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A systematic literature review on the state of research and practice of collaborative filtering technique and implicit feedback

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Abstract User profiles in collaborative filtering (CF) recommendation technique are built based on ratings given by users on a set of items. The most eminent shortcoming of the CF technique is the sparsity problem. This problem refers to the low ratio of rated items by users to the total number of available items; hence the quality of recommendation will be affected. Most researchers use implicit data as a solution for sparsity problem, to decrease the dependency of CF technique on the user's rating and this term is more common in this field. The aim of this research is to aggregate evidence on state of research and practice of CF and implicit data applying systematic literature review (SLR) which is a method for evidence-based software engineering (EBSE). EBSE has the potential value for synthesizing evidence and make this evidence available to practitioners and researchers with providing the best references and appropriate software engineering solutions for sparsity problem. We executed the standard systematic literature review method using a manual search in 5 prestigious databases and 38 studies were finally included for analyzing. This paper follows manifestation of Kitchenham's SLR guidelines and describes in a great detail the process of selecting and analyzing research papers. This paper is first academic systematic literature review of CF technique along with implicit data from user behaviors and activities to aggregate existing evidence as a synthesis of best quality scientific studies. The 38 research papers are categorized into eleven application fields (movie, shopping, books, Social systems, music and others) and six data mining techniques (dimensionality reduction, association rule, heuristic methods and other). According to the review results, neighborhood formation is a relevant aspect of CF and it can be improved with the use of user-item preference matrix as implicit feedback mechanism, the most common domains of CF are in e-commerce and movie software applications.

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1 Introduction

Recommender systems are tools to offer the appropriate product or service after identifying the customers' desires and preferences. Recommender systems have been an important and interesting research topic since the emergence of the first research article on CF in the mid 1990s (Resnick et al. 1994). CF provides recommendations by collecting the preferences of similar users in the recommender system. Neighborhood formation is a crucial aspect in CF technique (Kardan and Ebrahimi 2013; Lee et al. 2010). The objective of neighborhood formation is to find a set of similar users or nearest neighbors for each user and locate the closest neighbor to an active user to recommend the items to the user based on users with similar tastes (Zheng and Li 2011; Choi et al. 2012). The term neighbor here refers to other users who have similarly rated items which are similar to what an active user is interested in. By comparing the active user's rating and the neighbor's rating, recommendations can be made to the active user on what to purchase (Acilar and Arslan 2009; Kim and Yum 2011). In the case of a lack of user rating data, CF encounters the problem called rating sparsity that makes recommendation results unreliable. Thus, it is necessary to enhance elements in CF for preventing poor recommendation. It becomes necessary to extracting users' preferences through implicit data (such as their buying behavior, login times and history of purchased products or viewed) to decrease the dependency of CF technique on the user's rating and provide better recommendations by CF technique (Hu et al. 2008; Albadvi and Shahbazi 2009). Implicit data can improve the insufficient ratings by providing more evidence and information through the observation made on users' or consumers' behaviors (Rafeh and Bahrehmand 2012; Zheng and Li 2011). On the other hand, user profiles in CF recommendation technique are built based on ratings given by users on a set of items. The rating information maps the user–item pairs on a set of numerical values. To decrease the dependency of CF technique on the user's rating, user activities has become a rich resource for investigating, and exploiting knowledge about user preferences in order to build accurate user profiles (Lee et al. 2010; Zheng and Li 2011; Kim and Yum 2011; Choi et al. 2012).

More research is needed to investigate the literature to find the state of research and practice of CF technique and implicit data in order to enhance CF technique by considering user's behaviors and activities. Hence, in this paper, we investigate the state of research and practice of CF technique and implicit feedback. The objective of this research is to understand the trend of CF technique and implicit feedback research by examining the published articles, and to afford practitioners and researchers with insight and future direction on CF and implicit feedback. In order to perform this objective a systematic literature review (SLR) of the existing published studies related to topic area in CF technique and implicit feedback are conducted based on the original guidelines proposed by Kitchenham et al. (2009), Kitchenham and Brereton (2013), García-Borgoñon et al. (2014), Kitchenham and Charters (2007), Biolchini et al. (2005) and Kitchenham (2004). SLR is a method for Evidence-based Software Engineering (EBSE) to apply an evidence-based approach to software engineering research and practice. As mentioned in Kitchenham et al. (2009), EBSE is a method for aggregating evidence to provide the best references for researchers and can be readily observed in the scientific literature (Kitchenham et al. 2009; Kitchenham and Charters 2007). Thus, this research develop a SLR to define evidence and research outcomes of literature reviews as a synthesis of best quality scientific studies on state of-the-art in CF technique and implicit feedback research to identify needs and opportunities for future research work.

In other words, this paper makes the following contributions for providing a personalized set of recommendations: (1) it focuses on recommender systems that combine CF with implicit data and user activities in making recommendation and systematically demonstrates that user activities are important when predicting users' preferences, and (2) SLR is the research methodology used in this paper on gathering, filtering and analyzing relevant paper on CF and implicit feedback. This paper is first academic literature review of CF technique along with implicit data from user behaviors and activities. The paper identifies major elements in CF that can be enhanced by implicit data and summarizes potential user activities that can be integrated with CF which alleviating the sparsity problem. We hope that this research will supply guidelines for future research on recommender systems and provide researchers and practitioners with insight on CF recommendation research.

The rest of this paper is structured as follows: Sect. 2 introduces the method used for the systematic review. In Sect. 3, the results of the review are shown, and then, Sect. 4 presents discussions on these results. We present limitations of our research in Sect. 5, Finally, Sect. 6 states conclusions and future directions for our work.

2 Research methodology

Kitchenham et al. (2009) has stated that a SLR is a research technique to analyze the state of-the-art in a specific area of knowledge by formally presenting the problem statement, the sources of information, the search strings, the criteria for excluding and including of the papers identified in the searches, the quantitative analysis to be done, and the templates for ordering the information gathered from the papers. This paper is a manifestation of Kitchenham's SLR guidelines in which review plans, review conduction and reporting are solid. The objective of this study is to systematically review the literature related to the CF technique and implicit feedback to achieve the state of research and practice of CF technique and implicit feedback. By doing this, relevant data can be identified, assessed and interpreted according to this research objective.

As aforementioned, the review of literature of this research employs the guidelines proposed by Kitchenham et al. (2009), Kitchenham and Brereton (2013), García-Borgoñon et al. (2014), Kitchenham (2004), Kitchenham and Charters (2007) and Biolchini et al. (2005) in which they are widely applied in software engineering areas. According to these guidelines, a review of literature should comprise of three main stages which are Review planning, Review conduction and Results reporting. The Review planning stage involves the preparation of research work or developing the framework of the research for executing the review. It includes the development and establishment of research questions, the online database and query string we used to execute searches based on the identified inclusion and exclusion criteria, the data extracted from each selected study. The Review conduction stage is where the research work is done and finally, the Results reporting stage is where the findings are analyzed, discussed and interpreted based on the established research objective and literature review. Figure 1 outlines the overall 12 steps review process to be performed in each stage of the SLR for conducting a SLR. They will be described in detail in the following sub-sections.

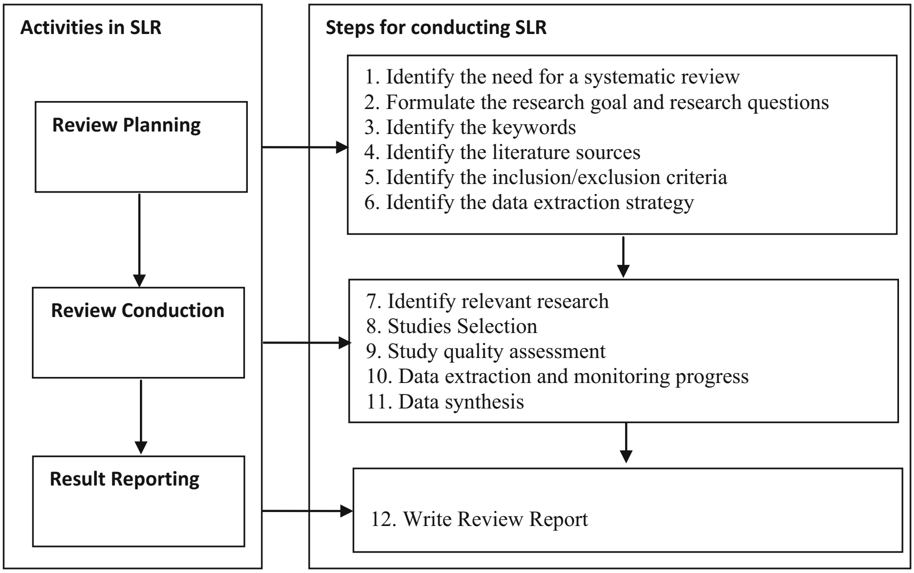

Fig. 1 Overview of SLR steps and activities (Biolchini et al. 2005; Kitchenham et al. 2009; Kitchenham and Brereton 2013; Kitchenham and Charters 2007)

2.1 Research questions

The aim of this research is to presents a review of literatures related to application of implicit data and user activities in CF technique. The SLR aimed to identify elements in CF that can be enhanced and identify the potential user activities that can be integrated with CF to improve sparsity problem. In order to achieve this aim, two research questions (RQ) have been identified to be addressed by this review:

RQ.1: What are list of user activities that can be integrated with the elements of CF technique to prevent from poor recommendation?
RQ.2: How can implicit feedback be adapted and fitted with the elements of CF technique in solving sparsity problem?

According to RQ1, we consider the aim of the study and identify elements in CF that can be enhanced with the potential user activities to decrease the dependency of CF technique on the user's rating. With regards to RQ2, we consider the distribution of research papers by used techniques and collect the data about which element of CF are supported by implicit data or user activities.

2.2 Search strategy

The third step of SLR is identifying the Keywords and conducting search strategy to be used for *Review planning stage.* At this stage, we carry out an exhaustive search for papers to answer *RQ1* and *RQ2*. We focus on major digital libraries since conference papers and journal articles are the objective to be covered. First of all, the relevant keywords for the search based on research questions and main goal of this study should be derived. At selecting keywords for the search, general terms are used with the aim of confirming that most of the research papers can be included in the study. The following relevant keywords and synonyms for the search

("Collaborative filtering" AND ("implicit feedback" OR "implicit rating" OR "implicit information" OR "implicit preferences" OR "user interaction" OR "user activity"))

Fig. 2 The final search string used in the SLR

will be selected: "collaborative filtering", "implicit feedback", "implicit rating", "implicit information", "implicit preferences", "user interaction", "user activity" (Zhao and Ordóñez de Pablos 2011; Hu et al. 2008; Zheng and Li 2011). After keywords and synonyms for the search have been identified, the search string will be specified and applied to prestigious online databases with the aim of including the most relevant research papers in ensuring a quality result of this study. The final search string is represented using the Boolean expression ("OR", "AND") in Fig. 2. A systematic literature review has been conducted by using this search string.

In this research, electronic journal databases to search for research papers involves: ACM Digital Library,[1] IEEE Xplore,[2] Springer-Link,[3] Science Direct[4] and Sage.[5] Piloting the searches is organized as a manual search process of journals and conference papers inside selected prestigious electronic journal databases. As result, 736 papers were retrieved by a manual search in 5 databases and 45 primary studies were included after retrieving full text papers. Then, after assessing the quality of the included papers, 38 papers have been chosen.

2.3 Study selection and the inclusion/exclusion criteria

In February 2014, a systematic literature search was conducted based on the inclusion and exclusion criteria defined in Table 1. The research papers were selected by following this inclusion and exclusion criteria to ensure only relevant works on CF technique and implicit feedback were accepted into the SLR. It is noteworthy that, the study selection process was performed in 7 phases as outlined in Table 1.

In this study selection process, there were two consensus meetings where authors jointly decided according to the agreed criteria at Table 1, whether the papers were considered relevant for the study. In the first meeting, authors reviewed titles, keywords and abstracts of papers whereas the second review was based on the full text and papers that were not truly related to CF and implicit data were deleted. It is noted that, we reviewed articles on CF technique and implicit feedback that were published in conference/academic journals without any start/end date restriction, in order to gain insights on state of research in CF technique and implicit feedback. Figure 3 presented the process followed for conducting the review. This figure checking whether each of the studies returned fulfills the inclusion/exclusion criteria defined at Table 1.

2.4 Quality assessment

Each accepted study in the final set is evaluated in terms of its quality. The quality evaluation procedure will be conducted simultaneously with the extraction of relevant data. This is done

1 http://portal.acm.org.
2 http://ieeexplore.ieee.org.
3 http://link.springer.com.
4 http://www.sciencedirect.com/science.
5 http://online.sagepub.com.

Table 1 Inclusion/exclusion criteria

Phase (P)	Inclusion/exclusion criteria
P1	Search based on final search string on major digital libraries to cover journal articles and conference papers
P2	Excluding unpublished working papers, news articles and non-English articles
P3	Excluding duplicate reports of the same study (removing duplicate reports that emerge due to the same search being performed in different electronic journal databases)
P4	Excluding discussion papers, tutorial and prefaces
P5	Excluding publications that were not truly related to CF technique and implicit feedback and did not contain the search strings
P6	Excluding short papers (e.g. poster presentation, summaries of tutorials) as these papers cannot answer to the research questions as well
P7	Review of full text papers and excluding studies that are not related to the research questions

to ensure the findings contribute significantly to the SLR (Brereton et al. 2007). In order to evaluate quality of each accepted study, a quality checklist from the guideline of Kitchenham et al. (2009) will be provided. In this SLR, four quality assessment questions with possible answers: Yes(Y), Partly (P) and No (N) should be filled for evaluating the quality of the included studies. The response score used was Yes (Y) = 1, Partly (P) = 0.5 or No (N) = 0. Table 2 shows the criteria described for each quality assessment question.

2.5 Data collection and analysis

Relevant information and findings emanating from the selected studies is extracted and recorded in data extraction forms. The following next section shows the forms to be used for tabulation of data extracted from the studies related to the research questions. The data extracted from each study are:

- The basic information of the papers to mean title, authors of each paper.
- Publication information referred to journal name and conference name, where the study was published and year of publication
- Information to deal with the problem addressed in each study and description of research papers with their application fields
- Elements enhanced of CF technique by considering user activities or implicit data

3 Results

This section presents the results obtained from performing SLR according to the research method described in Sect. 2. The search results are analyzed and results of assessing the quality of the obtained studies are shown.

3.1 Search results

In Sect. 2, we developed a protocol of SLR in specifying the plan by which a review is followed. Once the protocol during review planning phase has been described, it is executed. First, the study selection process was performed to identify the relevant CF technique articles

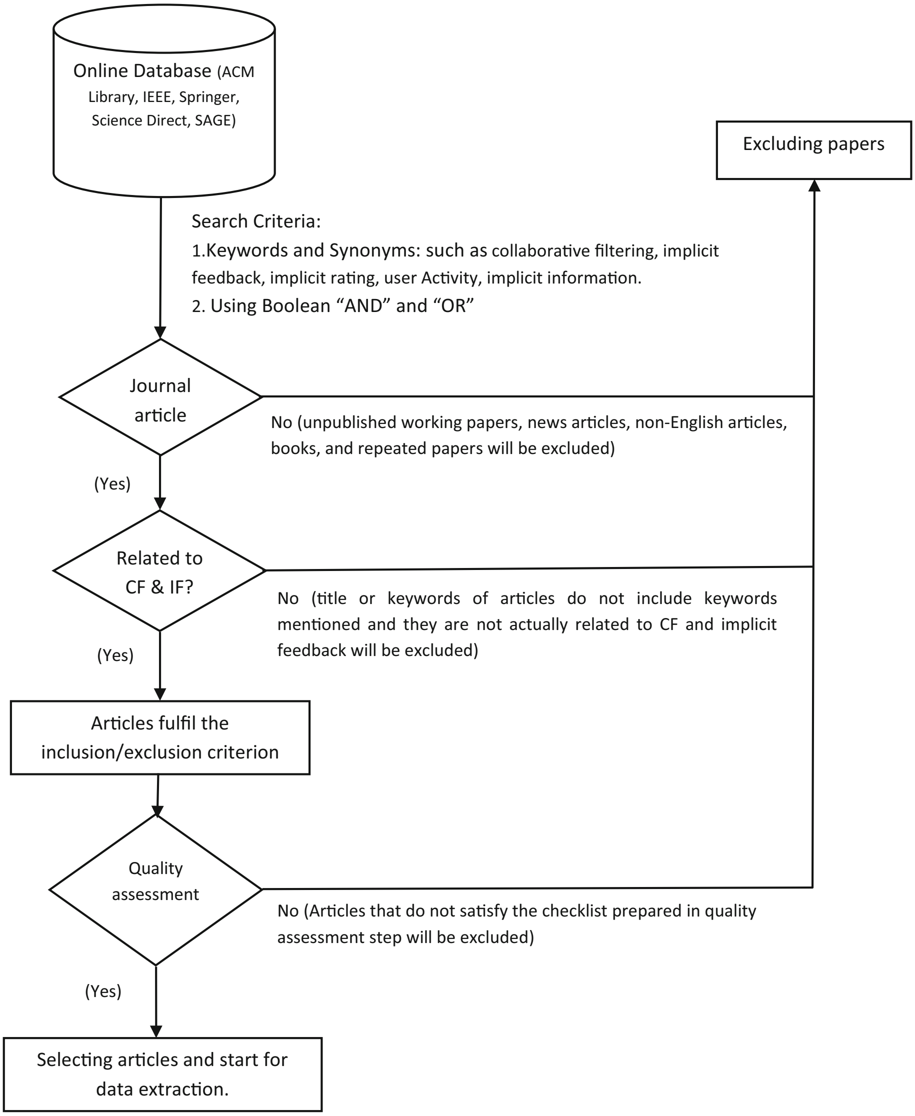

Fig. 3 Process followed to conduct the review

and implicit feedback for systematic review. The first step in study selection process was to search for the final search string represented in Fig. 2 in each search engine selected (ACM Library, IEEE Xplore, Springer-Link, Science Direct, and SAGE).

Figure 4 represents firstly, the results of executing the search in each search engine with the search string selected. The search string is general and it will be expected that not all studies found would be selected for the final phase in the selection process. The next step of study selection process was to show the number of papers that were included in this study following inclusion/exclusion criteria defined at Table 1. In other words, the study section process was done according to the seven phases previously presented at Table 1, whereby

Table 2 Quality assessment questions

N0.	Questions of quality assessment (QA) and response scores
QA1	Are the aims of the study stated clearly? • Yes: it explicitly describe aim of study • Partially: essential role of the research are not mentioned clearly • No: it did not mention any sentences for aim of research
QA2	Are the methods used in each paper clearly described? • Yes: it described clearly the method of research • Partially: it mentioned the method, but did not explain in detail • No: it did not explain the method
QA3	Are the findings stated clearly? Or Is there a clear statement of findings? • Yes: it explained what are these pioneering works about • Partially: it explained what are these pioneering works about, but how they did these is missing • No: it did not explain clear statement of findings
QA4	How clearly are the work limitations documented? • Yes: it clearly explained the limitation of study • Partially: it mentioned the limitation, but did not explain why • No: it did not mention the limitations of study

the number of selected papers decreased. Thus, the number of papers included in each phase of performing inclusion/exclusion criteria is represented in detail with the following Fig. 4. In this search process, 45 out of the 736 recovered studies were found to be relevant after reading full text of papers.

With following inclusion/exclusion defined and study section process showed in Fig. 4, we selected 45 primary studies after retrieving full text papers research papers on CF technique and implicit feedback and classified them according to search engines that found studies included in our analysis as shown in Table 3. Then, we selected 38 research papers out of the 45 relevant studies after assessing the quality of the research proposals.

As can been seen in Table 3, only 45 out of the 736 recovered studies were found to be relevant (6.11 %). It is clear that column 3 of Table 3 represents the number of papers retrieved from each search engine after reviewing the full text of each research paper, whereas column 4 shows the percentage of relevant studies found by each search engine (for example, 4.55 % of the studies found by the ACM library were identified as relevant studies). Among digital libraries, it can be observed that IEEE and Science Direct garnered the highest number of result as 17 of the relevant studies were found in IEEE and 11 of the studies returned by the Science Direct were identified as the relevant studies. Accordingly, it is worth noting that IEEE garnered the highest percentage (50 %). Regarding the low number of relevant studies included out of total number of research papers retrieved by the different digital libraries (6.11 %), this is mainly because of the fact that many of the returned research studies were found to contain some words of the query string, but when search results were analyzed, it showed that they did not satisfy the research questions defined in this SLR, so they were excluded.

It is worth mentioning that, column 5 shows the percentage of studies included in our analysis in each search engine with regards to the number of relevant studies selected from

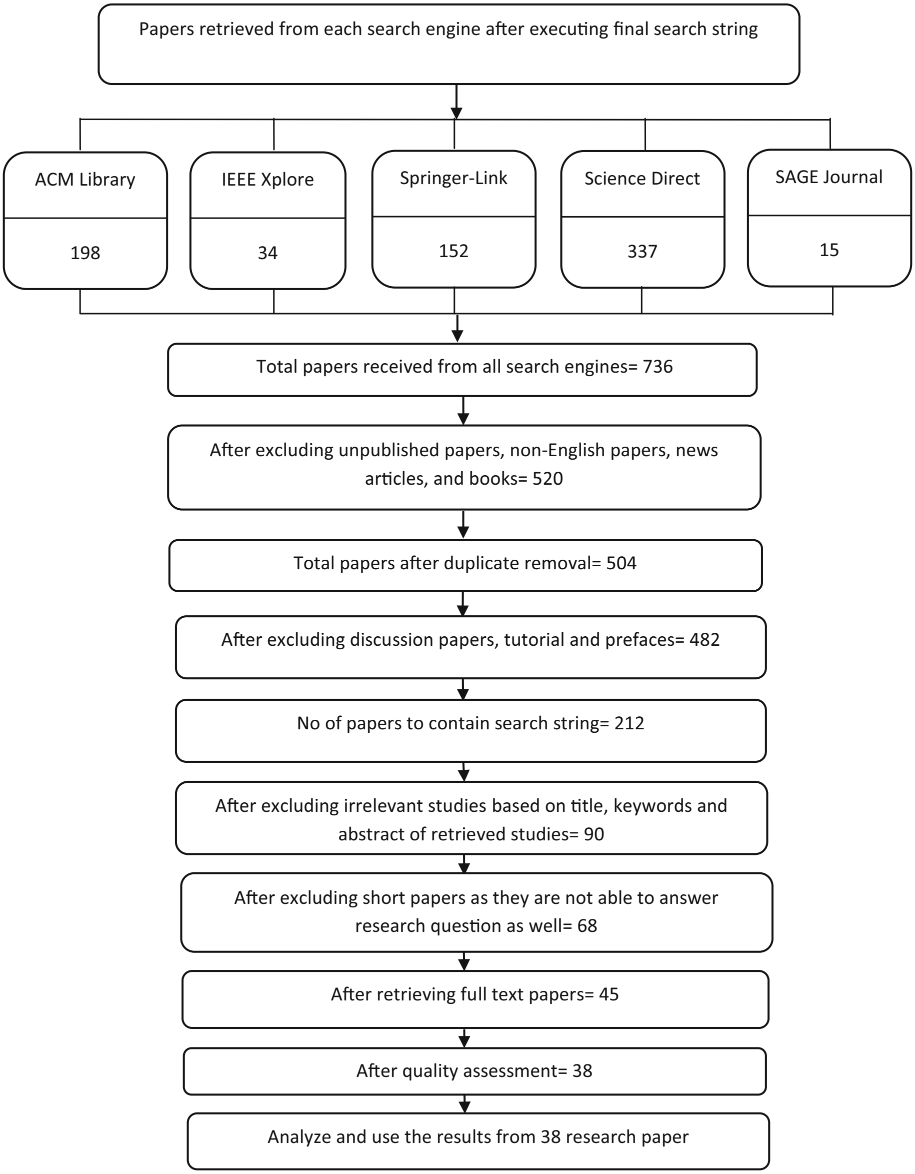

Fig. 4 Search result

all search engines, for example ACM returned 9 relevant studies which includes the 20 % of the 45 relevant studies retrieved in this review. The data in this column shows that most of the relevant studies were found in IEEE (37.78 %) and Science Direct (24.45 %) in contrast SAGE returned the smallest number of results (4.44 %).

All included papers (45 papers) are listed in the Table 4. It is noteworthy that we addressed inclusion/exclusion criteria in primary studies with following three levels. First level deals with checking the papers on table of contents, books and information related to proceedings of workshops and unpublished working papers, news articles, non-English articles, and short

Table 3 Search result

Search engine	Search result	Relevant studies	% of relevant studies	% of all the relevant studies
ACM	198	9	4.55	20
IEEE	34	17	50	37.78
SPRINGER	152	6	3.95	13.33
SCIENCE DIRECT	337	11	3.26	24.45
SAGE	15	2	13.33	4.44
All search engine	736	45	6.11	100

papers (e.g. Poster Presentation) will be excluded. In the second level, all the papers which will be found to be repeated will be excluded. Publication date of the articles will not use as a barrier for inclusion, if duplicate papers exist in different journals, the most recent and complete version of paper will be included in review. At third level, publications which main focus are not on application of implicit feedback in CF technique and are not having any of the mentioned keywords will be excluded.

The research papers will be analyzed by year of publication, by journals in which the research papers were published, and by application fields and elements of CF technique that can be enhanced with user activities. All of these research papers employ user activities and history of purchased products (such as tagging behavior, click stream data, user's purchase time and etc) to grasp and filter users' preferences for items. The details will be described in the following section. Table 4 shows the distribution of research papers after reading their full text in terms of year of publication, name of authors and journals in which the research papers were published.

3.2 Quality assessment results

Once the primary studies of SLR after reviewing full text of papers had been identified, we assessed the studies for quality using the quality assessment questions presented in Table 2 of Sect. 2.4. The four Quality Assessment (QA) questions were rated for evaluating the quality of each included paper. Then, responses to the quality questions are discussed in order to find their degree of coverage. The score assigned to each study for each question is defined in Table 5. Research papers that do not satisfy these quality questions will be excluded from the SLR. The last column ("% Max S") shows the percentage attained by each included studies out of the total score (i.e., 4).

$$\%\ \text{Max S} = \frac{\text{Total score for each included studies}}{4} \times 100$$

The penultimate row that entitled with "% Total score" shows the percentage of points obtained by all the primary studies with regard to the total number of points obtained by all the primary studies in all the QA questions.

$$\%\ \text{Total score} = \frac{45}{142.5} \times 100 \text{ or } \frac{28.5}{142.5} \times 100 \text{ or } \frac{30.5}{142.5} \times 100 \text{ or } \frac{38.5}{142.5} \times 100$$

The results of the quality analysis show that seven of primary studies (including S39, S40, S41, S42, S43, S44, S45) scored less than or equal to 1.5 points that are excluded from the SLR as the quality of these studies is low.

Table 4 Primary studies before quality assessment

ID	Title of paper	References	Publication type
S1	A cold-start recommendation algorithm based on new user's implicit information and multi-attribute rating matrix	Hang et al. (2009)	Hybrid intelligent systems
S2	A collaborative filtering algorithm based on user activity level	Cui et al. (2012)	Business intelligence and financial engineering
S3	Infrequent purchased product recommendation making based on user behaviour and opinions in e-commerce sites	Abdullah et al. (2010)	International conference on data mining
S4	A fast collaborative filtering algorithm for implicit binary data	Bu et al. (2009)	Computer-aided industrial design and conceptual design
S5	A study of Top-N recommendation on user behavior data	Qinjiao et al. (2012)	Computer science and automation engineering
S6	An approach to recommender system applying usage mining to predict users' interests	Gotardo et al. (2008)	International conference on signals and image processing
S7	A time-context-based collaborative filtering algorithm	He and Wu (2009)	International conference on granular computing
S8	Collaborative filtering recommender systems using tag information	Liang et al. (2008)	IEEE/WIC/ACM international conference on web intelligence
S9	Combining collaborative filtering and clustering for implicit recommender system	Renaud-Deputter et al. (2013)	International conference on advanced information networking and applications
S10	The intelligent recommendation system based on amended rating matrix in TTP	You et al. (2006)	Intelligent control and automation
S11	User activity-based CF algorithm in value-added services	Chunshan and Huaying (2011)	International conference on management science and industrial engineering (MSIE)
S12	Using online media sharing behavior as implicit feedback for collaborative filtering	Go et al. (2010)	International conference on privacy, security, risk and on social computing
S13	Consistent music recommendation in heterogeneous pervasive environment	Cao and Guo (2008)	International symposium on parallel and distributed processing with applications
S14	Collaborative filtering by mining association rules from user access sequences	Shyu et al. (2005)	Web information retrieval and integration
S15	A recommender system based on tag and time information for social tagging systems	Zheng and Li (2011)	Expert systems with applications
S16	A time-based approach to effective recommender systems using implicit feedback	Lee et al. (2008)	Expert systems with applications
S17	Recommender system based on click stream data using association rule mining	Kim and Yum (2011)	Expert systems with applications

Table 4 continued

ID	Title of paper	References	Publication type
S18	Development of a recommender system based on navigational and behavioral patterns of customers in e-commerce sites	Kim et al. (2005)	Expert systems with applications
S19	Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendations	Lee et al. (2010)	Information sciences
S20	An empirical study on effectiveness of temporal information as implicit ratings	Lee et al. (2009)	Expert systems with applications
S21	A novel approach to hybrid recommendation systems based on association rules mining for content recommendation in asynchronous discussion groups	Kardan and Ebrahimi (2013)	Information Science
S22	Personalized music recommendation by mining social media tags	Su et al. (2013)	Procedia computer science
S23	Collaborative filtering based on collaborative tagging for enhancing the quality of recommendation	Kim et al. (2010)	Electronic commerce research and applications
S24	A hybrid recommendation technique based on product category attributes	Albadvi and Shahbazi (2009)	Expert systems with applications
S25	A hybrid online-product recommendation system: combining implicit rating-based collaborative filtering and sequential pattern analysis	Choi et al. (2012)	Electronic commerce research and applications
S26	Hybrid recommenders: incorporating metadata awareness into latent factor models	Santos Junior et al. (2013)	Brazilian symposium on multimedia and the web
S27	Improving one-class collaborative filtering by incorporating rich user information	Li et al. (2010)	International conference on information and knowledge management
S31	Personalized search by tag-based user profile and resource profile in collaborative tagging systems	Cai and Li (2010)	ACM conference on information and knowledge management
S32	Efficient top-N recommendation for very large scale binary rated datasets	Aiolli (2013)	ACM conference on recommender systems
S33	Folksonomy-based user interest and disinterest profiling for improved recommendations: an ontological approach	Movahedian and Khayyambashi (2014)	Journal of Information Science
S34	An adaptive approach to dealing with unstable behaviour of users in collaborative filtering systems	Rafeh and Bahrehmand (2012)	Journal of Information Science
S28	Improved recommendation based on collaborative tagging behaviors	Zhao et al. (2008)	International conference on intelligent user interfaces
S29	Social ranking: uncovering relevant content using tag-based recommender systems	Zanardi and Capra (2008)	ACM conference on recommender systems

Table 4 continued

ID	Title of paper	References	Publication type
S30	Social media recommendation based on people and tags	Guy et al. (2010)	Research and development in information retrieval
S35	Tag based collaborative filtering for recommender systems	Liang et al. (2009)	Rough sets and knowledge technology
S36	A similarity measure for collaborative filtering with implicit feedback	Lee et al. (2007)	Springer-Verlag Berlin Heidelberg
S37	Automated collaborative filtering applications for online recruitment services	Rafter et al. (2000)	Springer-Verlag Berlin Heidelberg
S38	Tracommender—exploiting continuous background tracking information on smartphones for location-based recommendations	Wang et al. (2013)	Social informatics and telecommunications engineering
S39	A step towards high quality one-class collaborative filtering using online social relationships	Sopchoke and Kijsirikul (2011)	Conference on advanced computer science and information system
S40	Recommendation algorithms for implicit information	Bai et al. (2011)	Conference on service operations, logistics, and informatics
S41	Collaborative filtering for implicit feedback datasets	Hu et al. (2008)	Conference on data mining
S42	High quality recommendations for small communities: the case of a regional parent network	Strickroth and Pinkwart (2012)	ACM conference on recommender systems
S43	TFMAP: optimizing MAP for Top-N context-aware recommendation	Shi et al. (2012)	ACM conference on research and development in information retrieval
S44	Alleviating cold-start problem by using implicit feedback	Zhang et al. (2009)	Advanced data mining and applications
S45	Expectation-maximization collaborative filtering with explicit and implicit feedback	Wang et al. (2012)	Advances in knowledge discovery and data mining

In view of these results, eighteen of primary studies obtained the highest score with a score of 4 and the remaining reached 3 and 3.5 points. Note, the research papers that obtain the highest score are S2, S7, S8, S15, S16, S17, S18, S19, S20, S21, S22, S23, S24, S25 S33, S34, S35 and S36, since they provides answers for all the aspects evaluated in this work.

Figure 5 shows the coverage of every QA questions in the primary studies. It illustrates that QA1 and QA4 were covered in a rate higher than 80 % by Yes answers (respectively, 31.58 and 27.02 %). In contrast, QA2 and QA3 have less coverage (20 and 21 % of the total score, respectively).

4 Data extraction results and discussion

This literature review paper investigates recommender systems which combine collaborative filtering techniques with implicit feedback. Since user rating is not always available or may be insufficient, implicit data from user behaviors and activities is an important source to build

Table 5 Quality assessment (QA) of included papers

ID	QA1	QA2	QA3	QA4	Total score	% by Max S
S1	Y	P	P	Y	3	75
S2	Y	Y	Y	Y	4	100
S3	Y	P	P	Y	3	75
S4	Y	P	Y	Y	3.5	87.5
S5	Y	P	Y	Y	3.5	87.5
S6	Y	P	P	Y	3	75
S7	Y	Y	Y	Y	4	100
S8	Y	Y	Y	Y	4	100
S9	Y	P	P	Y	3	75
S10	Y	P	P	Y	3	75
S11	Y	P	P	Y	3	75
S12	Y	P	P	Y	3	75
S13	Y	P	P	Y	3	75
S14	Y	P	P	Y	3	75
S15	Y	Y	Y	Y	4	100
S16	Y	Y	Y	Y	4	100
S17	Y	Y	Y	Y	4	100
S18	Y	Y	Y	Y	4	100
S19	Y	Y	Y	Y	4	100
S20	Y	Y	Y	Y	4	100
S21	Y	Y	Y	Y	4	100
S22	Y	Y	Y	Y	4	100
S23	Y	Y	Y	Y	4	100
S24	Y	Y	Y	Y	4	100
S25	Y	Y	Y	Y	4	100
S26	Y	P	P	Y	3	75
S27	Y	P	P	Y	3	75
S28	Y	P	Y	Y	3.5	87.5
S29	Y	P	P	Y	3	75
S30	Y	P	Y	Y	3.5	87.5
S31	Y	P	Y	Y	3.5	87.5
S32	Y	P	P	Y	3	75
S33	Y	Y	Y	Y	4	100
S34	Y	Y	Y	Y	4	100
S35	Y	Y	Y	Y	4	100
S36	Y	Y	Y	Y	4	100
S37	Y	P	P	Y	3	75
S38	Y	P	P	Y	3	75
S39	Y	N	N	N	1	25
S40	Y	N	N	N	1	25
S41	Y	N	N	P	1.5	37.5
S42	Y	N	N	N	1	25

Table 5 continued

ID	QA1	QA2	QA3	QA4	Total score	% by Max S
S43	Y	N	N	N	1	25
S44	Y	P	N	N	1.5	37.5
S45	Y	N	N	N	1	25
Total	45	28.5	30.5	38.5	142.5	
% Total score	31.58	20	21.40	27.02	100	

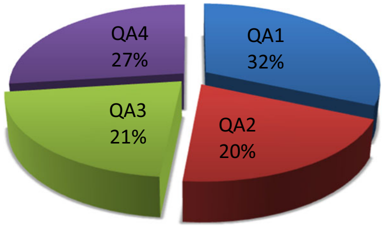

Fig. 5 Quality assessment results per question

user profiles thus to make good recommendations. The purpose of the review is to make aware of the trend of CF and implicit feedback to afford practitioners and academics with insight and future direction on recommender systems. This section presents an overview of the field of CF recommender systems and shows a large amount of research effort that has been devoted to developing algorithms for improving the accuracy of existing CF techniques. The empirical results discussed at research papers demonstrate the increase in accuracy and efficiency for CF techniques. At this section, we describe major elements in CF that can be enhanced by user activities and summarizes potential user activities that can be integrated with CF to improving the accuracy of existing CF technique. Thus, two research questions (RQ) posed in Sect. 2.1 have been identified to be addressed by this review. To answer question 1, all the selected research papers are considered from Generating user/item matrix, Neighbor formation and making recommendation aspects. To answer question 2, the paper described how each elements of CF have been enhanced by considering the user activities. To answer this question, we discuss the various solutions to the sparsity problems by verifying the distribution research articles on CF recommender systems and implicit feedbacks. In the following section, we will answer to the two research questions to fulfill the SLR in this research.

After identifying the primary studies and conducting the quality evaluation procedure with aim of measuring quality of each accepted studies to enable obtaining relevant conclusion, we extracted the data specified in Table 9 (see Appendix 1) from each study to answer RQ.1 and RQ.2.

- RQ.1: What are list of user activities that can be integrated with the elements of CF technique to prevent from poor recommendation?

This question was focused on studying the state of research and practice of CF technique to improve the recommendations for users by considering list of user activates. In general, CF technique can be divided into 3-elements (Lee et al. 2008; Kardan and Ebrahimi 2013):

1. Generating user-item preference matrix
2. Neighborhood Formation
3. Making the recommendation employing the neighbors

Fig. 6 A conceptual view of CF techniques

In order to evaluate the selected research papers according to this research question (RQ.1), we have divided the columns of Table 9 (see Appendix 1) consists of elements of CF (*user/item preferences matrix*, *neighborhood formation* and *make recommendation*) and described how each elements of CF have been enhanced by considering the user activities.

Figure 6 shows a conceptual view of the elements of CF technique and their relationships for generating recommendation.

For recommender systems, the individual preferences of users for items in a collection will be collected in *User-item preference matrix*. *User-item preference matrix* is a dominant framework for recommender systems that provides the basis for CF techniques. The *User-item preference matrix* is then utilized by the CF technique to find similar users or neighbours who have the same interests with the active user. Selecting the active user's neighbor or *Neighborhood Formation* is most important step in CF technique because of this step help to achieve a prediction of the future behaviour for the active user based on activities and preferences of similar users. Then making recommendatio will be done (Zheng and Li 2011; Choi et al. 2012).

It is noted that for improving recommendation systems, researchers consider recommendation scenarios in which information sources beyond the *User-item matrix* into two categories have been offered: (1) interaction information related to the interplay of users and items (2) and rich side information about users and items (Bae and Kim 2010; Kardan and Ebrahimi 2013). In this research paper, we analyze and summarize recommendation scenarios involving interaction between users on a set of items from implicit information and the CF algorithms that have been developed to address this information. As shown in Table 9 (in Appendix 1), *user/item preferences matrix* in the selected papers are built based on analyzing user behavior and interactions between users on a set of items. Furthermore, the information extracted from user's activities has become a rich resource for investigating, understanding and exploiting knowledge about user preferences, characteristics in order to build accurate user profiles, hence making the formation of neighborhood (identifying neighbors of active users) become correct. As a result, accurate recommendation is made.

It is noted, due to difficulties on obtaining significant numbers of ratings from users on items of system (users rate few items), the similarity between other user and active user is not easily computed. Distribution of research papers by the elements of CF that can be enhanced with implicit feedback in the case of lack of user rating data is represented in Table 9 (see Appendix 1).

- RQ.2: How can implicit feedback be adapted and fitted with the elements of CF technique in solving sparsity problem?

We aim to find how implicit feedback can be adapted with the elements of CF technique to improve accuracy of recommendation when using sparse data. As a way to answer the second research question posed, this section revisits the results obtained from selected research studies to collect the data about which element of CF are supported by implicit data or user activities. To sum up, according to the data collected in Table 9 (in Appendix 1), we have found that neighborhood formation can be improved with enriching user-item preference matrix by considering user activities. User activities acts as a basic in CF, for user similarity are discovered from user activities and resource recommendation are also calculated based on user activities.

In other words, one can argue that explicit feedback is not always available due to users may not assign any ratings to their preferences. In sparse data, neighbourhoods formation is incorrect since the recommender system suffers from lack of sufficient information. To help address the second research question, Table 9 (in Appendix 1) outlines the correspondence among implicit feedback with CF technique for improving accuracy of recommendations.

Finally, analyzing the discussion about the aforementioned research questions (RQ1, RQ2) by considering data summed up in Table 9 (Appendix 1), we have identified that implicit feedbacks deal with enriching users' preference information to find the closest neighbor to an active user for making recommendations. In the following subsection, for more detail and easier understanding, we summarize and analyze Table 9. For example, distribution of research papers by application fields and summary of the kinds of user activities that have been used to enhance collaborative recommendation systems is shown in Table 7 in order to answer the first research question. Furthermore, description of research papers by used techniques is shown in Table 8 in order to answer the second research question. Table 8 shows summary of research effort that has been devoted to developing techniques for making recommendations. In particular, Table 8 presents approaches in recommendation systems to be suited for integrating user activities with elements of CF.

Table 6 represents the description of each research paper in order to summarize Table 9 (in Appendix 1).

4.1 Summary of the RQ1

In order to answer the RQ1, research papers by application fields and summary of the kinds of user activities that have been used in recommender systems to enhance CF are represented in Table 7. The 38 research papers are categorized into eleven application fields (books, shopping, documents, movie, music, social systems, and others).

As shown at Table 7, we classify research papers by application fields such as movies, e-commerce, books, social systems, music, mobile and others. Noted, the majority of the research papers were related to e-commerce (10 out of 38 research papers) and movie (8 out of 38 research papers). Likewise, distribution of research papers by summary of user activities used was represented in Table 7. The review is carried out from an universe of 38 papers out of 736. The most important achievement of these research papers was to eliminate the dependency of proposed CF techniques on user ratings. According to the review results, the first step of building recommendation systems is generating user profiles. Theses and research papers enrich user profiles from implicit information and user activities instead of the user ratings on items to identify the user similarity neighborhood and recommend the correspondent items to users.

Recently, there has been an increasing interest in knowledge discovery based on tags. Among the application fields and user activities, most of social systems enhance CF with user's tagging behavior. Social tags on items are valuable implicit sources of information about the contents associated with the items to represent the user interests and preferences. Therefore, tagging information can be used to enrich item profiles and user profiles for improving the generated recommendations. However, more research papers are focusing on item recommendation from implicit feedback to grasp user's interests in order to provide better personalized services.

Table 6 summery of each research papers

ID	Description of each research paper
S1	To present a CF algorithm by considering the implicit information of the new users and multi-attribute rating matrix and Singular Value Decomposition (SVD)
S2	To bring user activity factor into CF and propose a new collaborative filtering
S3	To proposes a recommendation approach for infrequently purchased products based on user navigation and product review data
S4	To present a fast algorithm for speeding up computation of user based CF using cosine similarity
S5	To analyze the binary similarity from implicit feedback for recommendation
S6	To Predict User's Interests in Web-based Educational Systems based on the CF which takes into account implicit information about the users' navigation
S7	To incorporate the time-context into collaborative filtering algorithm
S8	To discusses how to recommend items to users utilizing tag information
S9	To combine clustering and matrix factorization to make recommendations while using implicit feedback on users purchase history
S10	To improve the traditional rating matrix with collecting the implicit degree-of-interest of users and then decreases the dimension of rating matrix
S11	To calculate the item rate which users don't have given rate in the real world, so as to solve the sparsity problem of CF
S12	To use the behavior of users on social media as implicit feedback by observing the entire aspects of the behavior of user for CF
S13	To propose a CF system to extracts users' interests from their listening histories like playlists for providing the music recommendation
S14	To propose data mining technique for mining user access patterns to allows the prediction of multiple non-consecutive Web pages
S15	To integrate tagging behaviors and time information in CF to make better personalized recommendations for social tagging systems
S16	To propose a method of building an effective collaborative filtering system with constructing pseudo rating data from the implicit feedback data
S17	To proposes a CF technique based on the customers' navigational and behavioral patterns in e-commerce sites
S18	To propose approach in this paper numerically determines users' preference levels from their navigational and behavioral patterns for making recommendation
S19	To proposes a CF-based recommendation technique based on both implicit ratings and less ambitious ordinal scales
S20	To propose a tool to use temporal information including user buying time, item launch time, the time difference between the two for improving the accuracy of CF
S21	To presents a hybrid recommendation system in which the combination of the collaborative and content-based filtering techniques has been implemented for the asynchronous discussion groups
S22	To propose a novel recommendation approach that utilizes social media tags and play counts instead of ratings to calculate the similarity between music pieces
S23	To provide an enhanced recommendation quality derived from user-created tags by proposing a CF
S24	To develop a hybrid recommendation technique and employs product taxonomy, attributes of product categories, web usage mining
S25	To derive implicit ratings deriving implicit ratings of users on items from transaction data and integrate CF and sequential pattern analysis for improving recommendation quality

Table 6 continued

ID	Description of each research paper
S26	To proposes a hybrid recommender which integrates users' demographics, items' metadata and implicit feedback into a unified latent factor model
S27	To improve CF by exploiting the rich user information, including a user's search query history, purchasing and browsing activities
S28	To improve the effectiveness of neighbor selection by proposing Tag-based Collaborative Filtering based on the semantic distance among tags assigned by different users
S29	To find the content that is relevant to a user's query by measuring users' similarity based on their past tag activity
S30	To propose a method for recommending based on collected relationships among people, tags, and items
S31	To implement personalized resource retrieval by using collaborative tagging systems in which users annotate resources with their own tags.
S32	To use positive feedback only and no explicit computation of the complete (user-by-user or item by- item) similarity matrix needs to be performed.
S33	To propose a method that filters social tags and generates semantic profiles for both users and items by discovering theses tag that are frequently generated by users
S34	To propose an adaptive CF algorithm which takes time into account for calculating users' similarity
S35	To recommend items to users based on user tagging behavior by proposing a tag-based collaborative filtering approach
S36	To propose a new similarity measure that is more appropriate for implicit ratings
S37	To combine implicit profiling methods and CF techniques to produce job recommendations
S38	To use background tracking information from smartphones to calculate a history of user paths (location sequences) and generate location-based recommendations

4.2 Summary of the RQ2

This research presents a SLR on the research landscape of CF and implicit feedback. Thus, all of research papers identify the user similarity neighborhood from implicit information being collected in the user/item preferences matrix in many different ways using data mining techniques. In particular, distribution of research papers by used techniques is shown in Table 8 to answer the second research question defined in this SLR paper. It is worthwhile to say that, the most important achievement of Table 8 is to present techniques in recommendation systems to extract or mine knowledge from data and lead decision making and predict the effect of decisions. It is meaningful to summarize the research papers according to used techniques. As shown at Table 8, research papers have used data mining techniques (clustering, association rule, sequential pattern analysis, k-nearest neighbor (CF) or classification, semantic knowledge base) to extract and mine knowledge from user behavior and fit implicit feedbacks with CF technique. In order to facilitate knowledge about data mining and provide researchers with insight on them, we briefly describe data mining techniques used in research paper: The 38 articles are classified into the following six main categorizes (Dimensionality reduction technique, association rule, Sequential pattern analysis, Semantic knowledge base, other heuristic methods and CF with implicit data).

(1) Dimensionality reduction technique:

Table 7 Distribution of research papers by application fields and user activities

Recommendation filed	User activities	Representative literature
Movie	Historical data and the browsing behavior of the user	S1
	Rating times and the percentage of the rating	S2
	User's visit of the item	S5
	Users' history rating data	S7
	History of the previous purchases of each user	S9
	View of item and item rated by the users	S26
	Filtering tags that are frequently generated by users	S33
	Rating time and rating order	S34
E-commerce	Product review data and user navigation data	S3
	Purchased or not purchased	S4
	Analyzing web log (user's visit time of web page) and combining them with the explicit rating matrix	S10
	User purchase time	S16
	Purchase navigational and behavioral patterns (Length of reading time, Print Status, Bookmarking Status, Number of visits)	S17
	User's purchase, navigational, and behavioral patterns (If the product is purchased, corresponding preference level is set to 1)	S18
	User' shopping behaviors on the web	S24
	Number of transactions of user including item	S25
	Search query logs, item clickthroughs, and transaction history	S27
	Page visits, page viewing times, and Web surfing paths	S36
Social systems	Users' sharing behavior	S12
	Users' tagging behaviors, bookmarking an item, the time when a user bookmarked a resource	S15
	Annotated tags of the item by user	S23
	User's tagging behavior	S28
	What tags a user has used and how often and bookmarking	S29
	User-tag relations and item-tag relations	S30
	Preference degree of a user on a tag	S31
E-learning	Frequency of the item used and last access to the item by each user	S6
Book	User's tagging behavior	S8
	User's tagging behavior	S35
Web dataset	Behavior from the user log records	S14
Mobile environment	How many times user uses item and how long users uses item	S11
	items that are pre-listened, clicked, purchased and ignore	S19
	Item launch time, user purchase time, and the time difference between the two	S20
Discussion Group	Implicit information (Tag, post, rating) and user's query	S21

Table 7 continued

Recommendation filed	User activities	Representative literature
Music	Implicit ratings from both songs and artists out of playlists	S13
	Tag information and play counts	S22
	User listening history	S32
Recruitment service	JobFinder's server logs	S37
Location-based services	User' dwell time on a single location	S38

Dimensionality reduction technique is aimed at reducing the dimensionality of the user-item interaction matrix directly. The strategy of this technique is to form clusters of items or users and then use these clusters as the basic unit in making recommendations. The technique addresses the sparsity problem by removing the insignificant consumers or products to condense the consumer-product interaction matrix. The application of the dimensionality reduction is based on the sparse feature of user's rating matrices in CF techniques. It can also extract information that is not informative for the task and even discard otherwise unobvious or latent interaction among user ratings (Hang et al. 2009; Kim and Yum 2011). However in doing this, potentially useful information might be lost.

Clustering techniques is most popular technique used to reduce the dimensionality of sparse rating matrices. The clustering techniques are unsupervised learning technique that provides a finite set of clusters or categories to describe data. Clustering is aimed at reducing the dimensionality of the user-item interaction matrix directly. The strategy of this technique is to form clusters of items or users and then use these clusters as the basic unit in making recommendations. Singular Value Decomposition (SVD) is a clustering technique to reduce the dimension of user-item preference matrix and get the initial neighbor set for active user for making recommendation. Thereby, clustering technique can improve sparsity problem in CF due to the dimensionality reduction (Kim and Yum 2011).

Classification techniques are another used technique for dimensionality reduction to assign items in a collection to target classes or categories. Classification is aimed to accurately predict the target category for each case in the data. These techniques are the supervised learning techniques that maps input data to a category which perform classification. The class labels of training data has been known that new data is classified based on the training set. Naïve Bayes approach is one of common classification technique to be defined by a set C of classes and a set A of attributes in which a generic class belonging to c is denoted by c_j and a generic attribute belonging to A as A_i. It is important to know, among the Classificationtechniques the most popular are k-nearest neighbor (K-NN), that known as *Collaborative Filtering(CF)* which makes recommendations to active user according to the opinion of users who have similar behaviors or similar purchase patterns. Thus, recommended items/products to active user will be the ones liked by users with similar preferences (Albadvi and Shahbazi 2009; Kim and Yum 2011). This research focuses on investigating the recent progress in CF area and CF is originally based on the nearest neighbor algorithm (also known as k-Nearest neighbor or K-NN). For that reason, we classified research papers by considering other their data mining techniques used.

(2) Association rule: Association rule technique refers to the search for correlations between items in a database and finds interesting correlations between them. This technique expresses how items are related to each other, and how they tend to cluster together. Association rules techniques indicate how frequently the items become visible in the

Table 8 Classification of recommender systems research by used techniques

Data mining techniques	The used technique	Representative literature
Dimensionality reduction	CF + Clustering+ implicit information	S1
	CF + Clustering + implicit information	S9
	CF + Semantic classifying + implicit degree-of-interest	S10
	CF + Product taxonomy + users' navigation	S18
	CF + tag information + Classifying	S23
	CF + web usage mining + product taxonomy	S24
	CF + implicit feedback + clustering algorithm	S38
Association rule	CF + user navigation + Association rule	S3
	CF + web Log/Navigation Path Analysis + association rule	S14
	CF + Association rule + users' navigation and behavioral patterns	S17
Sequential pattern analysis	CF + implicit rating + sequential pattern analysis	S25
Semantic knowledge base	CF + tagging behavior + Semantic similarity	S28
	CF + tagging behavior+ Other user activity + semantic similarity	S29
	CF + Semantic knowledge base + social tagging	S33
Heuristic methods	CF+ ordinal scale-based implicit ratings	S19
	CF + implicit information + Word Sense Disambiguation + Association rule	S21
	CF + implicit feedback+ new asymmetric similarity measure	S32
CF + implicit data/ user activities	CF + user activities factors	S2
	CF + Binary data from user's purchase basket	S4
	CF + user Behavior data	S5
	CF + users' navigation	S6
	CF + time-context of user's preference	S7
	CF + tagging information	S8
	CF + user contact degree	S11
	CF + user's online media sharing activities	S12
	CF + implicit Ratings from listening behaviors	S13
	CF + tag and time information	S15
	CF + pseudo rating data from the implicit feedback data	S16
	CF + item launch time + user buying time+ the time difference	S20
	CF + social media tags + implicit rating	S22
	CF + latent factor models + implicit feedback	S26
	CF + user information from implicit feedback	S27
	CF + tagging information	S30
	CF + tagging information	S31
	CF + time information on users' behaviour	S34
	CF + tagging behavior + new similarity measure method	S35
	CF + implicit feedback + new similarity measure	S36
	CF + implicit data	S37

database by measuring the percentage of transactions done by users on items. The number of times that frequently the items appear to each other shows the degree of correlation between itemsets. For example, when the shopping habits of customers are being analyzed; it is interesting to know the associations between the items that they place in their virtual shopping baskets as well as items that can be grouped together when they purchase these items. Association rule technique is the data mining technique to search for interesting relationships between items by finding the items which frequently appeared together in a transaction database. Association rule technique is the data mining technique to search for interesting relationships between items by finding the items which frequently appeared together in a transaction database (Kardan and Ebrahimi 2013; Kim and Yum 2011).

(3) Sequential pattern analysis: This technique finds statistically relevant patterns between data where the values are delivered in a sequence or find the complete set of frequent subsequences in a set of sequences given. Sequential pattern analysis finds the sequences of customer shopping and provides an ordered list of purchases for each customer for example, a customer first buy laptop, then extra ram, and then chip speed, within 2 months (Choi et al. 2012).

(4) Semantic knowledge base: Semantic knowledge base helps users to browse, search and navigate over enterprise vocabularies. This technique helps users to understand complex domains by using semantic relations between ontology concepts. Word Sense Disambiguation is most popular technique at semantic knowledge base (Kardan and Ebrahimi 2013; Movahedian and Khayyambashi 2014).

(5) Heuristic methods/techniques: several recommendation systems use a hybrid approach by combining more than one data mining technique or adding new method to existing techniques to avoid the weaknesses of each technique and increase the recommendations' accuracy of CF. These hybrid approaches is calling heuristic methods/techniques. Heuristic methods include the ontology method and mixture models (Park et al. 2012). It is noted that, research papers that use diverse technique that are not included in other categorize of data mining techniques have been classified at heuristic methods.

(6) CF+ implicit data/ user activities: Research papers that uses only implicit data for increase the recommendations' accuracy of CF (K-NN) without adding other data mining technique have been classified at this categorize. Theses and research papers propose a CF based recommender system that use a new similarity measure in CF or produce user profiles based on implicit feedback (such as click type, number of visits, length of reading time, basket placement status, purchase status and etc) (Lee et al. 2010; Zheng and Li 2011; Kim and Yum 2011; Choi et al. 2012).

With regards to Table 8, among the 38 research papers, 21 research papers involved only user activities or implicit data in CF. These research papers apply new way for combing CF with implicit data/user activities or propose new similarity measure in CF for improving the recommendation accuracy.

5 Limitations of our study

This paper has been undertaken as a systematic literature review based on guidelines proposed by Kitchenham et al. (2009) and Kitchenham and Brereton (2013). Nevertheless, our study has the following limitations:

- Firstly, although five digital libraries (ACM Digital Library, IEEE Xplore, SpringerLink, Science Direct, and Sage) were included to search research papers relevant to CF technique, but they are not exhaustive and consequently, they limit the research conducted. In addition, we executed the standard systematic literature review method using a manual search due to there is no standard way of conducting searches for all digital libraries.

- Secondly, our findings are based on articles published in English. Therefore, other publications (such as any technical report, discussion, editorial preface, tutorial), published in non-English, were excluded from this study.
- Finally, in the first phase of our review process, we gathered 736 studies to be reviewed, then, the first criterion of exclusion was based on unpublished papers, non-English papers, news articles, short papers and duplicated papers and the next criterion was based on titles, abstracts and keywords. In this view, if an initially retrieved study was unrelated to the CF technique and user activities topic in its title, abstract or keywords, it would be excluded. For improving this procedure, we analyzed all included articles based on their full text. It is worth mentioning that articles were evaluated by people who, based on their knowledge, assessed each of them with the determined schema. Although we performed consensus meetings and peer reviews, author bias is definitely an associated risk for evaluating the contributions of each article that can be avoided. For improving this work, a larger number of researchers in the review of each article can be considered.

6 Conclusion and future work

CF recommender systems have attracted the attention of academics and practitioners. SLR is the research methodology used for aggregating evidence in this paper. SLR is a method for EBSE to support the development of evidence-based guidelines for practitioners. The conducting a SLR guides us to polish our idea in area of research and practice on CF technique and implicit data. In this research, we have selected 38 research papers on CF recommender systems after conducting quality assessment phase, to understand the trend of CF and implicit feedback.

The results represented in this paper help to identify elements in CF that can be enhanced and identify the potential implicit feedback that can be adapted with CF which alleviating the sparsity problem. As result, neighborhood formation is a crucial aspect in CF technique and it can improve with enriching user-item preference matrix by considering implicit feedback or user activities. Our research is significant since research papers were selected from excellent digital libraries such as IEEE, ACM, Sage, Springer and Science Direct. We classified the papers by the application fields used and the data mining techniques used for recommendation. Based on examining the previous publications, our study will provide the academic and practitioner with guideline for future research on CF recommender systems. Table 9 (in Appendix 1) represented elements of CF that have been enhanced by considering the user activities. More research papers were related to movie recommendations and e-commerce applications. Therefore, more research is required on other application fields such as music, TV and etc. Table 8 presents approaches in recommendation systems to be suited for integrating user activities with elements of CF. However our research has the limitations to be mentioned at Sect. 5 and this provides researchers with some guidelines for future research on this topic. It might be a good idea to further classify the user activities. Also, comment on the effect of using different kinds of activities in different domains.

Appendix 1: Table of the systematic review results

See Table 9.

Table 9 Data extraction

ID	Elements of CF technique that can be enhanced by implicit feedbacks		
	Generating user/item preference matrix	*Neighborhood formation*	*Make recommendation*
S1	Collecting the preference of new users by *historical data* and by *the browsing behavior of the user* and creating user-item rating matrix based on the these implicit information of the user	Creating the initial neighbor set of active user through implicit information of the new users and changing the ratings given by the user to the item into the ratings to the item attributes and the ratings made from the user attributes to the item attributes. Singular Value Decomposition is used to reduce the dimensionality of the use-item rating matrix	When a new item or new user is added to the system, matching the attributes of the new items or new user with user-item attribute matrix to find respectively, the users giving the highest rating to the attributes or item attributes with the highest rating for making recommendation the new item or making recommendation to new user
S2	Consider the information implicated in user activity: *rating times and the percentage of the rating on each type* will be extracted	Acquire implicit ratings from user activates and find neighbour for the active user	Make recommendation to active user based on the interests of the active user's neighbor
S3	*Product review data* provided by previous users is used to generate product profiles, which represent associations between attribute values of the products. *User navigation data* is used to generate user profiles, which represents users' preferences to product attributes.	The user profiles are used to find the most similar user or neighbour for the active user	Product recommendations are given to the target user based on the products that have been liked by the active user's neighbour.
S4	Implicit binary rating whose range consists of two values *purchased or not purchased* is used to generate user profiles	To determine the most similar user for an active user, the algorithm first builds a user-to-user similarity matrix by iterating through all user pairs and computing their similarities	Make recommendation to specific user based on user's basket
S5	From implicit feedback (when *a user visits an item*), a binary matrix is used to represent the relationships between users and items	Selecting a nearest neighbor for the active user based on the binary matrix and considering the relationship between neighbors	Calculate the recommender score of each item based on the neighbors' user and choose the N items with the highest scores as the final recommendation
S6	Acquire interests of user on items by measuring interaction between the user and the items from implicit information about the *users' navigation* (*frequency of the item used and last access to the item by each user*)	Calculating the similarity between active user and the other ones by acquiring the values of users' interest on items from implicit information and selecting nearest neighbors	Generate the interest prediction and recommendation to active used based on neighboring users

Table 9 continued

ID	Elements of CF technique that can be enhanced by implicit feedbacks		
	Generating user/item preference matrix	*Neighborhood formation*	*Make recommendation*
S7	Collecting existent *users' history rating data* and creating matrix R { (Ui, Ij, rij, t) | i∈[1,m], j∈[1, n]} (As rij denotes the rating of user Ui on item Ij at the time t)	Dividing the history period into different length intervals and in every interval, analyzing rating data and finding out who have similar interest with active user at that time interval	Computing prediction and recommendation for each time interval neighbor according to these neighbors' most interested items
S8	Making user profile from *user's tagging behavior* based on three aspects: the tags used by the user, the items tagged by the user, and the relationship between the tags and the tagged items	The similarity of users is calculated based on tag information in user profiles such as the percentage of common tags used by the two users	Generating recommendation based on list of the items tagged of neighbour users
S9	Create a matrix containing all the information about the *history of the previous purchases of each user*. This matrix is a matrix with binary features to show whether or not a user has made a purchase	Using clustering technique to discover the relationships between the users in the neighborhood based on implicit feedback on past user purchase (or matrix factorization)	Sorting the products based on the number of purchases for each distinct cluster and creating recommendation list for active user based on the most popular products (the most number of purchases) from the active user's assigned cluster that the user has not previously purchased
S10	Acquire user's implicit degree-of-interest through **analyzing web log (such as user's visit time of web page) and combining them with the explicit rating matrix**. Then, on the basis of mixed rating matrix, the semantic classifying information (such as user role, resource category) is used to decrease the dimensions of users and items (or rating matrix's dimensions). As degree of data sparsity becomes lower in sub-matrix	Calculating item' similarity from amended rating matrix obtained through the combination of user's implicit degree-of-interest with explicit rating matrix and semantic information classifying	Generating recommendation based on item' similarity
S11	Generate the users-item score matrix based on the degree of user activity (including *how many times user uses item and how long users uses item*) to show whether the user is active for one item	Search of the nearest neighbor set for the active user which needs recommendation by analyzing the using user contact degree on items	Predict the item's score rating for the active user, to produce a recommendation list, which is the top-N recommendation

Table 9 continued

ID	Elements of CF technique that can be enhanced by implicit feedbacks		
	Generating user/item preference matrix	*Neighborhood formation*	*Make recommendation*
S12	Create binary data from *users' sharing behavior (Add to favorite list and uploading media segments)*, to infer user preferences of items by observing the media sharing behavior of users in community media sites. For example, $R_{u,i} = 1$, if user *u* upload or favorite item *i*	Computing the similarity between items from user-item interaction matrix constructed from Media Sharing Behavior. Also, view count (number of view on each item) is used as an item popularity indicator	Generating recommendation based on similarity between items
S13	Extracts implicit ratings for both *songs and artists out of playlists to store users' musical tastes in database*. (Artists are better carriers for users' musical tastes, because that they group similar types of songs)	Computing the similarity between two items (songs or artists) based on traditional CF	Execute recommendation for both songs and artists for active user
S14	Capture the user access *behavior from the user log records* to construct the user access sequences	The association rule mining technique is applied to find the frequent itemsets of Web pages from the user access sequences and to construct a set of rules based on those itemsets. Then, finding the shortest distances between Web pages from user access sequences	Predicts users' Web page requests to assist users in browsing the Web pages
S15	Generating user-item binary matrix based on *value of 1 if a user u has bookmarked an item r and 0 otherwise*. Then modifying binary matrix to rating matrix by *using tag and time information provided* (the time when a user *u* bookmarked a resource *r*) by users' tagging behaviors	Calculate user similarity based on the computed rating matrix from users' tagging behaviors to find neighbors for each user	Resource recommendation is implemented based on neighbors' ratings
S16	Constructs a pseudo rating matrix from implicit feedback by using both *item launch time and user purchase time*	Compute similar neighbors whose interests are similar to those of the active user's from the pseudo rating matrix	Recommend the top *N* items among all items that are recommended by the *M* neighbors

Table 9 continued

ID	Elements of CF technique that can be enhanced by implicit feedbacks		
	Generating user/item preference matrix	*Neighborhood formation*	*Make recommendation*
S17	Gather all the data related to the *purchase navigational and behavioral patterns (such as Length of reading time, Print Status, etc*)	The continuous variables are converted to categorical variables. Then, association rule mining is performed on the converted data and all pairwise combinations of products (CDs) that simultaneously appear in a transaction are identified. (The combinations with only two products are considered)	The proposed system computes the confidence levels between clicked products, between the products placed in the basket, and between purchased products, respectively, and then the preference level was estimated through the linear combination of the above three confidence levels. Finally, a Top-N list is recommended to customer
S18	Collect data related *user's purchase, navigational, and behavioral patterns*. Then, numerically determine users' preference levels for the products which are clicked but not purchased. If the product is purchased, corresponding preference level is set to 1	Finding the nearest neighbor set for the active user using the preference levels calculated in previous phase	Predicting the preference levels of a user for the products not clicked are predicted and a Top-N list of products is produced as a recommendation to the user
S19	Create the user profile based on the user's preference from information on his/her previous behaviors. (Weight 0, is allocated to music items that are ignored because the user passes them by and weights 2 and 1, are assigned to *items that are pre-listened and clicked-through*, respectively)	Representing user preference on an ordinal scale and computes the similarity between users and forms a neighborhood between an active user and a group of like-minded users	The preference for music items by the active user is estimated from the neighborhood of users and the music items are sorted in an ascending order of these estimated preferences, and the highly ranked *N* items are recommended
S20	Assigning weights based on temporal information including *item launch time, user purchase time, and the time difference between the two* for constructing rating matrix	Compute similar neighbors to the active user from weight assignment matrix created from temporal information	Recommending items by regarding the similar neighbors

Table 9 continued

ID	Elements of CF technique that can be enhanced by implicit feedbacks		
	Generating user/item preference matrix	*Neighborhood formation*	*Make recommendation*
S21	Extend user profile from *implicit* **information from a discussion group (Tag, post, rating)**. Also, the *user's query* is one of the main inputs that based on the keywords in this query; system recommends semantically similar contents to this query	Identify the similar users from retrieving implicit information being collected in a discussion group. To accomplish this purpose, the association rules mining technique is employed to find the relationships and similarities among the users. Furthermore, Finding similar and related items based on the semantic concepts by considering content-based filtering technique	The results obtained from the CBF (the related tags are semantically found and then the posts with candidate tags will be extracted) and CF (the posts will be selected that at least one of the similar users has contributed to or showed interest in them) are combined to obtain an accurate and consistent recommendation
S22	Capture tag information (*music tags, artist tags*) and play counts by user for each song	Calculating the item similarities by fusing two similarities, namely artist-tag-driven similarity and item-tag-driven similarity (the items are similar if the related tag distributions are similar). Then, deriving the rating statistically by play counts to describe the user's preferences and merging with item similarity calculation	Predict the user's ratings of items to describe the user's preferences by deriving the tag similarity between music and play counts
S23	Enriching users' preference information using *annotated tags of the item by user* and creating User–item binary matrix, *User–tag frequency matrix and Tag–item frequency* matrix	Measuring similarities between users with user-created tags and then identifying the latent tags for each user from tags similar to her/his tags in order to construct Candidate Tag Set	Applying the candidate tags for each user in order to recommend top-N items
S24	After forming product taxonomy and extracting product category attributes, user profile is created by implicit ratings of user to product attributes (*Web usage mining is employed to analyze user' shopping behaviors on the web* and collects their implicit ratings on the product attributes of each category)	Computing of similarity between users through comparing their profiles is used to identify neighbors of active user in CF approach and computing of similarity between users and products through product profile and user's profile is used in CBF approach to identify which product should be recommended to active user	To generate recommendation list for active user, candidate products are derived separately from two components: the products that are the most similar ones to active user (CBF component) and the neighbor set of active user in a given category (CF)
S25	Construct a user profile with deriving implicit ratings of users on items from *transaction data* (*The number of transactions of user u including item i*)	Calculating similarity score based on implicit ratings and finding neighbors	Calculating predicted preference and make recommendation based on interests of active user's neighbour

Table 9 continued

ID	Elements of CF technique that can be enhanced by implicit feedbacks		
	Generating user/item preference matrix	*Neighborhood formation*	*Make recommendation*
S26	Constructing an accurate profile by exploiting users' demographics, such as age, gender and occupation, along with *user actions based by considering users' demographic* and only genres items' metadata. (Capture a user's preference to different features of items by *user actions such as view of item and item rated by the users*)	Group personal information from users, items metadata and implicit feedback to capture the relationship between users' personal information and items' descriptions in order to capture the user's preferences according to the semantics associated with the content. First, segmenting all users by demographic characteristics and then applying a user clustering procedure to each segment according to the preference of items	The recommendation is computed by uncovering latent associations among users or items by capturing the user's preferences according to personal information and the semantics associated with the content
S27	Infer the *user's purchase preference from user information including search query logs (Search keywords), item clickthroughs, and transaction history*. Replacing the sparse transaction matrix with a denser clickthrough data matrix	Use the profiles of users for computing similarity of users and similarity between users and items. For example using title of the browsing items to compute the ranked list of items based on the similarity between the title description of a predicted item and the user's browsing profile or the Keywords in user's Search History	Predicting a sorted list of top-k items which match the user's actual purchased items
S28	Taking the semantic distance between tags assigned by different users on items by using a triple relation < *userID; pageID; tag* > to record which user puts which tag on which page	Finding the top-N nearest neighbors by using the semantic similarity among tags The similarity among users is based not only on the ratings given to co-rated items, but also based on their cognitions on the same items	Generating a top-M list of recommendations base on nearest neighbors
S29	Creating the relationship between users, resources and *tags* in order to extract: (1) information about *what tags a user has used and how often*; (2) the *number of times that tag* t_i *was associated to resource* p_j	Identifying the users with similar interests to active user based on their past tag activity and inferring tags' relationships based on their association to content. (As the more tags two users have used in common, the more similar they are, regardless of what resources they used it on and the more resources have been tagged with the same pair of tags, the more similar these tags are, regardless of the users who used them)	Resources tagged by similar users will be ranked higher and recommended

Table 9 continued

ID	Elements of CF technique that can be enhanced by implicit feedbacks		
	Generating user/item preference matrix	*Neighborhood formation*	*Make recommendation*
S30	To aggregate the user's related tags with considering the following *user-tag relations*: (1) used tags (direct relation based on tags the user has used) (2) incoming tags (direct relation based on tags applied on the user by others) and (3) indirect tags (indirect relation based on tags applied on items related to the user)	Relationship information among people, tags, and items, is extracted. The set of people related to the user is extracted by considering both direct (having the same manager) and indirect (people whose social activity overlaps with the user's social activity such as co-usage of the same tag, co-tagging of the same item)	The system recommends to the user items that are related to a user's tags and people within his personal profile
S31	Constructing users' profiles and resources' profiles from collaborative tags. User profile indicates the *preference degree of a user on a tag and resource profile indicates the degree of how relevant the resource is to the tag*	The matching degree of the profile of user *i* and the profile of resource *c* is measured (If a user is more interested in a tag, he will also be more likely interested in the resources which are relevant to the tag). Besides, based on an observation on user query behavior, measuring the number of matching tags between the query and resource profile into consideration	Recommend resources that match both user's personal interest and the query requirements to obtain the final resource ranking for a particular user query
S32	Creating the binary ratings $r_{ui} \in \{0, 1\}$ an entry $r_{ui} = 1$ represents the fact that *user u have listened to the song i*	Presenting a novel scoring function that results effective on implicit rating and a new asymmetric similarity measure for finding similarity between users and items	Defining the top-N recommendation based on similar user or items
S33	Filtering tags that are frequently generated by users and *constructing user and item semantic profiles based on set of tags* that the user applies frequently on items as user profile represents a user's preferences and an item profile specifies an item's characteristics	Semantic user profiles are further enriched by correlation with similar users and analysing neighbour profiles. Then, finding similarity between user and item profiles	Recommending a ranked list of relevant items based on finding the most similar item profiles to the active user profile

Table 9 continued

ID	Elements of CF technique that can be enhanced by implicit feedbacks		
	Generating user/item preference matrix	*Neighborhood formation*	*Make recommendation*
S34	Creating user–item binary matrix based on *transaction between user and item(Rating time and rating order)* to create the user–item graph	Defining a user–item graph to understand the relations between users and determine the similarity between the active user and direct neighbours by considering three factors rating time, rate difference and rating order. Then, the process of measuring the similarity continues through indirect neighbours of the active user). (Direct neighbours are connected to the active user by a direct edge and indirect neighbours are connected to the active user by more than one edge in graph)	Making recommendations based on the interest of neighbours in the items not rated by the active user.
S35	To profile *user's tagging behavior* in three aspects: the tags used by the user, the items tagged by the user, and the relationship between the tags and the tagged items	Based on user profiles, the neighborhood of users with similar tagging behavior (e.g. similarity of users' tags, the percentage of common items tagged by the two users and the similarity of the users' tag-item relationship) is generated	Making recommendations to the active user based on the neighbour users' item lists
S36	Analyzing the *Web log and capture implicit feedback including page visits, page viewing times, and Web surfing paths*	Capturing real similarity among users from implicit ratings with proposing a new similarity measure for implicit ratings to be called Inner Product	Recommending items from capturing similarities of implicit ratings
S37	User profiles are constructed by mining *JobFinder's server logs* including the amount of times that a user has accessed an information item and a JobFinder user can either email a job description to herself/himself, or apply for the job directly	More similar profiles to the active user profile are identified and then the jobs not already present in the active user profile are ranked	Draws job recommendations from the profiles of similar users
S38	Exploiting the *user' dwell time on a single location* and Creating a database with users, locations and the implicit ratings given by users to those locations computed by the dwell time frequency	Computes the similarity of users in terms of the locations they have visited and their dwell time at certain locations. Then, identify path patterns out of historical paths of the nearest neighbours and the current path of the active user in order to predict future locations on his current path	Providing the location recommendations to a user based on the opinions of like-minded users

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