Table IV. Data extraction form.

Data field	Description	Research question
ID	—	—
Title	—	—
Authors	—	—
Year of publication	—	—
Year of conference	—	—
Volume	—	—
Issue	—	—
Location	—	—
Proceeding title	—	—
ISBN	—	—
Publisher	—	—
Examiner	Name of person who performed data extraction	—
Publication source	—	—
Context	Environment in which study was conducted: industry, academic, government	—
Population	Study participants: students, academics, practitioners, etc.	—
Aims	Goals of the study (in our opinion when not clearly reported by authors)	—
Research problem	—	RQ2
Application domain	—	RQ5
Contributions	—	RQ3
Criteria and techniques for evaluation	—	RQ6
Findings	—	—
Limitations	—	RQ7
Future work	—	RQ7
Notes	—	—
Other information	—	—

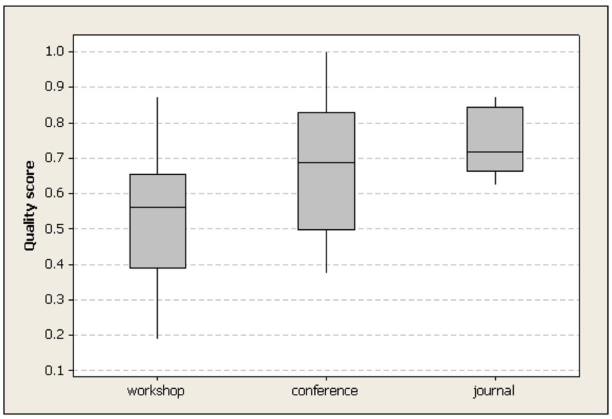

Figure 2. Quality score for different types of study.

- It is necessary to find relationships to link items.
- Social information is lacking.
- It is necessary to acquire content-descriptive metadata.
- Similarity measures that take into account semantic information are needed.

Complexity of information about items It is related to the complexity of information because of noisy metadata about features of items. Other causes for this problem are semantic heterogeneity and distribution of resources. The latter can impact on maintenance of the knowledge bases and can also decrease the accuracy of recommendations.

DOI: 10.1002/cpe

Table V. Distribution of studies according to the problems they addressed.

Problems	Number of studies
Lack of semantic information	13
Complexity of information about items	12
User dependency	8
Cold-start	6
Data quality	6
Computational complexity	5
Data sparsity	5
Domain dependency or specific and limited domain	4
Other problems	2

Table VI. Distribution of studies according to the contributions provided.

Contribution	Number of study
Algorithms	27
Similarity measures	12
Ontologies	8
Information aggregation or enrichment	8
Others	16

User dependency In a number of cases, RS require users to perform manual operations to acquire information about their profiles and interests. Such operations can be user feedback, ratings, filtering, attaching content-descriptive metadata, and semantic annotation of items.

Cold-start It is a well-known problem found mainly on RS based on collaborative-filtering approaches. Cold-start is a situation in which there are not enough ratings for items in order to generate recommendations.

Data quality This problem occurs when the knowledge base used to acquire information for providing recommendations is not reliable. Problems affecting data quality can range from poor reliability (e.g., wrong links between concepts or incorrect representations) to poor quality of recommended items.

Computational complexity It is related to the high computational demand that RS require to produce recommendations because of the large amount of data about items.

Data sparsity This is related to the lack of information about users or items and generates low density of significant data or connections.

Domain dependency It occurs when recommendations are only useful for items in a specific and limited domain without taking into account data that can be obtained from other related domains.

Other problems They include the need for recommending relevant and yet unknown items and the overspecialization of RS.

4.3. Contributions

In order to address RQ3, we classified the contributions provided by each study. Table VI shows the different kind of contributions and the number of studies in which they occurred (each study possibly reports more than one contribution).

The two main contributions are the definition or extension of a similarity measure and the definition or extension of an ontology, accounting for 12 and eight studies respectively. Algorithms are also addressed by 27 studies in total. Finally, information aggregation or enrichment and various other contributions account for eight and 16 studies, respectively. In the following, we describe each item of Table VI:

Algorithms Most of the selected studies proposed new algorithms or extensions of algorithms existing in the literature. In particular, four categories emerged: defining of a new algorithm,

DOI: 10.1002/cpe

adapting an algorithm to Linked Data, combining of algorithms to obtain a new hybrid algorithm, and extending of an existing algorithm. The definition of a new algorithm was the most frequent in 15 studies, while the adaptation of an algorithm to Linked Data, the combination of algorithms to obtain a new hybrid algorithm, and the extension to an algorithm each account for 4 studies. Furthermore, we can group algorithms into two classes:

- Graph-based algorithms, which compute relevance scores for items represented as nodes in a graph. A number of algorithms in this category are (*i*) the weight spreading activation algorithm, which propagates the initial score of a source node through its weighted edges; (*ii*) algorithms that update the scores of its linked nodes; (*iii*) algorithms that explore concepts and relations defined in an RDF graph; (*iv*) topic-based algorithms, which find similar items belonging to the same categories of an initial concept; and (*v*) path-based algorithms to find semantic paths between documents in the RDF graph.
- Algorithms to produce recommendations based on statistical information techniques applied to Linked Data such as support vector machine (SVM), latent Dirichlet allocation (LDA), random indexing (RI), and scaling methods. SVM analyzes and recognizes patterns in RDF triples; LDA is based on the co-occurrence of terms; RI uses distributional statistics to generate high-dimensional vector spaces; and scaling methods take into account the probability that an item could be selected based on its popularity (the number of entities is directly connected with the node). In addition, some algorithms define item-user matrices to compute semantic similarity based on path-lengths.

Similarity measures The selected studies applied a variety of similarity measures. These include pairwise cosine function for vector similarity computation between items, feature-based similarity to evaluate semantic distance on different datasets, rating-based similarity to compute the popularity of items among users, semantic relatedness defined by vocabulary meta-descriptions, content similarity that exploits lexical features, expressivity closeness based on the language constructs adopted, distributional relatedness derived from vocabulary usage, and topic-based similarity that captures the relatedness between items based on the categories they belong to.

Ontologies A number of studies proposed ontologies to assist or improve the recommendation process. New ontologies were proposed to facilitate the process of integration of datasets from a number of domains in order to make RS more flexible to changes, while a combination of existing ontologies described different types of entities such as users and items. Furthermore, it was found that reusing existing ontologies or vocabularies enable interoperability. Ontologies are also used to represent semantic distances, their explanations, user preferences, and item contents. A number of ontologies that are used in selected studies for these purposes are FOAF (Friend Of A Friend), SIOC (Semantically-Interlinked Online Communities), Resource List Ontology and Bibliographic ontology.

Information aggregation or enrichment This refers to the contributions about the aggregation of data to item collections and enrichment of existing ontologies or vocabularies. This is useful, for example, to obtain descriptive information about items and find entities in datasets in order to infer links between them. One contribution of this type is the aggregation of information from a specific domain when items have to be enriched with knowledge contained only on specialized datasets, another is the enrichment databases of RS with shared vocabularies.

Others Other contributions include the integration of other techniques such as opinion aggregators, exploitation of trust in web-based social networks to create predictive RS, and the use of social-based algorithms to improve the performance of the RS.

4.4. Use of Linked Data

Another interesting aspect that we studied was the use of Linked Data in RS, as underlined by RQ4. We classified the selected studies according to the way they used Linked Data to produce recommendations and grouped them into the following:

Linked Data driven RS that rely on the knowledge of the Linked Data to provide recommendations. For example, RS that calculate a semantic similarity based on diverse relationships that can

DOI: 10.1002/cpe

Table VII. Distribution of studies according to the use of Linked Data.

Category	Number of studies
Linked Data driven	37
Hybrid	29
Hybrid and Linked Data driven	21
Linked Data driven only	13
Representation only	10
Hybrid only	6
Exploratory search	4
Exploratory search and Linked Data driven	4
Exploratory search only	0

be found between concepts of Linked Data datasets and are related to features or descriptions of items. Such relationships can be paths, links, or shared topics among a set of items. This category can also include RS that use other techniques applied on data obtained from Linked Data datasets, for example, weight spreading activation, vector space model (VSM), SVM, LDA, and random indexing.

Hybrid RS that exploit Linked Data to perform some operations that can be used or not used to provide recommendations. This means that hybrid RS include Linked Data driven RS, which use recommendation techniques that rely on Linked Data, and RS that use Linked Data in other operations (not necessarily for recommending) that can be preliminary to the recommendation process (e.g., to aggregate more information from other datasets, to describe user profiles, or to annotate raw data in order to extract information to be integrated and used for recommending).

Representation only RS in this category exploit the RDF format to represent data and use at least one vocabulary or ontology to express the underlying semantics. However, no information is extracted from other dataset, and Linked Data are not used to provide recommendations. An example is an RS that represents the information about the users according to FOAF vocabulary but does not exploit Linked Data for other operations.

Exploratory search These systems are not RS, but their main duty is to assist users to explore knowledge and to suggest relevant to a topic or concept. Exploratory search systems and RS use Linked Data in a very similar way, although the key difference is that exploratory search systems still require an explicit input query (commonly a set of keywords). Additionally, users in these systems are not only interested in finding items but also in learning, discovering, and understanding novel knowledge on complex or unknown topics [16].

Each study may be assigned to more than one category; that is, it can be both Linked Data driven and hybrid, or both exploratory search and Linked Data driven. The only exception is for the representation-only category, in which studies cannot belong to other categories.

Table VII shows that most of the studies considered are Linked Data driven, and roughly 60% of them are also hybrid. Only 20% of hybrid studies were hybrid only, while the rest are also Linked Data driven. Moreover, 10 studies are representation only and just four exploratory search systems were included in the systematic literature review. All of the exploratory search studies are also Linked Data driven. This finding is consistent with the focus of the systematic literature review, which is on RS using Linked Data. It is worth noting that exploratory search is a broader topic; in this paper, we only consider the exploratory systems that recommend concepts to users.

The two most interesting categories are Linked Data driven and hybrid. Figure 3 shows the different techniques used by the studies in the first category to provide recommendations. The majority of them rely on datasets or on a similarity measure (about 43% and 35%, respectively), while the remaining 22% adapt natural language processing or content-based techniques or exploit reasoning.

Instead, Figure 4 illustrates the techniques that hybrid studies use together with Linked Data to provide recommendations. Most of them are natural language processing or collaborative-filtering methods (accounting for slightly less than 40% and about 35%, respectively) , and also reasoning or social networks are exploited in some cases.

DOI: 10.1002/cpe

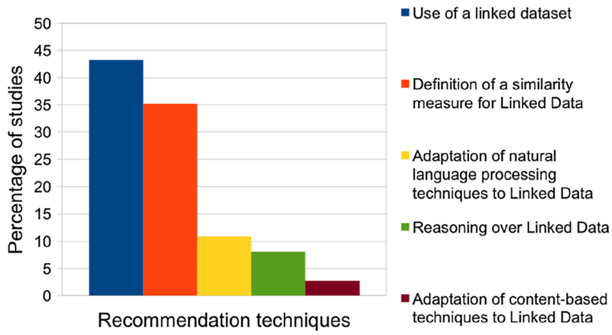

Figure 3. Distribution of Linked Data driven studies according to the recommendation techniques that they exploit (percentages refer to the total number of Linked Data-driven studies).

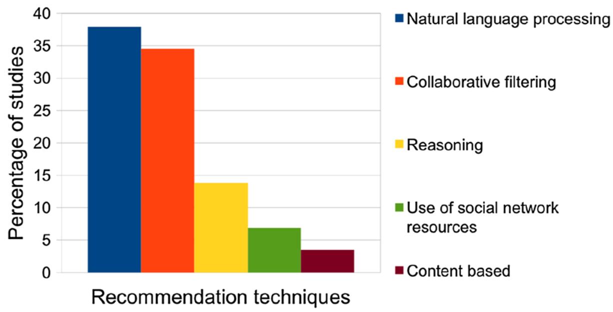

Figure 4. Distribution of hybrid studies according to the recommendation techniques that they exploit (percentages refer to the total number of hybrid studies).

Table VIII. Distribution of studies according to the Linked Data (LD) datasets on which they rely.

	Number of studies				
Dataset	General	LD driven	Hybrid	Hybrid and LD driven	LD driven only
DBpedia	31	28	20	16	12
Freebase	6	6	5	5	1
YAGO	4	3	3	2	1
Wordnet	4	2	3	2	0
DBLP	3	3	3	3	0
Dataset independent	3	3	3	3	0
LinkedMDB	3	3	3	3	0
Geonames	2	1	2	1	0
MusicBrainz	2	1	2	1	0
mySpace	2	2	2	2	0
ACM	1	1	1	1	0
IEEE	1	1	1	1	0
Eventseer2RDF	1	1	1	1	0
LinkedUp	1	1	0	0	1
mEducator	1	1	0	0	1
LinkedGeoData	1	0	1	0	0
LODE	1	1	1	1	0

In addition, we studied which datasets are used and the outcome is presented in Table VIII. It shows how many studies use a dataset overall and also considers the study category. It is possible to notice that DBpedia is used much more than the others. In fact, it is the biggest dataset, and it is the most curated.

DOI: 10.1002/cpe

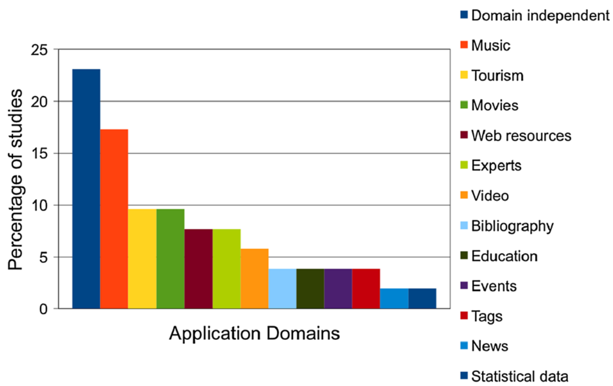

Figure 5. Distribution of studies according to the application domain.

Furthermore, it contains information about many different domains. Other commonly used datasets are Freebase, YAGO, and Wordnet, but the latter is used in just half of the cases by Linked Data-driven studies. In fact, it is also used with natural language processing techniques. On the contrary, the other datasets are used in most cases by Linked Data driven studies and often by studies which are both Linked Data driven and hybrid.

4.5. *Application domains*

Figure 5 illustrates the application domains considered by the studies selected for the systematic literature review. Most of the studies (about 23%) are not limited to any particular domain and can be used to recommend different kinds of items. Instead, an often occurring domain is music, which represents 17% and is followed by tourism and movies, accounting for roughly 10% each. Then there are web resources, expert recommendations, and video, with between 5% and 7% each, and a number of other domains are considered by the remaining 10% of the studies.

4.6. *Evaluation techniques*

RQ6 concerns RS evaluation, so we also dealt with this aspect. It is important to note that we focus on RS evaluation; thus, GUI evaluation is not considered, although some of the studies addressed it. RS are commonly evaluated according to their computational complexity and accuracy [17]. The former measures the execution time required to produce recommendations, which depends on the complexity of the algorithms used as well as the runtime of third-party systems needed to produce recommendations. The latter is the capacity of the RS to satisfy the individual user's need for information, and it can be evaluated by means of two techniques: user studies and comparison with similar methods. In this subsection, we detail both of them.

User studies involve users in order to compare recommendations generated by RS with the users' judgements or ratings. In these techniques, the most frequent measures are the following:

- Precision and recall, which evaluate the relevance of an RS taking into account the number of retrieved items, the number of items that evaluators considered as relevant, and the total number of available items.
- User ratings, which are techniques in which a list with results from different RS are presented to users who rate the lists according to their personal criteria [17].
- Ranking quality, which takes into account the retrieval correctness. The latter assigns an output ranking, a performance score based upon the available reference relevance judgments [18]. Common metrics to measure the ranking quality are the normalized discounted cumulated gain, average position, and presence.
- Unexpectedness of a concept suggestion, which is the degree of novelty of a recommendation for the evaluator.

DOI: 10.1002/cpe

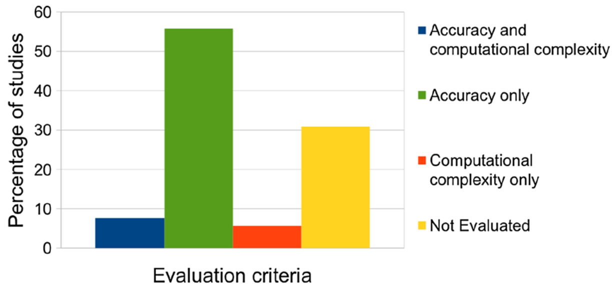

Figure 6. Distribution of studies according to the evaluation criteria (percentages refer to total number of studies).

Table IX. Distribution of studies according to the evaluation techniques.

Type	Technique	Number of papers
User studies	Precision and recall	18
	User ratings	9
	Ranking quality	3
	Unexpectedness	3
Comparison with similar methods	Precision and recall	5
	MAE and RMSE	3
Computational complexity	Execution time	7

MAE, mean absolute error; RMSE, root mean squared error.

In the case of comparisons with similar methods, recommendations generated by a specific RS are compared with well-known similar approaches. In the following, we mention the two main types:

- Precision and recall are measured, but in this case, items recommended by a well-known approach are considered as relevant.
- Mean absolute error (MAE) and root mean squared error (RMSE) are metrics to measure the predictive accuracy of an RS. MAE calculates the average absolute deviation between predicted similarities and similarity values in the real data set, while RMSE pays more attention to large errors [19].

Figure 6 shows the main evaluation techniques found in the selected studies, as well as their classification and their occurrence in these studies. Studies that provided an evaluation accounted for about 70% of the studies included in the systematic literature review. Among these, roughly 55% only used an accuracy technique, while roughly 2% only evaluated the computational complexity, and slightly less than 8% considered both accuracy and computational complexity.

Table IX details the techniques used in the studies included by considering the two types of accuracy evaluation and also computational complexity. The most frequent technique used to evaluate RS is the relevance measured with recall and precision metrics (used by 18 works in user studies and by about five in comparison with similar methods). We expected this result because these metrics are the ones most commonly deployed in information retrieval approaches. Other widely used techniques are user ratings, accounting for nine studies, and execution time, which is exploited by seven studies.

4.7. Future work

RQ7 is related to directions for future research. To address this, we summarized the future work that the selected studies proposed in order to extend or improve their approaches. Specifically, about 67% of studies included in the systematic literature review present diverse proposals for future work. Table X lists the most important, indicating for each one the number of studies in which it was mentioned. A deeper analysis of these results and a discussion of possible directions is presented in Section 5.

In the following, we provide a brief description of each item reported in Table X:

DOI: 10.1002/cpe

Table X. Distribution of studies according to the future work they propose.

Future work	Number of studies
Personalization of recommendations	8
Use more datasets	8
Create hybrid recommender systems	7
Similarity measures	4
Find more semantic relationships (item-user and item-item)	3
Other proposal for future work	3
Consider other domains	2

Personalization of recommendations The idea is to know to what extent personalization can improve recommendations without requiring user profile information or user intervention for manual operations (feedback, filtering, annotation, etc.).

Use more datasets It means to increase the range of data to annotate or match items to be recommended. It can also be useful to explore new domains because of the use of other datasets which can be from diverse domains.

Create hybrid RS This refer to exploring new ways to combine diverse recommendation techniques for creating hybrid approaches and improving the relevancy and quality of recommendations.

Similarity measures It is the creation of new similarity measures or the improvement of existing ones.

Find more semantic relationships It is the possibility of finding more semantic relationships between items and between users and items. It is considered by three studies.

Consider other domains Although domain dependency is one of the problems found in various studies, only two studies took into account exploring new application domains for providing recommendations.

Other proposal for future work This group includes applications in real life contexts, algorithms for categorization of recommendations, improving performance of algorithms, and the study of disambiguation techniques.

4.8. Limitations

The limitations reported in the selected studies are also related to RQ7 as these can help us to uncover the open issues in RS based on Linked Data and their relationships with proposals of future work. They are grouped into four main types: datasets, manual operations, personalization, and computational complexity. We detail each of them in the following:

Datasets This type describes limitations of RS due to the datasets used.

- A number of studies required a local copy of the entire dataset in a local server in order to reduce the runtime to produce recommendations. This had to be done as sometimes public datasets offer limited results, restricted access, and high timeout.
- Sometimes data had to be manually curated because of the poor reliability of public datasets.
- A number of RS are limited to the use of only one dataset. This can restrict the knowledge to which the RS can have access, avoiding data from diverse sources and domains being obtained.

Manual Operations It means that RS needed the user to perform manual operations in order to produce recommendations. Among these operations, we found:

- RS requiring manual selection of relevant concepts according to a specific application domain or interests. This is a difficult and tedious task considering the large amount of data that a typical Linked Data dataset can contain.
- RS that did not rank their results, so final users are faced with no priority in the recommendation.

DOI: 10.1002/cpe

Personalization It is about producing recommendations according to the user profile or some personal features.

Computational complexity RS still need to improve the performance because of high computational demand to analyze large amounts of items and information stored into datasets. Another problem is the poor performance of public endpoints to access them.

5. DISCUSSION

In the first part of this section, we present a discussion of the results considering each research question, while in the second part, we mention the limitations of our systematic literature review.

5.1. Specific research questions

This subsection discusses the research questions addressed in this systematic literature review according to the results reported in Section 4.

RQ1 is a general question regarding the studies that describe RS based on Linked Data. To provide an answer, we have followed the steps described in the protocol presented in Section 3 in order to search and select studies in this area. Firstly, we retrieved a total number of 7873 papers (including those duplicated) from scientific digital libraries. After each author filtered papers by title and abstract, we discussed disagreements, and we reach consensus on a final set of 69 papers to include in our study, which correspond to 52 unique studies.

RQ2 deals with research problems in the RS domain that researchers intended to solve by proposing approaches based on Linked Data. We found that the lack of semantic information and its complexity were the most notorious problems in RS.

Lack of semantics regards the need for rich semantic information about items. This is the main reason to devise novel strategies to represent items and user profiles using diverse semantic techniques exploiting several knowledge sources from the Linked Data cloud.

The complexity and heterogeneity of information and the subsequent cost of maintenance of knowledge bases make Linked Data a suitable solution that uses publicly available knowledge bases that are continuously growing and maintained by third parties. However, this poses new challenges, for example, the need for mechanisms to assure the reliability of these knowledge bases that are used to describe user profiles and items and to generate recommendations.

Domain dependency is another problem that has been also addressed by using Linked Data because it allows the possibility to exploit information from different datasets that can be domain-independent or belong to diverse domains. In fact this is one reason why the most used dataset is DBpedia as it is the most generic dataset that can be used for cross-domain RS. Nonetheless, some studies still report this problem as future work.

Computational complexity is a question that has not been widely addressed in the studies considered in this systematic literature review and remains as an open issue because most of the studies have concentrated only on semantic enrichment of items and inclusion of datasets in Linked Data cloud. Computational complexity needs to be addressed more because in RS not only accuracy is important but also scalability and responsiveness. For example, this problem can be critical in RS for mobile scenarios where users demand fast response times.

Other problems such as usability, cold-start, data quality, and data sparsity have been addressed by combining with Linked Data various techniques based on natural language processing, reasoning or social network resources, and creating hybrid RS that exploit both collaborative filtering and content-based approaches.

RQ3 inquires about the contributions proposed in RS based on Linked Data. The analysis showed that the majority of studies are focused not only on providing new algorithms but also on defining or extending a similarity measure of an ontology. Furthermore, adaptation, combination, or extension to algorithms is quite often addressed together with information aggregation

DOI: 10.1002/cpe

or enrichment. Accordingly, we found that Linked Data can be used in RS for several purposes such as the following:

- Defining different similarity functions between items or users by exploiting the large data available in the Linked Data cloud and the vast relationships already established such as properties or context-based categories. In this way, it is possible to extract semantic information from textual descriptions or other textual properties about the items in order to find semantic similarities based on the information stored in interlinked vocabularies of Linked Data. This can be useful in RS based on collaborative filtering to improve the neighborhood formation in user-to-user or item-to-item.
- Generating serendipitous recommendations, for example, to recommend items that are not part of the users' personal data cloud, that is, suggest new, possibly unknown items, to the user; or to guide users in the process of the exploration of the search space giving the possibility for serendipitous discovery of unknown information (for exploratory search systems).
- Offering the explanation of the recommendations given to the users by following the linked-data paths among the recommended items. In this way, users can understand the relationship between the recommended items and why these items were recommended.
- Domain-independency when creating RS as it is possible to access data from Linked Data datasets from different domains.
- Enrichment of information sources such as databases, repositories, and registries with information obtained from dataset in Linked Data cloud which manage huge amounts of data. It offers the possibility to enrich graphs representing users and/or items with new properties in order to improve graph-based recommendation algorithms. Additionally, it helps to mitigate the new-user, new-item, and sparsity problems.
- Annotating items and users with information from multiple sources facilitate RS to suggest items from different sources without changing their inner recommendation algorithms. Using such a semantic-based knowledge representation, recommendation algorithms can be designed independently from the domain of discourse.
- Obtaining hierarchical representation of items because the topic distribution that some datasets in Linked Data cloud offer. In this way, RS can base their recommendation on the exploration of items belonging to similar categories.

RQ4 regards the diverse ways in which Linked Data is used to provide recommendations. First of all, we classified the studies according to the way they exploited Linked Data. As reported in Section 4, four categories were identified: *Linked Data driven RS* rely mainly on Linked Data to perform their tasks, *hybrid RS* use Linked Data and also other techniques, *representation-only RS* do not provide Linked Data-based recommendations but use Linked Data for representing data based on RDF, and finally *exploratory search systems* that are not RS but may help users to find concepts or topics and have some similar features to RS especially in the use of Linked Data.

Table XI describes each category including the most important studies that adopted these strategies, as well as their advantages and disadvantages. The numbers of the studies corresponds to the identifiers in Appendix A.

Most of the studies belong to the first category, and many belong to both the first and the second category. These two categories are also the most interesting as they include RS to better exploit the advantages provided by Linked Data in order to reach best results. We also studied techniques to provide recommendations relying on Linked Data and slightly less than half of Linked Data driven RS used a dataset, almost one third define a similarity measure for Linked Data, while others adapt natural language processing or content-based methods or use reasoning.

With reference to the techniques used together with Linked Data, we found that natural language processing and collaborative filtering are the most used (both account for about one

DOI: 10.1002/cpe

Table XI. Classification of Linked Data-based RS approaches.

Approach	Techniques	Advantages	Disadvantages
Linked Data driven	– *Graph based*: weight spreading activation (S17), semantic exploration in an RDF graph (S29, S10, S3, S9, S19), and projections (S23) – *Reasoning*: (S1, S51) – *Statistical*: Matrix item-user (S29, S35, S31, S13, S37, S10), Scaling methods (S29) and topic discovery (S2)	– Generating serendipitous recommendations – Offering explanations of the recommendations following the linked-data paths – Creating domain-independent RS – Exploiting hierarchical information about items to categorize recommendations	– High cost of exploiting semantic features due to inconsistency of LD datasets – No personalization – No contextual information – High computational complexity – Need for manual operation – Need for dataset customization to address the computational complexity
Hybrid	– *Collaborative Filtering and Linked Data*: (S2, S4, S12, S25, S27, S3, S28, S26, S30, S35) – *Information aggregation and Linked Data*: opinions (S16), ratings (S19), and social tags (S32) – *Statistical methods and Linked Data*: Random Indexing (S10), VSM (S47, S31, S35), LDA (S35), Implicit feedback (S25), SVM (S13), Structure-based statistical semantics (S37)	– Overcoming the data sparsity problem – Allowing collaborative filtering RS to address the cold start problem	– High computational complexity
Representation only	– Item/user information representation using RDF-based ontologies (S36, S38, S20, S40, S14, S15, S42, S46)	– Improving scalability and reusability of ontologies – Easing data integration – Enabling complex queries	– Difficult to reuse the already available knowledge in the Linked Data Cloud
Explorative search	– Set nodes and associated lists (S49, S39, S34) – Spreading activation to typed graphs and graph sampling technique (S11)	– Enabling self-explanation of the recommendations	– No automation of the recommendation because explorative search approaches require frequent interaction with the user

DOI: 10.1002/cpe

third of hybrid RS) as they intended to provide personalized suggestions of items tailored to the preferences of individual users.

Other techniques are less common (less than 15%), and they are reasoning, use of social network resources, and content-based methods. Reasoning has not been widely used as its quality is still insufficient, and its coverage is not broad enough at the level of system components and knowledge elements [20]. Therefore, one solution is to develop RS based on reasoning-oriented natural language processing enriched with multilingual sources and able to support knowledge sources generated largely by people as Linked Data datasets.

As for the datasets used in the selected studies, we found that DBpedia is the most used Linked Data dataset. This is because DBpedia is a generic dataset and most of the studies are domain-independent that need to be evaluated in diverse scenarios. DBpedia is one of the biggest datasets that is frequently updated as it obtains data from Wikipedia that continuously grows into one of the central knowledge sources [21]. It makes Dbpedia multimodal and suitable for RS that need to be domain-independent and for knowledge-based RS where complexity and cost of maintenance of the knowledge base is high. However for RS of a single domain, it is better to use specific datasets but always implementing a linking interface with generic datasets in order to resolve ambiguities or to exploit unknown semantic relationships.

RQ5 concerns the application domains considered by RS based on Linked Data so far. We identified 12 domains, but we found that most of the RS are domain-independent (slightly more than one fifth of the studies). This is because most of the proposed recommendation algorithms can be applied in diverse domains by only changing the dataset or taking only a portion of it in order to obtain the data to generate the recommendations.

However, we also note that items of music, tourism, and movies are the most recommended as these belong to common domains in which there is a large amount of data and state-of-the-art datasets available, which allow the researchers to compare their results with several works developed in the community.

Accordingly, in a number of cases, the domain impacts also on datasets because they require a reduction of information; that is, only a subset of concepts is considered, which requires offline processing and more effort to maintain the dataset even if it improves the performance. For example, Passant developed RS named *dbrec* [22], which required to manually extract a subset of the data of DBpedia related with bands and musical artists.

RQ6 regards the evaluation techniques used to study RS based on Linked Data. We classified them into two types: accuracy and computational complexity. Accuracy evaluates recommendations according to their relevance for final users, while computational complexity measures the execution time required to produce them.

With regard to accuracy, our results demonstrate that researchers are more interested in evaluations made by final users than in comparisons with similar methods. This result was expected because usefulness of recommendations depends more on final user preferences than on comparing with similar approaches where evaluation may be biased as researchers must trust the results obtained. Therefore, future methodologies of evaluation should be user-centered in order to assure the quality of the results of RS.

Additionally as expected, most of the selected studies were more likely to evaluate their recommendations applying traditional methods of information retrieval such as precision and recall that are focused on percentages of true positives, false negatives, and false positives.

Interestingly, we found that few works evaluated the computational complexity of RS, which is a critical factor specially for applications that need responses with short timeouts. Therefore, it is still an open issue considering that accessing Linked Data datasets in most cases is time consuming and requires that researchers download dumps of the datasets to access them in local repositories.

RQ7 aimed to uncover the most promising directions for future research on RS based on Linked Data. To address this issue, we have reported not only future works but also limitations of the selected studies.

DOI: 10.1002/cpe

Section 4.7 summarized the future work reported in the selected studies. We found that the most frequently future works were the personalization of recommendations, the use of more datasets, and the creation of hybrid RS.

The lack of personalization of recommendations is still a common drawback in Linked Data-based RS. It concerns the fact that different users obtain the same set of results with the same input parameters. To solve this drawback, some RS need explicit feed back from users in order to differentiate the results based on information about the user's profile (e.g., browsing history and favorite music genre).

However, these approaches force the user to perform extra work like rating items or building an exhaustive user profiles. Consequently, there is a need of non-invasive personalization approaches supported by Linked Data in order to obtain implicit information from the neighborhood relationships user-to-user, item-to-item, and user-to-item. These relationships can be inferred from the links between concepts of datasets in Linked Data cloud related with properties of items and users.

Using more datasets is needed in order to increase the base of knowledge to produce recommendations. As presented in Section 4.8, there are some limitations of the current Linked Data-based RS with regard to the use of Linked Data datasets such as restricted access, poor reliability, computational complexity, low coverage of languages, domain dependency, and the need for installing a local copy of the dataset. For this reason, it is important to investigate new ways to integrate different datasets in order to (*i*) extend the knowledge base allowing the RS to access to other datasets in case that the main dataset fails or the data are not reliable; (*ii*) create scalable RS because they can be adapted to other domains by only accessing to the appropriate dataset and (*iii*) improve the performance by selecting datasets with better response time.

The creation of hybrid RS is not a new proposal, as could be seen in Section 4.4, combining diverse techniques of recommendation with Linked Data-based approaches is a frequent practice in the selected studies. However, we also found that it is still an open issue because it is necessary to investigate which combinations of techniques are more suitable for RS applied in diverse contexts. For example, combining Linked Data-based RS with social-based RS can be a good choice for applications that require information about the users and their interrelationships. In this way, RS can access information that sometimes is not available in Linked Data datasets such as items rating information, user profiles, and other social information.

The inclusion of user profile information (user profiling) is another aspect that is not widely considered in Linked Data recommender systems. The idea behind the user profiling is to obtain a meaningful concept-driven representation of user preferences in order to enable more precise specifications of user's preferences with less ambiguity. Therefore, this can be also useful to contribute to the personalization of Linked Data-based RS.

The automatic selection of the appropriate dataset according to the type of items or the application domain is another challenge that intend to improve the quality of recommendations. This dynamic process of selection can help the algorithms to choose the best strategy to find candidate items to be a recommender based on the implicit knowledge contained in Linked Data and the relationships with properties of items and users.

As a consequence, it is also important to study new similarity measures and techniques able to automatically combine information from different datasets and to deal with the diversity of data in these datasets. Furthermore, it can be possible to create a statistical models of user interests to overcome the topical diversity of rated items.

Finally, we found that there is still a need for building testbeds in order to allow for rigorous, transparent, and replicable testing and for studying new techniques (or adaptation of those existing) for evaluating the accuracy and computational complexity of RS based on Linked Data. This must also consider that Linked Data-based RS may have access to large amounts of information and that links among items can be unknown to the users. Additionally, large-scale RS should be also evaluated in terms of the ability to scale and provide recommendations with data coming from millions of users and/or items

DOI: 10.1002/cpe

5.2. *Limitations of our systematic literature review*

This section describes the main limitations we faced during our systematic literature review. Firstly, although some of selected papers were initially included because of their title or abstract, in the end they were excluded because we could not access them from our University.

Secondly, we only considered the most relevant paper for each study in order to calculate the frequency of problems, future work, contributions, and evaluation techniques. As a consequence, we could be biased, as some papers belonging to the same study may present a problem or contribution not reported in the most relevant paper.

Finally, we did not perform deep validation. Because of time issues, the majority of studies were read by one researcher, and cross-checking was performed only on about one third of the studies. Nonetheless, for some papers for which assessment was difficult, there was a discussion between the first three authors.

6. CONCLUSIONS

This systematic review has discussed 69 papers reporting 52 primary studies addressing RS that make use of the structured data published as Linked Data. We focused on identifying the most relevant problems that these studies aimed to solve and how they used Linked Data to provide recommendations. Although some of our results are already known, we defined a protocol to support our assumptions. Furthermore, we analyzed contributions, limitations, application domains, evaluation techniques they applied to assess their results, and the proposed directions for future research.

With regard to the research problems, we found that the most relevant ones were the lack of semantic information and the complexity of information about items. In order to overcome the lack of semantics, RS are enriched with diverse Linked Data datasets that are useful to describe users and items while reducing the ambiguity and exploiting the vast amount of links between related concepts stored in these datasets.

The majority of the selected studies have addressed these problems using Linked Data for several purposes, such as (*i*) finding new relationships or similarities based on links, paths, graphs, and created on the basis of Linked Data; (*ii*) generating serendipitous recommendations, that is, recommending items that are not expected by the users because of the links uncovered once the items are enriched with Linked Data; and (*iii*) explaining the recommendations, that is, allowing users to understand the reason of a recommendation by following the paths among items in the Linked Data cloud.

We also provided a classification of the selected studies according to the way they use Linked Data to provide recommendations. In particular, we identified four classes: Linked Data driven RS, which rely on techniques applied on datasets in Linked Data cloud such as categories, paths, number of input, and output links; hybrid RS that combine traditional techniques of recommendation (e.g., collaborative filtering and content based) with Linked Data; representation-only RS that uses Linked Data only to represent items or users but not for recommendations; and exploratory search systems that are not RS but help users to discover content through a guided search and are specially useful for users interested in learning or investigating a topic.

Additionally, we studied the most common datasets that RS use in order to obtain information, and we found that more than a half of these studies rely on DBpedia. This is because DBpedia is considered a central hub for the Linked Data cloud; it is linked to various datasets that gives the possibility to access diverse data from different application domains. Additionally, it makes DBpedia suitable for testing purposes in generic RS.

Concerning the evaluation techniques, the majority of the selected studies are focused on accuracy and rely more often on *user studies* than *comparison with other methods*. Computational complexity is also assessed in few cases; however, we think that it is an important factor to be evaluated especially for applications needing short responses such as RS in mobile environments. Additionally, we found that there is still a need for building testbeds to allow for testing and studying the results of RS based on Linked Data.

DOI: 10.1002/cpe

According to our findings, we identified that two recurrent issues in the selected studies are the high computational demand and the domain dependency. Therefore, we believe that further research is still needed to offer non-invasive personalization, exploit more datasets, and improve performance. Additionally, future work should focus on providing evaluation of RS considering the accuracy and computational complexity. With regard to application domains, music, movies, and tourism items are the most used in RS, and this may be due to the fact that in these domains, there are more datasets that help scientists to assess the results of their RS in comparison with similar approaches.

Finally, it is worth to mention that currently, we are working in the area of RS; in particular, we are developing RS that uses Linked Data as a source of information to recommend items for multiple application domains. The currently obtained results have been presented in [23], in which we describe how the RS based on Linked Data can be applied in the eTourism domain.

APPENDIX A. SELECTED PAPERS

Rows in italics identify papers (P) belonging to a study (S) already reported by other paper (e.g., papers 10, 19, and 54 belong to the same study S10).

Table A.1. Selected papers (P) and corresponding studies (S).

P	S	Authors	Year	Title	Publication details
1	S1	Fernández-Tobías, I., Cantador, I., Kaminskas, M., Ricci, F.	2011	A generic semantic-based framework for cross-domain recommendation	2nd International Workshop on Information Heterogeneity and Fusion in Recommender Systems - HetRec ’11, pp 25 - 32
2	S2	Kabutoya, Y., Sumi, R., Iwata, T., Uchiyama, T., Uchiyama, T.	2012	A Topic Model for Recommending Movies via Linked Open Data	International Conferences on Web Intelligence and Intelligent Agent Technology, pp 625–630
3	S3	Dell’Aglio, D., Celino, I., Cerizza, D.	2010	Anatomy of a Semantic Web-enabled Knowledge-based Recommender System	4th international workshop Semantic Matchmaking and Resource Retrieval in the Semantic Web, at the 9th International Semantic Web Conference, pp 115–130
4	S4	Mannens, E., Coppens, S., Wica, I., Dacquin, H., Van De Walle, R.	2013	Automatic News Recommendations via aggregated Profiling	Journal Multimedia Tools and Applications, 63 (2), pp 407–425
5	S5	Dzikowski, J., Kaczmarek, M.	2012	Challenges in Using Linked Data within a Social Web Recommendation Application to Semantically Annotate and Discover Venues	International Cross Domain Conference and Workshop, pp 360–374
6	S6	Wardhana, A.T.A.; Nugroho, H.T.	2013	Combining FOAF and Music Ontology for Music Concerts Recommendation on Facebook Application	Conference on New Media Studies, pp 1–5
7	S7	Passant, A., Raimond, Y.	2008	Combining Social Music and Semantic Web for music-related recommender systems	First Workshop on Social Data on the Web, pp 19–30
8	S8	Lindley, A., Graf, R.	2011	Computing Recommendations for Long Term Data Accessibility basing on Open Knowledge and Linked Data	5th ACM Conference on Recommender Systems, pp 51–58

DOI: 10.1002/cpe

Table A.1. *Continued.*

P	S	Authors	Year	Title	Publication details
9	S9	Passant, Alexandre	2010	dbrec–Music Recommendations Using DBpedia	The Semantic Web–ISWC 2010, pp 209–224
10	S10	Stankovic, M., Breitfuss, W., Laublet, P.	2011	Discovering Relevant Topics Using DBPedia: Providing Non-obvious Recommendations	2011 International Conferences on Web Intelligence and Intelligent Agent Technology, 1, pp 219–222
11	S11	Marie, N., Gandon, F., Ribière, M., Rodio, F.	2013	Discovery Hub : on-the-fly linked data exploratory	9th International Conference on Semantic Systems, pp 17–24 search
12	S12	Peska, L., Vojtas, P.	2013	Enhancing Recommender System with Linked Open Data	10th International Conference on Flexible Query Answering Systems, pp 483–494
13	S13	Di Noia, T., Mirizzi, R., Ostuni, V. C., Romito, D.	2012	Exploiting the web of data in model-based recommender systems	6th ACM conference on Recommender systems
14	S14	Golbeck, J.	2006	Filmtrust: movie recommendations from semantic web-based social networks	3rd IEEE Consumer Communications and Networking Conference, pp 1314–1315
15	S15	Celma, Ò., Serra, X.	2008	FOAFing the music: Bridging the semantic gap in music recommendation	Web Semantics: Science, Services and Agents on the World Wide Web, 6 (4), 250–256
16	S16	Varga, B., Groza, A.	2011	Integrating DBpedia and SentiWordNet for a tourism recommender system	7th International Conference on Intelligent Computer Communication and Processing, pp 133–136
17	S17	Kaminskas, M., Fernández-Tobías, I., Ricci, F., Cantador, I.	2012	Knowledge-based music retrieval for places of interest	Proceedings of the second international ACM workshop on Music information retrieval with user-centered and multimodal strategies– MIRUM '12, pp 19–24
18	S18	Dietze, S.	2012	Linked Data as facilitator & practice for TEL recommender systems in research	2nd Workshop on Recommender Systems for Technology Enhanced Learning, pp 7–10
19	*S10*	*Damljanovic, D., Stankovic, M., Laublet, P.*	*2012*	*Linked Data-Based Concept Recommendation : Comparison of Different Methods*	*9th Extended Semantic Web Conference, pp 24–38*
20	S19	Kitaya, K., Huang, H. H., Kawagoe, K.	2012	Music curator recommendations using linked data	Second International Conference on the Innovative Computing Technology, pp 337–339
21	S20	Jung, K., Hwang, M., Kong, H., Kim, P.	2005	RDF Triple Processing Methodology for the Recommendation System Using Personal Information	International Conference on Next Generation Web Services Practices, pp 241–246
22	S21	Calì, A., Capuzzi, S., Dimartino, M. M., Frosini, R.	2013	Recommendation of Text Tags in Social Applications Using Linked Data	ICWE 2013 Workshops
23	*S21*	*Calì, A., Capuzzi, S., Dimartino, M. M., Frosini, R.*	*2013*	*Recommendation of Text Tags Using Linked Data*	*3rd International Workshop on Semantic Search Over the Web, pp 1–3*
24	S22	Meymandpour, R., Davis, J. G.	2012	Recommendations using linked data	5th Ph.D. workshop on Information and knowledge– PIKM '12, pp 75–82
25	S23	Harispe, S., Ranwez, S., Janaqi, S., Montmain, J.	2013	Semantic Measures Based on RDF Projections: Application to Content-Based Recommendation Systems	On the Move to Meaningful Internet Systems: OTM 2013 Conferences SE–44, pp 606–615

Table A.1. *Continued.*

P	S	Authors	Year	Title	Publication details
26	S24	Hopfgartner, F., Jose, J. M.	2010	Semantic user profiling techniques for personalised multimedia recommendation	Multimedia Systems, 16 (4-5) pp 255–274
27	*S5*	*Łazaruk, S., Dzikowski, J., Kaczmarek, M., Abramowicz, W.*	*2012*	*Semantic Web Recommendation Application*	Federated Conference on Computer Science and Information Systems (FedCSIS), pp 1055–1062
28	S25	Ostuni, V. C., Di Noia, T., Di Sciascio, E., Mirizzi, R.	2013	Top-N recommendations from implicit feedback leveraging linked open data	Proceedings of the 7th ACM conference on Recommender systems, pp 85–92
29	S26	Ahn, J., Amatriain, X.	2010	Towards Fully Distributed and Privacy-Preserving Recommendations via Expert Collaborative Filtering and RESTful Linked Data	International Conference on Web Intelligence and Intelligent Agent Technology, pp 66–73
30	S27	Heitmann, B., Hayes, C.	2010	Using Linked Data to Build Open, Collaborative Recommender Systems	AAAI Spring Symposium: Linked Data Meets Artificial Intelligence, pp 76–81
31	S28	Zarrinkalam, F., Kahani, M.	2012	A multi-criteria hybrid citation recommendation system based on linked data	2nd International eConference on Computer and Knowledge Engineering (ICCKE), 2012, pp 283–288
32	S29	Lommatzsch, A., Kille, B., Kim, J. W., Albayrak, S.	2013	An Adaptive Hybrid Movie Recommender based on Semantic Data	10th Conference on Open Research Areas in Information Retrieval, pp 217–218
33	S30	Torres, D., Skaf-Molli, H., Molli, P.; Díaz, A.	2013	BlueFinder: Recommending Wikipedia Links Using DBpedia Properties	5th Annual ACM Web Science Conference, pp 413–422
34	S31	Ostuni, V. C., Di Noia, T., Mirizzi, R., Romito, D., Di Sciascio, E.	2012	Cinemappy : a Context-aware Mobile App for Movie Recommendations boosted by DBpedia	International Workshop on Semantic Technologies meet Recommender Systems & Big Data SeRSy 2012, pp 37–48
35	S33	Zhang, Y., Wu, H., Sorathia, V., Prasanna, V. K.	2008	Event recommendation in social networks with linked data enablement	15th International Conference on Enterprise Information Systems, pp 371–379
36	S34	Mirizzi, R., Di Noia, T.	2010	From exploratory search to web search and back	3rd workshop on Ph.D. students in information and knowledge management– PIKM ’10, pp 39–46
37	S35	Khrouf, H., Troncy, R.	2013	Hybrid event recommendation using linked data and user diversity	Proceedings of the 7th ACM conference on Recommender systems, pp 185–192
38	S36	Bahls, D., Scherp, G., Tochtermann, K., Hasselbring, W.	2012	Towards a Recommender System for Statistical Research Data	2nd International Workshop on Semantic Digital Archives
39	S37	Cheng, Gong; Gong, Saisai; Qu, Yuzhong	2011	An Empirical Study of Vocabulary Relatedness and Its Application to Recommender Systems	10th International Conference on The Semantic Web – Volume Part I, pp 98–113
40	S38	Wang, Y., Stash, N., Aroyo, L., Gorgels, P., Rutledge, L., Schreiber, G.	2008	Recommendations based on semantically enriched museum collections	Web Semantics: Science, Services and Agents on the World Wide Web, 6 (4), 283–290
41	*S11*	*Marie, N., Gandon, F., Legrand, D., Ribière, M.*	*2013*	*Discovery Hub: a discovery engine on the top of DBpedia*	*3rd International* Conference on Web Intelligence, Mining and Semantics
42	S31	Di Noia, T., Mirizzi, R., Ostuni, V. C., Romito, D., Zanker, M.	2012	Linked open data to support content–based recommender systems	8th International Conference on Semantic Systems

Table A.1. *Continued.*

P	S	Authors	Year	Title	Publication details
43	*S31*	*Ostuni, Vito Claudio; Gentile, Giosia; Noia, Tommaso Di; Mirizzi, Roberto; Romito, Davide; Sciascio, Eugenio Di*	*2013*	*Mobile Movie Recommendations with Linked Data*	*International Cross–Domain Conference, pp 400–415*
44	*S31*	*Mirizzi, R., Di Noia, T., Ragone, A., Ostuni, V. C., Di Sciascio, E.*	*2012*	*Movie recommendation with DBpedia*	*3rd Italian Information Retrieval Workshop, pp 101–112*
45	S39	Waitelonis, J., Sack, H.	2011	Towards exploratory video search using linked data	Multimedia Tools and Applications, 59 (2), pp 645–672
46	S40	Li, S., Zhang, Y., Sun, H.	2010	Mashup FOAF for Video Recommendation LightWeight Prototype	7th Web Information Systems and Applications Conference, pp 190–193
47	S41	Hu, Y., Wang, Z., Wu, W., Guo, J., Zhang, M.	2010	Recommendation for Movies and Stars Using YAGO and IMDB	12th International Asia–Pacific Web Conference, pp 123–129
48	S42	Ruotsalo, T., Haav, K., Stoyanov, A., Roche, S., Fani, E., Deliai, R., Mäkelä, E., Kauppinen, T., Hyvönen, E.	2013	SMARTMUSEUM: A mobile recommender system for the Web of Data	Web Semantics: Science, Services and Agents on the World Wide Web, 20, pp 50–67
49	S43	Stankovic, M., Jovanovic, J., Laublet, P.	2011	Linked Data Metrics for Flexible Expert Search on the Open Web	8th Extended Semantic Web Conference, pp 108–123
50	S44	Ozdikis, O., Orhan, F., Danismaz, F.	2011	Ontology-based recommendation for points of interest retrieved from multiple data sources	International Workshop on Semantic Web Information Management, pp 1–6
51	S45	Debattista, J., Scerri, S., Rivera, I., Handschuh, S.	2012	Ontology-based rules for recommender systems	International Workshop on Semantic Technologies meet Recommender Systems & Big Data, pp 49–60
52	S46	Codina, V.; Ceccaroni, L.	2010	Taking Advantage of Semantics in Recommendation Systems	2010 Conference on Artificial Intelligence Research and Development, pp 163–172
53	*S9*	*Passant, A., Decker, S.*	*2010*	*Hey! Ho! LetŠs Go! Explanatory Music Recommendations with dbrec*	*7th Extended Semantic Web Conference, pp 411–415*
54	*S10*	*Stankovic, M.,* Breitfuss, W., Laublet, P.	*2011*	*Linked-data based* suggestion of relevant topics	*7th International* Conference on Semantic Systems, pp 49–55
55	*S9*	*Passant, A.*	*2010*	*Measuring semantic distance on linking data and using it for resources recommendations*	*AAAI Spring Symposium: Linked Data Meets Artificial Intelligence, pp 93–98*
56	*S14*	*Golbeck, J.*	*2006*	*Generating Predictive Movie Recommendations from Trust in Social Network*	*4th International Conference, iTrust 2006, pp 93–104*
57	*S39*	*Sack, H.*	*2009*	*Augmenting Video Search with Linked Open Data*	*International Conference on Semantic Systems, pp 550–558*
58	S47	Baumann, S., Schirru, R., Streit, B.	2011	Towards a Storytelling Approach for Novel Artist Recommendations	8th International Workshop, AMR 2010, Linz, Austria, August 17–18, 2010, Revised Selected Papers, pp 1–15
59	S48	Corallo, A., Lorenzo, G., Solazzo, G.	2006	A Semantic Recommender Engine Enabling an eTourism Scenario	10th International Conference, pp 1092–1101

Table A.1. *Continued.*

P	S	Authors	Year	Title	Publication details
60	S49	Nuzzolese, A. G., Presutti, V., Gangemi, A., Musetti, A., Ciancarini, P.	2013	Aemoo: Exploring Knowledge on the Web	Proceedings of the 5th Annual ACM Web Science Conference, pp 272–275
61	*S49*	*Musetti, A., Nuzzolese, A., Draicchio, F., Presutti, V., Blomqvist, E., Gangemi, A., Ciancarini, P.*	*2012*	*Aemoo: Exploratory Search based on Knowledge Patterns over the Semantic Web*	*Semantic Web Challenge*
62	*S47*	*Baumann, S., Schirru, R.*	*2012*	*Using Linked Open Data for Novel Artist Recommendations*	*13th Internal Society for Music Information Retrieval Conference*
63	S50	Cantador, I., Castells, P.	2006	Multilayered Semantic Social Network Modeling by Ontology-Based User Profiles Clustering: Application to Collaborative Filtering	Proceedings of 15th International Conference, pp 334–349
64	*S34*	*Mirizzi, R., Ragone, A., Di Noia, T., Di Sciascio, E.*	*2010*	*Ranking the Linked Data: The Case of DBpedia*	*10th International Conference, pp 337–354*
65	S51	Heitmann, B., Hayes, C.	2010	Enabling Case-Based Reasoning on the Web of Data	The WebCBR Workshop on Reasoning from Experiences on the Web at International Conference on Case-Based Reasoning
66	S52	Alvaro, G., Ruiz, C., Córdoba, C., Carbone, F., Castagnone, M., Gómez-Pérez, J. M., Contreras, J.,	2011	miKrow : Semantic Intra-enterprise Micro-Knowledge Management System	8th Extended Semantic Web Conference, pp 154–168
67	*S50*	*Cantador, I., Castells, P., Bellogín, A.*	*2011*	*An Enhanced Semantic Layer for Hybrid Recommender Systems: Application to News Recommendation*	*Int. J. Semant. Web Inf. Syst., 7 (1), pp 44–78*
68	S32	Cantador, I., Konstas, I., Jose, J. M.	2011	Categorising social tags to improve folksonomy-based recommendations	Web Semantics: Science, Services and Agents on the World Wide Web, 9 (1), pp 1–15
69	*S29*	*Lommatzsch, A., Kille, B., Albayrak, S.*	*2013*	*A Framework for Learning and Analyzing Hybrid Recommenders based on Heterogeneous Semantic Data Categories and Subject Descriptors*	*10th Conference on Open Research Areas in Information Retrieval, pp 137–140*

REFERENCES

1. Hill W, Stead L, Rosenstein M, Furnas G. Recommending and evaluating choices in a virtual community of use. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI ’95: ACM Press/Addison-Wesley Publishing Co., New York, NY, USA, 1995; 194–201.
2. Resnick P, Iacovou N, Suchak M, Bergstrom P, Riedl J. GroupLens: an open architecture for collaborative filtering of netnews. *Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work—CSCW ’94*, 1994; 175–186.
3. Shardanand U, Maes P. Social information filtering: algorithms for automating “word of mouth”. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI ’95, ACM Press/Addison-Wesley Publishing Co., New York, NY, USA, 1995; 210–217.
4. Adomavicius G, Tuzhilin A. Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *Knowledge and Data Engineering, IEEE Transactions on* 2005; **17**(6):734–749.

DOI: 10.1002/cpe

5. Ricci F, Rokach L, Shapira B. Introduction to recommender systems handbook. In *Recommender Systems Handbook*. Springer, 2011.
6. Bizer C, Heath T, Berners-Lee T. Linked data—the story so far. *International Journal on Semantic Web and Information Systems* 2009; **5**(3):1–22.
7. Kitchenham B. Procedures for performing systematic reviews, Keele University: Eversleigh, Australia, 2004.
8. Kitchenham B, Charters S. Guidelines for performing systematic literature reviews in software engineering, University of Durham: Durham, UK, 2007.
9. Candillier L, Jack K, Fessant F, Meyer F. State-of-the-art recommender systems. *Collaborative and Social Information Retrieval and Access-Techniques for Improved User Modeling* 2009:1–22.
10. Lops P, De Gemmis M, Semeraro G. Content-based recommender systems: state of the art and trends. In *Recommender Systems Handbook*. Springer, 2011.
11. Bobadilla J, Ortega F, Hernando A, Gutiérrez A. Recommender systems survey. *Knowledge-Based Systems* 2013; **46**(0):109 –132.
12. Damljanovic D, Stankovic M, Laublet P. Linked data-based concept recommendation: comparison of different methods in open innovation scenario. In *The Semantic Web: Research and Applications*, Simperl E, Cimiano P, Polleres A, Corcho O, Presutti V (eds)., Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2012.
13. Felfernig A, Jeran M, Ninaus G, Reinfrank F, Reiterer S. Toward the next generation of recommender systems: applications and research challenges. In *Multimedia Services in Intelligent Environments*. Springer, 2013.
14. Dell'Aglio D, Celino I, Cerizza D. Anatomy of a semantic web-enabled knowledge-based recommender system. *CEUR Workshop Proceedings*, Vol. 667, 2010; 115–130.
15. Cruzes DS, Dybå T. Recommended steps for thematic synthesis in software engineering. *Proceedings of the 2011 International Symposium on Empirical Software Engineering and Measurement*, ESEM '11, IEEE Computer Society, Washington, DC, USA, 2011; 275–284.
16. Mirizzi R, Di Noia T. From exploratory search to web search and back. *Proceedings of the 3rd Workshop on PhD Students in Information and Knowledge Management*, PIKM '10, ACM, New York, NY, USA, 2010; 39–46.
17. Beel J, Langer S, Genzmehr M, Gipp B, Breitinger C, Nürnberger A. Research paper recommender system evaluation: a quantitative literature survey. *Proceedings of the International Workshop on Reproducibility and Replication in Recommender Systems Evaluation*: ACM, 2013; 15–22.
18. Küster U, König-Ries B. Measures for benchmarking semantic web service matchmaking correctness, The Semantic Web: Research and Applications, 2010; 45–59.
19. Baumann S, Schirru R, Streit B. Towards a storytelling approach for novel artist recommendations. In *Adaptive Multimedia Retrieval. Context, Exploration, and Fusion*, Detyniecki M, Knees P, Nrnberger A, Schedl M, Stober S (eds)., Lecture Notes in Computer Science. Springer Berlin Heidelberg, January 2011.
20. McShane M, Nirenburg S, Beale S. NLP with reasoning and for reasoning. In *Ontology and the Lexicon: A Natural Language Processing Perspective*, Huang C, Calzolari N, Gangemi A, Lenci A, Oltramari A, Prevot L (eds). Cambridge University Press: Cambridge, 2010.
21. Urbani J, Maassen J, Drost N, Seinstra F, Bal H. Scalable RDF data compression with MapReduce. *Concurrency and Computation: Practice and Experience* 2013; **25**(1):24–39.
22. Passant A. Dbrec—music recommendations using DBpedia. In *The Semantic Web ISWC 2010*, Patel-Schneider PF, Pan Y, Hitzler P, Mika P, Zhang L, Pan JZ, Horrocks I, Glimm B (eds)., Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2010.
23. Rodríguez Rocha O, Figueroa C, Vagliano I, Moltchanov B. Linked data-driven smart spaces. In *Internet of Things, Smart Spaces, and Next Generation Networks and Systems*, vol. 8638, Balandin S, Andreev S, Koucheryavy Y (eds)., Lecture Notes in Computer Science. Springer International Publishing, 2014 (English).

DOI: 10.1002/cpe