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Chapter · January 2019

DOI: 10.1007/978-981-15-1956-7_10

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A Practical Framework for Evaluating the Quality of Knowledge Graph

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Abstract. Knowledge graphs have become much large and complex during past several years due to its wide applications in knowledge discovery. Many knowledge graphs were built using automated construction tools and via crowdsourcing. The graph may contain significant amount of syntax and semantics errors that great impact its quality. A low quality knowledge graph produce low quality application that is built on it. Therefore, evaluating quality of knowledge graph is necessary for building high quality applications. Many frameworks were proposed for systematic evaluation of knowledge graphs, but they are either too complex to be practical or lacking of scalability to large scale knowledge graphs. In this paper, we conducted a comprehensive study of existing frameworks and proposed a practical framework for evaluating quality on "fit for purpose" of knowledge graphs. We first selected a set of quality dimensions and their corresponding metrics based on the requirements of knowledge discovery based on knowledge graphs through systematic investigation of representative published applications. Then we recommended an approach for evaluating each metric considering its feasibility and scalability. The framework can be used for checking the essential quality requirements of knowledge graphs for serving the purpose of knowledge discovery.

Keywords: Knowledge graph · Knowledge discovery · Quality dimension · Quality metric · Fit for purpose · Machine learning

1 Introduction

Knowledge Graph (KG) is a graph representation of knowledge in entities, edges and attributes, where the entity represents something in real world, the edge represents relationship, and the attribute defines an entity [6,14]. "A knowledge graph allows for potentially interrelating arbitrary entities with each other, and covers various topical domains" [14]. Many large scale knowledge graphs were

This research is partially supported by United States NSF award #1852249, China NSSFC 2019–2022 project 19BTQ075.

X. Zhu et al. (Eds.): CCKS 2019, CCIS 1134, pp. 111–122, 2019.
https://doi.org/10.1007/978-981-15-1956-7_10

built recently such as Freebase, Wikidata, DBpedia, Google KG, and Microsoft KG. Many large companies including Google, Facebook, LinkedIn, Amazon, and Microsoft also built large scale knowledge graphs for building knowledge discovery or intelligent systems. Since a knowledge graph better captures the context of individual entities than separated individual entities in a traditional database, it is getting more attention recently for building more intelligent systems. For examples, knowledge graphs have been used for building knowledge-based information retrieval systems, conversation systems, question and answer (Q&A) systems, topic recommendation systems, and many others [6]. However, the quality of knowledge graph can great impact the performance of knowledge based systems that are built on the it.

The quality of knowledge graph mainly concerns about the "fitness of purposes" to an application that is built on the graph. A high quality knowledge graph shall be correct, comprehensive and fresh [6]. Many frameworks have been developed for evaluating the quality in term of the correctness, freshness and comprehensiveness of knowledge graph. Zaveri et al. conducted a systematic literature review of quality frameworks of knowledge graphs and propose one that includes 18 quality dimensions/criteria in four categories and 69 metrics for measuring the criteria [24]. The metrics are classified according to the their common properties into four categories: accessibility, intrinsic, contextual and representational [24], which were first defined in the widely cited data quality paper authored by Wang and Strong [22]. Zaveri et al. also summarized 12 tools for evaluating the quality of knowledge graph [24]. Although the framework proposed by Zaveri et al. in [24] provides a comprehensive way for evaluating the quality of knowledge graph, some of these quality criteria are not necessary for evaluating the quality regarding "fit for purpose" of knowledge graph or not practical to be evaluated. For example, some quality criteria can be validated in application development phases, and some quality problems can be handled by the application directly. Knowledge graph especially a large scale knowledge graph is supposed to contain low quality items such as incorrect relations, erroneous entities and literals. An application developer shall be aware the potential problem in a knowledge graph and ensure the application can handle the problem in some degree. Therefore, quality evaluation of knowledge graph is to check whether a knowledge graph meets basic quality standard and to ensure it fits for the purpose. We need a quality framework for knowledge graph that can well balance between ensuring "fit for purpose" of knowledge graph and being practical for evaluation. In this research, we first identify a group of quality requirements of knowledge graph that were developed on representative publications of applications of knowledge graphs. The quality requirements are essential to the effectiveness of a knowledge based system built on the knowledge graph. We then map quality criteria that defined in [24] to quality requirements to select a subset of the criteria that can be used for evaluating basic quality standard of a knowledge graph. Each criterion is evaluated by one or more metrics, and each metric is measured by one or more approaches. We investigated existing evaluation approaches and tools to propose one practical approach for evaluating each metric or an alternative version of a metric if its evaluation is infeasible. The ultimate goal of this research is to provide a practical quality evaluation framework that can easily used for ensuring basic quality standard of knowledge graph.

This paper is organized as follows: Sect. 2 provides a background introduction of quality of knowledge graph. Section 3 presents a recommended framework for evaluating quality of knowledge graph. Section 4 presents related work and state-of-the-art research on quality of knowledge graphs. Summary and future work are briefly discussed in Sect. 5.

2 Quality of Knowledge Graph

In this section, we discuss basic representation of knowledge graph and concept of quality of knowledge graph.

2.1 Knowledge Graph

The term of Knowledge Graph was used by Google in 2012 to call its new searching strategy that searches for things but not strings [17]. The definition of knowledge graph could be significantly different, which could produce knowledge graphs in different representation, size and content. The definition of knowledge graph in this research is developed based on the definition of knowledge graph proposed by Paulheim in [14]. A knowledge graph is a graph, which includes entities as nodes, edges as relations among entities, and attributes are used for describing entities. It can be represented as a group of triples. A triple defines a relation among two entities, and each entity is described by its attributes. A knowledge graph usually is a large network including thousands of entities and millions of edges among the entities. For example: the last version of Freebase contains around 50 million entities, 1.9 billion triples, roughly 27,000 entity types and 38,000 relation types [4,14]. A knowledge graph normally is constructed using automated tools through crowdsourcing, errors including syntax and semantic errors do exist in knowledge graph. These errors may impact the performance of knowledge-based applications built on the knowledge graph since "garbage in, garbage out" still applies to knowledge graph. Therefore, it is necessary to evaluate the quality especially "fit for purpose" of a knowledge graph for building an application. Evaluation of the quality of knowledge graph includes two tasks: one is the identification of quality criteria for measuring the quality of knowledge graph, and the other is the approaches and tools for measuring each criterion.

2.2 Quality Metrics for Knowledge Graph

Wang and Strong proposed a comprehensive framework for data quality in 1996 [22], which has been widely used for evaluating data quality. Stvilia et al. conducted a theoretic research of information quality assessment focusing on linking roots of information quality problems and information activity types, and then proposed a framework for information quality assessment [18]. Many frameworks for evaluating data quality including the quality of knowledge graph were developed based on the two frameworks. Zaveri et al. proposed a quality assessment framework for linked data, which can be looked at a general format of knowledge graph. The framework is essentially similar to the framework proposed by Wang and Strong and the framework proposed by Stivilia. For example, Zaveri's framework categories quality dimensions into four categories: Accessibility, Intrinsic, Contextual, and Representational. Stvilia's framework has three categories of quality dimensions: Intrinsic, Contextual, and Reputational. Accessibility and Representational dimensions in Zaveri's framework are categorized into Contextual, and Reputational dimensions in Stvilia's framework are included in Contextual category as Trustworthiness dimension. Zaveri's framework includes more dimensions and metrics for evaluating the quality dimensions. The framework can be directly used for systematically evaluating the quality of knowledge graph. Therefore, the framework we develop in this research is built based on the framework proposed by Zaveri et al. in [24].

Zaveri et al. conducted a systematic literature review of quality assessment of linked data and analyzed 30 data quality evaluation approaches. They identified 18 quality dimensions that are classified into four categories: Accessibility, Intrinsic, Contextual, and Representational [24]. 69 quality metrics were developed for evaluating the 18 quality dimensions, whose measurability is defined as the ability to assess the variation along a dimension [18]. A quality metric is a procedure for measuring a data quality dimension [24]. Accessibility category includes dimensions: availability, licensing, interlinking, security, and performance. Intrinsic category includes dimensions: syntactic validity, semantic accuracy, consistency, conciseness, and completeness. Contextual category includes dimensions: relevancy, trustworthiness, understandability, and timeliness. Representational category includes dimensions: representational conciseness, interoperability, interpretability and versatility. Each quality dimension is evaluated by several quality evaluation metrics. For example, The metrics for dimension availability include "accessibility of the RDF dumps", "dereferenceability of the URI, and others. The metrics for dimension security include "usage of digital signatures", and "authenticity of the dataset". The metrics for dimension semantic accuracy include "no outliers", "no inaccurate values", "no misuse of properties", "no inaccurate annotations, labellings or classifications", and "detection of value rules". The metrics for evaluating each quality dimension is not complete but are important properties that are closely related to the dimension. It is infeasible to define a complete set of general metrics for adequately evaluating each dimension of data quality. But the metrics can be extended for a special domain or an application. For example, metric "usage of digital signature" is not necessary important for evaluating the security of knowledge graph, but many quality metrics such as privacy should be used for evaluating security dimension. Metrics for measuring security dimension should be defined on access control, flow control, inference control and cryptographic control. It is also same difficult to define metrics for evaluating other complex quality dimensions such as semantic accuracy and completeness.

2.3 Approaches and Tools for Evaluating Quality of Knowledge Graph

Most of quality dimensions such as Licensing and Availability in accessibility category are easily manually evaluated. Evaluation of dimension Interlinking is not difficult and several approaches and tools are available. Dimension Performance can be checked using the data management system that stores the knowledge graph, or it is not important if the knowledge graph is stored in files since performance should be concerned by the system that is built on the knowledge graph. A knowledge graph should be treated as shared resource that could be used by many different applications. Therefore, performance requirements from a special application is not a concern of construction of knowledge graph. Evaluation of dimension Security could be very difficult, but we don't think security is closely related to "fit for purpose" of knowledge graph. Security including privacy should be just evaluated for whether appropriate protection mechanisms are used for protecting the data for meeting security requirements.

Quality dimensions in representational category are also easy to be evaluated or they should be left for evaluation by the application that is built on the knowledge graph. For example, dimension Representation conciseness is a subjective dimension and it can be manually evaluated through sampling, and interoperability and versatility can be evaluated through checking related readme documents. Evaluation of dimension Interpretability can be implemented through parsing knowledge graph against standard documents.

Zaveri et al. conducted a systematic review of published approaches and tools for quality evaluation of linked data, and reviewed 30 selected approaches and 12 tools [24]. Each of the approach covers at least one quality dimension, and the 30 approaches together cover all 18 dimensions. Dimension Versatility, Performance and Security was only covered by one article, and Representation conciseness, Licensing, and Interoperability was covered by two articles. It confirms our observation that some dimensions are easy to be validated or not so important to quality regarding "fit for purpose". Dimensions such as Syntactic validity and Semantic accuracy that are more important for evaluating the fitness for purpose of knowledge graph are getting more attention. Dimensions Syntactic validity and Semantic accuracy was covered by 7 and 11 articles, respectively [24]. Paulheim conducted a survey of knowledge graph refinement, which includes adding missing knowledge or identifying and removing errors [14]. The approaches for knowledge refinement especially the one for identifying errors can be directly used for evaluating the quality of knowledge graph.

Some general approaches for evaluating knowledge quality were also developed. For example, Kontokostas et al. proposed a test driven evaluation for linked data quality. In the approach, test cases can be generated by solving constraints on data schemas, test patterns, and test requirements [9]. The test cases are queries for retrieving the linked data and queried results are checked for specific quality metrics. The approach provide an elegant and effective approach for evaluating most quality dimensions of knowledge graph. Recently, Gao et al. introduced a sampling approach for efficiently evaluating the accuracy of knowledge graph. The approach can "provide quality accuracy evaluation with strong statistical guarantee while minimizing human efforts [5]."

3 A Recommended Framework for Quality Evaluation of Knowledge Graph

A quality evaluation framework for knowledge graph is designed for evaluating "fit for purpose" of a knowledge graph for building knowledge based application. Therefore, a quality evaluation dimension in a framework should be linked to specific quality requirements of knowledge based applications that are built on the knowledge graph. For example, in knowledge graph-based question answering [7], dimensions Syntactic validity and Semantic accuracy of triples are critical while dimension Conciseness might not be necessary. In this section, we first review publications on knowledge based applications developed on knowledge graphs and develop a group of quality requirements, and then map the quality requirements to quality dimensions. Each dimension is measured by suggested quality metrics and evaluation approaches. We begin with a systematic analysis of major activities related to knowledge graph in each system, and link each activity to quality requirements of knowledge graph with considering the activity system context. Then each quality requirement is linked to a set of quality dimensions.

In order to analyze quality requirements of typical knowledge based applications built on knowledge graphs, we conducted a systematic analysis related literature of knowledge graph applications. We use "knowledge graph" as keyword to search digital libraries Google Scholar, Microsoft Academic, ISI Web of Science, ACM Digital Library, IEEE Xplore Digital Library, Springer Link, Science Direct, and PubMed. 80 articles from last five years were selected as potentially relevant primary studies. Then two Ph.D. students read the title and abstract of each article to identify potentially eligible articles. 41 articles were finally selected for this research. We summarize five categories of the applications of knowledge graph: 1. semantic search; 2. decision making; 3. knowledge management; 4. data mining; and 5. prediction. According to the literature, semantic search is the most popular application of knowledge graph, tasks such as recommendation, information retrieval, question answering are also popular applications of knowledge graphs.

In the recommendation case, knowledge graphs should contains three aspects of information: 1. semantic relatedness among items to help find their latent connections and improve the precision of recommended items; 2. relations with various types to extend a user's interests reasonably and increasing the diversity of recommended items; 3. users' historical records and the recommended ones to ensure explainability of recommender systems [19]. While in question answering case, knowledge graphs are composed of vast amounts of facts with various expressions [10]. The ambiguity of entity names and partial names is also an important component since many entities in a large knowledge graph may share same names and end users could use partial names in their utterances [27]. Besides, knowledge graphs for question answering should be robust to expand so that new entities and relations can be easily added to them [8], or new relations for non-neighbor entity pairs can be created [25]. However, in the application of information retrieval, especially text retrieval, entities in the knowledge graphs are typically associated with different names.

The central function of knowledge graph for decision making is to automatically generate practical knowledge for a given task in different fields such as medical and agriculture. Knowledge graphs are often used for knowledge management because the ability to connect different types of data in meaningful ways and support richer data services. The applications of knowledge graph in prediction can be used in industry and in academia. Except for accuracy, trustworthiness,consistency, relevancy, timeliness acts as an important factor to enhance the prediction performance [2].

Data mining becomes a hot topic with the development of machine learning and deep learning. Recently, knowledge graph proved to be useful in data mining. The accuracy of the entities and relation extraction is the precondition for mining. Meanwhile, if the constructed knowledge graph is incompleteness, the performance will also be affected.

Based on the analysis of the works mentioned above related to knowledge graph applications, we summarize 18 requirements on knowledge graph quality:

1. Triples should be concise [2,26].
2. Contextual information of entities should be captured [2].
3. Knowledge graph does not contain redundant triples [2].
4. Knowledge graph can be updated dynamically [12].
5. Entities should be densely connected [11,16,26].
6. Relations among different types of entities should be included [21].
7. Data source should be multi-field [8,10,21].
8. Data for constructing a knowledge graph should in different types and from different resources [15,21].
9. Synonyms should be mapped and ambiguities should be eliminated to ensure reconcilable expressions [8,10,21].
10. Knowledge graph should be organized in structured triples for easily processed by machine [21].
11. The scalability with respect to the KG size [20].
12. The attributes of the entities should not be missed [13].
13. Knowledge graph should be publicly available and proprietary [3].
14. Knowledge graph should be authority [26].
15. Knowledge graph should be concentrated [26].
16. The triples should not contradict with each other [8,20].
17. For domain specific tasks, the knowledge graph should be related to that field [1,2,26].
18. Knowledge graph should contain the latest resources to guarantee freshness [6,27].

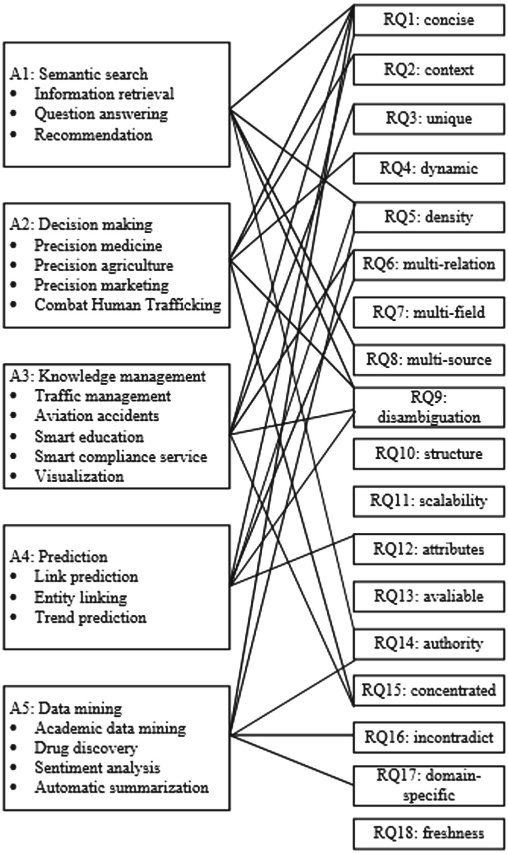

Fig. 1. Knowledge graph requirements produced from representative applications

The mapping between knowledge graph applications and the essential quality requirements is shown in Fig. 1.

Also, to incorporate with the knowledge graph quality evaluation dimensions mentioned in [24], we map the knowledge graph quality requirements mentioned above to the corresponding quality evaluation dimensions, as shown in Fig. 2. We do not take all of the dimensions since some of them didn't co-related with any requirements, for example, licensing, security, and representational-conciseness, interoperability, and versatility. In the meanwhile, we add two new dimensions robust and diversity to the representational and contextual categories respectively. Robust means that the knowledge graph should be easily expanded without affect the original knowledge graph too much, while diverse means the data for constructing a knowledge graph should be multi-source and multi-type. The metrics and tools proposed in [24] can be used for measuring the proposed dimensions here.

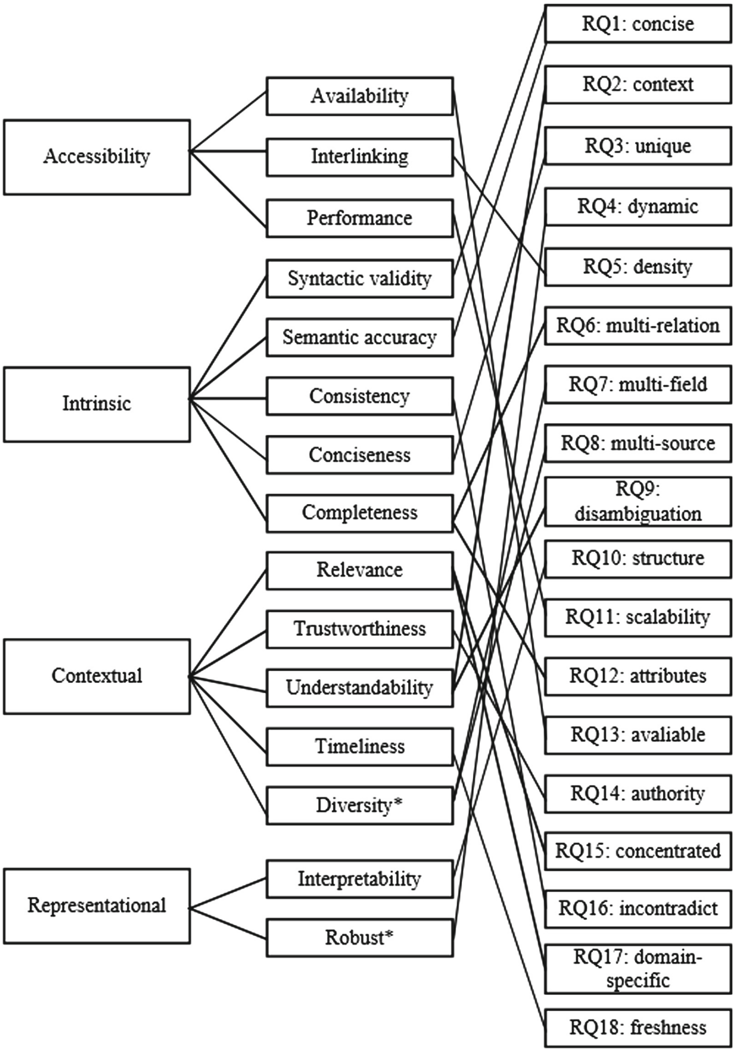

Fig. 2. Mapping knowledge graph requirements quality dimensions

4 Related Work

Wang and Strong [22] developed a hierarchical framework for defining data quality dimensions into four categories: which are intrinsic data quality, contextual data quality, representational data quality and accessibility data quality. They concluded that "high quality data should be intrinsically good, contextually appropriate to the task, clearly represented, and accessible to the data consumer" [22]. Stvilia et al. proposed a framework for information quality assessment [18]. They conducted a theoretical study to investigate root causes of change of information quality, the types of activities affected by the change, and the types of quality problems caused by the changes and the affected activities. The framework "consists of comprehensive typologies of information quality problems, related activities, and a taxonomy of information quality dimensions [18]".

Zaveri et al. developed a user-driven quality evaluation of knowledge graph DBPedia. The evaluation includes two phases: the first phase is to identify common quality problems and their types in a quality problem taxonomy, and the second phase is to evaluate each type of quality problem identified in the first phase via crowdsourcing [23]. They found 17 data quality problems, and near 12% of the evaluated DBPedia triples could have problem. The found incorrect entity values and incorrect or broken relationships were the most recurring quality problems in DBPedia [23]. Paulheim conducted a comprehensive survey of approaches and evaluation methods for detecting and fixing errors in knowledge graph. He reviewed and compared each method according to its refinement target, the type of the method, the basic idea of the method, the evaluation method, the knowledge graph the method is applied to, quality evaluation metric, whether the method is applied to whole knowledge graph or not, and the computational performance [14]. Zaveri et al. conducted a systematic review of quality evaluation frameworks for linked data, and they identified 18 quality dimensions in four categories and 69 quality metrics for measuring the quality dimensions [24]. They also investigated 30 published approaches and 12 tools for quality evaluation of linked data [24]. The framework we proposed in this paper is developed based on framework proposed by Zaveri et al. in [24] under theoretical guideline of the framework developed by Stvilia et al. in [18]. A test-driven evaluation of linked data quality was developed based on the support of the database management that is used for storing the linked data [9]. The tests defined as queries can retrieve needed information from the linked data against quality evaluation requirements [9]. The approach provides a practical solution for effectively evaluating the quality of large scale linked data including knowledge graph. A sampling method was developed recently for providing an efficient quality accuracy evaluation of knowledge graph with statistics guarantee [5]. Comparing to existing frameworks for quality evaluation of knowledge graph, the framework we proposed is to provide a practical one that is well balanced between evaluation comprehensiveness and evaluation efficiency so that the framework can be easily used for measuring the quality of knowledge graph for the basic level quality for building knowledge based applications.

5 Summary and Future Work

Knowledge graphs may contain significant amount of syntax and semantics errors that could great impact its quality of the knowledge based applications built on it. Existing frameworks for systematic evaluation of knowledge graphs are either too complex to be practical or lacking of scalability to large knowledge graphs. We conducted a comprehensive study of the proposed frameworks and proposed a practical framework for evaluating quality on "fit for purpose" of knowledge graphs. We selected a set of quality dimensions and their corresponding metrics based on the requirements of knowledge discovery applications built on a knowledge graph. Then we d an approach for evaluating each metric considering its feasibility and scalability. The framework can be used for checking the basic quality requirements of knowledge graphs for serving the purpose of knowledge discovery. In the future, we will evaluate the effectiveness of the framework on large knowledge graphs and conduct surveys from domain specialists including application developers, business analysts and knowledge graph researchers to evaluate and improve the framework.

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