review.
- EC2. Books, letters, notes, and patents are not included in the review.
- EC3. Graduate theses are not considered for review.
- EC4. The abstract does not provide enough information.
- EC5. The authors must have access to the studies, otherwise studies are not considered for review.
- EC6. Studies must be primarily in English or French. Studies in languages other than English or French are excluded.
- EC7. Studies must be unique. If a study is repeated, other copies of that study are not included in this review.
- EC8. Only primary studies are included in this review. For example, surveys of the literature are not considered for review.
- EC9. Studies that do not describe a recommender system approach are not considered for review.
- EC10. Studies that do not describe a machine learning approach are not considered for review.

Table 3.1
Number of studies in this systematic review.

Label		Number
Total retrieved		215
Initial exclusion criteria	Not peer-reviewed study	15
	Books, letters, notes, or patents	0
	Graduate Thesis	2
Subtotal retained		199
Additional exclusion criteria	Excluded after reading the abstract	17
	Not able to access study	5
	Study in foreign language	3
Subtotal retained		174
Additional exclusion criteria based on the entire study	Repeated studies	4
	Not primary studies	10
	Not about recommender systems	6
	Not about machine learning	0
	Does not explain algorithm	6
	Does not include validation study	8
	Does not include performance metrics	18
Total retained studies		121

EC11. Studies that do not describe a machine learning approach sufficiently well are not considered for review.
EC12. Studies that do not describe an experiment or validation study are not considered for review.
EC13. Studies that do not describe performance metrics (e.g. accuracy, precision, recall) are not included in this review.

There are some synonyms that denote RSs. Based on (Jannach, Zanker, Felfernig, & Friedrich, 2010) this systematic review considers RS terms that replace "recommender" by "recommendation" and it does not consider any "machine learning" synonyms. Synonyms for the term "experiment" are "experimentation," "evaluation," "assessment," and "validation." All of these terms were featured in the search query (SQ), which is presented as follows:

SQ. (("recommender system" OR "recommendation system") AND ("machine learning") AND ("experiment" OR "experimentation" OR "evaluation" OR "assessment" OR "validation"))

This search query inspects the study title, abstract and keywords, and attempts to find terms that relate to the field of RS, ML, and provide some indication that the proposed approach was validated. Studies must also contain the term "machine learning" in the title, abstract, or keywords. To retrieve studies that were assessed, the search query also looks for the terms "experiment" or its synonyms.

The search query was used on three popular academic search engines Scopus[1], Web of Science[2], and IEEEXplore[3] on August 26th, 2016. The search returned 215 publication entries that were reviewed for quality. Scopus returned 196 studies, followed by Web of Science with 33 studies, and IEEEXplore with 31 studies. The titles of the studies were inspected to find duplicates among search engines. After that they were ready to be filtered by the exclusion criteria previously explained. The results are summarized on Table 3.1.

The number of studies to be read in the systematic review decreased from 215 to 121 when filtered by the exclusion criteria. Fifteen of the study entries were conference or proceeding descriptions and are excluded because they are not written scientific work. After reading the abstract of the studies, the authors were confident that 17 studies were not related to the goal of this systematic review and decided to exclude them. The authors did not have access to five studies, even after asking help from colleagues and visiting libraries. These studies were then not inspected in this systematic review. Two studies were in Chinese and another one was in Japanese. Four studies had a copy returned by the search string. These studies present the same results and were not counted twice. Only the original study was considered in this systematic review. After reading the studies, those who did not focus their proposal on the key research fields of this review were excluded. Moreover, studies that did not explain the ML algorithm being used, or did not describe a validation study, or its results were also excluded from this systematic review. In the end, 121 primary studies were retained and analyzed. The list of all studies is presented in the Table A.1 in the Appendix.

One last important point to mention is that the studies reviewed may propose more than one ML algorithm. As a consequence, some of the results presented on the next chapter are focused on the number of studies, while others are focused on the number of algorithms. The 121 studies described a total of 205 ML algorithms that are either totally new, or modifications or optimization of existing ones. Finally, algorithms can be validated in one or more application domains. This also impacts some results shown in the next section.

4. Systematic review results

The reading process focused on finding three types of information: one that relates to the RS being described (its classification), another that relates to the ML algorithm (its type, application domain, and performance metrics), and finally information about the source of the study (publication venue). The abstract and introduction of each paper was read, as well as the description of the proposed approach. Sometimes, when pieces of data were well described the entire section did not need to be read. The conclusion and future work sections of each study ware also read looking for open problems or research directions.

The authors developed a spreadsheet with an identification of each study with many columns for noting the pieces of information previously described. After reading all the studies, the authors processed the information contained in the spreadsheet and organized it in a presentable manner. The results and conclusions are presented in the following sections.

[1] http://www.scopus.com.
[2] http://webofscience.com.
[3] http://ieeexplore.ieee.org.

Table 4.1
Classification of recommender systems.

Classification of recommendation system	Number of studies	Studies
Content-based filtering / Classifier-based	30	(Alemeye & Getahun, 2015; Baldominos et al., 2015; Banerjee, Bhowmick, Mukherjee, & Misra, 2012; Brouard & Pomot, 2016; Buettner, 2016; Costa, Furtado, Pires, Macedo, & Cardoso, 2012, 2013; De Gemmis, Lops, Semeraro, & Basile, 2008; Diaby, Viennet, & Launay, 2014; Elmongui et al., 2015; Haiduc et al., 2013; Hussain, Farooq, Luo, & Slack, 2015; Jin, Mobasher, & Zhou, 2005; Kong, Zhang, & Ding, 2013; Leopairote, Surarerks, & Prompoon, 2013; Li, Dong, & Li, 2008; Liu, Fan, Hu, & Du, 2011; Lops et al., 2009; Marović, Mihoković, Mikša, Pribil, & Tus, 2011; Musto, Narducci, Lops, De Gemmis, & Semeraro, 2010; Hernández del Olmo, Gaudioso, & Martin, 2009; Pantraki & Kotropoulos, 2015; Pecli et al., 2015; Pronoza, Yagunova, & Volskaya, 2016; Taghipour, Kardan, & Ghidary, 2007; Tsuji, Yoshikane, Sato, & Itsumura, 2014; Vialardi et al., 2011; Wang, Wang, Wang, & Hsu, 2014; Xin et al., 2014; Zhang & Tran, 2010)
Content-based filtering / Neighbor-based	15	(Banerjee et al., 2012; Das et al., 2013; Das Dôres, Alves, Ruiz, & Barros, 2016; Kao & Fahn, 2013; Liu, Ding, & Xie, 2014b; Lu, Stankovic, & Laublet, 2015; Marques, Guilherme, Nakamura, & Papa, 2011; Nicol, Mary, & Preux, 2014; Pecli et al., 2015; Pronoza et al., 2016; Szymański & Rzeniewicz, 2016; Tsapatsoulis, Agathokleous, Djouvas, & Mendez, 2015; Tsuji et al., 2014; Wei, Chen, & Liang, 2011; Xuan, Lu, Zhang, & Luo, 2014)
Collaborative filtering / Neighborhood-based	37	(Agarwal, 2011; Bjelica, 2010; Bouneffouf, Bouzeghoub, & Gançarski, 2012; Cai et al., 2010, 2012; Castro-Herrera, Cleland-Huang, & Mobasher, 2009; Devi & Venkatesh, 2013; Diaby, Viennet, & Launay, 2013; Fan, Chen, Zha, & Yang, 2016; Forsati, Rahbar, & Mahdavi, 2009; Ghazarian & Nematbakhsh, 2015; Halder, Seddiqui, & Lee, 2014; Hassan, Karim, Javed, & Arshad, 2010; Jun, 2005; Karahodza & Donko, 2015; Krzywicki et al., 2015; Lee & Tseng, 2012; Li, Wang, & Liang, 2014; Liang, Lu, Ji, & Li, 2014; Liu, Xiong, & Huang, 2014a; Luong, Huynh, Gauch, Do, & Hoang, 2012a; Luong, Huynh, Gauch, & Hoang, 2012b; Marović et al., 2011; McLaughlin & Herlocker, 2004; Nie, Wang, Huang, & Ding, 2013; Oyama, Hayashi, & Kashima, 2012; Roh, Oh, & Han, 2003; Song, Dillon, Goh, & Sung, 2011a; Song, Zhang, & Giles, 2011b; Szabó, Póczos, & Lorincz, 2012; Takács, Pilászy, Németh, & Tikk, 2008; Wan, Jamaliding, & Okamoto, 2009; Wang, Yin, Cheng, & Yu, 2012; Zahra et al., 2015; Zhang, Begole, Chu, Liu, & Yee, 2008; Zhang, Zhuang, Wu, & Zhang, 2009; Zhao & Pan, 2015)
Collaborative filtering / Model-based	29	(Anaissi & Goyal, 2015; Aouay, Jamoussi, & Gargouri, 2014; Bar, Rokach, Shani, Shapira, & Schclar, 2013; Bauer & Nanopoulos, 2014; Braida, Mello, Pasinato, & Zimbrão, 2015; Caraballo, Arruda, Nunes, Lopes, & Casanova, 2014; Dinuzzo et al., 2011; Gedikli, Bağdat, Ge, & Jannach, 2011; Hofmann, 2003, 2004; Huang & Nikulin, 2014; Krohn-Grimberghe, Busche, Nanopoulos, & Schmidt-Thieme, 2011; Li & Chen, 2013; Liu et al., 2014a; Lu, Hoi, Wang, & Zhao, 2013; Marović et al., 2011; Montañés, Quevedo, Díaz, & Ranilla, 2009; Moreno, Shapira, Rokach, & Shani, 2012; Paparrizos, Cambazoglu, & Gionis, 2011; Pessiot, Truong, Usunier, Amini, & Gallinar, 2007; Sun, Fan, Bakillah, & Zipf, 2015; Takács et al., 2008; Takáes, Pilászy, Németh, & Tikk, 2009; Yap, Tan, & Pang, 2005; Yuan, Murukannaiah, Zhang, & Singh, 2014; Zhai & Li, 2015; Zhang, Liu, & Dong, 2007; Zhang, 2007; Zhao, Zhang, Friedman, & Tan, 2015)
Hybrid filtering	18	(Bellogín, Cantador, Castells, & Ortigosa, 2011; Biancalana, Gasparetti, Micarelli, Miola, & Sansonetti, 2011; Buabin, 2012; Degemmis, Lops, & Semeraro, 2007; Fan & Chang, 2010; Forsati & Meybodi, 2010; Geng et al., 2016; Islam, Ding, & Chi, 2015; Jung & Lee, 2004; Lee & Lu, 2003; Li & Zaïane, 2004; Marović et al., 2011; Middleton, Shadbolt, & De Roure, 2004; Murfi & Obermayer, 2009; Nguyen, Richards, Chan, & Liszka, 2016; Verma, Hart, Bhatkar, Parker-Wood, & Dey, 2016; Yan, Xu, Yao, & Lu, 2013; Yeh & Wu, 2010)

4.1. Recommender systems

Recommender systems can be classified by content-based, collaborative, or hybrid filtering. Usually, content-based approaches use the following two strategies to recommend items to users, according to (Weng, 1998): classifier-based or neighbor methods. In the first method, users are associated with profiles, and a new item is presented to the classifier. The classifier then decides whether the item should be recommended or not based on the item's contents. Nearest-neighbor methods store items that the user has checked or rated and use an underlying network of items (where similar items have similar properties) to discover the user interest for a new item.

Collaborative filtering RSs are subdivided in the following categories, according to (Ning, Desrosiers, & Karypis, 2015): neighborhood-based and model-based methods. The first method also stores the relationship user-item (the user interest for an item) in a user profile, but it uses a similarity network of users to evaluate whether a new item should be recommended. In contrast, model-based methods use the stored ratings to produce a predictive model for the user. Hybrid approaches do not seem to follow any categorization.

Table 4.1 shows how many studies describe at least one approach in each of the classifications explained in previous paragraphs, as well as the studies themselves. Results point to a significant number of collaborative filtering approaches when developing RSs with ML algorithms. More than half of the studies describe a collaborative approach for filtering, with a stronger emphasis on a neighborhood-based method.

The authors decided to observe the timeline of the publication of each study. The results are shown in Fig. 4.1 and also confirms that collaborative filtering with a neighborhood-based method is well researched. In the figure, one clearly sees a spike in the year 2012 that indicates a trend in this research area in recent years. One reason might be the real-life applicability of collaborative filtering approaches in social networks for example, or on the web with spatial-temporal applications such as the online network platform for room renting AirBnb[4] or the transportation network company Uber[5].

Another important conclusion drawn from Table 4.1 and Fig. 4.1 is the minimal research effort focused on hybrid approaches. Hybrid filtering helps overcome limitations of the other two approaches. However, throughout the years, research on this type of filtering with ML algorithms has been low, despite the fact that some studies show that it gives more accurate recommendations than other types of filtering (Adomavicius & Tuzhilin, 2005).

4.2. Machine learning algorithms

ML algorithms can initially be classified as supervised, semi-supervised, unsupervised, or reinforcement learning. It is worth calculating the number in each category in this systematic review. However, since studies may propose more than one ML algorithm, it is more reasonable to do an analysis on the algorithm level, instead of the study one. Therefore, Table 4.2 shows the number of

[4] http://www.airbnb.com.
[5] http://www.uber.com.

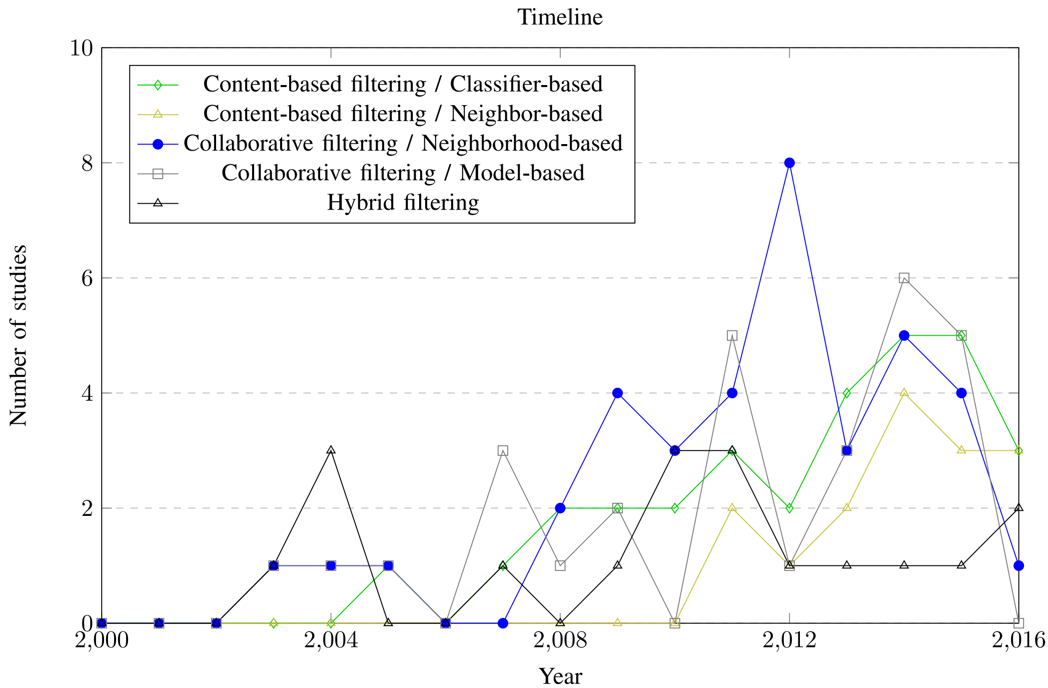

Fig. 4.1. Timeline of the classification of the studies.

Table 4.2
Machine learning approach.

Approach	Number of ML algorithms	Number of studies	Studies
Supervised learning	156	97	(Agarwal, 2011; Alemeye & Getahun, 2015; Anaissi & Goyal, 2015; Aouay et al., 2014; Baldominos et al., 2015; Banerjee et al., 2012; Bar et al., 2013; Bauer & Nanopoulos, 2014; Bellogín et al., 2011; Biancalana et al., 2011; Braida et al., 2015; Brouard & Pomot, 2016; Buabin, 2012; Cai et al., 2010, 2012; Caraballo et al., 2014; Castro-Herrera et al., 2009; Costa et al., 2012, 2013; Das et al., 2013; Das Dôres et al., 2016; De Gemmis et al., 2008; Diaby et al., 2013, 2014; Dinuzzo et al., 2011; Fan & Chang, 2010; Forsati & Meybodi, 2010; Forsati et al., 2009; Gedikli et al., 2011; Geng et al., 2016; Haiduc et al., 2013; Hofmann, 2003, 2004; Huang & Nikulin, 2014; Hussain et al., 2015; Islam et al., 2015; Jin et al., 2005; Jun, 2005; Jung & Lee, 2004; Kao & Fahn, 2013; Karahodza & Donko, 2015; Kong et al., 2013; Krohn-Grimberghe et al., 2011; Krzywicki et al., 2015; Lee & Lu, 2003; Leopairote et al., 2013; Li et al., 2008; Li & Chen, 2013; Liang et al., 2014; Liu et al., 2014a, 2011; Lops et al., 2009; Lu et al., 2013; Luong et al., 2012a; Marović et al., 2011; Marques et al., 2011; McLaughlin & Herlocker, 2004; Montañés et al., 2009; Moreno et al., 2012; Murfi & Obermayer, 2009; Musto et al., 2010; Nicol et al., 2014; Nie et al., 2013; Hernández del Olmo et al., 2009; Oyama et al., 2012; Pantraki & Kotropoulos, 2015; Paparrizos et al., 2011; Pecli et al., 2015; Pessiot et al., 2007; Pronoza et al., 2016; Roh et al., 2003; Song et al., 2011a, 2011b; Sun et al., 2015; Szabó et al., 2012; Szymański & Rzeniewicz, 2016; Takács et al., 2008; Takáes et al., 2009; Tsapatsoulis et al., 2015; Tsuji et al., 2014; Verma et al., 2016; Vialardi et al., 2011; Wan et al., 2009; Wang et al., 2012; Wei et al., 2011; Xin et al., 2014; Yan et al., 2013; Yap et al., 2005; Yeh & Wu, 2010; Yuan et al., 2014; Zhai & Li, 2015; Zhang & Tran, 2010; Zhang et al., 2007, 2008; Zhang, 2007; Zhang et al., 2009; Zhao et al., 2015)
Semi-supervised learning	1	1	(Das et al., 2013)
Unsupervised learning	46	24	(Bar et al., 2013; Bjelica, 2010; Bouneffouf et al., 2012; Buettner, 2016; Degemmis et al., 2007; Devi & Venkatesh, 2013; Elmongui et al., 2015; Fan et al., 2016; Ghazarian & Nematbakhsh, 2015; Halder et al., 2014; Hassan et al., 2010; Lee & Tseng, 2012; Li & Zaïane, 2004; Li et al., 2014; Liu et al., 2014b; Lu et al., 2015; Luong et al., 2012b; Marović et al., 2011; Middleton et al., 2004; Nguyen et al., 2016; Song et al., 2011b; Xuan et al., 2014; Zahra et al., 2015; Zhao & Pan, 2015)
Reinforcement learning	2	2	(Taghipour et al., 2007; Wang et al., 2014)

ML algorithms found in the studies of this systematic review that described themselves under one of these ML classifications.

There is a clear research interest in supervised learning ML algorithms for RSs. One main reason for this result is that most of the algorithms analyzed were modifications or optimization of well-known ML algorithms. Unsupervised learning had also an expressive result. Lastly, there is plenty of room for research in semi-supervised or reinforcement learning for RSs that new researchers may explore.

The authors also separated ML algorithms into types based on (Shalev-Shwartz & Ben-David, 2013) to present the number of ML algorithms of each type analyzed in this review. Some algorithms had clear classifications because they were small variations of well-established algorithms (e.g. incremental matrix factorization is a variant of the matrix factorization algorithm). Other algorithms, popular in the field, were not grouped with the algorithms of the same type (e.g. k Nearest Neighbors is a clustering algorithm, but has its own entry). However, some algorithms do not seem to fit in any category. For these cases, the algorithm was

Table 4.3
Types of machine learning algorithms.

Type of Machine Learning Algorithm	Number of ML algorithms	Number of studies	Studies
Ensemble	22	14	(Aouay et al., 2014; Bar et al., 2013; Biancalana et al., 2011; Braida et al., 2015; Buabin, 2012; Elmongui et al., 2015; Fan & Chang, 2010; Islam et al., 2015; Kao & Fahn, 2013; Middleton et al., 2004; Szymański & Rzeniewicz, 2016; Tsuji et al., 2014; Vialardi et al., 2011; Yan et al., 2013)
K Means	22	4	(Degemmis et al., 2007; Fan et al., 2016; Lee & Tseng, 2012; Zahra et al., 2015)
Support Vector Machines (SVM)	20	17	(Agarwal, 2011; Banerjee et al., 2012; Brouard & Pomot, 2016; Diaby et al., 2013, 2014; Ghazarian & Nematbakhsh, 2015; Jun, 2005; Kong et al., 2013; Pecli et al., 2015; Pronoza et al., 2016; Song et al., 2011a; Sun et al., 2015; Szymański & Rzeniewicz, 2016; Tsuji et al., 2014; Verma et al., 2016; Yap et al., 2005; Zhao & Pan, 2015)
Bayesian	14	12	(Aouay et al., 2014; Banerjee et al., 2012; Costa et al., 2012, 2013; De Gemmis et al., 2008; Lops et al., 2009; Musto et al., 2010; Hernández del Olmo et al., 2009; Paparrizos et al., 2011; Pecli et al., 2015; Pronoza et al., 2016; Zhang et al., 2007)
Decision Tree	14	13	(Alemeye & Getahun, 2015; Aouay et al., 2014; Banerjee et al., 2012; Bellogín et al., 2011; Caraballo et al., 2014; Costa et al., 2013; Haiduc et al., 2013; Hussain et al., 2015; Lee & Lu, 2003; Liu et al., 2011; Musto et al., 2010; Hernández del Olmo et al., 2009; Wei et al., 2011)
Matrix Factorization	13	7	(Bauer & Nanopoulos, 2014; Huang & Nikulin, 2014; Krohn-Grimberghe et al., 2011; Lu et al., 2013; Takács et al., 2008; Takáes et al., 2009; Zhai & Li, 2015)
k Nearest Neighbors	11	10	(Aouay et al., 2014; Castro-Herrera et al., 2009; Das Dôres et al., 2016; Kong et al., 2013; Liang et al., 2014; Liu et al., 2014b; Marović et al., 2011; McLaughlin & Herlocker, 2004; Hernández del Olmo et al., 2009; Pecli et al., 2015)
Latent Semantic Analysis	7	4	(Hofmann, 2003, 2004; Marović et al., 2011; Zhang et al., 2009)
Logistic Regression	7	6	(Cai et al., 2012; Das et al., 2013; Krzywicki et al., 2015; Montañés et al., 2009; Pronoza et al., 2016; Sun et al., 2015)
Various	6	6	(Anaissi & Goyal, 2015; Forsati & Meybodi, 2010; Jung & Lee, 2004; Marović et al., 2011; Murfi & Obermayer, 2009; Roh et al., 2003)
Clustering	5	4	(Bjelica, 2010; Hassan et al., 2010; Li & Zaïane, 2004; Xuan et al., 2014)
Slope One	5	1	(Wang et al., 2012)
Association Rule	4	2	(Leopairote et al., 2013; Zhang, 2007)
Kernel Methods	4	4	(Devi & Venkatesh, 2013; Dinuzzo et al., 2011; Li & Chen, 2013; Li et al., 2014)
Bandit	3	3	(Bouneffouf et al., 2012; Nicol et al., 2014; Wang et al., 2014)
Frequency Counting	3	1	(Luong et al., 2012a)
Least Squares	3	2	(Gedikli et al., 2011; Takács et al., 2008)
Neural Network	3	3	(Aouay et al., 2014; Geng et al., 2016; Marović et al., 2011)
Regression Tree	3	2	(Marović et al., 2011; Pecli et al., 2015)
Sim. metric - Cosine Similarity	3	3	(Banerjee et al., 2012; Halder et al., 2014; Li et al., 2008)
Dictionary Learning	2	1	(Szabó et al., 2012)
Gradient Descent	2	2	(Cai et al., 2010; Pessiot et al., 2007)
Latent Dirichlet Allocation	2	2	(Xin et al., 2014; Yeh & Wu, 2010)
Linear Model	2	2	(Moreno et al., 2012; Zhang & Tran, 2010)
Linear Regression	2	2	(Zhang et al., 2008; Zhao et al., 2015)
Pearson Correlation	2	2	(Halder et al., 2014; Wan et al., 2009)
Staked Regression	2	1	(Liu et al., 2014a)
Cross-temporal Link Prediction	1	1	(Oyama et al., 2012)
Euclidean Distance	1	1	(Buettner, 2016)
Gaussian Processes	1	1	(Song et al., 2011b)
Graphical Model	1	1	(Yuan et al., 2014)
Learning Automata	1	1	(Forsati et al., 2009)
Mahalanobis Classifier	1	1	(Tsapatsoulis et al., 2015)
Markov Model	1	1	(Baldominos et al., 2015)
Lagrange Multiplier	1	1	(Nie et al., 2013)
Mixture Model	1	1	(Song et al., 2011b)
Optimal Path Forest	1	1	(Marques et al., 2011)
Personality Diagnosis	1	1	(Marović et al., 2011)
Probabilistic Latent Semantic Analysis	1	1	(Jin et al., 2005)
Q-Learning	1	1	(Taghipour et al., 2007)
Regularization Methods	1	1	(Takács et al., 2008)
Shortest Path	1	1	(Luong et al., 2012b)
Simil. metric - Geosemantic Proximity	1	1	(Lu et al., 2015)
Simil. metric - Aggregate Function	1	1	(Karahodza & Donko, 2015)
Simil. metric - WordNet Class Distance	1	1	(Nguyen et al., 2016)
Single Value Decomposition (SVD)	1	1	(Pantraki & Kotropoulos, 2015)

Table 4.4
Types of machine learning algorithms (alternative classification).

Type of Machine Learning Algorithm	Number of ML algorithms	Number of studies	Studies
Clustering	38	18	(Aouay et al., 2014; Bjelica, 2010; Castro-Herrera et al., 2009; Das Dôres et al., 2016; Degemmis et al., 2007; Fan et al., 2016; Hassan et al., 2010; Kong et al., 2013; Lee & Tseng, 2012; Li & Zaïane, 2004; Liang et al., 2014; Liu et al., 2014b; Marović et al., 2011; McLaughlin & Herlocker, 2004; Hernández del Olmo et al., 2009; Pecli et al., 2015; Xuan et al., 2014; Zahra et al., 2015)
Kernel Methods	25	22	(Agarwal, 2011; Banerjee et al., 2012; Brouard & Pomot, 2016; Devi & Venkatesh, 2013; Diaby et al., 2013, 2014; Dinuzzo et al., 2011; Ghazarian & Nematbakhsh, 2015; Jun, 2005; Kong et al., 2013; Li & Chen, 2013; Li et al., 2014; Pecli et al., 2015; Pronoza et al., 2016; Song et al., 2011a, 2011b; Sun et al., 2015; Szymański & Rzeniewicz, 2016; Tsuji et al., 2014; Verma et al., 2016; Yap et al., 2005; Zhao & Pan, 2015)
Ensemble	22	14	(Aouay et al., 2014; Bar et al., 2013; Biancalana et al., 2011; Braida et al., 2015; Buabin, 2012; Elmongui et al., 2015; Fan & Chang, 2010; Islam et al., 2015; Kao & Fahn, 2013; Middleton et al., 2004; Szymański & Rzeniewicz, 2016; Tsuji et al., 2014; Vialardi et al., 2011; Yan et al., 2013)
Matrix Factorization	21	12	(Bauer & Nanopoulos, 2014; Hofmann, 2003, 2004; Huang & Nikulin, 2014; Krohn-Grimberghe et al., 2011; Lu et al., 2013; Marović et al., 2011; Pantraki & Kotropoulos, 2015; Takács et al., 2008; Takáes et al., 2009; Zhai & Li, 2015; Zhang et al., 2009)
Decision Tree	17	15	(Alemeye & Getahun, 2015; Aouay et al., 2014; Banerjee et al., 2012; Bellogín et al., 2011; Caraballo et al., 2014; Costa et al., 2013; Haiduc et al., 2013; Hussain et al., 2015; Lee & Lu, 2003; Liu et al., 2011; Marović et al., 2011; Musto et al., 2010; Hernández del Olmo et al., 2009; Pecli et al., 2015; Wei et al., 2011)
Graphical Model	17	15	(Aouay et al., 2014; Banerjee et al., 2012; Costa et al., 2012, 2013; De Gemmis et al., 2008; Lops et al., 2009; Musto et al., 2010; Hernández del Olmo et al., 2009; Paparrizos et al., 2011; Pecli et al., 2015; Pronoza et al., 2016; Xin et al., 2014; Yeh & Wu, 2010; Yuan et al., 2014; Zhang et al., 2007)
Regression	16	13	(Cai et al., 2012; Das et al., 2013; Gedikli et al., 2011; Halder et al., 2014; Krzywicki et al., 2015; Liu et al., 2014a; Montañés et al., 2009; Pronoza et al., 2016; Sun et al., 2015; Takács et al., 2008; Wan et al., 2009; Zhang et al., 2008; Zhao et al., 2015)
Similarity Metric	7	7	(Banerjee et al., 2012; Buettner, 2016; Halder et al., 2014; Karahodza & Donko, 2015; Li et al., 2008; Lu et al., 2015; Nguyen et al., 2016)
Various	6	6	(Anaissi & Goyal, 2015; Forsati & Meybodi, 2010; Jung & Lee, 2004; Marović et al., 2011; Murfi & Obermayer, 2009; Roh et al., 2003)
Slope One	5	1	(Wang et al., 2012)
Association Rule	4	2	(Leopairote et al., 2013; Zhang, 2007)
Bandit	3	3	(Bouneffouf et al., 2012; Nicol et al., 2014; Wang et al., 2014)
Neural Network	3	3	(Aouay et al., 2014; Geng et al., 2016; Marović et al., 2011)
Frequency Counting	3	1	(Luong et al., 2012a)
Dictionary Learning	2	1	(Szabó et al., 2012)
Gradient Descent	2	2	(Cai et al., 2010; Pessiot et al., 2007)
Linear Model	2	2	(Moreno et al., 2012; Zhang & Tran, 2010)
Cross-temporal Link Prediction	1	1	(Oyama et al., 2012)
Learning Automata	1	1	(Forsati et al., 2009)
Mahalanobis Classifier	1	1	(Tsapatsoulis et al., 2015)
Markov Model	1	1	(Baldominos et al., 2015)
Lagrage Multiplier	1	1	(Nie et al., 2013)
Mixture Model	1	1	(Song et al., 2011b)
Optimal Path Forest	1	1	(Marques et al., 2011)
Personality Diagnosis	1	1	(Marović et al., 2011)
Probabilistic Latent Semantic Analysis	1	1	(Jin et al., 2005)
Q-Learning	1	1	(Taghipour et al., 2007)
Regularization Methods	1	1	(Takács et al., 2008)
Shortest Path	1	1	(Luong et al., 2012b)

listed under a new category with its own name (e.g. Personality diagnosis).

Other important considerations are that some studies described approaches that involve many ML algorithms. When identified, these approaches were listed under the "Ensemble" entry. The ensemble strategy for machine learning has several ways of being implemented (e.g. bagging, boosting, random forest). However, this systematic review does not differentiate among them in the analysis. Other studies do not follow traditional ensemble techniques, and use different ML algorithms in different parts of a greater recommendation strategy. These approaches were listed under the "Various" entry. Table 4.3 shows detailed results, while Table 4.4 provides an alternative classification.

When inspecting the tables, one can observe again the emergence of collaborative filtering approaches with clustering algorithms being the one most researched in RS development. Together with Support Vector Machines (SVM), collaborative approaches constitute a quarter of the results. Ensemble methods are also at the top of the tables, but this result happened because many researchers trying different methods opted to combine their methods in an Ensemble as one additional trial.

Some ML algorithms ranked low in this systematic review despite their popularity. It is the case of the Neural Network or the K Means algorithms. Since this systematic review is focused on the application domain of RS development, these algorithms are not being researched enough, which opens opportunities for future studies.

Table 4.5
Big Data technologies.

Big Data Technologies	Number of studies	Studies
Yes	3	(Baldominos et al., 2015; Dinuzzo et al., 2011; Geng et al., 2016)
No	118	Other studies

4.3. Big data technologies

ML algorithms, by definition, improve their performance with access to more data. Similarly, the more data that is provided to an RS, the better should be its recommendations. The evolution of technology has spawned research into new ways of handling data. One such phenomenon is called Big Data (Chen, Mao, & Liu, 2014), which has produced the Hadoop distributed infrastructure (Shvachko, Kuang, Radia, & Chansler, 2010) and the MapReduce programming model (Dean & Ghemawat, 2008). Because Big Data has a direct impact in RS development and ML algorithms (Leskovec, Rajaraman, & Ullman, 2014), the authors decided to look for studies that have a discussion of Big Data in the description of their proposed algorithms. Table 4.5 shows the number of studies that included Big Data in their discussion or proposals.

Among the studies that described some Big Data adaptations, Baldominos, Albacete, Saez, and Isasi (2015) used Big Data for storage. The proposed architecture that provides on demand tools for analysis uses the storage technologies HDFS (Hadoop Distributed File System) (Shvachko et al., 2010) and HBase[6] for persistence logs and structured information about the execution and predictions. Another study (Dinuzzo, Pillonetto, & De Nicolao, 2011), in the health domain, uses data from distributed datasets to make predictions. The description of the Big Data technologies used in the prediction process was not the focus of the study. Lastly, Geng, Zhang, Bian, and Chua (2016) proposes a neural network-based algorithm that is applied to the image domain and, according to the authors, easily scales to large networks.

Although as mentioned earlier, it is clear that few studies had their proposals adapted for a Big Data reality, with distributed technologies or performance-optimized programming paradigms. This Big Data apporach appears to represent a large research opportunity for RS development.

4.4. Application domains

This systematic review investigates the application domains used in the studies analyzed. A primary study may propose multiple algorithms, which may be validated in many different application domains. This means that the authors may investigate the application domains on a per algorithm or a per study basis. The authors opted for the latter approach so that the number of algorithms proposed in a single study does not affect the final result of the application domain analysis. The results of the analysis are shown on Table 4.6.

The application domain of Movies is the one mostly used with 31 occurrences among the 121 studies. One reason for this result is the ease of access to data in the movie domain. The University of Minnesota maintains a dataset with several movie ratings, named MovieLens[7], which is widely used. Another source of user ratings is the Internet Movie Database (IMDb)[8], which contains millions of titles and ratings that can be used to build a testing dataset.

The social domain ranks in the second place. This domain accounts for algorithms aimed to work on social networks, or applications that connects different users. This use confirms the trend of collaborative approaches in RS development with ML algorithms. The tourism and the coding domains ranked low, revealing opportunities for research, since data in these domains are rich and easily accessible.

4.5. Performance metrics

The main goal of this systematic review is to identify trends of ML algorithm use in RS development that can assist future researchers in their studies. The authors decided to take a deeper look at how the algorithms are being used by inspecting the performance metrics that researchers use to describe ML algorithms. These metrics may be accuracy metrics, such as Precision or Recall, or alternative metrics, such as User Preference or Coverage.

The analysis starts with an understanding of some of the performance metrics that have been proposed. Fig. 4.2 shows a tree containing several metrics at the leaf nodes, followed by their classifications as one goes up in the tree. Although not complete, this tree provides an overview of the many metrics that can be used to evaluate ML algorithms.

In this systematic review, the authors found many of the metrics expressed by Fig. 4.2, but also found many other metrics not described in the figure. Table 4.7 present metrics that were used to describe an algorithm. Note that the numbers do not add up to 121 studies or 205 algorithms. The reason is that an algorithm may use one or more metrics to describe its performance. Therefore, since there is at least one metric per algorithm, one should expect the number of metrics to be greater than the number of algorithms. Another consideration is sorting of the methods. The authors decided to sort the results, where well-known performance metrics were together and specific metrics were at the bottom of the table.

By inspecting Table 4.7, one may note that Precision, Recall and F-measure, are among the most popular performance metrics used in the studies of this systematic review, totalling almost 50% of all occurrences. One reason that may explain this result is that these metrics are the ones most often explained in textbooks. Most of the times, studies provided the three metrics together, since they are related, but as seen in the table, it is not for all the cases. Some studies provide only the Precision, or only the F-measure. The authors did not calculate the missing values so the results would not be affected. Two variants of the F-measure metric were used by studies, created by changing one of the parameters of the metrics. The studies does not explain the reason for the change.

Accuracy ranks high as well with 49 occurrences, mainly because of its intuitive nature when evaluating ML algorithms. Another important result is the large number of studies evaluating their proposals in terms of the error in the prediction by using the RMSE (Round Mean Squared Error) and the MAE (Mean Absolute Error) metrics. MAE had 123 occurrences, and ranks in the first position. The simplicity of the calculation of these metrics may be the reason for this result.

A study of the occurrence of each metric shows the popularity of some metrics, as well introduces other metrics to researchers. However, the authors decided to break down the most popular metrics and observe how the algorithms actually performed, as reported by the studies. The authors decided to plot all of the values for some of the performance metrics displayed at the top of Table 4.7 to discover any trends, or any studies that stand out. However, plotting tens of studies is not feasible. Many values are overwritten by others values and the figure becomes unreadable. Therefore, the authors display the best and worst value of each

[6] http://hbase.apache.org.
[7] http://movielens.org.
[8] http://www.imdb.com.

Table 4.6
Application Domains.

Domain	Number of studies	Studies
Movie	31	(Banerjee et al., 2012; Bar et al., 2013; Biancalana et al., 2011; Bjelica, 2010; Braida et al., 2015; Das et al., 2013; Degemmis et al., 2007; Devi & Venkatesh, 2013; Gedikli et al., 2011; Halder et al., 2014; Hofmann, 2003, 2004; Jun, 2005; Karahodza & Donko, 2015; Lee & Lu, 2003; Li et al., 2014; Liang et al., 2014; Liu et al., 2014a; Lu et al., 2013; Marović et al., 2011; McLaughlin & Herlocker, 2004; Nie et al., 2013; Pessiot et al., 2007; Roh et al., 2003; Takács et al., 2008; Takáes et al., 2009; Wang et al., 2012; Yeh & Wu, 2010; Zahra et al., 2015; Zhang et al., 2007, 2009)
Social	14	(Aouay et al., 2014; Cai et al., 2010, 2012; Diaby et al., 2013; Elmongui et al., 2015; Hassan et al., 2010; Islam et al., 2015; Krzywicki et al., 2015; Song et al., 2011b; Verma et al., 2016; Wan et al., 2009; Yan et al., 2013; Yuan et al., 2014; Zhao & Pan, 2015)
Academic	12	(Das et al., 2013; Huang & Nikulin, 2014; Krohn-Grimberghe et al., 2011; Luong et al., 2012a, 2012b; Middleton et al., 2004; Montañés et al., 2009; Hernández del Olmo et al., 2009; Oyama et al., 2012; Pecli et al., 2015; Vialardi et al., 2011; Xin et al., 2014)
News	11	(Bellogín et al., 2011; Brouard & Pomot, 2016; Buabin, 2012; Das et al., 2013; Fan et al., 2016; Lee & Lu, 2003; Leopairote et al., 2013; Li et al., 2008; Nguyen et al., 2016; Nicol et al., 2014; Nie et al., 2013)
E-commerce	10	(Anaissi & Goyal, 2015; Bauer & Nanopoulos, 2014; Buettner, 2016; Castro-Herrera et al., 2009; Nie et al., 2013; Pecli et al., 2015; Wei et al., 2011; Zhai & Li, 2015; Zhang & Tran, 2010; Zhao et al., 2015)
Webpages	10	(Forsati & Meybodi, 2010; Forsati et al., 2009; Jin et al., 2005; Jun, 2005; Kao & Fahn, 2013; Li & Zaïane, 2004; Liu et al., 2014b, 2011; Musto et al., 2010; Taghipour et al., 2007)
Documents	9	(Alemeye & Getahun, 2015; Bouneffouf et al., 2012; Caraballo et al., 2014; Jung & Lee, 2004; Lu et al., 2013; Murfi & Obermayer, 2009; Nie et al., 2013; Szymański & Rzeniewicz, 2016; Xuan et al., 2014)
Music	6	(Bauer & Nanopoulos, 2014; Ghazarian & Nematbakhsh, 2015; Marques et al., 2011; Moreno et al., 2012; Wang et al., 2014; Zahra et al., 2015)
Books	4	(Li & Chen, 2013; Tsuji et al., 2014; Xin et al., 2014; Zahra et al., 2015)
Health	4	(Agarwal, 2011; Dinuzzo et al., 2011; Hussain et al., 2015; Song et al., 2011a)
Images	4	(Geng et al., 2016; Kong et al., 2013; Pantraki & Kotropoulos, 2015; Pecli et al., 2015)
Tourism	4	(Costa et al., 2012, 2013; Lu et al., 2015; Sun et al., 2015)
Games	3	(Baldominos et al., 2015; Castro-Herrera et al., 2009; Moreno et al., 2012)
Pictures	3	(De Gemmis et al., 2008; Lops et al., 2009; Musto et al., 2010)
Clothing	2	(Li & Chen, 2013; Zhang et al., 2008)
E-mail	2	(Agarwal, 2011; Oyama et al., 2012)
Industry	2	(Castro-Herrera et al., 2009; Das et al., 2013)
Jobs	2	(Diaby et al., 2014; Paparrizos et al., 2011)
Restaurant	1	(Pronoza et al., 2016; Yap et al., 2005)
Advertisement	1	(Fan & Chang, 2010)
Algorithm	1	(Das Dôres et al., 2016)
Antenna	1	(Agarwal, 2011)
Code	1	(Haiduc et al., 2013)
Elections	1	(Tsapatsoulis et al., 2015)
Jokes	1	(Szabó et al., 2012)
Mobile Phones	1	(Zhang, 2007)
Railway	1	(Castro-Herrera et al., 2009)
Video	1	(Lee & Tseng, 2012)

plot, and in another plot, the authors present the top 10 studies for each metric analyzed.

Some important considerations are as follows. The analysis of the performance metrics is per algorithm, which means that studies that proposed more than one algorithm are repeated in the plots. Moreover, as a study may validate its ML algorithm with different versions of the same data, the authors decided to report the results related to the richer data. For example, MovieLens provides three sizes of their movie ratings dataset: 100K, 1M, and 10M data values, where K is thousands and M is millions. This systematic review analyzes the results related only to the larger dataset. This is done to simulate the real world as much as possible.

A similar decision is taken regarding parameters of the algorithms. Many times, studies report the results of an ML algorithm assuming many different parameters. In this case, this systematic review considers the best result for analysis. This is done for the benefit of other researchers who may be searching for an algorithm that is better than a certain threshold.

Lastly, performance results may be reported using the 0–100 range or a 0–1 range. For the former case the authors reduced the result to the range of 0–1 simply by dividing the reported result by 100. This is done to make results comparable, and it does not affect the final result of the analysis.

Fig. 4.3 presents the plots for Precision (Figs. 4.3a and 4.3b), Recall (Figs. 4.3c and 4.3d), and F-measure (Figs. 4.3e and 4.3f), followed by a discussion of the results.

Fig. 4.3 shows that one study ranked very well on Precision, Recall, and F-measure. This study (Costa, Furtado, Pires, Macedo, & Cardoso, 2013) uses Bayesian algorithms (BayesNet and Naive Bayes) as well as Decision Trees (J48 pruned and unpruned) to recommend points of interest (POIs) to users. According to the authors, the two main differences from other approaches are the use of a user's context, because at different contexts, different items may be relevant or not to the user. A multi-agent system (MAS) is also developed to handle requests.

Overall, many algorithms performed well in Precision, Recall, and F-measure. The best for each metric is shown in the top 10 plot.

Fig. 4.4 shows the results for the Accuracy metric (Figs. 4.4a and 4.4b). There is a quick drop in accuracy among the algorithms, with few ranking above 80% accuracy. The accuracy metric is one of the most intuitive ones, and should not be overlooked, since it gives an initial perception of how the ML algorithm is performing.

Fig. 4.5 shows the breakdown of performance results for RMSE (Round Mean Squared Error) (Figs. 4.5a and 4.5b), MAE (Mean Absolute Error) (Figs. 4.5c and 4.5d), and MAP (Mean Average Precision) (Figs. 4.5e and 4.5f).

Two important points to be mentioned are as follows. One may notice that plots of the ML algorithms related to error metrics, such as RMSE and MAE, show the lower values on top, instead of the bottom, so that the best performing studies are shown on the top. The second point relates to MAP. This metric did not have a

Table 4.7
Performance metrics.

Metrics	Number of ML algorithms	Number of studies	Studies
Precision	98	44	(Agarwal, 2011; Aouay et al., 2014; Baldominos et al., 2015; Banerjee et al., 2012; Biancalana et al., 2011; Brouard & Pomot, 2016; Cai et al., 2010, 2012; Caraballo et al., 2014; Costa et al., 2012, 2013; De Gemmis et al., 2008; Devi & Venkatesh, 2013; Elmongui et al., 2015; Fan & Chang, 2010; Fan et al., 2016; Forsati & Meybodi, 2010; Forsati et al., 2009; Ghazarian & Nematbakhsh, 2015; Islam et al., 2015; Jun, 2005; Kao & Fahn, 2013; Leopairote et al., 2013; Li & Zaïane, 2004; Li & Chen, 2013; Liang et al., 2014; Liu et al., 2011; Lops et al., 2009; Luong et al., 2012a; McLaughlin & Herlocker, 2004; Murfi & Obermayer, 2009; Musto et al., 2010; Nguyen et al., 2016; Nie et al., 2013; Pantraki & Kotropoulos, 2015; Pecli et al., 2015; Song et al., 2011b; Szymański & Rzeniewicz, 2016; Verma et al., 2016; Wan et al., 2009; Yap et al., 2005; Yuan et al., 2014; Zhang & Tran, 2010; Zhao & Pan, 2015)
Recall	58	32	(Aouay et al., 2014; Baldominos et al., 2015; Banerjee et al., 2012; Cai et al., 2010, 2012; Caraballo et al., 2014; Costa et al., 2012, 2013; De Gemmis et al., 2008; Devi & Venkatesh, 2013; Elmongui et al., 2015; Fan & Chang, 2010; Fan et al., 2016; Krzywicki et al., 2015; Leopairote et al., 2013; Li & Chen, 2013; Liang et al., 2014; Liu et al., 2011; Lops et al., 2009; McLaughlin & Herlocker, 2004; Murfi & Obermayer, 2009; Musto et al., 2010; Nguyen et al., 2016; Nie et al., 2013; Pantraki & Kotropoulos, 2015; Song et al., 2011b; Szymański & Rzeniewicz, 2016; Verma et al., 2016; Yap et al., 2005; Yuan et al., 2014; Zhang & Tran, 2010; Zhao & Pan, 2015)
F-measure	80	29	(Banerjee et al., 2012; Buabin, 2012; Caraballo et al., 2014; Costa et al., 2012, 2013; Das et al., 2013; Elmongui et al., 2015; Fan & Chang, 2010; Fan et al., 2016; Hassan et al., 2010; Leopairote et al., 2013; Li & Chen, 2013; Li et al., 2014; Liang et al., 2014; Lops et al., 2009; Lu et al., 2015; Montañés et al., 2009; Murfi & Obermayer, 2009; Pantraki & Kotropoulos, 2015; Pronoza et al., 2016; Song et al., 2011b; Szymański & Rzeniewicz, 2016; Tsapatsoulis et al., 2015; Verma et al., 2016; Xuan et al., 2014; Yap et al., 2005; Yuan et al., 2014; Zhang & Tran, 2010; Zhao & Pan, 2015)
R-Precision	1	1	(Brouard & Pomot, 2016)
F(0.5)	5	1	(De Gemmis et al., 2008)
F[3,1298]	1	1	(Zhang et al., 2008)
RMSE	56	22	(Bar et al., 2013; Braida et al., 2015; Dinuzzo et al., 2011; Gedikli et al., 2011; Hofmann, 2003, 2004; Jun, 2005; Karahodza & Donko, 2015; Krohn-Grimberghe et al., 2011; Li et al., 2014; Liu et al., 2014a; Lu et al., 2013; Marović et al., 2011; Szabó et al., 2012; Takács et al., 2008; Takáes et al., 2009; Wang et al., 2014, 2012; Yan et al., 2013; Yeh & Wu, 2010; Zhai & Li, 2015; Zhao et al., 2015)
MAE	123	20	(Bauer & Nanopoulos, 2014; Braida et al., 2015; Castro-Herrera et al., 2009; Degemmis et al., 2007; Devi & Venkatesh, 2013; Fan & Chang, 2010; Ghazarian & Nematbakhsh, 2015; Hofmann, 2004; Jung & Lee, 2004; Karahodza & Donko, 2015; Liu et al., 2014a; Lu et al., 2013; McLaughlin & Herlocker, 2004; Moreno et al., 2012; Takáes et al., 2009; Wang et al., 2012; Wei et al., 2011; Yan et al., 2013; Zahra et al., 2015; Zhang et al., 2009)
Normalized MAE	2	1	(Nie et al., 2013)
MAP	7	4	(Biancalana et al., 2011; Elmongui et al., 2015; Kao & Fahn, 2013; Tsapatsoulis et al., 2015)
Accuracy	49	26	(Alemeye & Getahun, 2015; Banerjee et al., 2012; Bellogín et al., 2011; Bjelica, 2010; Cai et al., 2012; Castro-Herrera et al., 2009; Halder et al., 2014; Hussain et al., 2015; Jin et al., 2005; Kong et al., 2013; Krzywicki et al., 2015; Lee & Tseng, 2012; Lee & Lu, 2003; Li et al., 2008; Liu et al., 2014b, 2011; Luong et al., 2012b; Marques et al., 2011; Middleton et al., 2004; Paparrizos et al., 2011; Song et al., 2011a; Sun et al., 2015; Taghipour et al., 2007; Vialardi et al., 2011; Xin et al., 2014; Zhang, 2007)
ROC	9	4	(Costa et al., 2012, 2013; Li & Chen, 2013; Roh et al., 2003)
AUC	14	8	(Agarwal, 2011; Anaissi & Goyal, 2015; Cai et al., 2012; Diaby et al., 2013, 2014; Fan & Chang, 2010; Oyama et al., 2012; Song et al., 2011a)
Click Through Rate (CTR)	2	1	(Bouneffouf et al., 2012)
Kullback-Leibler divergence	1	1	(Zhang et al., 2007)
NARG (Intrusion Cost)	3	1	(Hernández del Olmo et al., 2009)
NDPM (Normalized Distance-based Performance Measure)	1	1	(Musto et al., 2010)
Shortcut Gain	2	2	(Li & Zaïane, 2004; Taghipour et al., 2007)
MSE (Mean Squared Error)	2	1	(Degemmis et al., 2007)
Jaccard Coefficient	10	1	(Xuan et al., 2014)
Folkes & Mallows	10	1	(Xuan et al., 2014)
Rank Score Measure (RSM)	1	1	(Jung & Lee, 2004)
PPE (Percentage of Positive Evaluations)	2	1	(Tsuji et al., 2014)
DCG	3	1	(Agarwal, 2011)
NDCG (Normalized Discount Cumulative Gain)	4	3	(Elmongui et al., 2015; Geng et al., 2016; Kao & Fahn, 2013)
Rank Score	4	2	(Jung & Lee, 2004; Li & Chen, 2013)
Average Absolute Deviation (AAD)	6	1	(Marović et al., 2011)
Absolute Error	1	1	(Hofmann, 2003)
0/1 loss	4	2	(Hofmann, 2003; 2004)
R	1	1	(Zhang et al., 2008)
R^2	1	1	(Zhang et al., 2008)
Convergence	1	1	(Huang & Nikulin, 2014)
Error function	1	1	(Buettner, 2016)
Mean Ranking Error (MRE)	1	1	(Pessiot et al., 2007)

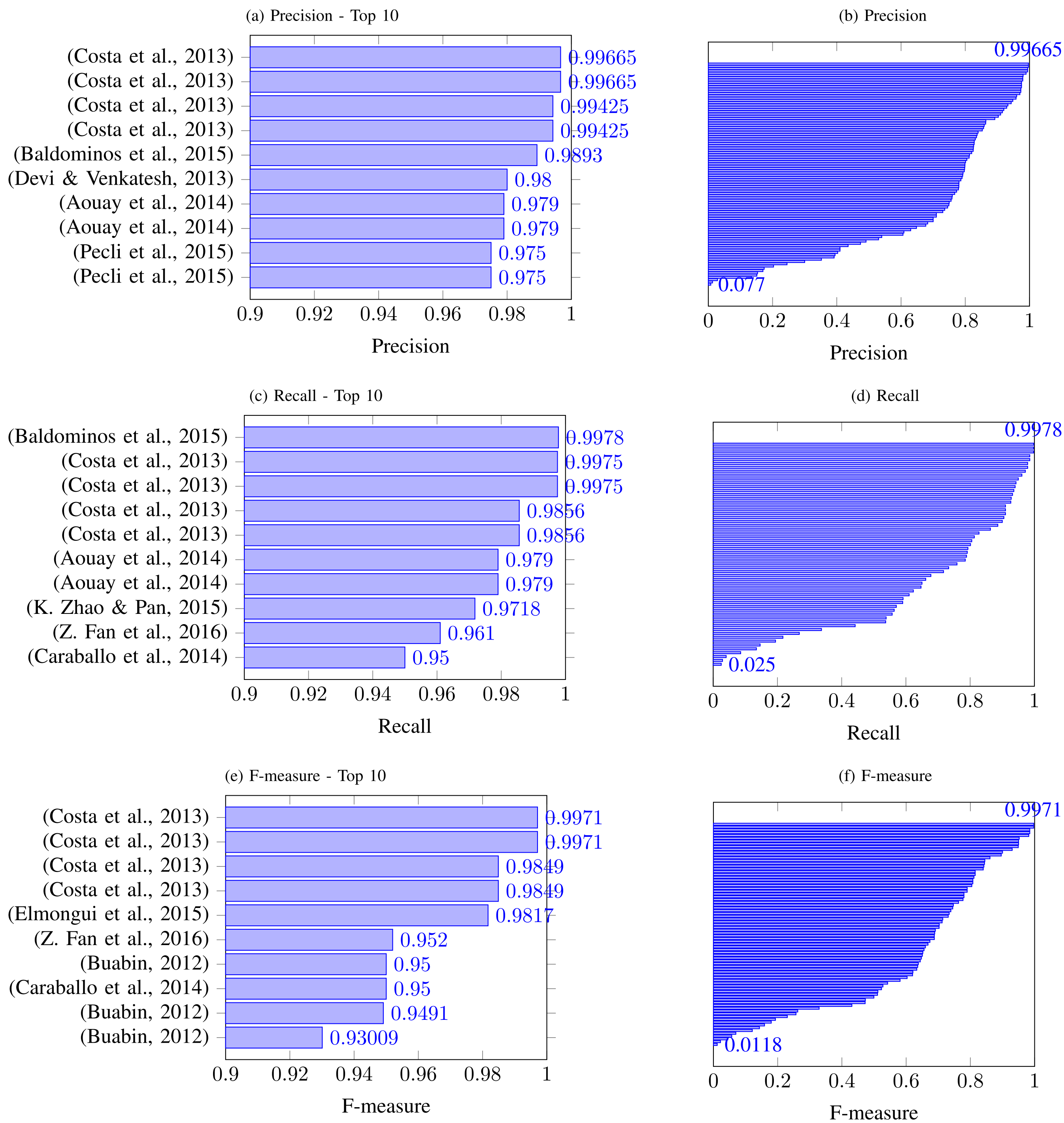

Fig. 4.3. A breakdown of the performance results for Precision, Recall, and F-measure.

relevant number of occurrences and for that reason, the two plots about this metric are very similar. The MAP plot about all studies was included for completeness.

On the plots for both the RMSE and the MAE metrics, few studies had an excellent result. In the RMSE case, most of the studies that reported this metric had a value greater than 0.8. Care should be taken since the greater the error the larger difference between what is expected and what is predicted. In the RMSE result, Dinuzzo et al. (2011) reported the value of 5.2, and in the MAE result, Bauer & Nanopoulos (2014) reported the value of 4.0234. Few studies reported MAP values, but the plots were included in this discussion because of the simplicity of the metric and the possible interest of researchers in the results.

Finally, Fig. 4.6 shows the breakdown of results for the metrics ROC (Receiver Operating Characteristic curve) (Figs. 4.6a and 4.6b) and AUC (Area Under the ROC Curve) (Figs. 4.6c and 4.6d). It should be noted that both metrics did not have a large number of occurrences in the studies analyzed in this systematic review, but they were included in this discussion owing to their academic importance.

It should be noticed that the study (Costa et al., 2013) also reported a high value of ROC for their algorithms. In terms of AUC,

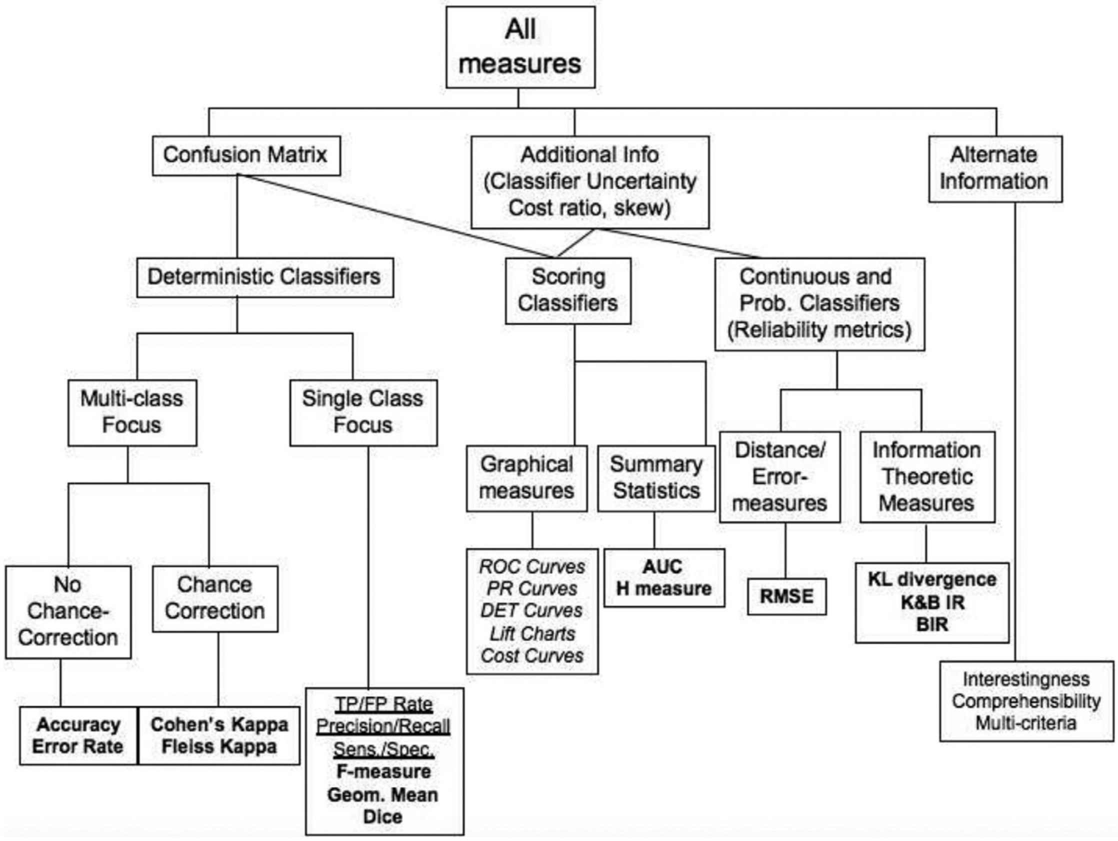

Fig. 4.2. An overview of performance metrics (from (Japkowicz & Shah , 2011)).

Table 4.8
Alternative performance metrics.

Metrics	Textual/ Numeric	Number of ML algorithms	Number of studies	Studies
User Preference	Textual	0	0	
	Numeric	7	6	(Bellogín et al., 2011; Ghazarian & Nematbakhsh, 2015; Li et al., 2008; Middleton et al., 2004; Wang et al., 2014; Yap et al., 2005)
Coverage	Textual	1	1	(Karahodza & Donko, 2015)
	Numeric	27	8	(Braida et al., 2015; Forsati & Meybodi, 2010; Forsati et al., 2009; Karahodza & Donko, 2015; Li & Zaïane, 2004; Middleton et al., 2004; Taghipour et al., 2007; Zahra et al., 2015)
Diversity	Textual	0	0	
	Numeric	1	1	(Geng et al., 2016)
Scalability	Textual	2	2	(Baldominos et al., 2015; Degemmis et al., 2007)
	Numeric	0	0	
Transparency	Textual	1	1	(Degemmis et al., 2007)
	Numeric	0	0	
Quality	Textual	0	0	
	Numeric	1	1	(Das Dôres et al., 2016)
Perplexity	Textual	0	0	
	Numeric	1	1	(Xin et al., 2014)
Sensitivity	Textual	0	0	
	Numeric	12	1	(Das et al., 2013)

most of the studies performed well and reported high values of AUC. Although not very popular, these two metrics can also be used by other researchers in their analysis to improve the findings or the amount of detail of their proposals.

4.6. Alternative performance metrics

This section presents alternative metrics that can also be used to describe the performance of ML algorithms in RS development. These metrics are well described in another study (Gunawardana & Shani, 2015) with examples and suggested ways of capturing data

Table 4.9
Secondary studies retrieved in this systematic review.

Reference	Secondary Study Name
(Bouza & Bernstein, 2014)	(Partial) user preference similarity as classification-based model similarity
(Lahlou, Mountassir, Benbrahim, & Kassou, 2013b)	A Text Classification based method for context extraction from online reviews
(Bertin-Mahieux, Eck, & Mandel, 2010)	Automatic tagging of audio: The state-of-the-art
(Carbone & Vlassov, 2015)	Auto-Scoring of Personalised News in the Real-Time Web: Challenges, Overview and Evaluation of the State-of-the-Art Solutions
(Lahlou, Benbrahimand, Mountassir, & Kassou, 2013a)	Context extraction from reviews for Context Aware Recommendation using Text Classification techniques
(Cremonesi, Garzotto, Negro, Papadopoulos, & Turrin, 2011)	Looking for “good” recommendations: A comparative evaluation of recommender systems
(Bagchi, 2015)	Performance and quality assessment of similarity measures in collaborative filtering using mahout
(Feuerverger, He, & Khatri, 2012)	Statistical significance of the netflix challenge
(Shani & Gunawardana, 2013)	Tutorial on application-oriented evaluation of recommendation systems
(Jannach, Lerche, Gedikli, & Bonnin, 2013)	What recommenders recommend - An analysis of accuracy, popularity, and sales diversity effects

Table 4.10
Secondary studies shared by domain experts.

Reference	Secondary Study Name
(Ning et al., 2015)	A comprehensive survey of neighborhood-based recommendation methods
(Elahi, Ricci, & Rubens, 2016)	A survey of active learning in collaborative filtering recommender systems
(Rubens, Elahi, Sugiyama, & Kaplan, 2015)	Active learning in recommender systems
(Koren & Bell, 2015)	Advances in collaborative filtering
(Sarwar, Karypis, Konstan, & Riedl, 2000)	Analysis of Recommendation Algorithms for E-Commerce
(Aggarwal, 2016a)	Content-Based Recommender Systems
(Breese, Heckerman, & Kadie, 1998)	Empirical analysis of predictive algorithms for collaborative filtering
(Karypis, 2001)	Evaluation of item-based top-N recommendation algorithms
(Deshpande & Karypis, 2004)	Item-based top-N recommendation algorithms
(Aggarwal, 2016b)	Model-Based Collaborative Filtering
(Aggarwal, 2016c)	Neighborhood-Based Collaborative Filtering
(Amatriain & Basilico, 2015)	Recommender systems in industry: A netflix case study

Table 4.11
Sources retrieved in this systematic review.

Source Name	Year
17th International Conference on Passive and Active Measurement, PAM 2016	2016
8th Asian Conference on Intelligent Information and Database Systems, ACIIDS 2016	2016
14th Mexican International Conference on Artificial Intelligence, MICAI 2015	2015
2014 International Conference on Sensors Instrument and Information Technology, ICSIIT 2014	2014
KDIR 2014 - Proceedings of the International Conference on Knowledge Discovery and Information Retrieval	2014
SIGIR 2014 - Proceedings of the 37th International ACM SIGIR Conference on Research and Development in Information Retrieval	2014
9th IFIP WG 12.5 International Conference on Artificial Intelligence Applications and Innovations, AIAI 2013	2013
2012 IEEE International Workshop on Machine Learning for Signal Processing - Proceedings of MLSP 2012	2012
3rd IFIP TC 12 International Conference on Artificial Intelligence, IFIP AI 2010 As part of 21st IFIP World Computer Congress, WCC 2010	2010
Proceedings - Artificial Intelligence Applications and Innovations - 6th IFIP WG 12.5 International Conference, AIAI 2010	2010
2009 2nd International Workshop on Managing Requirements Knowledge, MARK 2009	2009
Proceedings - 7TH. International Conference on Hybrid Intelligent Systems, HIS 2007	2007
16th Brazilian Symposium on Artificial Intelligence, SBIA 2002	2002
1st Asia-Pacific Conference on Web Intelligence: Research and Development, WI 2001	2001

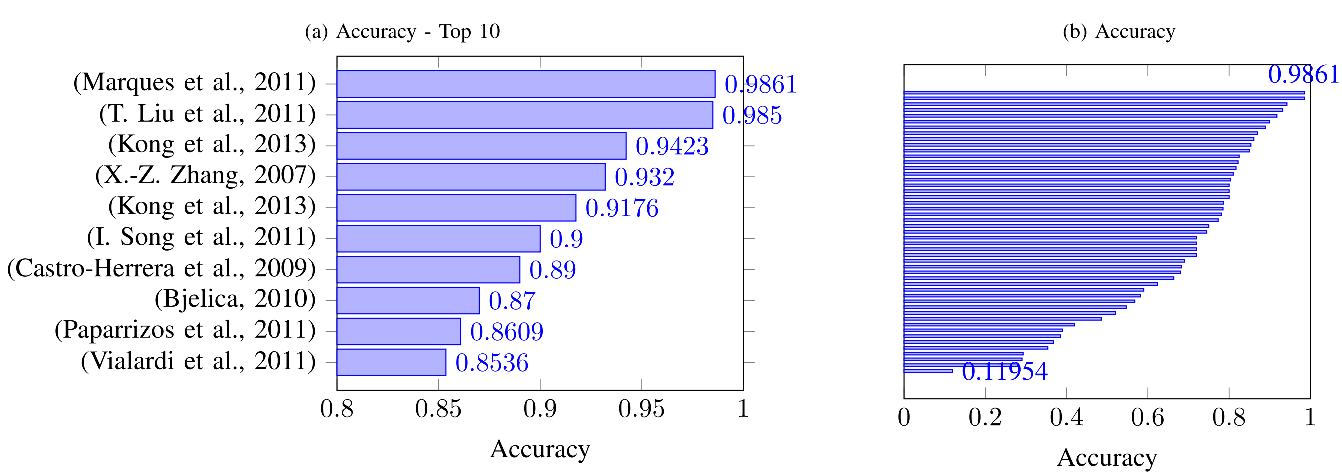

Fig. 4.4. A breakdown of the performance results for Accuracy.

Table 4.12
Sources of the primary studies of this systematic review.

Source Name	Number
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	14
Expert Systems with Applications	7
ACM International Conference Proceeding Series	3
CEUR Workshop Proceedings	3
Decision Support Systems	3
2007 International Conference on Machine Learning and Cybernetics	2
ACM Transactions on Information Systems	2
Communications in Computer and Information Science	2
IEICE Transactions on Information and Systems	2
Journal of Machine Learning Research	2
RecSys'08: Proceedings of the 2008 ACM Conference on Recommender Systems	2
User Modeling and User-Adapted Interaction	2
2008 2nd ACM/IEEE International Conference on Distributed Smart Cameras, ICDSC 2008	1
2008 International Conference on Machine Learning and Cybernetics	1
2010 2nd International Conference on Computer Engineering and Applications, ICCEA 2010	1
2010 Ninth International Conference on Machine Learning and Applications (ICMLA)	1
2011 International Conference on Machine Learning and Cybernetics (ICMLC)	1
2013 35th International Conference on Software Engineering (ICSE)	1
2014 17th International Conference on Computer and Information Technology, ICCIT 2014	1
2014 IEEE 13th International Conference on Trust, Security and Privacy in Computing and Communications	1
2014 IEEE Fourth International Conference on Big Data and Cloud Computing (BdCloud)	1
2015 2nd Asia-Pacific World Congress on Computer Science and Engineering, APWC on CSE 2015	1
2015 IEEE 25th International Workshop on Machine Learning for Signal Processing (MLSP)	1
31st International Conference on Machine Learning, ICML 2014	1
4th International Multi-Conference on Computing in the Global Information Technology, ICCGI 2009	1
ACM Transactions on Multimedia Computing Communications and Applications	1
ACM Transactions on the Web	1
AI Communications	1
Artificial Intelligence	1
CCIS 2014 - Proceedings of 2014 IEEE 3rd International Conference on Cloud Computing and Intelligence Systems	1
Chinese Journal of Electronics	1
Computational Linguistics and Intelligent Text Processing (CICLING 2015), PT II	1
Computers, Environment and Urban Systems	1
Electronic Markets	1
Future Generation Computer Systems	1
IEEE Access	1
IEEE AFRICON Conference	1
IEEE Transactions on Consumer Electronics	1
IEEE Transactions on Neural Networks	1
Information Sciences	1
INFORSID 2016 - Actes du 8e Forum Jeunes Chercheurs du Congres	1
Intelligent Techniques in Recommendation Systems: Contextual Advancements and New Methods	1
International Conference on Computational Intelligence and Software Engineering, 2009. CiSE 2009.	1
International Conference on Information Technology: Coding and Computing (ITCC'05) - Volume II	1
International Journal of Human Computer Studies	1
International Journal of Parallel Programming	1
International Journal on Artificial Intelligence Tools	1
Journal of Electronic Commerce Research	1
Journal of Intelligent Information Systems	1
KDIR 2012 - Proceedings of the International Conference on Knowledge Discovery and Information Retrieval	1
Knowledge and Information Systems	1
Lecture Notes in Computer Science	1
LWA 2011 - Technical Report of the Symposium "Lernen, Wissen, Adaptivitat - Learning, Knowledge, and Adaptivity2011" of the GI Special Interest Groups KDML, IR and WM	1
Neurocomputing	1
PACIS 2011 - 15th Pacific Asia Conference on Information Systems: Quality Research in Pacific	1
Personal and Ubiquitous Computing	1
Preference Learning	1
Proceedings - 13th IEEE International Conference on Commerce and Enterprise Computing, CEC 2011	1
Proceedings - 2014 IIAI 3rd International Conference on Advanced Applied Informatics, IIAI-AAI 2014	1
Proceedings - 2015 25th International Conference on Information, Communication and Automation Technologies, ICAT 2015	1
Proceedings - 2015 IEEE Symposium Series on Computational Intelligence, SSCI 2015	1
Proceedings - ICEIS 2015 - 17th International Conference on Enterprise Information Systems	1
Proceedings - IEEE International Conference on Data Mining, ICDM	1
Proceedings - IEEE SSCI 2014 - 2014 IEEE Symposium Series on Computational Intelligence - CIBD 2014: 2014 IEEE Symposium on Computational Intelligence in Big Data	1
Proceedings - MIPRO 2011 - 34th International Convention on Information and Communication Technology, Electronics and Microelectronics	1
Proceedings - Sixth International Conference on Mobile Data Management, MDM'05	1
Proceedings - SocialCom 2010: 2nd IEEE International Conference on Social Computing	1
Proceedings of IEEE/ACS International Conference on Computer Systems and Applications, AICCSA	1
Proceedings of Sheffield SIGIR - Twenty-Seventh Annual International ACM SIGIR Conference on Research and Development in Information Retrieval	1

(*continued on next page*)

Table 4.12 (*continued*)

Source Name	Number
Proceedings of the 11th SIAM International Conference on Data Mining, SDM 2011	1
Proceedings of the 12th International Society for Music Information Retrieval Conference, ISMIR 2011	1
Proceedings of the 2013 10th International Joint Conference on Computer Science and Software Engineering, JCSSE 2013	1
Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2013	1
Proceedings of the ACM Symposium on Applied Computing	1
Proceedings of the IEEE International Conference on Computer Vision	1
Proceedings of the IEEE International Conference on Requirements Engineering	1
Proceedings of the International Joint Conference on Neural Networks	1
Proceedings of the ISCA 27th International Conference on Computers and Their Applications, CATA 2012	1
RecSys 2014 - Proceedings of the 8th ACM Conference on Recommender Systems	1
RecSys 2015 - Proceedings of the 9th ACM Conference on Recommender Systems	1
RecSys'07: Proceedings of the 2007 ACM Conference on Recommender Systems	1
RecSys'09 - Proceedings of the 3rd ACM Conference on Recommender Systems	1
RecSys'11 - Proceedings of the 5th ACM Conference on Recommender Systems	1
Scientific World Journal	1
SIGIR Forum (ACM Special Interest Group on Information Retrieval)	1
Social Network Analysis and Mining	1
Studies in Computational Intelligence	1
WWW 2015 Companion - Proceedings of the 24th International Conference on World Wide Web	1

and calculating results. The eight metrics are user preference, coverage, confidence, trust, novelty, serendipity, diversity, utility, risk, robustness, privacy, and scalability. Some of them are discussed in the next few paragraphs.

User preference, as its name suggests, relates to the opinion of the user about the recommendations made by the RS. Users are more likely to choose approaches that predict items that match their preferences. Although the description is easy, gathering user data to achieve high user preference is not. The main method to obtain data about user preference is the use of questionnaires. The coverage metric relates to the items that can be recommended to the users that can receive recommendations. There are specific ways to calculate the coverage and one should refer to (Gunawardana & Shani, 2015) for more details.

Two additional alternative metrics are diversity and scalability. To discuss diversity, one must understand similarity, since these two concepts are antagonistic. If the results are not similar, then that means they are diverse. Lastly, scalability does not mean much to the user, but important both to researchh and performance. Scalability relates to how well-prepared the algorithms is to handle growth in the amount of data. Most of the time, algorithms need more memory or computation power to manipulate large amounts of data.

Table 4.8 shows the number of algorithms that included a discussion on alternative metrics in its description. The difference between the "Textual" and "Numeric" entries in the table is because that discussion can be in the written form, with considerations or suppositions, or it can be based on a formula. The last column shows the studies that discussed the algorithms. The difference between the number of algorithms presented in the third column, and the number of studies of the fourth column exists because a study may propose more than one algorithm.

In addition, Table 4.8 displays four new alternative metrics: transparency, quality, perplexity, and sensitivity. The papers that reported values for those metrics do not provide a formal definition. For that reason, they were presented in this systematic review, but not explained. One final note is that the perplexity metric is the closest one to another metric defined in (Gunawardana & Shani, 2015): serendipity, which describes how surprising the successful recommendations are.

Many studies have a numeric discussion of coverage with formulas to describe their values. By inspecting these studies, the authors noticed that they use specific formulas and no standard is defined. The same happened to the sensitivity metric. This table describes many alternative performance metrics used to evaluate ML algorithms in RS development and introduces these metrics to those that did not know them.

Other metrics described in (Gunawardana & Shani, 2015) did not have any occurrence in the studies of this systematic review and therefore were not included in the results table.

4.7. Analysis of the sources

This section describes a different perspective on the analysis of the primary studies, and helps researchers find more information about ML algorithms for RS development. The discussion focuses on other surveys and sources (e.g. conferences, journals) related to this systematic review.

This systematic review adopted an exclusion criteria that limited the papers included in our study to primary studies. This means that secondary studies such as other literature reviews were not analyzed. However, these secondary studies hold valuable knowledge that improves the research on the field and may be beneficial to other researchers. For that reason, Table 4.9 presents the secondary studies that were excluded from this systematic review.

These secondary studies were not assessed for quality, but they were returned by the search string of this systematic review and are expected to cover the main research fields of interest, such as recommender systems and machine learning algorithms. The full reference to each secondary study is found at the end of this study.

Moreover, domain experts that contributed to this work shared other secondary studies that also relate to at least one of the research fields of this systematic review. They are different from those presented on Table 4.9 and may be also beneficial to researchers in the field. Secondary studies suggested by domain experts were not included in the analysis of this systematic review because of the exclusion criteria previously explained. The studies are shown in Table 4.10.

The search string used in this systematic review also returned conference and journal entries. Since these entries are not peer-reviewed, they were not inspected based on the exclusion criteria. However, researchers may find it beneficial to know the conferences or journals that are reporting on the research fields of recommender systems and machine learning algorithms. Table 4.11 lists the sources (e.g. conferences, journals) returned by

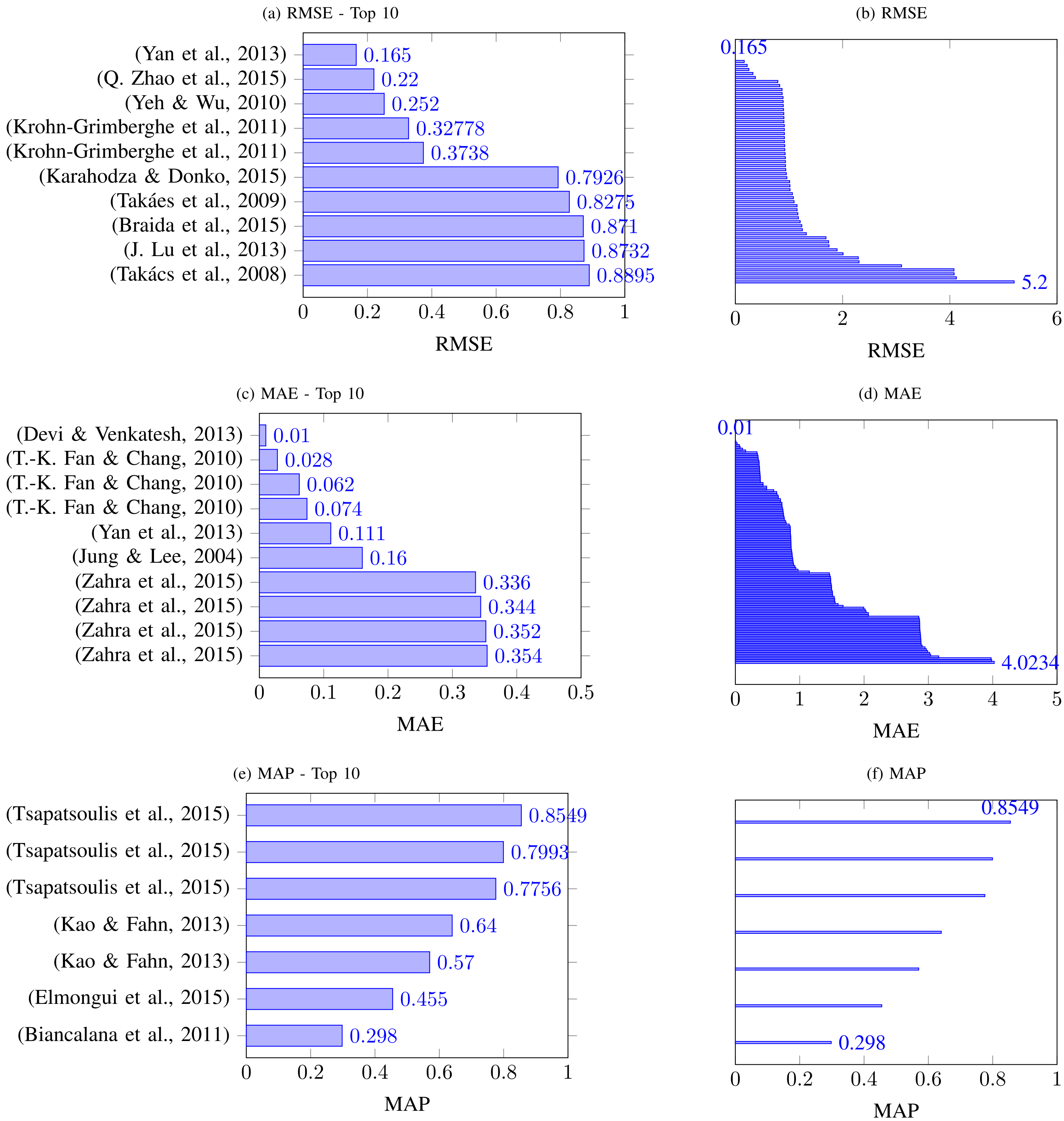

Fig. 4.5. A breakdown of the performance results for RMSE, MAE, and MAP.

the search string of this systematic review with the year in which they were held. The list is sorted by year.

Finally, the authors decided to list the sources of the primary studies inspected in this review and rank them by the number of studies found in each source. Popular sources may contain papers with similar interests to the research fields of this systematic review and indicate possible places to submit publications. Table 4.12 present the sources of the primary studies with the number of studies retrieved from each source. In the table, two of the sources show up as important sources of RS and ML algorithms: “Lecture Notes in Computer Science” and “Expert Systems with Applications”.

5. Conclusions and future work

Currently, recommender systems (RS) are widely used in e-commerce, social networks, and several other domains. Since the introduction of RSs in mid 1990s, research in RSs has been evolving. One progressive step in RS history is the adoption of machine learning (ML) algorithms, which allow computers to learn based on user information and to personalize recommendations further. Machine learning is an Artificial Intelligence (AI) research field that encompasses algorithms whose goal is to predict the outcome of data processing. ML has made major breakthroughs in the fields of image recognition, search engines, and security. However, the ML

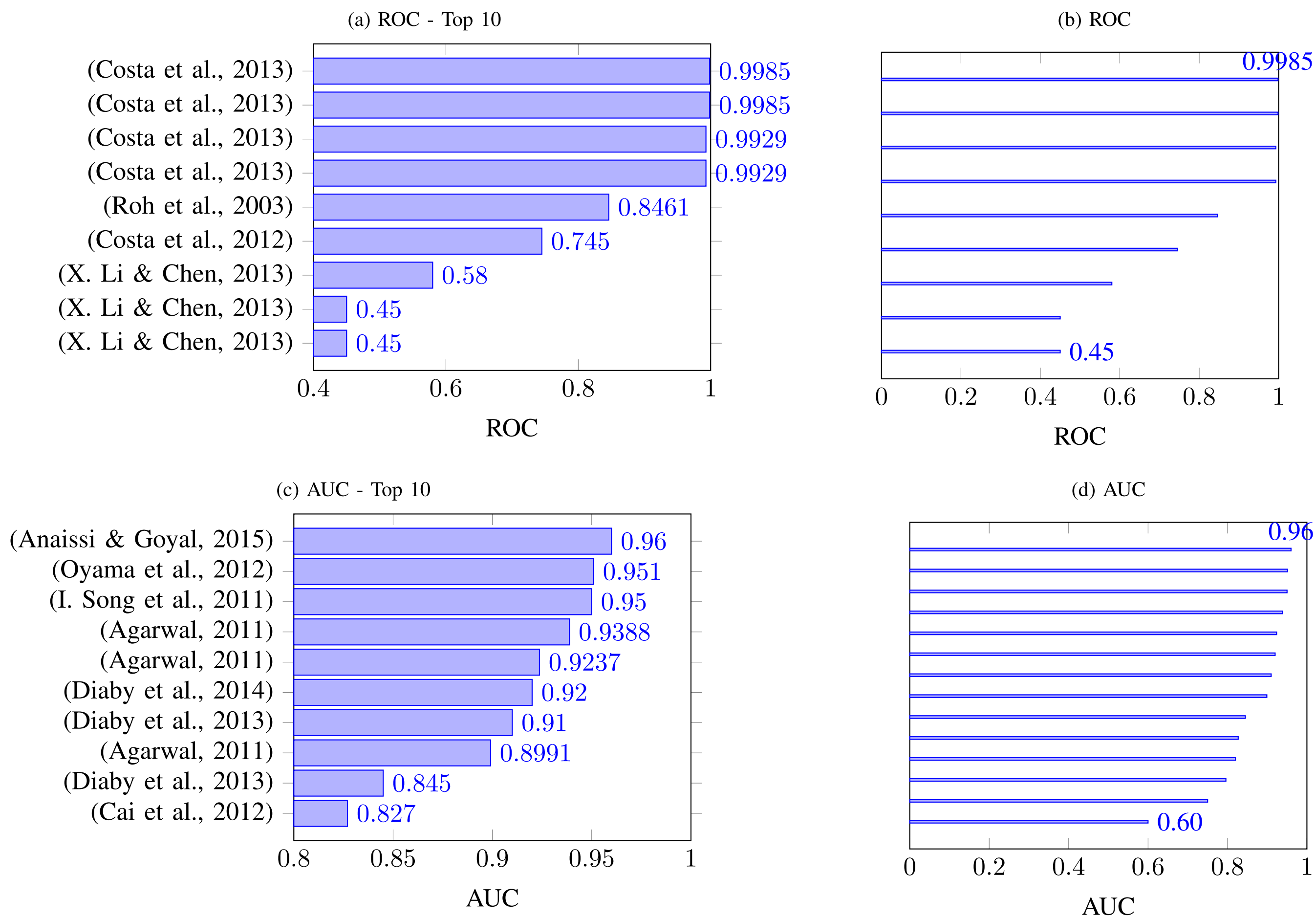

Fig. 4.6. A breakdown of the performance results for ROC and AUC.

field has several algorithms described in the literature, with varied characteristics. The literature lacks a classification system for algorithms showing the environment in which they are most suitable. Therefore, researchers in RSs do not have a clear view of the trends in ML algorithm usage to decide on where to focus their research efforts. This study then proposes a systematic review to observe the ML algorithms that are used in RSs as well as the trends and open questions in this research field.

The systematic review collected 121 primary studies, after filtering out some based on exclusion criteria. All publications were read and the conclusions are as follows. There is a trend for collaborative approaches in RS development, especially with the use of neighborhood-based methods. Hybrid approaches are still a research opportunity. A timeline with the number of primary studies published in recent years confirms the trends and the opportunities mentioned.

Regarding the ML algorithms, both supervised and unsupervised learning are being well researched. Clustering algorithms, as well Ensemble, and Support Vector Machines (SVM) are among the ones most used. One may note again the presence of neighborhood-based approaches among the ML algorithms. The focus on Big Data technologies still remains a research opportunity, with few studies even mentioning massive data storage and analysis. The application domain of movies ranks as first among others mainly because of MovieLens, a simple dataset available online. Finally, MAE, Precision, Recall, and F-measure are the most used performance metrics to evaluate ML algorithms in RS development, and Coverage is the most used alternative metric.

This systematic review has also included an analysis of the sources of the primary studies that were selected. The analysis presents surveys of the literature as well as conferences and journals that may be of interest to researchers working on similar topics.

This study has several contributions to research in expert and intelligent systems. It presents a comprehensive overview of ML algorithms in RSs that assists application developers by helping them to identify the algorithms, their types, and trends in the use of specific algorithms. This study also provides existing classes of evaluation metrics and ranks the ML algorithms based on these metrics. From this result, researchers and practitioners are able not only to be familiar with the most used evaluation metrics, but also to investigate further the approaches that have the high rankings. In addition, this study identifies and presents trends in the use of ML algorithms for RSs in different application domains. For example, researchers and practitioners can become aware of the algorithms that have been applied in a specific domain (e.g. movie, news, e-commerce). Lastly, sources of primary and secondary studies are provided. These sources can help researchers and developers to position new research activity in this domain appropriately.

In the future, more studies on the use of Clustering, Ensemble, and SVM algorithms in RSs can be developed to observe the implications of their use, performance, and utility. Moreover, RS development lacks studies analyzing early stages, such as requirements and design, and late stages, such as maintenance. Other research opportunities involve the investigation of Big Data technologies, which offer a wide variety of methods to support the storage and analysis of massive data. The authors also believe that many other open questions involving research topics related to RSs and ML algorithms should be investigated, including the application of collaborative approaches in social networks and spatial-temporal domains.

Acknowledgment

The authors would like to thank the reviewers for their valuable comments, which helped to improve our systematic review. The authors also thank the Natural Sciences and Engineering Research Council of Canada (NSERC), and the Ontario Research Fund of the Ontario Ministry of Research, Innovation, and Science for their financial support for this research.

Appendix A

Table A1
The list of the studies inspected in this systematic review.

Reference	Title
(Agarwal, 2011)	The infinite push: A new support vector ranking algorithm that directly optimizes accuracy at the absolute top of the list
(Alemeye & Getahun, 2015)	Cloud readiness assessment framework and recommendation system
(Anaissi & Goyal, 2015)	SVM-based association rules for knowledge discovery and classification
(Aouay et al., 2014)	Feature based link prediction
(Baldominos et al., 2015)	A scalable machine learning online service for big data real-time analysis
(Banerjee et al., 2012)	Experiments on synopsis-based TV program recommendation
(Bar et al., 2013)	Improving simple collaborative filtering models using ensemble methods
(Bauer & Nanopoulos, 2014)	Recommender systems based on quantitative implicit customer feedback
(Bellogín et al., 2011)	Discerning relevant model features in a content-based collaborative recommender system
(Biancalana et al., 2011)	Context-aware movie recommendation based on signal processing and machine learning
(Bjelica, 2010)	Towards TV recommender system: Experiments with user modeling
(Bouneffouf et al., 2012)	Exploration / exploitation trade-off in mobile context-aware recommender systems
(Braida et al., 2015)	Transforming collaborative filtering into supervised learning
(Brouard & Pomot, 2016)	SpecificSearch : Un outil de recommandation automatique pour la veille d'information sur le web
(Buabin, 2012)	Hybrid neural architecture for intelligent recommender system classification unit design
(Buettner, 2016)	Predicting user behavior in electronic markets based on personality-mining in large online social networks: A personality-based product recommender framework
(Cai et al., 2010)	Learning collaborative filtering and its application to people to people recommendation in social networks
(Cai et al., 2012)	Reciprocal and heterogeneous link prediction in social networks
(Caraballo et al., 2014)	TRTML - A tripleset recommendation tool based on supervised learning algorithms
(Castro-Herrera et al., 2009)	Enhancing stakeholder profiles to improve recommendations in online requirements elicitation
(Costa et al., 2012)	Context and intention-awareness in POIs recommender systems
(Costa et al., 2013)	Recommending POIs based on the user's context and intentions
(Das Dôres et al., 2016)	A meta-learning framework for algorithm recommendation in software fault prediction
(Das et al., 2013)	End-user feature labeling: Supervised and semi-supervised approaches based on locally-weighted logistic regression
(De Gemmis et al., 2008)	Integrating tags in a semantic content-based recommender
(Degemmis et al., 2007)	A content-collaborative recommender that exploits WordNet-based user profiles for neighborhood formation
(Devi & Venkatesh, 2013)	Smoothing approach to alleviate the meager rating problem in collaborative recommender systems
(Diaby et al., 2014)	Exploration of methodologies to improve job recommender systems on social networks
(Diaby et al., 2013)	Toward the next generation of recruitment tools: An online social network-based job recommender system
(Dinuzzo et al., 2011)	Client-Server multitask learning from distributed datasets
(Elmongui et al., 2015)	TRUPI: Twitter recommendation based on users' personal interests
(Fan & Chang, 2010)	Learning to predict ad clicks based on boosted collaborative filtering
(Fan et al., 2016)	A Text Clustering Approach of Chinese News Based on Neural Network Language Model
(Forsati & Meybodi, 2010)	Effective page recommendation algorithms based on distributed learning automata and weighted association rules
(Forsati et al., 2009)	Effective page recommendation algorithms based on distributed learning automata
(Gedikli et al., 2011)	RF-REC: Fast and accurate computation of recommendations based on rating frequencies
(Geng et al., 2016)	Learning image and user features for recommendation in social networks
(Ghazarian & Nematbakhsh, 2015)	Enhancing memory-based collaborative filtering for group recommender systems
(Haiduc et al., 2013)	Automatic query reformulations for text retrieval in software engineering
(Halder et al., 2014)	An entertainment recommendation system using the dynamics of user behavior over time
(Hassan et al., 2010)	Self-optimizing a clustering-based tag recommender for social bookmarking systems
(Hofmann, 2003)	Collaborative Filtering via Gaussian Probabilistic Latent Semantic Analysis
(Hofmann, 2004)	Latent semantic models for collaborative filtering
(Huang & Nikulin, 2014)	Two algorithms under stochastic gradient descent framework for recommender systems
(Hussain et al., 2015)	A novel ontology and machine learning inspired hybrid cardiovascular decision support framework
(Islam et al., 2015)	Personalized recommender system on whom to follow in twitter
(Jin et al., 2005)	A Web recommendation system based on maximum entropy
(Jun, 2005)	Web usage mining using support vector machine
(Jung & Lee, 2004)	User preference mining through hybrid collaborative filtering and content-based filtering in recommendation system
(Kao & Fahn, 2013)	A multi-stage learning framework for intelligent system
(Karahodza & Donko, 2015)	Feature enhanced time-aware recommender system
(Kong et al., 2013)	Minimal shrinkage for noisy data recovery using Schatten-p norm objective
(Krohn-Grimberghe et al., 2011)	Active learning for technology enhanced learning
(Krzywicki et al., 2015)	Collaborative filtering for people-to-people recommendation in online dating: Data analysis and user trial
(Lee & Lu, 2003)	Customising WAP-based information services on mobile networks
(Lee & Tseng, 2012)	Easy-to-explain feature synthesis approach for recommending entertainment video
(Leopairote et al., 2013)	Evaluating software quality in use using user reviews mining

(continued on next page)

Table A1 (*continued*)

Reference	Title
(Li & Chen, 2013)	Recommendation as link prediction in bipartite graphs: A graph kernel-based machine learning approach
(Li & Zaïane, 2004)	Combining usage, content, and structure data to improve web site recommendation
(Li et al., 2008)	Research of information recommendation system based on reading behavior
(Li et al., 2014)	A multi-theoretical kernel-based approach to social network-based recommendation
(Liang et al., 2014)	Difference factor' KNN collaborative filtering recommendation algorithm
(Liu et al., 2011)	Lawyer information integration and recommendation by multi-source information validation
(Liu et al., 2014b)	Catlinks - A category clustering algorithm based on multi-class regression
(Liu et al., 2014a)	Combining user-based and item-based models for collaborative filtering using stacked regression
(Lops et al., 2009)	A semantic content-based recommender system integrating folksonomies for personalized access
(Lu et al., 2013)	Second order online collaborative filtering
(Lu et al., 2015)	Leveraging semantic web technologies for more relevant e-tourism behavioral retargeting
(Luong et al., 2012b)	Exploiting social networks for publication venue recommendations
(Luong et al., 2012a)	Publication venue recommendation using author network's publication history
(Marović et al., 2011)	Automatic movie ratings prediction using machine learning
(Marques et al., 2011)	New trends in musical genre classification using optimum-path forest
(McLaughlin & Herlocker, 2004)	A collaborative filtering algorithm and evaluation metric that accurately model the user experience
(Middleton et al., 2004)	Ontological user profiling in recommender systems
(Montañés et al., 2009)	Collaborative tag recommendation system based on logistic regression
(Moreno et al., 2012)	TALMUD: Transfer learning for multiple domains
(Murfi & Obermayer, 2009)	A two-level learning hierarchy of concept based keyword extraction for tag recommendations
(Musto et al., 2010)	Integrating a content-based recommender system into digital libraries for cultural heritage
(Musto et al., 2010)	Integrating a content-based recommender system into digital libraries for cultural heritage
(Nguyen et al., 2016)	RedTweet: recommendation engine for reddit
(Nicol et al., 2014)	Improving offline evaluation of contextual bandit algorithms via bootstrapping techniques
(Nie et al., 2013)	Joint Schatten lp-norm robust matrix completion for missing value recovery
(Hernández del Olmo et al., 2009)	The task of guiding in adaptive recommender systems
(Oyama et al., 2012)	Link prediction across time via cross-temporal locality preserving projections
(Pantraki & Kotropoulos, 2015)	Automatic image tagging and recommendation via PARAFAC2
(Paparrizos et al., 2011)	Machine learned job recommendation
(Pecli et al., 2015)	Dimensionality reduction for supervised learning in link prediction problems
(Pessiot et al., 2007)	Learning to rank for collaborative filtering
(Pronoza et al., 2016)	Aspect-based restaurant information extraction for the recommendation system
(Roh et al., 2003)	The collaborative filtering recommendation based on SOM cluster-indexing CBR
(Song et al., 2011a)	A health social network recommender system
(Song et al., 2011b)	Automatic tag recommendation algorithms for social recommender systems
(Sun et al., 2015)	Road-based travel recommendation using geo-tagged images
(Szabó et al., 2012)	Collaborative filtering via group-structured dictionary learning
(Szymański & Rzeniewicz, 2016)	Identification of category associations using a multilabel classifier
(Taghipour et al., 2007)	Usage-based web recommendations: A reinforcement learning approach
(Takács et al., 2008)	Matrix factorization and neighbor based algorithms for the netflix prize problem
(Takáes et al., 2009)	Scalable collaborative filtering approaches for large reeommender systems
(Tsapatsoulis et al., 2015)	On the design of social voting recommendation applications
(Tsuji et al., 2014)	Book recommendation using machine learning methods based on library loan records and bibliographic information
(Verma et al., 2016)	Improving Scalability of Personalized Recommendation Systems for Enterprise Knowledge Workers
(Vialardi et al., 2011)	A data mining approach to guide students through the enrollment process based on academic performance
(Wan et al., 2009)	Discovering social network to improve recommender system for group learning support
(Wang et al., 2014)	Exploration in interactive personalized music recommendation: A reinforcement learning approach
(Wang et al., 2012)	Learning to recommend based on slope one strategy
(Wei et al., 2011)	Estimating trust strength for supporting effective recommendation services
(Xin et al., 2014)	Constructing topic models of internet of things for information processing
(Xuan et al., 2014)	Extension of similarity measures in VSM: From orthogonal coordinate system to affine coordinate system
(Yan et al., 2013)	Enhancing trustworthiness evaluation in internetware with similarity and non-negative constraints
(Yap et al., 2005)	Dynamically-optimized context in recommender systems
(Yeh & Wu, 2010)	Recommendation based on latent topics and social network analysis
(Yuan et al., 2014)	Exploiting sentiment homophily for link prediction
(Zahra et al., 2015)	Novel centroid selection approaches for KMeans-clustering based recommender systems
(Zhai & Li, 2015)	Refine social relations and differentiate the same friends' influence in recommender system
(Zhang, 2007)	Building personalized recommendation system in E-Commerce using association rule-based mining and classification
(Zhang & Tran, 2010)	Helpful or Unhelpful: A Linear Approach for Ranking Product Reviews
(Zhang et al., 2009)	Applying probabilistic latent semantic analysis to multi-criteria recommender system
(Zhang et al., 2008)	Real-time clothes comparison based on multi-view vision
(Zhang et al., 2007)	An online Bayesian networks model for E-commercial personalized recommendation system
(Zhao & Pan, 2015)	A machine learning based trust evaluation framework for online social networks
(Zhao et al., 2015)	E-commerce recommendation with personalized promotion

References

Adomavicius, G., Mobasher, B., Ricci, F., & Tuzhilin, A. (2011). Context-aware recommender systems. *AI Magazine, 32*(3), 67–80.

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering, 17*(6), 734–749. doi:10.1109/TKDE.2005.99.

Agarwal, S. (2011). *The infinite push: A new support vector ranking algorithm that directly optimizes accuracy at the absolute top of the list* (pp. 839–850).

Aggarwal, C. C. (2016a). Content-based recommender systems. In *Recommender Systems: The Textbook* (pp. 139–166). Cham: Springer International Publishing. doi:10.1007/978-3-319-29659-3_4.

Aggarwal, C. C. (2016b). Model-based collaborative filtering. In *Recommender Systems: The Textbook* (pp. 71–138)). Cham: Springer International Publishing. doi:10.1007/978-3-319-29659-3_3.

Aggarwal, C. C. (2016c). Neighborhood-based collaborative filtering. In *Recommender Systems: The Textbook* (pp. 29–70)). Cham: Springer International Publishing. doi: 10.1007/978-3-319-29659-3_2.

Ahmed, A., Kanagal, B., Pandey, S., Josifovski, V., Pueyo, L., & Yuan, J. (2013). *Latent factor models with additive and hierarchically-smoothed user preferences* (pp. 385–394). doi:10.1145/2433396.2433445.

Alemeye, F., & Getahun, F. (2015). *Cloud readiness assessment framework and recommendation system*: 2015-November. doi:10.1109/AFRCON.2015.7331995.

Amatriain, X., & Basilico, J. (2015). *Recommender systems in industry: A netflix case study*. Springer US. doi:10.1007/978-1-4899-7637-11.

Anaissi, A., & Goyal, M. (2015). *Svm-based association rules for knowledge discovery and classification*. doi:10.1109/APWCCSE.2015.7476236.

Aouay, S., Jamoussi, S., & Gargouri, F. (2014). *Feature based link prediction: 2014* (pp. 523–527). doi:10.1109/AICCSA.2014.7073243.

Apte, C. (2010). *The role of machine learning in business optimization* (pp. 1–2).

Bagchi, S. (2015). *Performance and quality assessment of similarity measures in collaborative filtering using mahout: 50* (pp. 229–234). doi:10.1016/j.procs.2015.04.055.

Baldominos, A., Albacete, E., Saez, Y., & Isasi, P. (2015). *A scalable machine learning online service for big data real-time analysis*. doi:10.1109/CIBD.2014.7011537.

Banerjee, S., Bhowmick, P., Mukherjee, D., & Misra, P. (2012). *Experiments on synopsis-based tv program recommendation* (pp. 258–263).

Bar, A., Rokach, L., Shani, G., Shapira, B., & Schclar, A. (2013). Improving simple collaborative filtering models using ensemble methods. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7872 LNCS*, 1–12. doi:10.1007/978-3-642-38067-9_1.

Bauer, J., & Nanopoulos, A. (2014). Recommender systems based on quantitative implicit customer feedback. *Decision Support Systems, 68*, 77–88. doi:10.1016/j.dss.2014.09.005.

Bellogín, A., Cantador, I., Castells, P., & Ortigosa, A. (2011). *Discerning relevant model features in a content-based collaborative recommender system*. doi:10.1007/978-3-642-14125-6_20.

Bertin-Mahieux, T., Eck, D., & Mandel, M. (2010). *Automatic tagging of audio: The state-of-the-art*. doi:10.4018/978-1-61520-919-4.ch014.

Biancalana, C., Gasparetti, F., Micarelli, A., Miola, A., & Sansonetti, G. (2011). *Context-aware movie recommendation based on signal processing and machine learning* (pp. 5–10). doi:10.1145/2096112.2096114.

Bjelica, M. (2010). Towards tv recommender system: Experiments with user modeling. *IEEE Transactions on Consumer Electronics, 56*(3), 1763–1769. doi:10.1109/TCE.2010.5606323.

Bouneffouf, D., Bouzeghoub, A., & Gançarski, A. (2012). Exploration / exploitation trade-off in mobile context-aware recommender systems. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7691 LNAI*, 591–601. doi:10.1007/978-3-642-35101-3_50.

Bouneffouf, D., Bouzeghoub, A., & Gancarski, A. (2013). Risk-aware recommender systems. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8226 LNCS*(PART 1), 57–65. doi:10.1007/978-3-642-42054-2_8.

Bouza, A., & Bernstein, A. (2014). (Partial) user preference similarity as classification-based model similarity. *Semantic Web, 5*(1), 47–64. doi:10.3233/SW-130099.

Braida, F., Mello, C., Pasinato, M., & Zimbrão, G. (2015). Transforming collaborative filtering into supervised learning. *Expert Systems with Applications, 42*(10), 4733–4742. doi:10.1016/j.eswa.2015.01.023.

Breese, J. S., Heckerman, D., & Kadie, C. (1998). Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of the fourteenth conference on uncertainty in artificial intelligence*. In *UAI'98* (pp. 43–52). San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.

Brouard, C., & Pomot, C. (2016). *Specificsearch : Un outil de recommandation automatique pour la veille d'information sur le web* (pp. 101–116).

Buabin, E. (2012). *Hybrid neural architecture for intelligent recommender system classification unit design*. doi:10.4018/978-1-4666-2542-6.ch010.

Buettner, R. (2016). Predicting user behavior in electronic markets based on personality-mining in large online social networks: A personality-based product recommender framework. *Electronic Markets*, 1–19. doi:10.1007/s12525-016-0228-z.

Burhans, D., & Kandefer, M. (2004). *Dustbot: Bringing a vacuum-cleaner agent to life: 1* (pp. 82–84).

Cai, X., Bain, M., Krzywicki, A., Wobcke, W., Kim, Y., Compton, P., & Mahidadia, A. (2010). *Learning collaborative filtering and its application to people to people recommendation in social networks* (pp. 743–748). doi:10.1109/ICDM.2010.159.

Cai, X., Bain, M., Krzywicki, A., Wobcke, W., Kim, Y., Compton, P., & Mahidadia, A. (2012). Reciprocal and heterogeneous link prediction in social networks. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7301 LNAI*(PART 2), 193–204. doi:10.1007/978-3-642-30220-6_17.

Caraballo, A., Arruda, J., N. M., Nunes, B., Lopes, G., & Casanova, M. (2014). Trtml - a tripleset recommendation tool based on supervised learning algorithms. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8798*, 413–417. doi:10.1007/978-3-319-11955-7_58.

Carbone, P., & Vlassov, V. (2015). *Auto-scoring of personalised news in the real-time web: Challenges, overview and evaluation of the state-of-the-art solutions* (pp. 169–180). doi:10.1109/ICCAC.2015.9.

Castro-Herrera, C., Cleland-Huang, J., & Mobasher, B. (2009). *Enhancing stakeholder profiles to improve recommendations in online requirements elicitation* (pp. 37–46). doi:10.1109/RE.2009.20.

Celebi, M., & Aydin, K. (2016). *Unsupervised learning algorithms*. doi:10.1007/978-3-319-24211-8.

Chapelle, O., Schölkopf, B., & Zien, A. (2006). *Semi-Supervised learning* (1st). The MIT Press.

Chen, L.-S., Hsu, F.-H., Chen, M.-C., & Hsu, Y.-C. (2008). Developing recommender systems with the consideration of product profitability for sellers. *Information Sciences, 178*(4), 1032–1048. doi:10.1016/j.ins.2007.09.027.

Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile Networks and Applications, 19*(2), 171–209. doi:10.1007/s11036-013-0489-0.

Costa, H., Furtado, B., Pires, D., Macedo, L., & Cardoso, A. (2012). Context and intention-awareness in pois recommender systems.(vol. 889).

Costa, H., Furtado, B., Pires, D., Macedo, L., & Cardoso, A. (2013). Recommending pois based on the user's context and intentions. *Communications in Computer and Information Science, 365*, 166–177. doi:10.1007/978-3-642-38061-7_17.

Cremonesi, P., Garzotto, F., Negro, S., Papadopoulos, A., & Turrin, R. (2011). Looking for "good" recommendations: A comparative evaluation of recommender systems. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 6948 LNCS*(PART 3), 152–168. doi:10.1007/978-3-642-23765-2_11.

Cui, Q., Bai, F.-S., Gao, B., & Liu, T.-Y. (2015). Global optimization for advertisement selection in sponsored search. *Journal of Computer Science and Technology, 30*(2), 295–310. doi:10.1007/s11390-015-1523-4.

Das, S., Moore, T., Wong, W.-K., Stumpf, S., Oberst, I., McIntosh, K., & Burnett, M. (2013). End-user feature labeling: Supervised and semi-supervised approaches based on locally-weighted logistic regression. *Artificial Intelligence, 204*, 56–74. doi:10.1016/j.artint.2013.08.003.

Das Dôres, S., Alves, L., Ruiz, D., & Barros, R. (2016). *A meta-learning framework for algorithm recommendation in software fault prediction: 04-08-April-2016* (pp. 1486–1491). doi:10.1145/2851613.2851788.

De Gemmis, M., Lops, P., Semeraro, G., & Basile, P. (2008). *Integrating tags in a semantic content-based recommender* (pp. 163–170). doi:10.1145/1454008.1454036.

Dean, J., & Ghemawat, S. (2008). Mapreduce: Simplified data processing on large clusters. *Communications of the ACM, 51*(1), 107–113. doi:10.1145/1327452.1327492.

Degemmis, M., Lops, P., & Semeraro, G. (2007). A content-collaborative recommender that exploits wordnet-based user profiles for neighborhood formation. *User Modeling and User-Adapted Interaction, 17*(3), 217–255. doi:10.1007/s11257-006-9023-4.

Deshpande, M., & Karypis, G. (2004). Item-based top-n recommendation algorithms. *ACM Transactions on Information Systems, 22*(1), 143–177. doi:10.1145/963770.963776.

Devi, M., & Venkatesh, P. (2013). Smoothing approach to alleviate the meager rating problem in collaborative recommender systems. *Future Generation Computer Systems, 29*(1), 262–270. doi:10.1016/j.future.2011.05.011.

Diaby, M., Viennet, E., & Launay, T. (2013). *Toward the next generation of recruitment tools: An online social network-based job recommender system* (pp. 821–828). doi:10.1145/2492517.2500266.

Diaby, M., Viennet, E., & Launay, T. (2014). Exploration of methodologies to improve job recommender systems on social networks. *Social Network Analysis and Mining, 4*(1), 1–17. doi:10.1007/s13278-014-0227-z.

Dinuzzo, F., Pillonetto, G., & De Nicolao, G. (2011). Client-server multitask learning from distributed datasets. *IEEE Transactions on Neural Networks, 22*(2), 290–303. doi:10.1109/TNN.2010.2095882.

Elahi, M., Ricci, F., & Rubens, N. (2016). A survey of active learning in collaborative filtering recommender systems. *Computer Science Review, 20*, 29–50. doi:10.1016/j.cosrev.2016.05.002.

Elmongui, H., Mansour, R., Morsy, H., Khater, S., El-Sharkasy, A., & Ibrahim, R. (2015). Trupi: Twitter recommendation based on users' personal interests. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 9042*, 272–284. doi:10.1007/978-3-319-18117-2_20.

Fan, T.-K., & Chang, C.-H. (2010). *Learning to predict ad clicks based on boosted collaborative filtering* (pp. 209–216). doi:10.1109/SocialCom.2010.37.

Fan, Z., Chen, S., Zha, L., & Yang, J. (2016). A text clustering approach of chinese news based on neural network language model. *International Journal of Parallel Programming, 44*(1), 198–206. doi:10.1007/s10766-014-0329-2.

Feuerverger, A., He, Y., & Khatri, S. (2012). Statistical significance of the netflix challenge. *Statistical Science, 27*(2), 202–231. doi:10.1214/11-STS368.

Forsati, R., & Meybodi, M. (2010). Effective page recommendation algorithms based on distributed learning automata and weighted association rules. *Expert Systems with Applications, 37*(2), 1316–1330. doi:10.1016/j.eswa.2009.06.010.

Forsati, R., Rahbar, A., & Mahdavi, M. (2009). *Effective page recommendation algorithms based on distributed learning automata* (pp. 41–46). doi:10.1109/ICCGI.2009.14.

Friedman, N., Geiger, D., & Goldszmidt, M. (1997). Bayesian network classifiers. *Machine Learning, 29*(2–3), 131–163.

Gedikli, F., Bağdat, F., Ge, M., & Jannach, D. (2011). *Rf-rec: Fast and accurate computation of recommendations based on rating frequencies* (pp. 50–57). doi:10.1109/CEC.2011.24.

Gemmis, M., Iaquinta, L., Lops, P., Musto, C., Narducci, F., & Semeraro, G. (2011). *Learning preference models in recommender systems*. doi:10.1007/978-3-642-14125-6_18.

Geng, X., Zhang, H., Bian, J., & Chua, T.-S. (2016). *Learning image and user features for recommendation in social networks: 11-18-December-2015* (pp. 4274–4282). doi:10.1109/ICCV.2015.486.

Ghazarian, S., & Nematbakhsh, M. (2015). Enhancing memory-based collaborative filtering for group recommender systems. *Expert Systems with Applications, 42*(7), 3801–3812. doi:10.1016/j.eswa.2014.11.042.

Goldberg, D., Nichols, D., Oki, B., & Terry, D. (1992). Using collaborative filtering to weave an information tapestry. *Communications of the ACM, 35*(12), 61–70. doi:10.1145/138859.138867.

Gunawardana, A., & Shani, G. (2015). *Evaluating recommender systems*. Springer US. doi:10.1007/978-1-4899-7637-6_8.

Haiduc, S., Bavota, G., Marcus, A., Oliveto, R., De Lucia, A., & Menzies, T. (2013). *Automatic query reformulations for text retrieval in software engineering* (pp. 842–851). doi:10.1109/ICSE.2013.6606630.

Halder, S., Seddiqui, M., & Lee, Y.-K. (2014). *An entertainment recommendation system using the dynamics of user behavior over time* (pp. 41–46). doi:10.1109/ICCITech.2014.7073094.

Hassan, M., Karim, A., Javed, F., & Arshad, N. (2010). *Self-optimizing a clustering-based tag recommender for social bookmarking systems* (pp. 601–606). doi:10.1109/ICMLA.2010.93.

Hofmann, T. (2003). Collaborative filtering via gaussian probabilistic latent semantic analysis. *SIGIR Forum (ACM Special Interest Group on Information Retrieval)*, (SPEC. ISS.), 259–266.

Hofmann, T. (2004). Latent semantic models for collaborative filtering. *ACM Transactions on Information Systems, 22*(1), 89–115. doi:10.1145/963770.963774.

Huang, T.-H., & Nikulin, V. (2014). Two algorithms under stochastic gradient descent framework for recommender systems. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8643*, 219–230. doi:10.1007/978-3-319-13186-3_21.

Hussain, A., Farooq, K., Luo, B., & Slack, W. (2015). *A novel ontology and machine learning inspired hybrid cardiovascular decision support framework* (pp. 824–832). doi:10.1109/SSCI.2015.122.

Isazadeh, A. (2004). Software engineering: The trend. *Informatica (Ljubljana), 28*(2), 129–137.

Islam, M., Ding, C., & Chi, C.-H. (2015). *Personalized recommender system on whom to follow in twitter* (pp. 326–333). doi:10.1109/BDCloud.2014.84.

Jain, A., Murty, M., & Flynn, P. (1999). Data clustering: A review. *ACM Computing Surveys, 31*(3), 264–323. doi:10.1145/331499.331504.

Jannach, D., Lerche, L., Gedikli, F., & Bonnin, G. (2013). What recommenders recommend - an analysis of accuracy, popularity, and sales diversity effects. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7899 LNCS*, 25–37. doi:10.1007/978-3-642-38844-6_3.

Jannach, D., Zanker, M., Felfernig, A., & Friedrich, G. (2010). *Recommender systems: An introduction*. doi:10.1017/CBO9780511763113.

Japkowicz, N., & Shah, M. (2011). *Evaluating learning algorithms: A classification perspective*. Cambridge University Press. doi:10.1017/CBO9780511921803.

Jin, X., Mobasher, B., & Zhou, Y. (2005). *A web recommendation system based on maximum entropy: 1* (pp. 213–218).

Jun, S.-H. (2005). *Web usage mining using support vector machine: 3512* (pp. 349–356).

Jung, K.-Y., & Lee, J.-H. (2004). User preference mining through hybrid collaborative filtering and content-based filtering in recommendation system. *IEICE Transactions on Information and Systems, E87-D*(12), 2781–2790.

Kao, C.-Y., & Fahn, C.-S. (2013). A multi-stage learning framework for intelligent system. *Expert Systems with Applications, 40*(9), 3378–3388. doi:10.1016/j.eswa.2012.12.046.

Karahodza, B., & Donko, D. (2015). *Feature enhanced time-aware recommender system*. doi:10.1109/ICAT.2015.7340527.

Karimanzira, D., Otto, P., & Wernstedt, J. (2006). *Application of machine learning methods to route planning and navigation for disabled people* (pp. 366–371).

Karypis, G. (2001). *Evaluation of item-based top-n recommendation algorithms* (pp. 247–254).

Kitchenham, B. (2004). Procedures for Performing Systematic Reviews. *Technical Report*. Keele University, Department of Computer Science, and Empirical Software Engineering National ICT Australia Ltd.

Kong, D., Zhang, M., & Ding, C. (2013). Minimal shrinkage for noisy data recovery using schatten-p norm objective. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8189 LNAI*(PART 2), 177–193. doi:10.1007/978-3-642-40991-2_12.

Kononenko, I. (2001). Machine learning for medical diagnosis: History, state of the art and perspective. *Artificial Intelligence in Medicine, 23*(1), 89–109. doi:10.1016/S0933-3657(01)00077-X.

Koren, Y., & Bell, R. (2015). *Advances in collaborative filtering*. Springer US. doi:10.1007/978-1-4899-7637-6_3.

Kotsiantis, S. (2007). Supervised machine learning: A review of classification techniques. *Informatica (Ljubljana), 31*(3), 249–268.

Krohn-Grimberghe, A., Busche, A., Nanopoulos, A., & Schmidt-Thieme, L. (2011). *Active learning for technology enhanced learning* (pp. 28–31).

Krzywicki, A., Wobcke, W., Kim, Y., Cai, X., Bain, M., Mahidadia, A., & Compton, P. (2015). Collaborative filtering for people-to-people recommendation in online dating: Data analysis and user trial. *International Journal of Human Computer Studies, 76*, 50–66. doi:10.1016/j.ijhcs.2014.12.003.

Kulkarni, S. (2012). *Machine learning algorithms for problem solving in computational applications: Intelligent techniques*. IGI Global. doi:10.4018/978-1-4666-1833-6.

Lahlou, F., Benbrahimand, H., Mountassir, A., & Kassou, I. (2013a). *Context extraction from reviews for context aware recommendation using text classification techniques*. doi:10.1109/AICCSA.2013.6616512.

Lahlou, F., Mountassir, A., Benbrahim, H., & Kassou, I. (2013b). *A text classification based method for context extraction from online reviews*. doi:10.1109/SITA.2013.6560804.

Lee, T.-J., & Tseng, S.-S. (2012). Easy-to-explain feature synthesis approach for recommending entertainment video. *Neurocomputing, 92*, 61–68. doi:10.1016/j.neucom.2011.09.034.

Lee, W.-P., & Lu, C.-C. (2003). Customising wap-based information services on mobile networks. *Personal and Ubiquitous Computing, 7*(6), 321–330. doi:10.1007/s00779-003-0247-6.

Leopairote, W., Surarerks, A., & Prompoon, N. (2013). *Evaluating software quality in use using user reviews mining* (pp. 257–262). doi:10.1109/JCSSE.2013.6567355.

Leskovec, J., Rajaraman, A., & Ullman, J. (2014). *Mining of massive datasets: Second edition*. doi:10.1017/CBO9781139924801.

Li, J., & Zaïane, O. (2004). Combining usage, content, and structure data to improve web site recommendation. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 3182*, 305–315.

Li, Q.-C., Dong, Z.-H., & Li, T. (2008). *Research of information recommendation system based on reading behavior: 3* (pp. 1626–1631). doi:10.1109/ICMLC.2008.4620666.

Li, X., & Chen, H. (2013). Recommendation as link prediction in bipartite graphs: A graph kernel-based machine learning approach. *Decision Support Systems, 54*(2), 880–890. doi:10.1016/j.dss.2012.09.019.

Li, X., Wang, M., & Liang, T.-P. (2014). A multi-theoretical kernel-based approach to social network-based recommendation. *Decision Support Systems, 65*(C), 95–104. doi:10.1016/j.dss.2014.05.006.

Liang, W., Lu, G., Ji, X., & Li, J. (2014). Difference factor' knn collaborative filtering recommendation algorithm. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8933*, 175–184.

Liu, J., Dolan, P., & Pedersen, E. (2010). *Personalized news recommendation based on click behavior* (pp. 31–40). doi:10.1145/1719970.1719976.

Liu, Q., Xiong, Y., & Huang, W. (2014a). Combining user-based and item-based models for collaborative filtering using stacked regression. *Chinese Journal of Electronics, 23*(4), 712–717.

Liu, R., Ding, L., & Xie, L. (2014b). *Catlinks - a category clustering algorithm based on multi-class regression* (pp. 323–326). doi:10.1109/CCIS.2014.7175752.

Liu, T., Fan, B., Hu, H., & Du, X.-Y. (2011). *Lawyer information integration and recommendation by multi-source information validation: 4* (pp. 1909–1913). doi:10.1109/ICMLC.2011.6016956.

Longo, L., Barrett, S., & Dondio, P. (2009). *Toward social search from explicit to implicit collaboration to predict users' interests* (pp. 693–696).

Lops, P., De Gemmis, M., Semeraro, G., Musto, C., Narducci, F., & Bux, M. (2009). A semantic content-based recommender system integrating folksonomies for personalized access. *Studies in Computational Intelligence, 229*, 27–47. doi:10.1007/978-3-642-02794-9_2.

Lu, C., Stankovic, M., & Laublet, P. (2015). *Leveraging semantic web technologies for more relevant e-tourism behavioral retargeting* (pp. 1287–1292). doi:10.1145/2740908.2742001.

Lu, J., Hoi, S., Wang, J., & Zhao, P. (2013). Second order online collaborative filtering. *Journal of Machine Learning Research, 29*, 325–340.

Luong, H., Huynh, T., Gauch, S., Do, L., & Hoang, K. (2012a). Publication venue recommendation using author network's publication history. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7198 LNAI*(PART 3), 426–435. doi:10.1007/978-3-642-28493-9_45.

Luong, H., Huynh, T., Gauch, S., & Hoang, K. (2012b). *Exploiting social networks for publication venue recommendations* (pp. 239–245).

Lv, H., & Tang, H. (2011). *Machine learning methods and their application research* (pp. 108–110). doi:10.1109/IPTC.2011.34.

Marović, M., Mihoković, M., Miksă, M., Pribil, S., & Tus, A. (2011). *Automatic movie ratings prediction using machine learning* (pp. 1640–1645).

Marques, C., Guilherme, I., Nakamura, R., & Papa, J. (2011). *New trends in musical genre classification using optimum-path forest* (pp. 699–704).

Martens, H. (1959). Two notes on machine "learning". *Information and Control, 2*(4), 364–379.

McLaughlin, M., & Herlocker, J. (2004). *A collaborative filtering algorithm and evaluation metric that accurately model the user experience* (pp. 329–336).

Michalski, R., Carbonell, J., & Mitchell, T. (1985). Machine learning: An artificial intelligence approach. *Artificial Intelligence, 25*(2), 236–238. doi:10.1016/0004-3702(85)90005-0.

Michalski, R. S., Carbonell, J. G., & Mitchell, T. M. (2013). *Machine learning: An artificial intelligence approach*. Springer Science & Business Media.

Middleton, S., Shadbolt, N., & De Roure, D. (2004). Ontological user profiling in recommender systems. *ACM Transactions on Information Systems, 22*(1), 54–88. doi:10.1145/963770.963773.

Montañés, E., Quevedo, J., Díaz, I., & Ranilla, J. (2009). *Collaborative tag recommendation system based on logistic regression: 497* (pp. 173–188).

Moreno, O., Shapira, B., Rokach, L., & Shani, G. (2012). *Talmud: Transfer learning for multiple domains* (pp. 425–434). doi:10.1145/2396761.2396817.

Murfi, H., & Obermayer, K. (2009). *A two-level learning hierarchy of concept based keyword extraction for tag recommendations: 497* (pp. 201–214).

Musto, C., Narducci, F., Lops, P., De Gemmis, M., & Semeraro, G. (2010). Integrating a content-based recommender system into digital libraries for cultural heritage. *Communications in Computer and Information Science, 91 CCIS*, 27–38. doi:10.1007/978-3-642-15850-6_4.

Nguyen, H., Richards, R., Chan, C.-C., & Liszka, K. (2016). Redtweet: Recommendation engine for reddit. *Journal of Intelligent Information Systems, 47*(2), 247–265. doi:10.1007/s10844-016-0410-y.

Nicol, O., Mary, J., & Preux, P. (2014). *Improving offline evaluation of contextual bandit algorithms via bootstrapping techniques: 2* (pp. 1390–1398).

Nie, F., Wang, H., Huang, H., & Ding, C. (2013). Joint schatten lp-norm robust matrix completion for missing value recovery. *Knowledge and Information Systems, 42*(3), 525–544. doi:10.1007/s10115-013-0713-z.

Ning, X., Desrosiers, C., & Karypis, G. (2015). *A comprehensive survey of neighborhood-based recommendation methods*. Springer US. doi:10.1007/978-1-4899-7637-6_2.

O'Donovan, J., & Smyth, B. (2005). *Trust in recommender systems* (pp. 167–174). doi:10.1145/1040830.1040870.

Hernández del Olmo, F., Gaudioso, E., & Martin, E. (2009). The task of guiding in adaptive recommender systems. *Expert Systems with Applications, 36*(2 PART 1), 1972–1977. doi:10.1016/j.eswa.2007.12.070.

Oyama, S., Hayashi, K., & Kashima, H. (2012). Link prediction across time via cross-temporal locality preserving projections. *IEICE Transactions on Information and Systems, E95-D*(11), 2664–2673. doi:10.1587/transinf.E95.D.2664.

Pantraki, E., & Kotropoulos, C. (2015). *Automatic image tagging and recommendation via parafac2*: 2015-November. doi:10.1109/MLSP.2015.7324363.

Paparrizos, I., Cambazoglu, B., & Gionis, A. (2011). *Machine learned job recommendation* (pp. 325–328). doi:10.1145/2043932.2043994.

Patrick, E., & Fischer III, F. (1970). A generalized k-nearest neighbor rule. *Information and Control, 16*(2), 128–152. doi:10.1016/S0019-9958(70)90081-1.

Pecli, A., Giovanini, B., Pacheco, C., Moreira, C., Ferreira, F., Tosta, F., et al. (2015). *Dimensionality reduction for supervised learning in link prediction problems: 1* (pp. 295–302).

Pessiot, J.-F., Truong, T.-V., Usunier, N., Amini, M.-R., & Gallinar, P. (2007). *Learning to rank for collaborative filtering: AIDSS* (pp. 145–151).

Pressman, R. S. (2015). *Software engineering: A Practitioner's approach* (8th). McGrawHill Higher Education.

Pronoza, E., Yagunova, E., & Volskaya, S. (2016). Aspect-based restaurant information extraction for the recommendation system. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 9561*, 371–385. doi:10.1007/978-3-319-43808-5_28.

Rodriguez, M., Posse, C., & Zhang, E. (2012). *Multiple objective optimization in recommender systems* (pp. 11–18). doi:10.1145/2365952.2365961.

Roh, T., Oh, K., & Han, I. (2003). The collaborative filtering recommendation based on som cluster-indexing cbr. *Expert Systems with Applications, 25*(3), 413–423. doi:10.1016/S0957-4174(03)00067-8.

Rubens, N., Elahi, M., Sugiyama, M., & Kaplan, D. (2015). *Active learning in recommender systems*. Springer US. doi:10.1007/978-1-4899-7637-6_24.

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2000). Analysis of recommendation algorithms for e-commerce. In *Proceedings of the 2nd acm conference on electronic commerce*. In *EC '00* (pp. 158–167). New York, NY, USA: ACM. doi:10.1145/352871.352887.

Shalev-Shwartz, S., & Ben-David, S. (2013). *Understanding machine learning: From theory to algorithms*. Cambridge University Press. doi:10.1017/CBO9781107298019.

Shani, G., & Gunawardana, A. (2013). Tutorial on application-oriented evaluation of recommendation systems. *AI Communications, 26*(2), 225–236. doi:10.3233/AIC-130551.

Shvachko, K., Kuang, H., Radia, S., & Chansler, R. (2010). *The hadoop distributed file system*. doi:10.1109/MSST.2010.5496972.

Song, I., Dillon, D., Goh, T., & Sung, M. (2011a). A health social network recommender system. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7047 LNAI*, 361–372. doi:10.1007/978-3-642-25044-6_29.

Song, Y., Zhang, L., & Giles, C. (2011b). Automatic tag recommendation algorithms for social recommender systems. *ACM Transactions on the Web, 5*(1). doi:10.1145/1921591.1921595.

Steck, H. (2013). *Evaluation of recommendations: Rating-prediction and ranking* (pp. 213–220). doi:10.1145/2507157.2507160.

Sun, Y., Fan, H., Bakillah, M., & Zipf, A. (2015). Road-based travel recommendation using geo-tagged images. *Computers, Environment and Urban Systems, 53*, 110–122. doi:10.1016/j.compenvurbsys.2013.07.006.

Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction* (1st). Cambridge: MIT Press.

Szabó, Z., Póczos, B., & Lorincz, A. (2012). Collaborative filtering via group-structured dictionary learning. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7191 LNCS*, 247–254. doi:10.1007/978-3-642-28551-6_31.

Szymański, J., & Rzeniewicz, J. (2016). Identification of category associations using a multilabel classifier. *Expert Systems with Applications, 61*, 327–342. doi:10.1016/j.eswa.2016.05.039.

Taghipour, N., Kardan, A., & Ghidary, S. (2007). *Usage-based web recommendations: A reinforcement learning approach* (pp. 113–120). doi:10.1145/1297231.1297250.

Takács, G., Pilászy, I., Németh, B., & Tikk, D. (2008). *Matrix factorization and neighbor based algorithms for the netflix prize problem* (pp. 267–274). doi:10.1145/1454008.1454049.

Takáes, G., Pilászy, I., Németh, B., & Tikk, D. (2009). Scalable collaborative filtering approaches for large reeommender systems. *Journal of Machine Learning Research, 10*, 623–656.

Thrun, S. (2007). *Self-driving cars -an ai-robotics challenge* p. 12.

Torralba, A., Fergus, R., & Weiss, Y. (2008). *Small codes and large image databases for recognition*. doi:10.1109/CVPR.2008.4587633.

Tsapatsoulis, N., Agathokleous, M., Djouvas, C., & Mendez, F. (2015). On the design of social voting recommendation applications. *International Journal on Artificial Intelligence Tools, 24*(3). doi:10.1142/s0218213015500098.

Tsuji, K., Yoshikane, F., Sato, S., & Itsumura, H. (2014). *Book recommendation using machine learning methods based on library loan records and bibliographic information* (pp. 76–79). doi:10.1109/IIAI-AAI.2014.26.

Verma, C., Hart, M., Bhatkar, S., Parker-Wood, A., & Dey, S. (2016). Improving scalability of personalized recommendation systems for enterprise knowledge workers. *IEEE Access, 4*, 204–215. doi:10.1109/ACCESS.2015.2513000.

Vialardi, C., Chue, J., Peche, J., Alvarado, G., Vinatea, B., Estrella, J., & Ortigosa, A. (2011). A data mining approach to guide students through the enrollment process based on academic performance. *User Modeling and User-Adapted Interaction, 21*(1–2), 217–248. doi:10.1007/s11257-011-9098-4.

Wan, X., Jamaliding, Q., & Okamoto, T. (2009). *Discovering social network to improve recommender system for group learning support*. doi:10.1109/CISE.2009.5363890.

Wang, Y., Wang, X., Wang, Y., & Hsu, D. (2014). Exploration in interactive personalized music recommendation: A reinforcement learning approach. *ACM Transactions on Multimedia Computing, Communications and Applications, 11*(1). doi:10.1145/2623372.

Wang, Y., Yin, L., Cheng, B., & Yu, Y. (2012). Learning to recommend based on slope one strategy. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7235 LNCS*, 537–544. doi:10.1007/978-3-642-29253-8_47.

Wei, C.-P., Chen, H.-C., & Liang, M.-K. (2011). *Estimating trust strength for supporting effective recommendation services*.

Weng, L.-T. (1998). *Information Enrichment for Quality Recommender Systems*. Brisbane, Australia: Queensland University of Technology Ph.D. thesis.

Xin, J., Cui, Z., Zhang, S., He, T., Li, C., & Huang, H. (2014). Constructing topic models of internet of things for information processing. *Scientific World Journal, 2014*. doi:10.1155/2014/675234.

Xu, Z., Mo, M., & King, I. (2012). *Semi-supervised learning*.

Xuan, J., Lu, J., Zhang, G., & Luo, X. (2014). *Extension of similarity measures in vsm: From orthogonal coordinate system to affine coordinate system* (pp. 4084–4091). doi:10.1109/IJCNN.2014.6889693.

Yan, G., Xu, F., Yao, Y., & Lu, J. (2013). *Enhancing trustworthiness evaluation in internetware with similarity and non-negative constraints*. doi:10.1145/2532443.2532459.

Yap, G.-E., Tan, A.-H., & Pang, H.-H. (2005). *Dynamically-optimized context in recommender systems* (pp. 265–272). doi:10.1145/1071246.1071289.

Yeh, J.-H., & Wu, M.-L. (2010). *Recommendation based on latent topics and social network analysis: 1* (pp. 209–213). doi:10.1109/ICCEA.2010.48.

Yuan, G., Murukannaiah, P., Zhang, Z., & Singh, M. (2014). *Exploiting sentiment homophily for link prediction* (pp. 17–24). doi:10.1145/2645710.2645734.

Zahra, S., Ghazanfar, M., Khalid, A., Azam, M., Naeem, U., & Prugel-Bennett, A. (2015). Novel centroid selection approaches for kmeans-clustering based recommender systems. *Information Sciences, 320*, 156–189. doi:10.1016/j.ins.2015.03.062.

Zhai, H., & Li, J. (2015). Refine social relations and differentiate the same friends' influence in recommender system. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 9468*, 504–514. doi:10.1007/978-3-319-26832-3_47.

Zhang, D., & Tsai, J. (2006). *Advances in machine learning applications in software engineering*. doi:10.4018/978-1-59140-941-1.

Zhang, R., & Tran, T. (2010). Helpful or unhelpful: A linear approach for ranking product reviews. *Journal of Electronic Ccommerce Research, 11*(3), 220–230.

Zhang, S.-Z., Liu, L., & Dong, Y.-Z. (2007). *An online bayesian networks model for e-commercial personalized recommendation system: 6* (pp. 3506–3511). doi:10.1109/ICMLC.2007.4370754.

Zhang, W., Begole, B., Chu, M., Liu, J., & Yee, N. (2008). *Real-time clothes comparison based on multi-view vision*. doi:10.1109/ICDSC.2008.4635727.

Zhang, X.-Z. (2007). *Building personalized recommendation system in e-commerce using association rule-based mining and classification: 7* (pp. 4113–4118). doi:10.1109/ICMLC.2007.4370866.

Zhang, Y., Zhuang, Y., Wu, J., & Zhang, L. (2009). Applying probabilistic latent semantic analysis to multi-criteria recommender system. *AI Communications, 22*(2), 97–107. doi:10.3233/AIC-2009-0446.

Zhao, K., & Pan, L. (2015). *A machine learning based trust evaluation framework for online social networks* (pp. 69–74). doi:10.1109/TrustCom.2014.13.

Zhao, Q., Zhang, Y., Friedman, D., & Tan, F. (2015). *E-commerce recommendation with personalized promotion* (pp. 219–225). doi:10.1145/2792838.2800178.