A method of knowledgebase curation using RDF Knowledge Graph and SPARQL for a knowledge-based clinical decision support system

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Abstract

Clinical decisions are considered crucial and lifesaving. At times, healthcare workers are overworked and there could be lapses in judgements or decisions that could lead to tragic consequences. The clinical decision support systems are very important to assist heath workers. But in spite of a lot of effort in building a perfect system for clinical decision support, such a system is yet to see the light of day. Any clinical decision support system is as good as its knowledgebase. So, the knowledgebase should be consistently maintained with updated knowledge available in medical literature. The challenge in doing it lies in the fact that there is huge amount of data in the web in varied format. A method of knowledgebase curation is proposed in the article using RDF Knowledge Graph and SPARQL queries.

Keywords

Clinical Decision Support System, RDF Knowledge Graph, Knowledgebase Curation.

1. Introduction

Decision Support has been a crucial part of a healthcare unit. In every area of a health care facility, critical and urgent decisions have to be made. In such extreme situations, leaving lives at stake totally to mere human knowledge and memory is a very big risk. It can often lead to untold misery to the stakeholders and disaster to such facilities. In 2009 when Health Information Technology for Economic and Clinical Health (HITECH) was promulgated in the United States of America, monetary aid was disbursed for success in the implementation of Clinical Decision Support System(CDSS). It was because CDSS, although being far from a perfect system, was found to be better than mere human decisions. Since then, a lot of study and research is being done to perfect the CDSS.

One of the enlightening issues that came to the forefront during the recent pan-demic outbreak was the lack of widespread knowledge and awareness in the diagnosis and treatment of the disease. Although there were many breakthroughs published in medical literature globally, down-to-earth use of any of them were slow and far-between. It would have not been the case had there been CDSS that was capable of automatically acquiring reliable knowledge from authenticated medical literature. Such CDSS could alter heath workers with an all-round advanced knowledge at the moment of crucial decisions.

In the article, some aspects of the recent advances in the technology used in CDSS are described together with related works carried out in the development of knowledge-based CDSS before the proposed method of knowledgebase curation in CDSS is explained. In the section 2 that follows, a brief background is given into re-cent developments in knowledge-based CDSS. In section 3, some recent works on possible methods of knowledge base curation are mentioned. Then the proposed method is explained in section 4 and that is followed by a brief discussion on the proposed method in section 5. Finally, in section 6, a summarized conclusion is made.

2. Background

CDSS has evolved gradually with the ample technological developments that has happened in the past few decades. The system is essentially centered on high adaption and effective use of constantly updated knowledge. With the evolution of CDSS over the years, there has also been a consistent evolution in its definition from a mere use of information technology for data entry to a hi-tech complex system that provides individual specific, intelligently filtered and efficiently presented knowledge for clinicians, staff, patients, or other individuals [1, 2]

CDSS can be broadly classified as knowledge-based CDSS and non-knowledge-based CDSS. The knowledge-based CDSS are designed to mimic the knowledge processed by a human expert. Such systems were earlier termed as the expert systems. Non-knowledge-based systems, on the other hand, rely on statistical data that is available to help in decision making. These systems make full use of the machine learning and neural network algorithms to predict possible outcomes [3, 4, 5, 6].

2.1. Knowledge-based CDSS

Knowledge-based systems evolved from expert systems. While the expert systems were built on the knowledge of human experts, the knowledge-based systems have the capability to acquire knowledge from different sources and build upon it. So, while the expert system could be ranked according to the knowledge of the expert, the knowledge-based systems had the capacity of greater knowledge [7, 8].

The knowledgebase of the knowledge-based CDSS ultimately determines the effectiveness of the CDSS [9]. The acquisition, representation and the integration of knowledge base in the workflow is vital for the success of CDSS [10]. The process of selecting, organizing, and looking after the knowledge in the knowledge base makes the knowledgebase efficient and the CDSS successful. The two important facets of the curation process is the method of knowledge acquisition and knowledge representation [11].

One way to build a cost effective knowledge-based CDSS is to use commercial knowledgebases that are available. It could reduce cost of the development time of the CDSS and also because of the common availability of such knowledgebases, it could also be cost effective in terms of price [12]. But such knowledge acquisition might lead to the knowledge-acquisition bottleneck as certain standards and formalization will have to be maintained for the knowledge portability. Such a knowledge-acquisition bottleneck could harm the effectiveness of the CDSS and freeing the CDSS of the bottleneck makes the knowledge acquisition process complex and difficult [12], [13]. Another bottleneck in the curation of knowledgebase lies in the maintenance of the knowledgebase [14]. Together with creation of knowledgebase, its verification and constant updating is equally important. The verification and validation of the knowledgebase involves transparency, updatability, adaptability, and learnability [15].

A knowledgebase is judged by its accuracy, completeness and the quality of its data. So, the construction of the knowledgebase is done in such a manner that these three factors are enhanced to the maximum. The methods of constructing knowledgebases can be classified into four main groups. There are closed methods in which the knowledgebase is are manually fixed by experts, open methods in which knowledgebases are curated by volunteers, automated semi-structured methods in which the knowledgebases are procured from semi-structured texts automatically by using rules that are programmed into the system and the automated unstructured methods that use artificial intelligence algorithms to extract knowledge from unstructured texts [16].

2.2. Knowledge Graphs for knowledge base

Knowledge graphs are knowledgebases in which knowledge is expressed in a graph structure having nodes to represent the concepts or entities and edges between the nodes to represent the relationship between those entities or concepts [16, 17, 18, 19, 20, 21, 22, 23]. There are diverse definitions for knowledge graphs varying according to the purpose for which the knowledge graph is created or by the knowledge graph model [24]. Although Google is credited for the popularity of knowledge graphs from 2012 [24, 25, 26], the term knowledge graph was used in a report in 1973 with a very similar meaning [27] and later in 1982 the term was used to represent textual

concepts using graphs. There has been decades of study in representing knowledge using graphs [28].

The maintenance of knowledge graphs has the processes of creation, hosting, curation and deployment. The process of creation can be manual as in the case of expert systems or semi-automatic or automatic. Apart from these, there is also a method of annotation by mapping the knowledgebase entities to the source without actually keeping the entities in the knowledgebase. Hosting or storage processes use various methods of keeping knowledge in the knowledgebase. The curation processes involve three steps, namely, the assessment of new knowledge, its cleaning and its enrichment by detecting the source of the knowledge, integrating it with existing knowledgebase, detecting duplication and correcting entity relations. Once the knowledgebase is ready, it is deployed in appropriate application [29].

There are various sources of knowledge that can be utilized for the creation of knowledge base. Textual knowledge that can be in the form of newspapers, books, scientific articles, social media, emails, web crawls, and so on is a very rich source of knowledge for building a knowledge graph for CDSS. However, the process of extracting knowledge from text is complex and involves the application of Natural Language Processing(NLP) and Information Extraction(IE) techniques. Curation of the knowledgebase using these techniques may follow a combination of five stages. In the pre-processing stage, the text is analyzed for atomic terms and symbols. Some of the techniques used in the pre-processing stage are Tokenization, Part-of-Speech(POS)tagging, Dependency Parsing and Word Sense Disambiguation(WSD). After the pre-processing stage is the Named Entity Recognition (NER) stage in which the various concepts or entities that forms the nodes of the graph are identified. The NER is followed by the Entity Linking (EL) stage in which an association is made between the entities that are identified in the text and the entities in the existing knowledge graphs so that the similar entities could be placed side-by-side. During the Relation Extraction (RE) stage, the relation between the various entities taken from the text are considered using a various RE techniques. Finally the extracted relation is joint to the entities in the last stage of the text processing [22].

2.3.   RDF Knowledge Graphs

Resource Description Framework(RDF) is a World Wide Web Consortium (W3C) specification to represent knowledge in the form of triples (subject, predicate, object) containing references, literals or blank [30], [31]. RDF can be modelled as directed label graphs in which the subject and object are represented by the vertices or nodes and the corresponding predicate are represented by the labelled edges [32, 33, 34, 35]. RDF graphs are widely used to represent knowledge graphs like in the cases of Freebase, Yago, and Linked Data since the billions of triples scattered across the web can be captured and integrated with the existing knowledge using powerful abstraction for representing heterogeneous, partial, scant, and potentially noisy knowledge graphs [36], [37]. Unlike property graphs that is also quite popular representation of knowledge graphs due to its property and value representation for its edges, the use of metadata in RDF knowledge graphs allows the convenient distributed storage of knowledge. That also makes RDF graphs more flexible than property graphs [37, 38].

RDF knowledge graphs are stored as triples in a Triple store or RDF stores. The flexibility of RDF stores is its greatest advantage. Since the RDF knowledge graph has the ability to link any number of entities with their relations, the RDF stores are also flexible enough to store them without restriction on size. Moreover any kind of knowledge can be expressed and stored using RDF knowledge graphs that allows its extraction and reuse by different applications [39].

In the case of textual knowledge, RDF knowledge graphs are helpful in finding the Thematic Scope or the Topic Model of a text. The topic category or the semantic entities in a set of documents is abstracted using the Thematic Scope or the Topic Model [38, 40]. Since the RDF knowledge graphs of a document is represented as a set of triples in which each triple is considered a word or an entity, there is the possibility of detecting word and phrase patterns automatically by clustering word groups that best characterize a document. Some of the methods of the Topic Modelling of RDF knowledge graphs are Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Indexing (pLSI) and   Latent Dirichlet

Allocation (LDA). The challenges faced in Topic Modelling include sparseness of the entities, a lack of context especially when words used have multiple meanings especially when the entities are sparce and the use of unnatural language like the use of special characters or unusual casing of letters which normally are removed while pre-processing the text. Normally, these challenges are overcome by supplementing the text or modifying the method of Topic Modelling [40, 41, 42]. Entity summarization which is the best way of summarize an entity by identifying a limited number of ordered RDF triples is one of the problems that is solved using Topic Models of RDF knowledge graphs [41, 42]. Entity summarization has many applications like search engines and is useful for research activities. The existing entity summarization techniques can be classified into the generic techniques that apply to a wide range of domains, applications and users and the specific techniques that make use of external resources or factors that are effective only in specific domains or applications. While the generic techniques make use of universal features like frequency and centrality, informativeness, and diversity and coverage, the specific techniques make use of domain knowledge, context awareness and personalization [43].

3. Related works

Extracting knowledge from unstructured textual sources has been a challenge. Several studies have been done in order to solve the problem of retrieving meaningful and relevant knowledge from literature since it is crucial for decision support in systems like the CDSS. Some relevant techniques have been delt with in the earlier sections on knowledge graphs and RDF knowledge graphs. As part of the proposed method, certain other related techniques have to be explained in order to have a complete picture of the complexity of the problem of curating the knowledgebase for CDSS.

3.1. Question Answering using SPARQL

Question-answering (QA) is a process of retrieving knowledge from different sources using a part or the whole expression of a question in natural language. The question in the natural language can be interrogative in which case it will be a factoid type of question and its answer will be a fact from the knowledge source or the question could be statement in which case the answer will be in the form of either a list or a definition or hypothetical statement or a causal remark or a relationship description or procedural explanation or just a confirmation. The sources of knowledge are normally unstructured and is a set of documents, video clips, audio clips, or text files that are given as input to the systems [44]. QA systems make use of Information Retrieval, Information Extraction and Natural Language Processing(NLP) techniques [45].

QA systems have a long history of development starting with the earliest popular system BASEBALL in 1961 and LUNAR made in 1972. The Text REtrieval Conference (TREC) that began in 1992 for large scale information retrieval accelerated interest and growth in QA systems. Other forums and campaigns such as the Cross Language Evaluation Forum (CLEF) and NIITest Collections for IR systems (NTCIR) campaigns also enhanced the QA systems. Noteworthy QA systems include IBM Watson, and the other commercial personal assistant software like Apple's Siri, Amazon's Alexa, Google's Assist and Microsoft's Cortana [44, 45, 46, 47, 48, 49].

SPARQL is a query language in which a pattern in a query is matched with that in a graph from different sources. The matching is done in three stages. It begins with the pattern matching involving features like optional parts, union of patterns, nesting, filtering or constraining values of matches, and selecting the data source to be matched by a pattern. Once these features are applied, the output is computed using standard operators like projection, distinct, order, limit, and offset to modify the values that is got from pattern matching. Finally, the result of the SPARQL query is given in one of the many forms like Boolean answers, the pattern matching values, new triples from the values, and resources description. Working with RDF knowledge graphs require the use of SPARQL [50, 51]. In order to apply NLP techniques used in the QA systems over SPARQL queries, query builders such as QUaTRO2, OptiqueVQS, NITELIGHT, QueryVOWL, Smeagol,

SPARQL Assist language-neutral query composer, XSPARQL-Viz, Ontology Based Graphical Query Language, NL-Graphs and so on are used [52]. Some of the challenges in the use of SPARQL for QA systems include lexical gap, ambiguity, multilingualism, use of complex operators, distributed knowledge and in the use of procedural, temporal, spatial templates [53].

3.2. Ranked RDF Triples and Federated Search

Ranking SPARQL query results is an important process for applications involving searches, QA and entity summarization techniques. Ranking of RDF triples can be over resources, properties, or triples as a whole but a combined ranking of both the triples and its entities are important for RDF knowledge graphs for faster and efficient searches in the knowledgebase [54]. Ranking can be done on structured data using structured queries that results in a structured graph. Such rankings are structure-based ranking and mostly use an extension of ranking algebra that was earlier used in relational database. Content-based ranking on the other hand tries to rank the content of structure or unstructured data. In content-based ranking, the ranking is done according to the match between the pattern of the query and its holistic match in the knowledgebase. Further classification of query ranking can be as keyword queries on unstructured data like documents, structured queries on structured data, keyword queries on structured data, and keyword-augmented structured queries on structured data [55]. Ranking can also be based on the relevance or importance of the SPARQL query results with the topic on which the query is made. The relevance ranking requires the subject of the query to be clearly defined so that the results of the query can be ranked according its relevance to the subject. The importance ranking on the other hand specifies the importance that is given to the query result. In the importance ranking factors such as authoritative, trustworthy, and so on are placed for the ranking purpose for which human cognitive results are taken for consideration [56]. The ranking is placed along with the triple using tokens in an Extended Knowledge Graphs [57]

or more prevalently using graph embeddings [58, 59].

Knowledge graphs can be centralized or distributed. Both the centralized and distributed knowledge graphs have their advantages and disadvantages [60]. When it comes to distributed knowledge graphs, federated query processing is used in which the result of the query is computed from different data source. The federated query processing accesses different autonomous, distributed, and heterogeneous data sources to without having any control over the sources. Federated query processing is more complex than the centralized system because of the many parameters involved in the query processing. Federated query processing makes use of federated query engine to search for the results over distributed sources [61]. The federated SPARQL query processing can be done either over different SPARQL endpoints or over linked data or over Distributed Hash Tables. The federated SPARQL query processing can also be classified either as catalog or index assisted processing or as catalog or index free processing or a combination of both [62].

3.3. Open Information Extraction

Information Extraction(IE) is an automated process of collecting a set of corresponding information of interest from a given sequences of unstructured data. IE has many applications such as part-of-speech tagging, named entity recognition, shallow parsing, table extraction, contact information extraction and so on. Methods used for IE can be classified as rule learning based extraction methods, classification based extraction methods, and sequential Labeling based extraction methods [63]. Open Information Extraction(OIE) is a text IE paradigm that enables relations discovery independent of the domain that is readily scalable to the variations in size and content of the web. OIE is technically capable of meeting the challenges of the IE, namely, automation of the process, heterogeneity of the web corpus and efficiency in extraction of information [64]. The OIE like Text Runner, Clause IE, OLLIE, and the like were data based using training data that were represented either by dependency parsing or parts-of-speech tagged text. The Rule-based OIE were manually programmed using the dependency

trees or parts-of-speech tagged text. Two examples of Rule-based OIE are clauseIE and ExtrHech [65]. Another method of OIE is by linguistic analysis that shows the canonical ways in which verbs in a text is used to express relationship between entities. RE-VERB, ARGLEARNER and R2A2(combination of REVERB and ARGLEARNER) are examples of the linguistic analysis method. The earlier methods were based on the label, learn and extract stages of IE. The main drawback of the three-stage process was that the information extracted were either incoherent or uninformative and therefore they were of little use to applications. The linguistic-statistical analysis for extractions on the other hand identifying a more meaningful and informative relation phrase [66].

The biggest advantage of OIE is its ability to extract relationship between entities allowing queries like "(?, kill, bacteria)" or "(Bill Gates, ?, Microsoft)" to extract resultant missing relationships from a text corpus. Moreover, OIE will result in a compressed data for a knowledgebase [67]. Other than populating knowledgebases, OIE is also used for question answering, semantic indexing, semantic search and such target applications. Converting OIE triples into RDF knowledge graph is possible since the longer sentences are broken into triples with entities and relationship between entities leaving out the determiners and propositions. Knowledgebase populating using OIE has been a very useful application domain [68, 69]. Integrating the OIE triples with the exiting knowledgebase has been a research challenge and there have been many solutions proposed for it like the predicate or attribute level schema where similarity on names, types, descriptions, instances, and so on are mapped and universal schema to apply inferences got from OIE and the existing knowledge mapped at the instance-level. One of the problems of using universal schema is that the process ignores unseen entities and entity pairs and tries to overfit the space entities to large number of parameters. Rowless Universal Schema attempts to find inferences between predicated and relations so that the problem of unseen entities and entity pairs are solved. But it tends to completely ignore the existence of entities and thus it functions like the predicate or attribute level schema [69].

4. Proposed Method of Knowledgebase Curation

A CDSS is as efficient as its knowledgebase is. If the knowledgebase of the CDSS is highly adaptive to automatically and constantly update itself reflecting recent advances and local practice, then that will be a robust CDSS. The flexibility of the knowledgebase to accept knowledge from diverse sources and portability of the knowledgebase for various practice settings will make the knowledgebase more effective [9, 70].

4.1. Motivation

CDSS requires quick and reliable knowledge. Therefore, a centralized knowledgebase will be better than a federated search. Since knowledge on most of the advances found in medical literature, the knowledge extracted from the literature has to be found in the knowledgebase. The information extraction from medical literature can be done using OIE. If the user interface of the CDSS allows natural language questions to be asked, the questions can be converted through a QA system as a SPARQL query linked to through the knowledge graph. If answers are not found in the existing knowledgebase of the CDSS, it can than be passed through the OIE to relevant medical literature and the resultant knowledge can be integrated to the existing knowledgebase. The knowledgebase is so enhanced that most answer to query will be found in it and the updating will be done automatically once new knowledge is found in any form on the web.

There are many advantages of such centralized knowledge graphs. Centralized knowledge graphs can be controlled by a single entity when it comes to strategic issues such as symptoms for diagnostic systems of the CDSS. Such control increases the survivability and robustness of the CDSS. The uniform use of terms in centralized knowledgebase make it more stable. The fixed curation method of the knowledgebase of the centralized systems make the knowledge consistent and improves its quality. Moreover, the fixed schema of the centralized knowledge graphs allows uniform usage. The knowledge graphs allows the use of

application programming interface (API) for knowledge retrieval and query processing [60].

4.2. Proposed Approach

The proposed approach of knowledgebase curation for CDSS has three stages. In the first stage, new knowledge is extracted from a medical literature using an OIE application. The OIE application is for knowledge extraction since it will result in triples that can be integrated to the existing knowledge graph of the CDSS. The triples got from the OIE application on the medical literature is queried using keywords from the CDSS interface for relevant knowledge using a QA system. If the query results in new knowledge being found, then those triples in RDF from are added to the existing knowledge graph of the CDSS. A table is maintained with the list of medical literature already checked for knowledge so that they need not be looked for new knowledge again. The algorithm for the proposed system is as shown in Algorithm 1.

Algorithm 1.

Curating the CDSS knowledge base using RDF Knowledge Graph

URI (Uniform Resource Identifier) table U = {u_1, u_2, …, u_n}
RDF Knowledge Graph G ={V,E} where V Є {v_1,v_2,….,v_n} and E Є {e_1,e_2,…,e_n}
RDF triple S = {s, p, o} (subject(s), predicate(p), object(o))
Keyword K = {k_1, k_2,…k_n} taken from the QA system of CDSS
1 Read u_i //URI of a new document
2 If u_i Є U GOTO Step 12
3   Else use OpenIE to create G
4   For every K
5   use QA system with SPARQL query to find k_i in G
6   For every S found
7   If S not in CDSS knowledge base
8   Append S to CDSS knowledge base
9   END For loop
10   END For loop
11   END Else
12 If another document exists GOTO Step 1
13 Else STOP

4.3. Evaluation of the Proposed Method

For the evaluation of the proposed algorithm, the precision and recall method are used as it is the typical form of evaluation metrics used in information extraction. During the process of information extraction or retrieval, there could be two types of knowledge that is obtained from the knowledge source. There is knowledge that can be considered important to the application and there is knowledge relevant to the query. In the proposed approach, since the query is based on keywords from the QA system, only knowledge relevant to the query is selected rather than all knowledge that is deemed important from the knowledge source. Therefore, the results of the OIE is restricted to just the knowledge relevant to the query. The application of the evaluation metrics is also bound by the consideration that only the sum total of the relevant knowledge found by the system proportionate to all the relevant knowledge that can be manually counted on the same medical literature is calculated rather that taking in consideration all the important knowledge present in the literature that is used in the test. The precision evaluation metric is given by the formula in equation (1)

$$Precision = \frac{relevant\,RDF\,triples\, \cap\, retrived\,RDF\,triples}{retrived\,RDF\,triples} \quad (1)$$

A contingency matrix can be formed using the relevance of the RDF triple as shown in table 1. If the triple retrieved by the system is relevant to the query than it is true positive otherwise it is false positive. So also, if a relevant triple in the knowledge source is not retrieved by the system then it is false negative and if a triple that is not relevant and is ignored by the system it is true negative.

Table 1

Contingency matrix according to the relevance of RDF triples

	Relevant	Not Relevant
RDF triple retrieved	True positive	False positive
RDF triple not retrieved	False negative	True negative

The formula to calculate the precision of the system using the contingency matrix can be given as in equation (2)

$$Precision = \frac{total\,number\,of\,true\,positives}{total\,number\,of\,true\,positives\,and\,false\,positives} \quad (2)$$

The percentage of the precision can also be calculated as in equation (3)

$$Precision\% = \frac{total\ number\ of\ true\ positives}{total\ number\ of\ true\ positives\ and\ false\ positives} \times 100 \quad (3)$$

For recall we take into consideration the proportion of the retrieved triples to the total relevant triples as in equation (4)

$$Recall = \frac{relevant\ RDF\ triples\ \cap\ retrived\ RDF\ triples}{relevant\ RDF\ triples} \quad (4)$$

Using the contingency matrix, the formula to calculate recall is as in equation (5)

$$Recall = \frac{total\ number\ of\ true\ positives}{total\ number\ of\ true\ positives\ and\ false\ negatives} \quad (5)$$

5. Discussion for Further Study and Development

The proposed method of knowledgebase curation using RDF Knowledge Graph and SPARQL for a knowledge-based CDSS is pretty straightforward and simple. Its efficiency depends on the underlying OIE method chosen for extracting knowledge. The system provides the automatic updating of the knowledgebase and in turn offers reliability to the CDSS. Being a centralized system, the fixed curation method of the knowledgebase will consistently improve its quality and make room for its usefulness in decision making processes.

However, there is a lot of improvement possibilities that can make the system much more efficient and robust as a perfect system. One of the improvements that can be worked into the system is to use ranked RDF triples which can serve in two ways. First of all, it can give weightage to the decision suggestion and secondly, it can help in removing redundant triple from the knowledgebase allowing the CDSS to work faster. The ranked triples can be evaluated using the precision and recall curves that can give a better appraisal of the system. Another approach to removing redundant knowledge is to formalize forgetting. Formalizing forgetting in knowledge graphs implies a method of removing either the redundant entities or the redundant relations. Entities may not exist without relations. So, by removing relations would mean new updated relations replacing old relations.

6. Conclusion

CDSS has been considered a very important system in the healthcare sector. That is the reason for the numerous studies that has been done on developing a perfect system that is highly efficient while at the same time reliable. Since the CDSS requires a very quick response to queries, a centralized system is to be considered. At the same time, the knowledgebase of such a system requires being maintained with constant and consistent updating from various sources of medical literature. Knowledge graphs have proved to be a very formidable approach to represent huge amount of knowledge that is now available in the web. RDF triples are reliable storage method for knowledge graphs in the form of RDF knowledge graphs. Curation of the RDF knowledge graph can be done through a QA system that converts natural language questions into SPARQL queries which when matched with RDF triples from an OIE process can enhance the knowledgebase. Therefore, a method is proposed to curate knowledge base of a CDSS using RDF Knowledge graph. It is possible to evaluate the system using precision and recall methods and give an appraisal of its efficiency in acquiring knowledge from various sources.

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