

KQA: A Knowledge Quality Assessment Model for Clinical Decision Support Systems

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Abstract

Informatics researchers have developed many methods for using computers to utilize knowledge in decision making in the form of clinical decision support systems (CDSSs). These systems can enhance human decision making in the healthcare domain. The knowledge acquisition bottleneck is one of the well-known issues in developing knowledge-based systems such as CDSS. It can be considered as a flow of knowledge from different knowledge sources to the main system. Most existing methods for extracting knowledge from knowledge resources suffer from the lack of a proper mechanism for extracting high-quality knowledge. In this paper, we propose a framework to discover high-quality knowledge by utilizing Semantic Web technologies.

Keywords:

Decision Support Systems, Clinical; Knowledge Management, Information Storage and Retrieval

Introduction

Decision making is an essential activity for clinicians in the healthcare domain. Since 1954, Clinical Decision Support Systems (CDSSs) have been developed to enhance health care systems and improve human decision-making [1]. CDSS is a particular type of decision support system [2] that guides experts in the decision-making process via electronically stored clinical knowledge [3-4]. These systems might use different approaches to assist patients by using alerts, reminders, interpretation system, etcetera.

The CDSS is built from a knowledge base (KB), inference/reasoning engine, and user/communication interaction [5]. It receives patient data and inquiry as inputs and generates a decision as an output. In this scenario, the KB plays an important role in collecting, classifying and sharing knowledge [6].

The knowledge acquisition (KA) bottleneck is one of the well-known issues in CDSS [7]. It is the process of capturing knowledge from external knowledge sources [8]. It is vital to provide an appropriate platform for interacting CDSSs and KBs. Every CDSS needs to rely on high-quality knowledge retrieved from KBs since the CDSS will not be effective if it uses out of date, limited or incomplete knowledge [9]. In addition, finding the latest accurate clinical knowledge to support decision-making is difficult. This issue is partly due to the enormous amount of research, guidelines and other knowledge published every year [10]. Clinical knowledge may need to be extracted from diverse locations and sources that use different formats. In this regard, many biomedical researchers are looking at developing methods to manage and analyze clinical knowledge in this changeable environment [1,11-13]. One of

the recent technologies that they applied in knowledge acquisition is Semantic Web (SW) technologies [14] to solve the problem of knowledge management, representation, and interoperability of knowledge sources. They have created some Semantic Web-based systems such as COCOON [15], ARTEMIS [16], Semantic-DB [17], Knowledge-Centric Clinical Decision Support Systems [18-19], detecting Alzheimer disease (AD) [20], Semantic-CT [21], sharable CDSS [22], and others. Most existing methods suffer from a lack of a proper mechanism for identifying high-quality knowledge. There exist two main questions: "whether the CDSS contains enough knowledge for diagnosing an unusual disease" and "how to make sure that the knowledge used by CDSS are reliable."

Regarding the above questions, in this paper, we aim at proposing a semi-automatic approach called Knowledge Quality Assessment (KQA) to discover and assess the clinical knowledge for CDSS.

Research Motivation

The motivation of this research has been inspired by the result retrieved from PubMed search engine. Consider the following query shown in Table 1 which is about "Tuberculosis Arthritis" disease.

Table 1 – The characteristic of a query used in PubMed

[Title/Abstract]	Tuberculosis Arthritis
[Language]	English

The PubMed search engine extracts 18 relevant results for the above query. All of these results are valid, but the question here is "how can practitioners identify the most relevant and accurate result for decision-making process?". By assessing the abstract/title of the articles, we find out that some knowledge items which are ranked on top of the search results contain little or no useful knowledge.

- 9. [Tuberculosis arthritis. A review of 27 cases.](#)
- 10. Al-Saleh S, Al-Arfaj A, Naddaf H, Memish Z. *Ann Saudi Med.* 1998 Jul-Aug;18(4):368-9. No abstract available. PMID: 17344697 [Similar articles](#)
- 11. [Septic arthritis in patients with human immunodeficiency virus.](#)
- 12. Zalavras CG, Dellamaggiora R, Patzakis MJ, Bava E, Holtom PD. *Clin Orthop Relat Res.* 2006 Oct;451:46-9. PMID: 16906073 [Similar articles](#)
- 13. [Advanced imaging of tuberculosis arthritis.](#)
- 14. Leigh Moore S, Raffi M. *Semin Musculoskelet Radiol.* 2003 Jun;7(2):143-53. Review. PMID: 12920652 [Similar articles](#)

Figure 1- The sample result in PubMed

Figure 1 shows a fragment of the result achieved by the query in PubMed. The “Tuberculosis arthritis: A review of 27 cases” article, which is ranked before the “Advanced imaging of Tuberculosis arthritis”, does not contain an abstract and explanation related to the query. In other words, this article is less useful and has lower quality knowledge compared with “Advanced imaging of Tuberculosis arthritis.” Although one can set up a filter for results only with abstracts, even so, the relevancy does not correspond exactly with the knowledge value of the article. To solve this problem, this research proposes a framework to assess the quality of extracted knowledge for decision making.

Methods

In this section, we first explain the framework of KQA. Then, we describe the candidate metrics for assessing the quality of knowledge. At the end of this section, we also describe a survey, which has been used to rate and validate the importance of candidate metrics.

The KQA framework

Figure 2 shows a detailed view of the KQA framework. In this framework, a query submitted by a user, which represents a knowledge request, will be given to electronic knowledge sources and central knowledge base. Electronic knowledge sources that are used in this project are PubMed, MeSH, and UMLS. They include different clinical knowledge provided through journals, books, and electronic databases, etcetera. The central knowledge base is a machine-readable centralized repository that contains knowledge-based rules extracted from guidelines along with knowledge structure of a particular subject in health domain (e.g. Arthritis). After receiving a query, the KQA system will check the existing knowledge in central knowledge base to find a related result. If the knowledge exists in the knowledge base, the system will deliver the knowledge immediately, if it does not exist, the new knowledge will be extracted from electronic knowledge resources based on query characteristics. The extracted knowledge will be converted to the ontological format and annotated by other information to enrich the knowledge by using Ontology Web Language (OWL). After checking the quality of knowledge by using different quality metrics, the high-quality knowledge will be sent to attach a knowledge quality indicator (KQI) to knowledge item. The KQI indicates the quality of extracted knowledge. Finally, the high-quality knowledge will be used to update the knowledge base.

To update the central knowledge base, the candidate knowledge needs to be checked and approved by the domain experts. This is because it may contradict existing knowledge, and we do not believe at the moment that fully automatic knowledge updating is desirable. However, just being made aware of new highly rated knowledge is an advantage over existing approaches. The approved knowledge will be added to the central knowledge base.

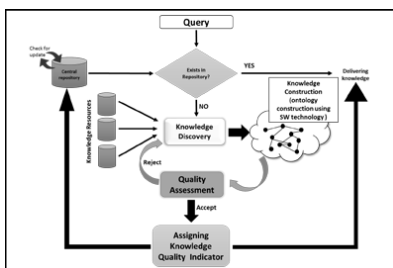


Figure 2 – The KQA framework

Quality assessment metrics

Knowledge quality assessment is a process for checking the quality of extracted knowledge from knowledge sources. Kyoon Yoo et al. [13] noted that knowledge quality should be intrinsically right, contextually relevant, and practically actionable. Based on the Kyoon Yoo model, knowledge quality metrics can be classified into three general categories, including intrinsic, contextual, and actionable metrics. OntoQA [23] is another study which only considered intrinsic metrics. In this paper, we modified the Kyoon Yoo and OntoQA models for categorizing knowledge quality metrics. Table 2 shows three categories of quality metrics proposed in this paper. Based on our categorization, intrinsic metrics are known as the backbone of knowledge. Contextual metrics show how much this knowledge is relevant to a user query. Given a set of actionable metrics indicating that the knowledge is mature, and it can be expanded and adapted for further usage.

Table 2 – Proposed Quality Metrics for KQA

Metric	Description
Age of resource	The age of knowledge should be declared.
Provenance	The knowledge should be based on valid authority.
Locality	The location of a resource which is relevant to should be declared.
Structure	The knowledge should be in a form that computerized DSS can use, in a consistent structure. E.g. XML. The knowledge should also be rich in concepts (classes) and connections among them (relationships).
Citation	The knowledge should be backed up by accessible citations to research.
Accuracy	How accurate is the knowledge source?
Reliability	The knowledge source will produce the same answer for the same question in different resources.
Relevancy	The resource contains relevant knowledge to support the user query.
Completeness	The answers to queries are complete.
Adoption	The knowledge source gives answers that are useful.
Scalability	The knowledge can be accessed from many systems without losing its meaning.
Timeliness	The resource produces an answer in an appropriate time

Survey for metrics rating and validation

To rate and validate the proposed quality metrics, we conducted a survey among health informatics scholars and practitioners in Health Informatics New Zealand (HiNZ) and the Australasian College of Health Informatics (ACHI) which is also available in [24]. The survey is a questionnaire that has been used for rating the quality metrics through participants. In addition, the participants can propose their own metrics.

Results

We collected the results from 10 experts. Table 3 shows the candidate metrics, which are ranked by participants for knowledge quality assessment for CDSSs.

In this table, the rating is on a scale between 1-5 (1: Not at all Important, 2: Slightly Important, 3: Moderately Important, 4: Quite Important, 5: Extremely Important).

By the survey result, every CDSSs requires an intelligent procedure to check the accuracy, reliability, and relevancy of the extracted knowledge. The accuracy of retrieved knowledge indicates how accurate the knowledge is. It checks the correctness of extracted knowledge against knowledge in the central knowledge base. The reliability metric shows how much the extracted knowledge from different knowledge sources might be similar to each other by using the same query. The relevancy shows how relevant the extracted knowledge is to support the user query. Based on the survey results, in this paper, we focus on developing KQA by assessing accuracy, reliability, and relevancy mentioned in the contextual metrics category shown in Table 3.

As seen in Table 3, the provenance metric has the higher rating average to compare with relevancy. Provenance relates to the perceived reliability of the source of the knowledge. In this research, we put trust on the most well-known knowledge sources for extracting knowledge such as PubMed. There are some metrics that are annotated in the body of extracted knowledge, such as the age of resource, locality, and citation. Such metrics are easy to retrieve and use. The aim of KQA is to check the quality of knowledge before incorporating it in the decision making process. However, there are some metrics (e.g., Adoption, Scalability, and Timeliness) that belong to the actionable category that are related to the quality of knowledge after being incorporated into the decision making process. These may have to be assessed using a study of how knowledge is used operationally in a CDSS.

In the following section, there are some comments collected from participants that identify some metrics that could be useful for further development of KQA.

Person A: *Level of evidence and level of recommendation. This gives flexibility to the CDSS so that it gives more freedom to the clinicians. These metrics are found in practice guidelines.*

Person B: *The knowledge is in a form that computerized DSS can use. It is equally important that the knowledge is in a form that the user can use - presentation of information to the user within a CDSS is vital for its safe and effective use.*

Person C: *Validity (the knowledge can be confirmed by using different sources)*

Person D: *Normalization (in the database sense: 3NF). All the ills of denormalized databases are being presented to us as clinicians because database professionals have ignored the importance of normalization.*

Person E: *Weighting. No diagnosis is cast in stone; no observation is 100% "right." At autopsy, 8% to 30% of diagnoses are incorrect. Diagnoses should always be considered to be reputable diagnostic hypotheses. It is important to know how sure a clinician is about an assertion, an affordance not provided by most current EHRs and the like.*

Person F: *Ability to give feedback (to point out possible error or exception)*

Person G: *To me, the structure is NOT just plonking things in XML. It is about the optimal presentation of the minimum of necessary data required for the clinician to do their job. It is difficult, and not well done (as shown in the Epic co-*

trimoxazole incident, and many others besides. Epic may well be better than most).

Person H: *Citations are tricky. It is important that evidence can be traced to its source but not always practicable to include citations in rapid easy to read guidelines.*

Discussion

Based on the results obtained from the survey, we aimed to measure the accuracy, reliability, and relevancy of knowledge that will be used in the CDSS as these are the most highly rated aspects. In this way, we are going to use some SW technology techniques such as ontology matching, ontology similarity, and ontology comparison. However, the process of evaluating results not only relies on proper measures but also user intervention. More precisely, the quality of retrieved results currently will be checked via domain experts. We are currently building a browser to support such knowledge ratings via the SW. A more automated approach that allows crowdsourcing or other approaches may be used in the future. One example may include comparing the outcomes of decisions made on current knowledge with expected outcomes using new knowledge on a database of cases.

In future research, we are going to use PubMed knowledge source to extract knowledge based on Extensible Markup Language (XML) format. We will manually convert the textual information into the ontological-based structure using Protégé ontology editor. We believe that ontological-based structure will be useful for storing knowledge since this structure embrace semantics along with proper annotations. As seen in this research, we assume that textual knowledge is converted to the ontological-based structure. In the future, we would like to develop an approach that automatically converts text structure to ontological structure for further use.

Conclusion

One of the most important activities in healthcare domain is decision making. CDSS can support decision making and may improve patient safety. However extracting up-to-date and high-quality knowledge from the growing mass of knowledge available is difficult and leads to the KA bottleneck. There are many methods and mechanisms for a CDSS to extract and use knowledge to help an expert to make a decision. The CDSS can improve the level of decision making by proposing appropriate knowledge. However, it cannot support how much of the knowledge is accurate, reliable and relevance in the case of comorbidities. Inappropriate knowledge can have negative effects on the decision-making process. Hence, there needs to be a system to check the quality of knowledge used in CDSS to help practitioners make good decisions. This paper aimed to propose a framework for assessing knowledge quality. To validate and rate the candidate quality metrics, we performed a survey among HiNZ and ACHI experts. This has led to a ranking of metrics that we will investigate.

Table 3 – Survey results

Metric	Participants (Rating 1-5)										Average	Total	Count				
	A	B	C	D	E	F	G	H	I	J			1	2	3	4	5
Accuracy	5	4	5	5	5	4	5	5	5	4	4.7	47	N/A				
Reliability	5	4	5	5	5	4	5	5	5	4	4.7	47	3 7				
Timeliness	5	3	4	4	3	3	4	3	5	4	3.8	38	4 4 2				
Age of resource	4	2	4	4	5	3	5	3	5	3	3.8	38	1 3 3 3				
Provenance	4	4	4	5	5	4	4	2	5	4	4.1	41	1 6 3				
Locality	5	2	2	3	3	2	3	3	4	4	3.1	31	3 4 2 1				
Relevancy	4	3	5	4	5	3	3	3	5	4	3.9	39	4 3 3				
Completeness	4	2	4	4	5	2	4	4	4	4	3.7	37	2 7 1				
Adoption	5	4	5	4	5	2	3	3	5	3	3.9	39	1 3 2 4				
Scalability	5	2	4	4	5	2	4	4	5	3	3.8	38	2 1 4 3				
Citation	4	3	4	5	4	2	3	3	4	4	3.6	36	1 3 5 1				
Structure	N/A	3	4	4	5	3	3	4	4	4	3.4	34	3 5 1 1				

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