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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 recommender systems 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 has 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. Copyright © 2014 John Wiley & Sons, Ltd.

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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, 2, 3]. In fact the interest in this area remains high because of the abundance of practical applications that help users to deal with different kind 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

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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 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 led to semantically interlink and connect different resources at data level regardless the structure, authoring, location etc. Data published on the Web using Linked Data has 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) project¹, 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 evidence 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, 10, 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 Recommender Systems. Section 3 summarizes the methodology and defines objectives and research questions. Section 4 outlines the results of the review organized according 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-Lee² 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 reality [6]. The set of Linked Data principles are:

- Use URIs as names for things.

¹ <http://www.w3.org/wiki/SweoIG/TaskForces/CommunityProjects/LinkingOpenData>

² <http://www.w3.org/Talks/WWW94Tim>

- Use HTTP 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, e.g. songs, places, news, books, films, events, etc. 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 which 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, disk space, etc) [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 towards 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 suggest 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.

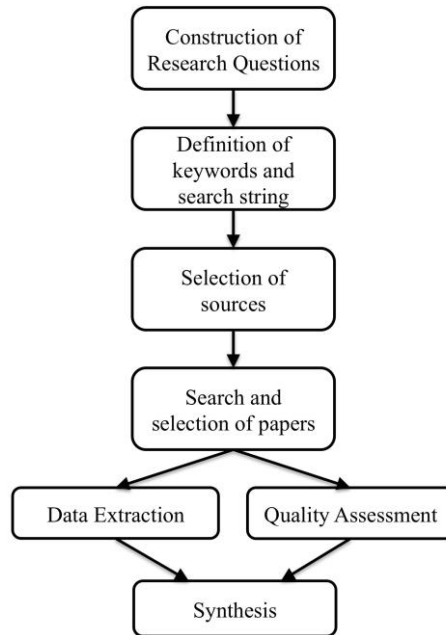


Figure 1. Systematic literature review at a glance

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 author while third and fourth author validate 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, 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:

("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").

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.

| 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 |

Table I. Sources selected for the search process

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.

Inclusion Criteria

Papers presenting 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 recommends 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 which 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 which 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 Ph.D. thesis would add much more information with respect to journal and conference papers.

Table II. Inclusion and exclusion criteria

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

| Question | Score |
|--|--|
| Q1. Did the study clearly describe the challenges and yes / partly / no (1 / 0.5 / 0) problems that is addressing? | |
| 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? | <ul style="list-style-type: none"> - 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) |

Table III. Quality assessment checklist

Data extraction was done in parallel with the quality assessment. We split the set of included studies into two disjoint subsets. First and second author 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 Dyba [° 15]. This methodology define 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 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, since it was done in parallel with them.

| 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 |
| Notes | - | - |
| Other Information | - | - |
| Future work | | RQ7 |

Table IV. Data extraction form

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 studies selected in order to answer the proposed research questions. A further discussion and analysis of these results is 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 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, i.e. rather good according to the quality criteria defined in section 3.3.

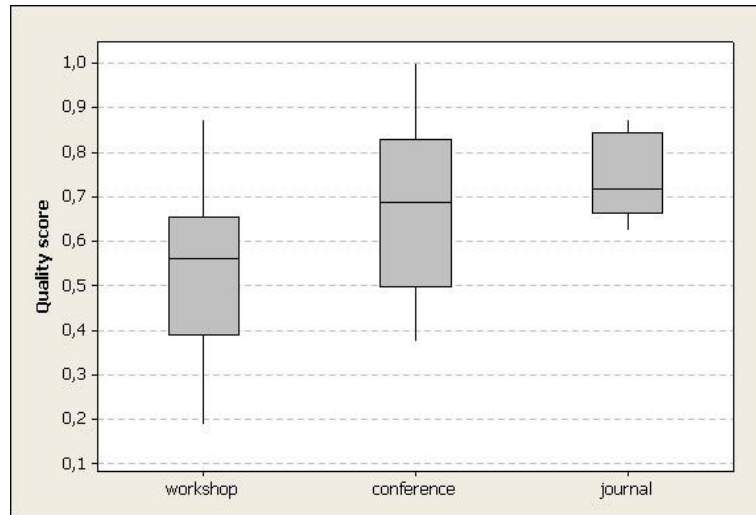


Figure 2. Quality score for different types of study

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 studies selected, which may be addressed in more than one study. The same applies for the rest of the results reported in this section.

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

In the following we describe each item of Table V:

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

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

User dependency In a number of cases RS requires 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 due to 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).

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

Table VI. Distribution of studies according to the contributions provided

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 8 studies respectively. Algorithms are also addressed by 27 studies in total. Finally, information aggregation or enrichment and various other contributions account for 8 and 16 studies, respectively. In the following we describe each item of Table VI:

Algorithms Most of the studies selected proposed new algorithms or extensions of algorithms existing in the literature. In particular, four categories emerged: defining of a new algorithm, adapting an algorithm to Linked Data, and combining of algorithms to obtain a new hybrid algorithm or extending of an existing algorithm. The definition of a new algorithm was the most frequent with 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 directly connected with the node). In addition, some algorithms define item-user matrices to compute semantic similarity based on path-lengths.

Similarity measures The studies selected applied a variety 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 which are used in studies selected 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 socialbased 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 studies selected according to the way they used Linked Data to produce recommendations and grouped them into:

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 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 exploits 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, i.e. 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.

| 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 |

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

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 4 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.

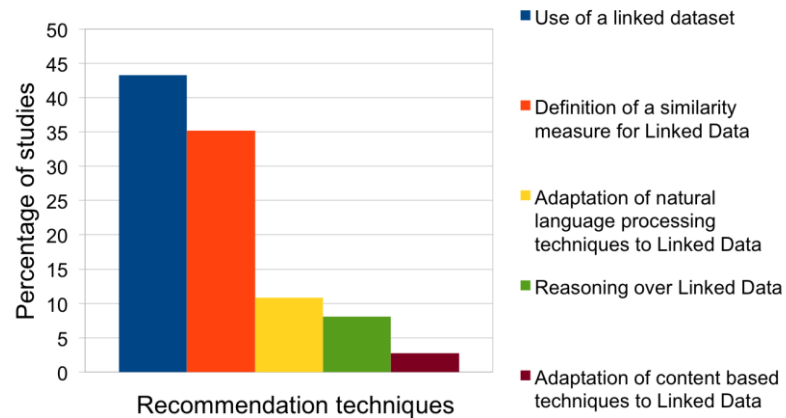


Figure 3. Distribution of Linked Data driven studies according to the recommendation techniques that they exploit (percentages refer to the total number of Linked Data driven studies)

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 (respectively about 43% and 35%), while the remaining 22% adapt natural language processing or content based techniques or exploit reasoning.

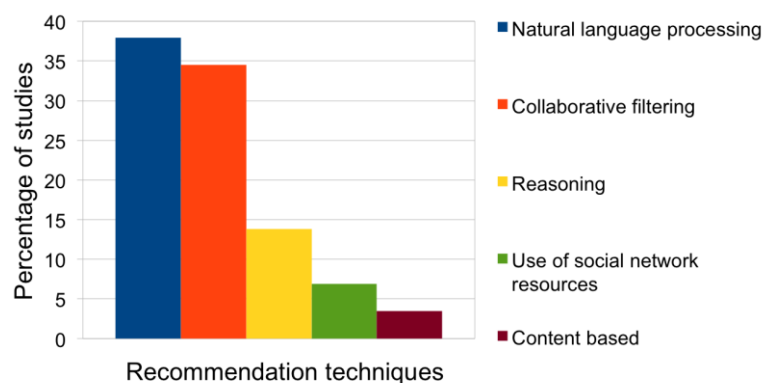


Figure 4. Distribution of hybrid studies according to the recommendation techniques that they exploit (percentages refer to the total number of hybrid studies).

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) , but also reasoning or social networks are exploited in some cases.

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.

| Dataset | Number of studies | | | | |
|---------------------|-------------------|-----------|--------|-------------------------|----------------|
| | 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 |

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

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.

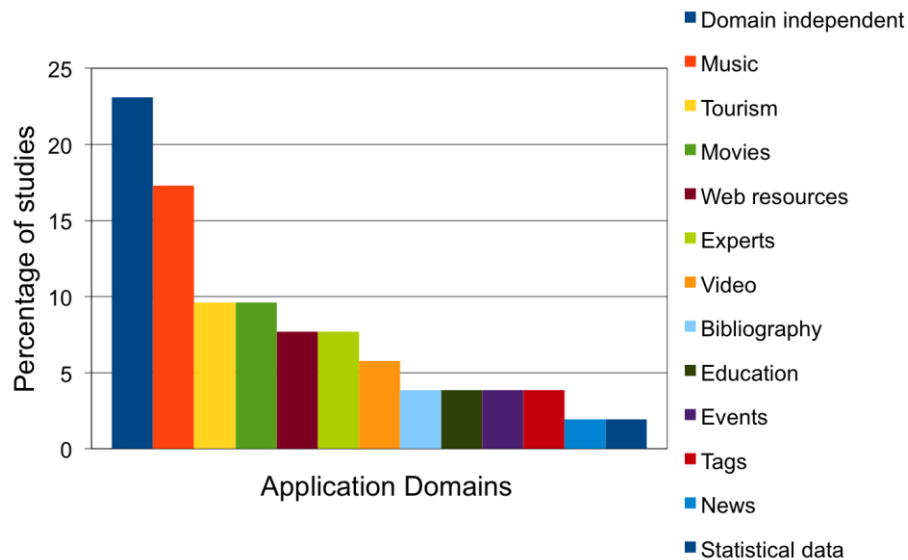


Figure 5. Distribution of studies according to the application domain

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:

- 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 (NDCG), average position and presence.
- Unexpectedness of a concept suggestion, which is the degree of novelty of a recommendation for the evaluator.

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].

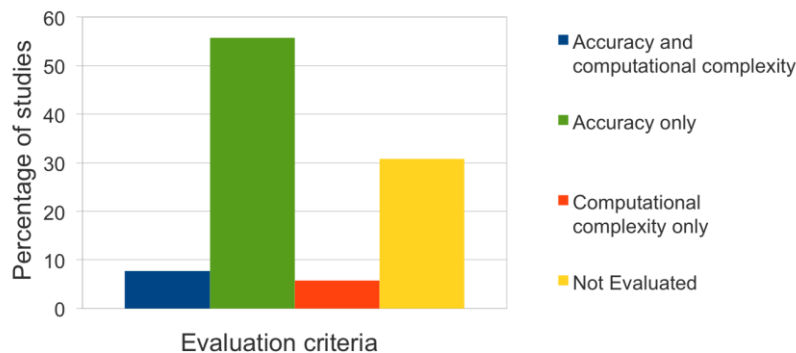


Figure 6. Distribution of studies according to the evaluation criteria (percentages refer to total number of studies)

Figure 6 shows the main evaluation techniques found in the studies selected, as well as their classification and their occurrence in these studies. Studies which 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 5 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 9 studies, and execution time, which is exploited by 7 studies.

| Type | Technique | Number of papers |
|------|-----------|------------------|
|------|-----------|------------------|

| Precision and Recall | | |
|---------------------------------|----------------------|---|
| 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 |

Table IX. Distribution of studies according to the evaluation techniques

4.7. Future Work

RQ7 is related to directions for future research. To address this, we summarized the future work that the studies selected 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.

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

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

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

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 due to 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 a 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 which did not rank their results, so final users are faced with no priority in the recommendation.

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

Computational complexity RS still need to improve the performance due to 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 makes 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 Linked Data datasets. 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 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 or enrichment. Accordingly, we found that Linked Data can be used in RS for several purposes such as:

- 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 user's personal data cloud, i.e. 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, registries etc with information obtained from Linked Data datasets which manage huge amounts of, linked open data triples. 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 Linked Data datasets 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* relies mainly on Linked Data to perform their tasks, *hybrid RS* uses Linked Data but also other techniques, *representation only RS* does not provide Linked Data-based recommendations but it uses 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 the appendix A.

| Approach | Techniques | Advantages | Disadvantages |
|--------------------|---|---|--|
| Linked Data-driven | <ul style="list-style-type: none"> - <i>Graph based:</i> weight spreading activation (S17), semantic exploration in an RDF graph (S29, S10, S3, S9, S19), and projections (S23) - <i>Reasoning:</i> (S1, S51) - <i>Statistical:</i> Matrix itemuser (S29, S35, S31, S13, S37, S10), Scaling methods (S29) and topic discovery (S2) | <ul style="list-style-type: none"> - 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 | <ul style="list-style-type: none"> - 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 | <ul style="list-style-type: none"> - <i>Collaborative Filtering and Linked Data:</i> (S2, S4, S12, S25, S27, S3, S28, S26, S30, S35) - <i>Information aggregation and Linked Data:</i> opinions (S16), ratings (S19), and social tags (S32) - <i>Statistical methods and Linked Data:</i> Random Indexing (S10), VSM (S47, S31, S35), LDA (S35), Implicit feedback (S25), SVM (S13), Structure-based statistical semantics (S37) | <ul style="list-style-type: none"> - Overcoming the data sparsity problem - Allowing collaborative filtering RS to address the cold start problem | <ul style="list-style-type: none"> - 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 |

Table XI. Classification of Linked Data-based RS approaches

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 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 enough broad 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 studies selected, 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 recommendation

algorithms proposed 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 impact also on datasets because they require a reduction of information, i.e, 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 a 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 usercentered in order to assure the quality of the results of RS.

Additionally, as expected most of the studies selected 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 to 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 studies selected.

Section 4.7 summarized the future work reported in the studies selected. 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 Databased 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, favorite music genre, etc).

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 Linked Data datasets 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 (iii) and 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 studies selected. 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 a RS applied in diverse contexts. For example, combining Linked Data-based RS with social-based RS can be a good choose for applications that require information about the users and their inter-relationships. 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 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 also must consider that Linked Data-based RS may 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/items.

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 their title or abstract, in the end they were excluded because we could not access them from our University.

Secondarily, 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. Due to 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 discussion between the first three authors.

6. CONCLUSIONS

This systematic review has discussed 69 papers reporting 52 primary studies addressing Recommender Systems (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 have conducted 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 studies selected 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, i.e. recommending items that are not expected by the users due the links uncovered once the items are enriched with Linked Data *(iii)* and explaining the recommendations, i.e. 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 studies selected 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 Linked Data datasets such as categories, paths, number of input and output links; hybrid RS that combine traditional techniques of recommendation (e.g. Collaborative Filtering, Content based etc) 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, i.e. it is linked to various datasets which gives the possibility to access to 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 studies selected 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 there is still a need for building testbeds to allow for testing and studying the results of RS based on Linked Data.

According to our findings, we identified that two recurrent issues in the studies selected 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 provide 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 which 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 a 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 a RS based on Linked Data can be applied in the eTourism domain.

A. SELECTED PAPERS

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

| P | S | Authors | Year | Title | Publication details |
|----|-----|---|------|---|--|
| 1 | S1 | Fernandez-Tobías, I., Cantafiumi, F., Kaminskis, 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 | Music 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 |
| 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., Ribiere, M., Rodio, F. | 2013 | Discovery Hub : on-the-fly linked data exploratory search | 9th International Conference on Semantic Systems, pp 17 – 24 |
| 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., D. model-based recommender systems | 2012 | Exploiting the web of data in | 6th ACM conference on Recommender Systems, V. C., Romito, |
| 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, O., 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 |

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|--------|--|--|--|
| 17 S17 | Kaminskas, M., Fernandez-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 for TEL recommender systems in research & practice | 2nd Workshop on Recommender Systems for Technology Enhanced Learning, pp 7 – 10 |
| 19 S10 | Damjanovic, 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 |
| 26 S24 | Hopfgartner, F., Jose, J. M. | 2010 Semantic user profiling techniques for personalised multimedia recommendation | Multimedia Systems, 16 (4-5), pp 255 – 274 |
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