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A literature review and classification of recommender systems research

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ABSTRACT

Recommender systems have become an important research field since the emergence of the first paper on collaborative filtering in the mid-1990s. Although academic research on recommender systems has increased significantly over the past 10 years, there are deficiencies in the comprehensive literature review and classification of that research. For that reason, we reviewed 210 articles on recommender systems from 46 journals published between 2001 and 2010, and then classified those by the year of publication, the journals in which they appeared, their application fields, and their data mining techniques. The 210 articles are categorized into eight application fields (books, documents, images, movie, music, shopping, TV programs, and others) and eight data mining techniques (association rule, clustering, decision tree, k-nearest neighbor, link analysis, neural network, regression, and other heuristic methods). Our research provides information about trends in recommender systems research by examining the publication years of the articles, and provides practitioners and researchers with insight and future direction on recommender systems. We hope that this paper helps anyone who is interested in recommender systems research with insight for future research direction.

1. Introduction

Recommender systems have become an important research area since the emergence of the first research paper on collaborative filtering in the mid-1990s (Resnick, Iakovou, Sushak, Bergstrom, & Riedl, 1994; Shardanand & Maes, 1995). In general, recommender systems directly help users to find content, products, or services (such as books, digital products, movies, music, TV programs, and web sites) by aggregating and analyzing suggestions from other users, which mean reviews from various authorities, and users (Frias-Martinez, Chen, & Liu, 2009; Frias-Martinez, Magoulas, Chen, & Macredie, 2006; Kim, Ji, Ha, & Jo, 2010). These systems use analytic technology to compute the probability that a user will purchase one of the products at each place, so that users will receive recommendations for the right products to purchase.

Recommender systems are generally classified into collaborative filtering (CF) and content-based filtering (CB). In general, CF uses an information filtering technique based on the user's previous evaluation of items or history of previous purchases. However, this technique has been known to reveal two major issues: sparsity problem and the scalability problem (Claypool et al., 1999; Sarwar, Karypis, Konstan, & Riedl, 2000a, 2000b). In contrast, CB analyzes a set of documents rated by an individual user and uses the contents of the documents, as well as the provided ratings, to infer a user profile that can be used to recommend additional items of interest (Basu, Hirsh, & Cohen, 1998). However, the syntactic nature of CB, which detects similarities between items that share the same attribute or characteristic, causes overspecialized recommendations that only include items very similar to those of which the user is already aware (Lopez-Nores, Garca-Duque, Frenandez-Vilas, & Bermejo-Munoz, 2008).

Over the last decade, most of researchers have studied new approaches of recommender systems in order to solve these problems of CF and CB, and to implement them into real world situations. Specifically, applying data mining techniques to recommender systems has been effective in providing personalized information to the user by analyzing his or her preferences.

However, more research is needed to be applicable in real world situations because research fields on recommender systems are still broader and less mature than in other research areas. Therefore, the existing articles on recommender systems must be reviewed with an eye toward the next generation of recommender systems, which will improve recommendation methods to offer more useful and appropriate information to users.

In this research, we reviewed and classified articles on recommender systems that were published in academic journals between 2001 and 2010, in order to gain insight on recommender systems. This research is organized as follows:

(1) The research methodology used in this study is reported.
(2) Criteria for classification of research papers on recommender systems are presented.

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(3) Research papers on recommender systems are analyzed and the results of their classifications are presented.
(4) Conclusions are presented, and the limitations and implications of this study are discussed.

We hope that this research will accentuate the importance of recommender systems and provide researchers and practitioners with insight on recommender systems research.

2. Research methodology

The purpose of this study is to understand the trend of recommender systems research by examining the published articles, and to afford practitioners and academics with insight and future direction on recommender systems.

Hence, we will verify the distribution of research papers on recommender systems by their year of publication, and classify the research papers by the data mining techniques used for recommendation and by the application fields used. However, considering the nature of research on recommender systems, it would be difficult to confine each paper to a specific discipline. Additional proof of this difficulty can be seen from the fact that research papers on recommender systems are scattered across diverse journals such as marketing, information technology, information science, computer science, and management. As a result, it is necessary to compile the increasing number of research papers on recommender systems systematically. The following electronic journal databases were searched to provide a comprehensive bibliography of research papers on recommender systems:

- ABI/INFORM Database;
- ACM Portal;
- EBSCO Academic Search Premier;
- EBSCO Business Source Premier;
- IEEE/IEE Library;
- Science Direct.

The search process of research papers on recommender systems was performed on the top 125 MIS journals. The search was performed based on five descriptors: "Recommender system", "Recommendation system", "Personalization system", "Collaborative filtering", and "Contents filtering". Two authors reviewed the full text of each research paper, and papers that were not truly related to recommender systems were deleted if the two authors agreed to do so. If the authors' opinions were different, another author reviewed the paper and decided whether to delete it or not. The following research papers, set forth in the description below, were excluded because they were unfit for our research:

- Conference papers, master's and doctoral dissertations, textbooks, unpublished working papers, non-English papers, and news articles were eliminated, Unlike these publications, papers published by academic journals are thought to be reliable and worthy of comment, because they are published after peer review.
- Because research on recommender systems is relatively current, we have only searched research articles published between 2001 and the end of 2010. This 10-year period is considered to be representative of recommender systems research.
- Only research papers that described how recommender systems can be applied were chosen.

We selected 210 research papers on recommender systems from 46 journals. Each research papers was prudently reviewed and classified into one of the eight categories in the application fields and data mining techniques. Although the investigation was not exhaustive, it provides as a comprehensive basis for understanding recommender system research.

3. Classification method

Our classification framework consists of recommendation fields and data mining techniques. In this research, we classify the research papers that were reviewed into eight categories of application fields and eight categories of data mining techniques. The overall graphical classification framework for recommender systems research papers is presented in Fig. 1.

3.1. Classification framework for application fields

Many recommender systems have been used to provide users with information to help them decide which products to purchase (Schafer, Joseph, & Riedl, 2001). However, it is not easy to find papers that classify research papers systematically, even though recommender systems have been applied to diverse business areas. Accordingly, it is meaningful to investigate application fields. Our research adopts the basic classification scheme of Schafer et al., 2001, who have classified recommendation applications by real world, such as books, movies, music, shopping and others. We classify research papers by application fields such as books, documents, images, movies, music, shopping, TV programs and others. Through in-depth reviews of research papers, classifying shopping fields involves online, offline, and mobile shopping product, classifying document fields involves papers, blogs and web pages. Also, other fields involve a minority of recommendation fields such as hotel, travel, and food.

3.2. Classification framework for data mining techniques

In general, data mining techniques are defined as extracting or mining knowledge from data. These techniques are used for the exploration and analysis of large quantities of data in order to discover meaningful patterns and rules (Berry & Linoff, 2004). They can be used to lead decision making and to predict the effect of decisions. Significantly, many researchers have used data mining techniques to improve the performance of recommender systems. Consequently, it is meaningful to classify the research papers according to data mining techniques. We widely classified data mining techniques into the following eight categories: association rule, clustering, decision tree, k-nearest neighbor, link analysis, neural network, regression, and other heuristic methods.

(1) *Association rule:* Association rule mining refers to the discovery of all association rules that are above user-specified minimum support and minimum confidence levels. Given a set of transactions in which each transaction contains a set of items, an association rule applies the form $X \Rightarrow Y$, where X and Y are two sets of items (Cho, Kim, & Kim, 2002).
(2) *Clustering:* The clustering method identifies a finite set of categories or clusters to describe data. Among the clustering methods, the most popular are *K*-means and self-organizing map (SOM). *K*-means takes the input parameter, *K*, and partitions a set of n objects into *K* clusters (Berry & Linoff, 2004). SOM is a method for an unsupervised learning, based on an artificial neurons clustering technique (Lihua, Lu, Jing, & Zongyong, 2005).
(3) *Decision tree:* Most popular classification methods are decision tree induction. Decision tree induction techniques build decision trees to label or categorize cases into a set of known

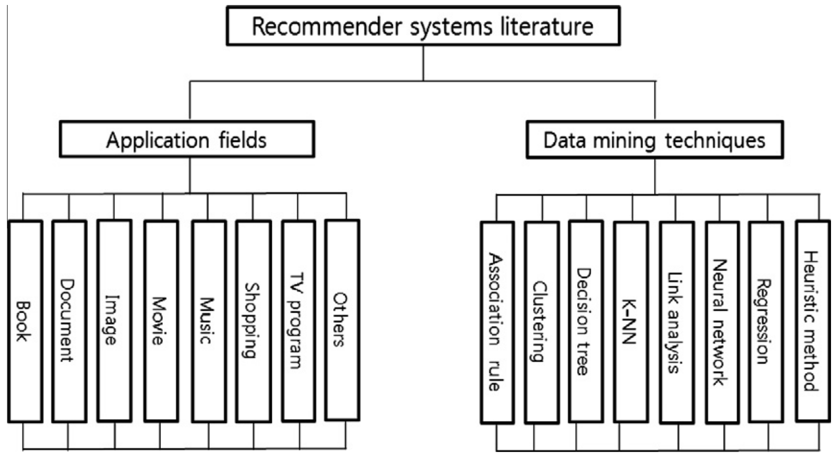

Fig. 1. Classification framework.

classes. The top node in a tree is called as a root node. A decision tree is a tree in which each internal (non-leaf) node represents a test on an attribute, each branch represents an outcome of the test, and each terminal (leaf) node represents a class prediction (Kim, Cho, Kim, Kim, & Suh, 2002).

(4) *k-Nearest* neighbor: The k-NN (k-nearest neighbor) model, a typical traditional CF-based recommender system, makes recommendations according to the following three phases. (1) Recommender systems construct a user profile using the user's preference ratings, which are obtained either directly from explicit ratings of items or indirectly from purchase or usage information. (2) Recommender systems apply statistical or machine learning techniques to discover k users, known as neighbors or recommenders, who in the past have shown similar behaviors. A neighborhood is formed based on the degree of similarity between a mark user and other users. (3) Once a neighborhood is formed for a target user, recommender systems make a top-n item set that the target user is most likely to purchase by analyzing the items in which neighbors have exhibited interest (Kim, Kim, & Ryu, 2009).

(5) *Neural network:* A neural network is a parallel distributed information processing system that is able to learn and self-organize. This system consists of a large number of uncomplicated processing entities which are interconnected to form a network that conducts complex computational tasks (Ibnkahla, 2000). A neural network builds a class of very pliable model that can be used for a diversity of different applications, such as prediction, non-linear regression, or classification (Anders & Korn, 1999).

(6) *Link analysis:* Link analysis discovers relations between domains in large databases. One type of link analysis, social network analysis is a sociological approach for analyzing patterns relationships and interactions between social actors in order to find a fundamental social structure. Also, link analysis has presented great potential in improving the accuracy of web searches. Link analysis consists of PageRank and HITS algorithms. Most link analysis algorithms handle a web page as a single node in the web graph (Cai, He, Wen, & Ma, 2004).

(7) *Regression:* Regression analysis is a powerful process for analyzing associative relationships between dependent variables and one or more independent variables. It has been used for curve fitting, prediction, and testing systematic hypotheses about relationships between variables (Malhotra, 2007).

(8) *Other heuristic methods:* Heuristic methods have been developed by adding new method to existing methods. Heuristic methods include mixture models and the, ontology method.

3.3. Classification process

Each of the selected research papers was reviewed and classified according to the proposed classification framework by two of the four authors of this paper (first team). The other two authors (second team) made a final verification of the classification results. The classification process is composed of the following four steps:

(1) Electronic database search.
(2) Initial classification by one of the two researchers in the first team.
(3) Independent verification of classification results by the other researcher in the first team.
(4) Final verification of classification results discussed by the second team.

The selected criteria and evaluation framework is represented in Fig. 2. The research papers were analyzed by year of publication, by journals in which the research papers were published, and by application fields and data mining techniques.

4. Classification of research papers

We selected a total of 210 research papers from 46 journals and classified them according to the classification framework. The results of our analysis will supply guidelines for future research on recommender systems. The details are described below.

4.1. Distribution by year of publication

The distribution of research papers by year of publication between 2001 and 2010 is shown in Fig. 3. It is apparent that publications related to recommender systems steadily increased between 2000 and 2004, and rapidly increased between 2007 and 2010. The decrease of research papers between 2005 and 2006 is thought to be because recommender systems research apparently extended a new application field between 2005 and 2006. Whereas a majority of recommender systems research between 2005 and 2006 were limited to movie and shopping fields,

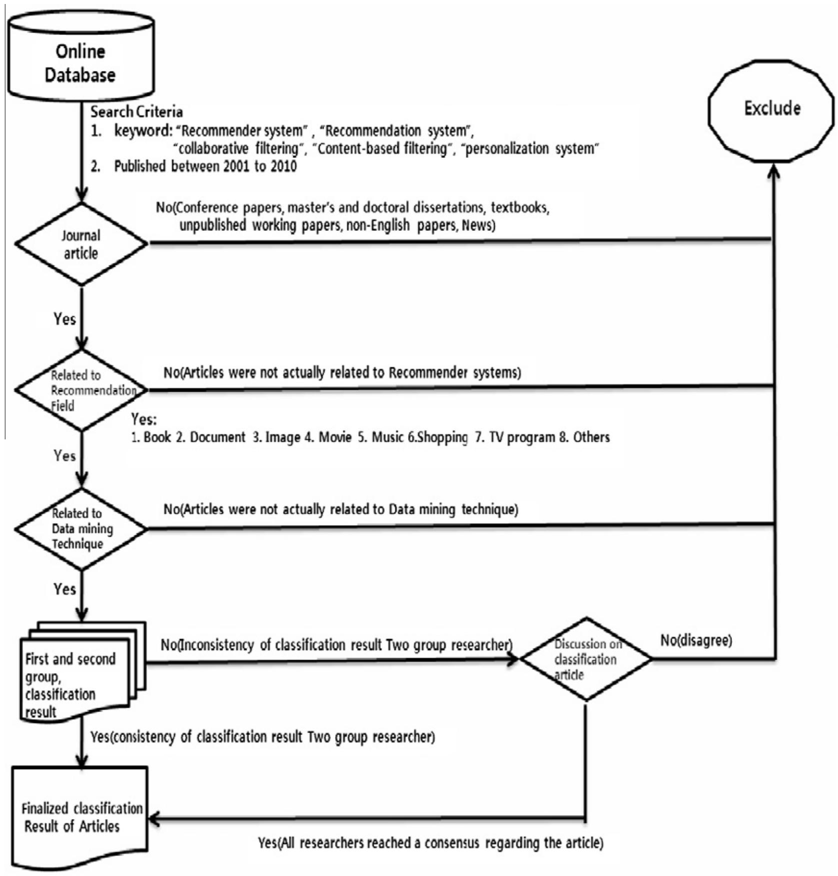

Fig. 2. Selection criteria and evaluation framework.

this research began to extend to other fields such as books, documents, music and other fields in 2007.

4.2. Distribution by journal

Research papers are selected from a total of 46 different journals. Distribution of research papers by journal is presented in Table 1. Expert Systems with Applications published more than 33% (70 out of 210 research papers, or 33.33%) of the total number of research papers. IEEE Intelligent System (21 out of 210 research papers, or 10.00%), along with, Decision Support Systems and ACM Transactions on Information Systems (12 out of 210 research papers, or 5.71%), published the second and third largest percentage of recommender systems-related research papers among the journals. The most research papers were published in Expert Systems with Applications, because this journal focuses on knowledge of the application of expert and intelligent system by industry, governments and universities worldwide (Ngai, Xiu, & Chau, 2009).

4.3. Distribution by application fields and data mining techniques

Distribution of research papers by application fields is represented in Fig. 4. The majority of the research papers were related to movie (53 out of 210 research papers, or 25.2%) and shopping (42 out of 210 research papers, or 20.0%). Because recommender systems in movie and shopping fields have a larger number of practical applications than other fields, it is inferred that although many research papers were published, few of them were related to image fields (7 out of 210 research papers, or 3.3%), and music, and TV program fields (9 out of 210 research papers, or 4.2% respectively). In particular, because the data of MovieLens (www.movielens.org/) are freely accessed, many recommendation methodologies have been proposed and evaluated with MovieLens data, which explains why there is more the recommender systems researches in movie fields than in other fields.

Distribution of research papers by application fields and journal is represented in Table 2. Among the application fields and journals, Expert Systems with Applications included most of the application fields. However, research papers about recommending music and TV programs were usually published in more specific journals. Because music and TV program related papers are usually published at the specific journals.

Distribution of research papers by data mining techniques is shown in Fig. 5, and distribution of the 210 research papers classified by the suggested classification framework is shown in Table 3. Among data mining techniques, the heuristic and k-NN (k-nearest

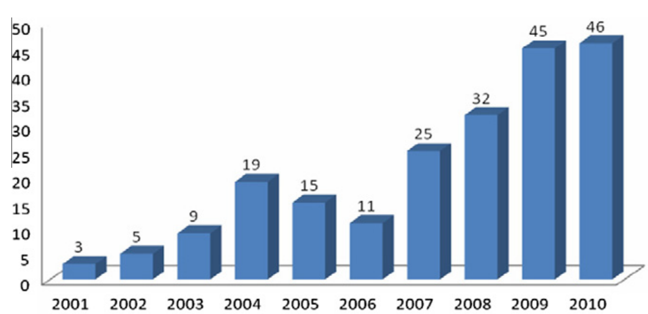

Fig. 3. Distribution of research papers by year of publication.

Table 1
Distribution of research papers by journal in which the research papers were published.

Journal title	Amount	Percentage (%)
Expert Systems with Applications	70	33.33
IEEE Intelligent Systems	21	10.00
ACM Transactions on Information Systems	12	5.71
Decision Support Systems	12	5.71
Knowledge-Based Systems	11	5.24
IEEE Internet Computing	9	4.29
IEEE Transactions on Consumer Electronics	9	4.29
International Journal of Electronic Commerce	7	3.33
Electronic Commerce Research & Applications	6	2.86
IEEE Transactions on Knowledge and Data Engineering	6	2.86
IEEE Transactions on Audio, Speech, and Language Processing	3	1.43
International Journal of Human Computer Studies	3	1.43
Journal of Systems & Software	3	1.43
Behavior & Information Technology	2	0.95
Computers in Human Behavior	2	0.95
Information Processing & Management	2	0.95
IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans	2	0.95
Management Science	2	0.95
ACM Transactions on Computer–Human Interaction	1	0.48
ACM Transactions on Knowledge Discovery from Data	1	0.48
AI Magazine	1	0.48
Communications of the ACM	1	0.48
Computer	1	0.48
Computer Supported Cooperative Work	1	0.48
Computers & Operations Research	1	0.48
Electron Markets	1	0.48
IEEE Circuits and Systems for Video Technology	1	0.48
IEEE Pervasive Computing	1	0.48
IEEE Security & Privacy	1	0.48
IEEE Software	1	0.48
IEEE Spectrum	1	0.48
IEEE Transactions on Fuzzy Systems	1	0.48
IEEE Transactions on Information Forensics and Security	1	0.48
IEEE Transactions on Multimedia	1	0.48
IEEE Transactions on Pattern Analysis and Machine Intelligence	1	0.48
IEEE Transactions on Services Computing	1	0.48
IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews	1	0.48
Information & Management	1	0.48
Information Systems	1	0.48
International Journal of Information Management	1	0.48
International Journal of Technology Management	1	0.48
IT Professional	1	0.48
Journal of Computer Information Systems	1	0.48
Journal of Software Maintenance	1	0.48
Journal of Management Information Systems	1	0.48
Journal of Information Science	1	0.48
Total	210	100.00

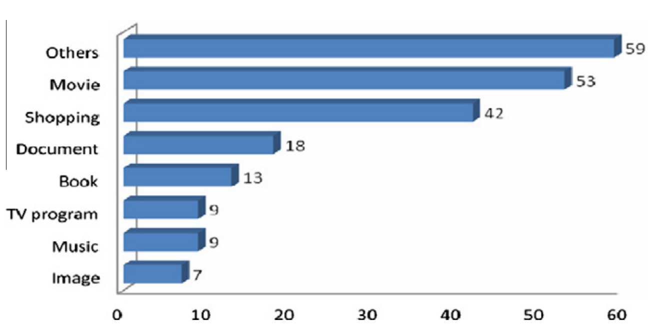

Fig. 4. Distribution of research papers by application fields.

neighbor) models have been used the most often in application fields. Because, the heuristic model is not one method but instead involves adding on new methods to existing diverse methods, it is used to expand advanced research. Also, the CF system is one of the most successful methodologies in recommender systems, and k-NN is a popular type of CF, so k-NN has been applied in most of the application fields.

4.4. Distribution of research papers by publication years and application fields

Distribution of research papers by publication years and application fields is shown in Fig. 6, which shows decreases in most of the application fields during 2006. Until 2006, most recommender systems research was focused on movies and shopping fields. However, the focus of recommender systems research has extended not only to movie and shopping fields, but also to books, documents, music, and other fields beginning in 2007.

4.5. Distribution of research papers by publication years and data mining techniques

Distribution of research papers by publication years and data mining techniques is shown in Fig. 7. Among the data mining techniques, most of the techniques are decreased in 2006, except that the heuristic method increased steadily and reached a peak in 2010. Because the heuristic method is not only one method, but rather involves diverse methods that are not included in other server data mining techniques, its usage has increased annually.

Table 2
Distribution of research papers by recommendation field and journals.

Field	Journal	Amount	
Book	ACM Transactions on Information Systems	2	
	Decision Support Systems	2	
	Electronic Commerce Research & Applications	2	
	IEEE Internet Computing	2	
	Computers in Human Behavior	1	
	Expert Systems with Applications	1	
	International Journal of Information Management	1	
	Knowledge-Based Systems	1	
	Management Science	1	
			13
Document	Expert Systems with Applications	5	
	IEEE Intelligent Systems	3	
	ACM Transactions on Information Systems	2	
	Decision Support Systems	2	
	IEEE Internet Computing	1	
	IEEE Transactions on Information Forensics and Security	1	
	Journal of Computer Information Systems	1	
	Journal of Systems & Software	1	
	Knowledge-Based Systems	1	
	International Journal of Human Computer Studies	1	
			18
Image	Expert Systems with Applications	4	
	Journal of Information Science	1	
	IEEE Intelligent Systems	1	
	IEEE Transactions on Multimedia,	1	
			7
Movie	Expert Systems with Applications	21	
	ACM Transactions on Information Systems	6	
	Knowledge-Based Systems	5	
	International Journal of Electronic Commerce	4	
	IEEE Intelligent Systems	3	
	Electronic Commerce Research & Applications	2	
	IEEE Internet Computing	2	
	IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans	2	
	ACM Transactions on Knowledge Discovery from Data	1	
	Behavior & Information Technology	1	
	Communications of the ACM	1	
	Computer	1	
	Decision Support Systems	1	
	IEEE Circuits and Systems for Video Technology	1	
	IEEE Transactions on Knowledge and Data Engineering	1	
	Information Processing & Management	1	
			53
Music	IEEE Transactions on Audio, Speech, and Language Processing	3	
	Expert Systems with Applications	2	
	ACM Transactions on Information Systems	1	
	IEEE Intelligent Systems	1	
	IEEE Transactions on Consumer Electronics	1	
	Information Processing & Management	1	
			9
Others	Expert Systems with Applications	22	
	IEEE Intelligent Systems	8	
	IEEE Transactions on Knowledge and Data Engineering	5	
	Decision Support Systems	4	
	IEEE Internet Computing	3	
	IEEE Transactions on Consumer Electronics	3	
	International Journal of Electronic Commerce	2	
	Computer Supported Cooperative Work	1	
	Electron Markets	1	
	IEEE Pervasive Computing	1	
	IEEE Security & Privacy	1	
	IEEE Software	1	
	IEEE Spectrum	1	
	IEEE Transactions on Fuzzy Systems	1	
	IEEE Transactions on Pattern Analysis and Machine Intelligence	1	
	IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews	1	
	IT Professional	1	
	Knowledge-Based Systems	1	
	Management Science	1	
			59
Shopping	Expert Systems with Applications	14	
	IEEE Intelligent Systems	5	

Table 2 (*continued*)

Field	Journal	Amount	
	Decision Support Systems	3	
	Electronic Commerce Research & Applications	2	
	International Journal of Human Computer Studies	2	
	Knowledge-Based Systems	2	
	ACM Transaction on Computer–Human Interaction	1	
	ACM Transactions on Information Systems	1	
	AI Magazine	1	
	Behavior & Information Technology	1	
	Computers & Operations Research	1	
	IEEE Transactions on Consumer Electronics	1	
	IEEE Transactions on Services Computing	1	
	Information & Management	1	
	Information Systems	1	
	International Journal of Electronic Commerce	1	
	International Journal of Technology Management	1	
	Journal of Software Maintenance	1	
	Journal of Systems & Software	1	
	Journal of Management Information Systems	1	
			42
TV program	IEEE Transactions on Consumer Electronics	4	
	Computers in Human Behavior	1	
	Expert Systems with Applications	1	
	IEEE Internet Computing	1	
	Journal of Systems & Software	1	
	Knowledge-Based Systems	1	
			9
Total			210

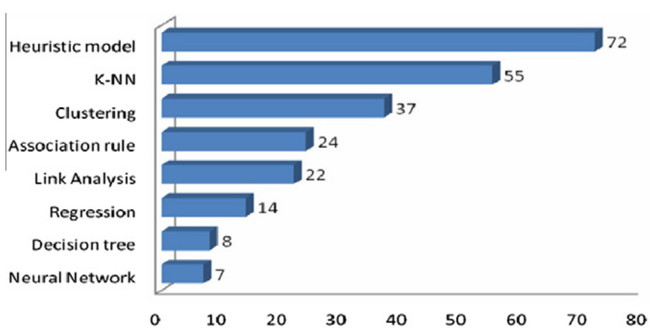

Fig. 5. Distribution of research papers by data mining techniques.

Based on their previous rates of change, more heuristic methods are expected to be used significantly in the future.

5. Conclusion, research implication and future work

Recommender systems have attracted the attention of academics and practitioners. In this research, we have identified 210 research papers on recommender systems, which were published between 2001 and 2010, to understand the trend of recommender systems-related research and to provide practitioners and researchers with insight and future direction on recommender systems. The results represented in this paper have several significant implications:

- Based on previous publication rates, interest in recommender systems related research will grow significantly in the future.
- Fifty-three research papers were related to movie recommendations, whereas image recommendations were identified in only seven research papers. Image field, and Music, and TV program recommendations were identified in nine research papers respectively. Therefore, more research is required to for image, music and TV program recommendations. This result was due to the easy use of the MovieLens data set. Therefore, it looks to be necessary to prepare data sets in other fields.
- Among the 210 research papers, 55 research papers used k-NN and 72 research papers have used heuristic models in the recommender system domain. k-NN creates applied user profile using the user's preference ratings obtained either directly from the user's explicit ratings of items or indirectly from the user's purchase or usage information. Therefore, it is not surprising that the k-NN method has been used in an extensive range of recommender systems domains. Also, because the heuristic model is not a single method, but one that consist of existing diverse methods, its use will be increased.
- Research papers using clustering and association rule techniques rank behind k-NN. From this, we know that both clustering and association rule techniques have been widely used in real business application than other techniques.
- Recently, social network analysis has been used in various applications. However studies on recommender systems using social network analysis are still deficient. Henceforth, we expect that new recommendation approaches using social network analysis will be developed. Therefore, developing the recommendation system research using social network analysis will be an interesting area further research.
- The number of heuristic methods is increasing every year. This result has been caused by the many researchers developing new methodologies and mixed technique model.
- Our research is significant because the majority of recommender systems research has been published in 125 MIS journals, such as ACM, IEEE publications. However, recommender systems research has shifted from the MIS field to various business fields, so we expect to see more recommender systems research published in management and business journals.

Our classification model will provide the practitioner and academic with guideline for future research on recommender systems. However our research has the following limitations: First,

Table 3
Distribution of research papers by application fields and journals.

Recommendation field	Data mining techniques	Reference
Book	Heuristic model	Riedl (2001)
	Clustering	Linden, Smith, and York (2003)
	k-NN	McSherry (2004)
	Link analysis	Huang, Chen, and Zeng (2004)
	Link analysis	Huang, Zeng, and Chen (2007a, 2007b)
	Link analysis	Ziegler and Golbec (2007)
	Regression	Hernández del Olmo and Gaudioso (2008)
	Clustering	Rosaci, Sarné, and Garruzzo (2009)
	k-NN, heuristic model	Kim, Kim, Oh, and Ryu (2010)
	Association rule, k-NN	Kim et al. (2010)
	Heuristic model, link analysis	Hwang, Wei, and Liao (2010)
	Heuristic model	Crespo et al. (2010)
Document	k-NN, neural network, regression	Lee, Hui, and Fong (2002)
	Association rule, clustering	Wang and Shao (2004)
	Heuristic model	Middleton, Shadbolt, and De Roure (2004)
	Clustering, neural network	Lihua et al. (2005)
	Heuristic model	Melamed, Shapira, and Elovici (2007)
	Link analysis	Liang, Yang, Chen, and Ku (2008)
	Heuristic model	Weng and Chang (2008)
	Clustering	Wei, Yang, and Hsiao (2008)
	k-NN, regression	Tang and McCalla (2009)
	Clustering	Lai and Liu (2009)
	Association rule, clustering, Link analysis	Göksedef and Gündüz-Öğüdücü (2010)
	Heuristic model	Champin, Briggs, Coyle and Smyth (2010)
	Heuristic model	Moens, De Beer, Boiy, and Gomez (2010)
	Clustering, heuristic model	Jalali, Mustapha, Sulaiman, and Mamat (2010)
	Link analysis	Dell'Amico and Capra (2010)
Image	Heuristic model	Kwon (2003)
	Heuristic model	Kim, Lee, Cho, and Kim (2004)
	Heuristic model	Boutemedjet and Ziou (2008)
	k-NN	Lee, Park, and Park (2008)
	k-NN, link analysis	Kim, Kim, and Cho (2008)
	k-NN	Lee, Park, and Park (2009)
	Heuristic model, k-NN	Nan Zheng, Li, Liao, and Zhang (2010)
Movie	k-NN	Naren, Benjamin, Batul, Ananth, and George (2001)
	Association rule	Herlocker and Konstan (2001)
	Association rule, decision tree, k-NN	Cheung, Kwok, Law, and Tsui (2003)
	Clustering, k-NN	Roh, Oh, and Han (2003)
	Clustering	Cheung, Tsui, and Liu (2004)
	k-NN	Han, Xie, Yang, and Shen (2004)
	Clustering, k-NN	Weng and Liu (2004)
	k-NN	Zeng, Xing, Zhou, and Zheng (2004)
	k-NN	Herlocker, Konstan, Terveen, and Riedl (2004)
	Link analysis	Miller, Konstan, and Riedl (2004)
	Clustering, k-NN	Min and Han (2005)
	k-NN	Li, Lu, and Xuefeng (2005)
	Clustering	Kim and Yum (2005)
	Regression	Lee, Jun, Lee, and Kim (2005)
	Heuristic model	Adomavicius, Sankaranarayanan, Sen, and Tuzhilin (2005)
	Heuristic model	Salter and Antonopoulos (2006)
	Association rule, k-NN	Du Boucher-Ryan and Bridge (2006)
	Heuristic model	Prangl, Szkaliczki, and Hellwagner (2007)
	k-NN	Hurley, O'Mahony and Silvestre (2007)
	Heuristic model	Im and Hars (2007)
	Clustering, k-NN	Symeonidis, Nanopoulos, and Manolopoulos (2008)
	k-NN	Symeonidis, Nanopoulos, Papadopoulos, and Manolopoulos (2008)
	k-NN	Chen, Cheng, and Chuang (2008)
	Association rule	Leung, Chan, and Chung (2008)
	Heuristic model	Russell and Yoon (2008)
	k-NN	Lee and Olafsson (2009)
	k-NN	Jeong, Lee, and Cho (2009a)
	k-NN	Jeong, Lee, and Cho (2009b)
	Clustering, k-NN	Merve and Arslan (2009)
	k-NN	Koren, Bell, and Volinsky (2009)
	k-NN	Chen, Wang, and Zhang (2009)
	Clustering	Kwon, Cho, and Park (2009)
	Heuristic model	Cho, Kwon, and Park (2009)
	Heuristic model	Yang and Li (2009)
	k-NN	Bobadilla, Serradilla, and Hernando (2009)
	Heuristic model	Julià, Sappa, Lumbreras, Serrat, and López (2009)
	Heuristic model	Koren (2010a)
	Heuristic model	Winoto and Tang (2010)
	Heuristic model	Ahn, Kang, and Lee (2010)

Table 3 (*continued*)

Recommendation field	Data mining techniques	Reference
	Heuristic model, link analysis, regression	Hwang (2010)
	k-NN	Bobadilla, Serradilla, and Bernal (2010)
	Regression	Ozok, Fan, and Norcio (2010)
	Heuristic model, k-NN	Koren (2010b)
Music	k-NN	Ganesan, Garcia-Molina, and Widom (2003)
	Clustering, regression	Zhu, Shi, Kim, and Eom (2006)
	Clustering	Li, Myaeng, and Kim (2007)
	Association rule, k-NN	Yoshii, Goto, Komatani, Ogata, and Okuno (2008)
	Link analysis	Shao, Ogihara, Wang, and Li (2009)
	Clustering, heuristic model	Su, Yeh, Yu, and Tseng (2010)
	Heuristic model	Nanopoulos, Rafailidis, Symeonidis, and Manolopoulos (2010)
	Clustering, neural network	Liu, Hsieh, and Tsai (2010)
Others	Heuristic model	Taab, Werther, Ricci, Zipf, and Gretzel (2002)
	Neural network	Yuan and Tsao (2003)
	Clustering	Chau, Zeng, Chen, Huang, and Hendriawan (2003)
	Heuristic model	Yang, Knoblock, and Wu (2004)
	Heuristic model	Adomavicius and Tuzhilin (2005)
	Heuristic model	Wei, Moreau, and Jennings (2005a)
	Clustering	Ha (2006)
	Heuristic model	McGinty and Smyth (2006)
	Heuristic model	Park, Kang, and Kim (2006)
	Regression	Gretzel and Fesenmaier (2006)
	Heuristic model	Alexander, Gerhard, and Lars (2007)
	Link analysis	Reichling, Veith, and Wulf (2007)
	Association rule	Adda, Valtchev, Missaoui, and Djeraba (2007)
	Clustering, neural network	Martín-Guerrero, Lisboa, Soria-Olivas, Palomares, and Balaguer (2007)
	k-NN, regression	Lee, Ahn, and Han (2007)
	Clustering	Lee and Park (2007)
	Heuristic model	Adomavicius and Kwon (2007)
	Heuristic model	Ricci and Nguyen (2007)
	Link analysis	Zeng, Wang, Zheng, Yuan, and Chen (2008)
	Heuristic model	Lin (2008)
	Heuristic model	Liang (2008)
	Heuristic model	Hernández del Olmo and Gaudioso (2008)
	Link analysis	Malinowski, Weitzel, and Keim (2008)
	Clustering	Linden (2008)
	Regression	Moon and Russell (2008)
	Association rule, k-NN	Hsu (2008)
	Link analysis	Wang and Chiu (2008)
	Decision tree , k-NN	Hernández del Olmo, Gaudioso, and Martin (2009)
	Heuristic model	Hsu (2009)
	Heuristic model	Schiaffino and Amandi (2009)
	Heuristic model	Porcel, López-Herrera, and Herrera-Viedma (2009a)
	Heuristic model	Zhen, Huang, and Jiang (2009a)
	Decision tree	Wang, Chiang, Hsu, Lin, and Lin (2009)
	Association rule	Yang and Wang (2009)
	Heuristic model	Porcel, Moreno, and Herrera-Viedma (2009b)
	Link analysis	Arazy, Kumar, and Shapira (2009)
	Heuristic model	Zhen, Huang, and Jiang (2009b)
	Heuristic model	Kim, Jeong, and Baik (2009)
	Heuristic model, neural network	Han and Chen (2009)
	Heuristic model	Lesk (2009)
	Association rule, Clustering, regression	Kwon and Kim (2009)
	Association rule, k-NN	Schiaffino and Amandi (2009)
	Link analysis	Li and Kao (2009)
	Link analysis	Kuo, Chen, and Liang (2009)
	Heuristic model	Symeonidis, Nanopoulos, and Manolopoulos (2010)
	Heuristic model	Pillonetto, Dinuzzo, and De Nicolao (2010)
	Heuristic model	Zhen, Huang, and Jiang (2010)
	Heuristic model	Jalali et al. (2010)
	Heuristic model	Porcel and Herrera-Viedma (2010)
	Heuristic model	Zhan et al. (2010)
	Heuristic model, k-NN	Munoz-Organero, Ramíez-González, Muñoz-Merino, and Kloos (2010)
	Heuristic model, k-NN	Blanco-Fernandez, Lopez-Nores, Pazos-Arias, Gil-Solla, and Ramos-Cabrer (2010)
	Heuristic model	Yager, Reformat, and Gumrah (2010)
	Heuristic model	Bergamaschi, Guerra, and Leiba (2010)
	Heuristic model	Backhaus et al. (2010)
	Link analysis, regression	Kato, Kashima, Sugiyama, and Asai (2010)
Shopping	Association rule, decision tree	Kim et al. (2002)
	Association rule, decision tree	Cho, Kim & Kim (2002)
	Association rule, clustering	Ha (2002)
	k-NN	Vezina and Militaru (2004)
	Regression	Ant Ozok, Quyin, and Norcio (2004)
	Association rule, k-NN	Wang, Chuang, Hsu, and Keh (2004)

(*continued on next page*)

Table 3 (*continued*)

Recommendation field	Data mining techniques	Reference
	k-NN	Cho and Kim (2004)
	Association rule, k-NN	Liu and Shih (2005a)
	Association rule, k-NN	Liu and Shih (2005b)
	Association rule, clustering	Cho, Cho & Kim (2005)
	k-NN, regression	Kim, Yum, Song, and Kim (2005)
	Decision tree	Yu, Ou, Zhang, and Zhang (2005)
	Heuristic model	Wei, Moreau, and Jennings (2005b)
	Clustering	Choi, Kang, and Jeon (2006)
	Heuristic model	Garfinkel, Gopal, Tripathi, and Yin (2006)
	k-NN	Zanker, Jannach, Gordea, and Jessenitschnig (2007)
	Association rule	Zhang and Jiao (2007)
	Association rule	Pu and Chen (2007)
	Clustering, link analysis	Wang, Dai, and Yuan (2008b)
	Clustering	Kim and Ahn (2008)
	Association rule, k-NN	Wang and Wu (2009)
	k-NN	Albadvi and Shahbazi (2009)
	Heuristic model	Pu and Chen (2009)
	k-NN	Kim et al. (2009)
	Association rule, k-NN	Robillard and Dagenais (2009)
	Heuristic model	Moosavi, Nematbakhsh, and Farsani (2009)
	Heuristic model	Martin-Vicente, Gil-Solla, Ramos-Cabrer, Blanco-Fernandez, and Lopez-Nores (2010)
	Heuristic model	Ochi, Rao, Takayama and Nass (2010)
	Heuristic model	Funk, Rozinat, Karapanos, Alves de Medeiros, and Koca (2010)
	Link analysis	Yuan, Guan, Lee, Lee, and Hur (2010)
	Heuristic model	Taha and Elmasri (2010)
	Heuristic model, k-NN	Wang and Wu (2010)
	Heuristic model	Pathak, Garfinkel, Gopal, Venkatesan, and Yin (2010)
	Association rule, heuristic model	Chen and Pu (2010)
TV program	Decision tree	Lee and Yang (2003)
	Heuristic model, link analysis	Blanco-Fernandez, Pazos-arias, Gil-Solla, Ramos-Cabrer, and Lopez-Nores (2008)
	Heuristic model, k-NN	Martinez et al. (2010)
	Heuristic model, k-NN	Martin-Vicente et al. (2010)
	Clustering, heuristic model	Cantador and Castells (2010)

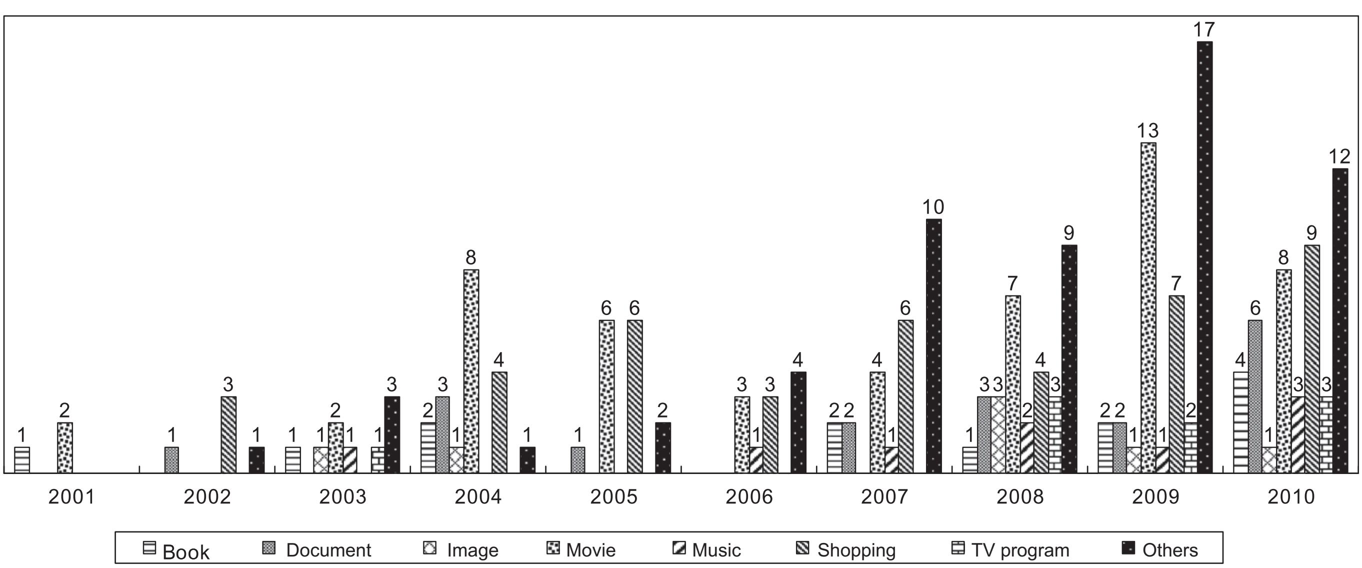

Fig. 6. Distribution of research papers by publication year and application fields.

due to the limitations of time and manpower, we only surveyed research papers published between 2001 and 2010, and our searches were based on the top 125 MIS. Therefore, if the research had been extended to cover other journals such as those focused on computer science and, marketing, the results might have been different. Second, our findings are based on articles that were selected solely from academic journals. If articles from conferences had been included, the results would have been more diverse. Third, our study was conducted based on a search of the following keywords: “Recommender system”, “Recommendation system”, “Personalization system”, “Collaborative filtering”, and “Contents filtering”. Besides these five keywords, we did not search additional keywords, such as “Hybrid Filtering”. Research papers that referred to recommender systems, but did not include any of the five key-words, could not be extracted. We think that recommender systems research also has been published in other lan-

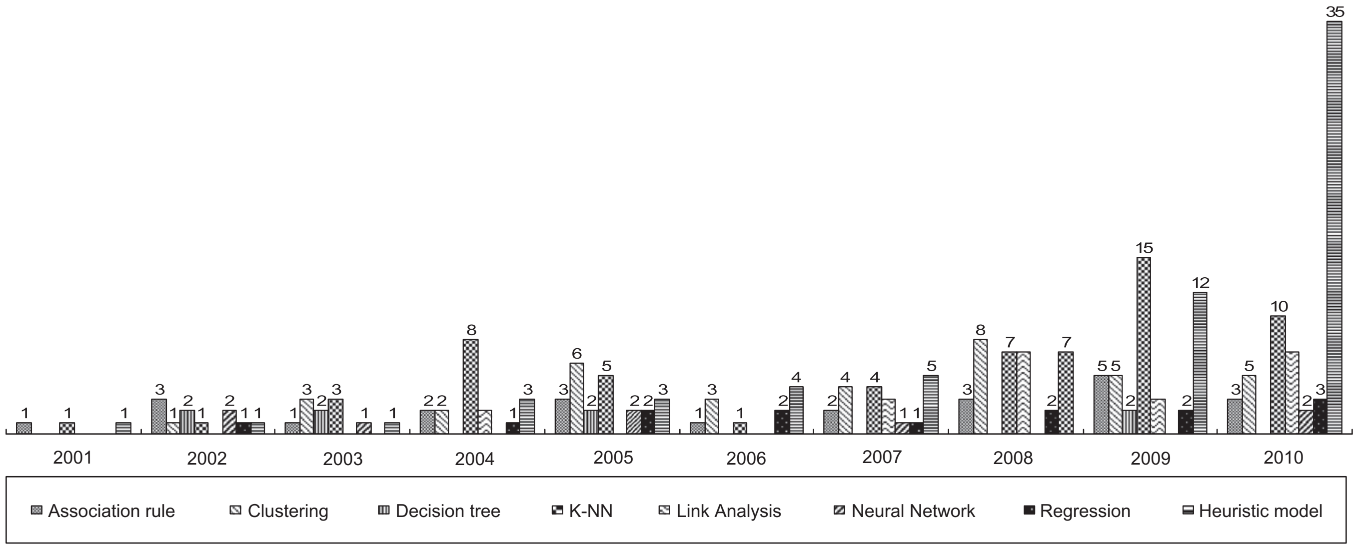

Fig. 7. Distribution of research papers by publication year and data mining technique.

guages. Finally, we classified data mining techniques, but not data mining model.

Accordingly, we will continue to classify articles on an ongoing basis. Moreover, it is also necessary to include conference papers and non-English papers in order to extend our classification model.

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RESEARCH ARTICLE

A systematic literature review of Linked Data-based recommender systems

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SUMMARY

Recommender systems (RS) are software tools that use analytic technologies to suggest different items of interest to an end user. Linked Data is a set of best practices for publishing and connecting structured data on the Web. This paper presents a systematic literature review to summarize the state of the art in RS that use structured data published as Linked Data for providing recommendations of items from diverse domains. It considers the most relevant research problems addressed and classifies RS according to how Linked Data have been used to provide recommendations. Furthermore, it analyzes contributions, limitations, application domains, evaluation techniques, and directions proposed for future research. We found that there are still many open challenges with regard to RS based on Linked Data in order to be efficient for real applications. The main ones are personalization of recommendations, use of more datasets considering the heterogeneity introduced, creation of new hybrid RS for adding information, definition of more advanced similarity measures that take into account the large amount of data in Linked Data datasets, and implementation of testbeds to study evaluation techniques and to assess the accuracy scalability and computational complexity of RS.

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KEY WORDS: Linked Data; recommender systems; systematic review; web of data

1. INTRODUCTION

The increasing amount of heterogeneous information available on the Web has led to the difficulty in recommending relevant items that meet the requirements of end users. It has attracted the attention of researchers and has become an interesting research area from the development of the first *recommender systems* (RS) in the mid-1990s [1–3]. In fact, the interest in this area remains high because of the abundance of practical applications that help users to deal with different kinds of information [4].

Nowadays, RS are increasingly common in many application domains, as they use analytic technologies to suggest different items or topics that can be interesting to an end user. However, one of the biggest challenges in these systems is to generate recommendations from the large amount of heterogeneous data that can be extracted from the items. Accordingly, some RS have evolved to exploit the knowledge associated to the relationships between data of items and data obtained from different existing sources [5]. This evolution has been possible, thanks to the rise of the Web

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supported by a set of best practices for publishing and connecting structured data on the Web known as *Linked Data* [6].

Linked Data principles have lead to semantically interlink and connect different resources at data level regardless of the structure, authoring, location, and so on. Data published on the Web using Linked Data have resulted in a global data space called the Web of Data. Moreover, thanks to the efforts of the scientific community and the W3C Linked Open Data (LOD) project‡, more and more data have been published on the Web of Data, helping its growth and evolution.

This work summarizes the state of the art of RS that make use of the structured data published as Linked Data on the Web. We undertook a systematic literature review, which is a form of secondary study that uses a well-defined methodology to identify, analyze, and interpret all available evidences related to specific research questions in a way that is unbiased and (to a degree) repeatable [7, 8]. We considered the most relevant problems that RS intended to solve, the way in which studies addressed these problems using Linked Data, their contributions, application domains, and evaluation techniques that they applied to assess their recommendations. Analyzing these aspects, we deduced current limitations and possible directions of future research. Unlike other works reporting the state of the art in RS [4, 9–11], our systematic literature review is the first to study RS that obtain information from Linked Data in order to generate recommendations.

The remainder of this paper is structured as follows. Section 2 provides a background information about Linked Data and RS. Section 3 summarizes the methodology and defines objectives and research questions. Section 4 outlines the results of the review organized according to each research question defined in Section 3. Section 5 discusses the results as well as the limitations of our systematic literature review. Section 6 contains the conclusions and future work. Finally, we list the selected papers in Appendix A.

2. BACKGROUND

2.1. Linked Data

In 1994, Tim Berners-Lee§ uncovered the need of introducing semantics into the Web to extend its capabilities and to publish structured data on it, which became known as *Semantic Web*. The set of good practices or principles for publishing and linking structured data on the Web is known as Linked Data. While the Semantic Web is the goal, Linked Data provides the means to make it a reality [6]. The set of Linked Data principles are as follows:

- Use URI (uniform resource identifiers) as names for things.
- Use HTTP (Hypertext Transfer Protocol) URIs, so that people can look up those names.
- Use of standard mechanisms to provide useful information when someone looks up a URI, for example, RDF (Resource Description Framework) to represent data as graphs and SPARQL (SPARQL Protocol and RDF Query Language) to query Linked Data.
- Include links to other URIs, so that they can discover more things.

The main benefit of using Linked Data as a source for generating recommendations is the large amount of available concepts and the relationships between them that can be used to infer relations more effectively in comparison to derive the same kind of relationships from text [12]. As Linked Data information is machine-readable, it is possible to query datasets on a fine-grained level in order to collect information without having to take manual actions; therefore, information is explicitly represented, which allows for applying reasoning techniques when querying datasets and making implicit knowledge explicit.

2.2. Recommender systems

RS are software tools and techniques that provide suggestions of items to a user. These items can belong to different categories or types, for example, songs, places, news, books, films, and events.

‡http://www.w3.org/wiki/SweoIG/TaskForces/CommunityProjects/LinkingOpenData
§http://www.w3.org/Talks/WWW94Tim

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According to Adomavicius and Tuzhilin [4], the roots of RS can be traced back to the works in cognitive science, approximation theory, information retrieval, forecasting theories, management science, and consumer choice modeling in marketing.

Nowadays, RS are focused on the recommendation problem of guiding users in a personalized way to interesting items in a large space of possible options [10]. Typically, RS are classified as content based, collaborative filtering, knowledge based, and hybrid [5].

Content-based RS make suggestions that take into account the ratings that users give to items according to their preferences and the content of the items (e.g., extracted keywords, title, pixels, and disk space) [10]. Collaborative-filtering RS generate recommendations of items to a user taking into account ratings that users with similar preferences have given to these items [13]. Knowledge-based RS infer and analyze similarities between user requirements and features of items described in a knowledge base that models users and items according to a specific application domain [14]. Hybrid RS combine one or more of the aforementioned techniques in order to improve recommendations.

With the evolution of the Web toward a global space of connected and structured data, a new kind of knowledge-based RS has emerged known as Linked Data-based RS. This kind of RS suggests items taking into account the knowledge of datasets published under the Linked Data principles. The systematic literature review presented in this paper is focused on this kind of RS.

3. RESEARCH METHODOLOGY

This work studies the state of the art in Linked Data-based RS. It follows the guidelines set out by Kitchenham and Charters [8] for systematic literature reviews in software engineering. These guidelines provide a verifiable method of summarizing existing approaches as well as identifying challenges and future directions in the current research. Figure 1 presents the protocol for our systematic literature review.

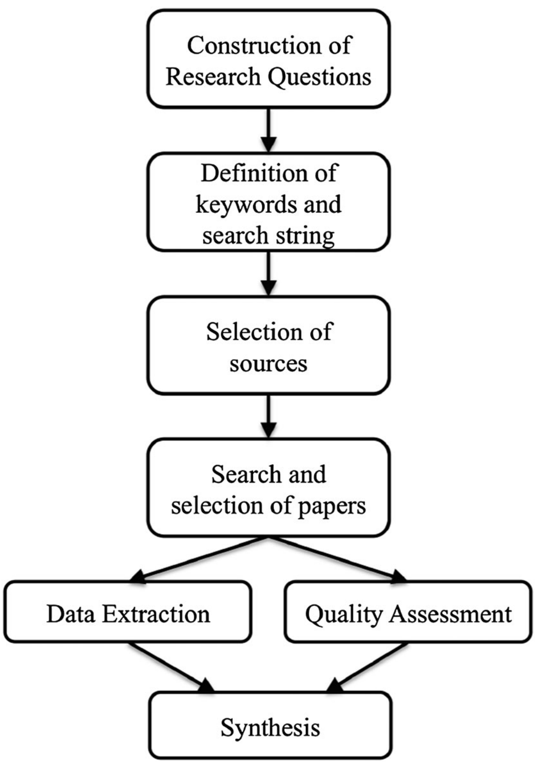

Figure 1. Systematic literature review at a glance.

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The protocol is defined in order to setup the steps to conduct the systematic literature review. In our work, it was developed by the first and second authors, while the third and fourth authors validated it.

3.1. Construction of research questions, definition of keywords and search string, and selection of sources

The goal of our systematic literature review is to understand how the implicit knowledge, stored in Linked Data datasets and represented as concepts and relations between them, can be exploited to make recommendations. Accordingly, we have defined the following research questions:

RQ1 What studies present RS based on Linked Data?
RQ2 What challenges and problems have been faced by researchers in this area?
RQ3 What contributions have already been proposed (e.g., algorithms, frameworks, and engines)?
RQ4 How is Linked Data used to provide recommendations?
RQ5 What application domains have been considered?
RQ6 What criteria and techniques are used for evaluation?
RQ7 Which directions are the most promising for future research?

Afterwards, a preliminary set of keywords was defined: {*Linked Data, Recommender system*}. This set was then extended by searching for synonyms in order to obtain the final set of keywords used to define a search string. The search string is the query to look for papers in a set of online digital libraries. In this work, the search string that we defined is as follows:

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("semantic web" OR "linked data" OR "web of data" OR "linked open data") AND (recommendation OR "recommender system" OR "recommendation system" OR "semantic recommendation" OR "semantic recommender").
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Furthermore, we selected seven scientific digital libraries that represent primary sources for computer science research publications as can be seen in Table I. Other sources like DBLP, CiteSeer, and Google Scholar were not considered as they mainly index data from the primary sources.

3.2. Search and selection

The studies selected in this systematic literature review were identified from the selected sources during March 2014. In Table II, a set of inclusion/exclusion criteria were defined in order to determine whether or not a study should be included.

3.3. Quality assessment, data extraction, and synthesis

We have defined a set of quality criteria that are listed in the checklist provided in Table III. Quality for each question is typically scored with values 1, 0.5, and 0, in order to represent the answers *'yes'*, *'partly'*, and *'no'*.

First and second authors evaluated the selected studies using this checklist. To do this, the total set of selected papers was split into two disjoint subsets, and each author selected only one of these

Table I. Sources selected for the search process.

Source	URL
IEEExplore	http://ieeexplore.ieee.org
SpringerLink	http://link.springer.com
Scopus	http://www.scopus.com
ACM Digital Library	http://dl.acm.org
Science Direct	http://www.sciencedirect.com
ISI Web of Knowledge	http://apps.webofknowledge.com
Wiley Online Library	http://onlinelibrary.wiley.com

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Table II. Inclusion and exclusion criteria.

Inclusion criteria
Papers presenting recommender systems (RS) using Linked Data to provide recommendations.
Papers addressing exploratory search systems using Linked Data. Exploratory search refers to cognitive consuming search such as learning or topic investigation. Exploratory search systems also recommend relevant topics or concepts, although the key difference with respect to RS is that they still require an input query (commonly a set of keywords).
Papers from conferences and journals.
Papers published from 2004 to 2014. Linked Data is a relative new technology; therefore, RS approaches exploiting it are also recent.
Only papers written in English language.
Short and workshop papers that fulfill the above criteria: we had no reason to believe that they would fail to provide sufficient levels of detail about their studies.
Exclusion criteria
Papers not addressing RS neither exploratory search systems.
Papers addressing RS or exploratory search systems that do not exploit Linked Data to produce recommendations.
Papers addressing similarity measures but not RS. Similarity is a broader topic than RS.
Papers that use Semantic Web techniques (e.g., rule-based or ontology-based reasoning) but not Linked Data.
Papers that report only abstracts or slides of presentations because of the lack of information.
Grey literature. We do not think that technical reports, unpublished studies, and PhD thesis would add much more information with respect to journal and conference papers.

subsets to evaluate the papers. After this evaluation, cross-checking of the assessment was done on arbitrary studies (about 30 % of selected papers) by the third author. Finally, an agreement on differences was reached by discussion.

Data extraction was done in parallel with the quality assessment. We split the set of included studies into two disjoint subsets. First and second authors performed the task on a subset, then the third author cross-checked a random sample of 30% of studies. The data extracted are presented in Table IV.

The synthesis step is based on the methodology for thematic synthesis described by Cruzes and Dybå [15]. This methodology defines codes as descriptive labels applied to segments of text from each study. We defined an initial set of codes based on research questions, and subsequently, we performed a second coding with more precise codes, which were closer to the content of selected papers. The coding was performed by first and second authors: each of them addressed a subset of the papers as for data extraction and quality assessment, because it was done in parallel with them. Then, the third author performed again the coding on a random sample of 30% of papers for cross-checking; afterwards, disagreements were solved by discussion.

4. RESULTS

This section summarizes the relevant information found in the selected studies in order to answer the proposed research questions. A further discussion and analysis of these results are addressed in Section 5.

4.1. Included studies

RQ1 regards the studies that present RS based on Linked Data. We retrieved 69 papers to include in the systematic literature review, corresponding to 52 unique primary studies (a study is a unique research work that can include one or more papers). These studies were published in conferences, workshops, and journals between 2004 and 2014. The criteria for deciding the most significant

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Table III. Quality assessment checklist.

Question	Score
Q1. Did the study clearly describe the challenges and problems that is addressing?	yes / partly / no (1 / 0.5 / 0)
Q2. Did the study review the related work for the problem?	yes / partly / no (1 / 0.5 / 0)
Q3. Did the study discuss related issues and compare with the alternatives?	yes / partly / no (1 / 0.5 / 0)
Q4. Did the study recommend the further continuous research?	yes / partly / no (1 / 0.5 / 0)
Did the study describe the components or architecture of the proposed recommender system?	yes / partly / no (1 / 0.5 / 0)
Q5. Did the study describe the components or architecture of the proposed recommender system?	yes / partly / no (1 / 0.5 / 0)
Q6. Did the study provide empirical results?	– The study provided an implementation of its work with an empirical evaluation and it was used in real applications, e.g., by other services (1)
	– The study provided an implementation of its work and an empirical evaluation but was not referred or used in other studies/applications (0.75)
	– The study provided an implementation only (0.5)
	– The study did not provide any implementation but it was referred by other works as a base on which start (0.25)
	– The study did not provide any implementation and was not referred by other works (0)
Q7. Did the study provides a clear description of the context in which the research was carried out?	yes / partly / no (1 / 0.5 / 0)
Q8. Did the study presents a clear statement of findings?	yes / partly / no (1 / 0.5 / 0)

paper for each study were completeness and publication year. The final set of selected papers and corresponding studies can be found in Appendix A.

With regard to the quality assessment, *journals* and *conference* studies have better quality than *workshop* studies as shown in Figure 2. Conference studies have the biggest spread, while journal studies, the lowest. In any case, the quality score is higher than 0.5 for all paper types, that is, rather good according to the quality criteria defined in Section 3.3.

4.2. Research problems

In order to address RQ2, we summarize the main problems involved in the studies considered and regarding the production of accurate recommendations. Table V lists these problems according to the number of studies in which they occurred. The number of studies represents the occurrence of each problem in the selected studies, which may be addressed in more than one study. The same applies for the rest of the results reported in this section.

In the following, we describe each item of Table V:

Lack of semantic information It was the most frequent problem in the selected studies, and it concerns the need for exploiting the rich semantics of information about items. Possible causes of this problem are as follows:

- Data about items are unstructured.
- A categorization of the items is needed.

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