Knowledge Graph Curation: A Practical Framework

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ABSTRACT
Knowledge Graphs (KGs) have shown to be very important for applications such as personal assistants, question-answering systems, and search engines. Therefore, it is crucial to ensure their high quality. However, KGs inevitably contain errors, duplicates, and missing values, which may hinder their adoption and utility in business applications, as they are not curated, e.g., low-quality KGs produce low-quality applications that are built on top of them. In this vision paper, we propose a practical knowledge graph curation framework for improving the quality of KGs. First, we define a set of quality metrics for assessing the status of KGs. Second, we describe the verification and validation of KGs as cleaning tasks. Third, we present duplicate detection and knowledge fusion strategies for enriching KGs. Furthermore, we give insights and directions toward a better architecture for curating KGs.

CCS CONCEPTS
• Information systems → Information integration; Deduplication; Data cleaning; Entity resolution; Extraction, transformation, and loading.

KEYWORDS
Knowledge graph curation; Knowledge graph assessment; Knowledge graph cleaning; Knowledge graph enrichment

1 INTRODUCTION
Knowledge graph curation (aka knowledge graph refinement [16]) is the process of improving the quality of knowledge graphs (KGs). In this context, knowledge assessment, cleaning, and enrichment are critical tasks to provide reliable, correct, and complete knowledge. “Knowledge Graphs are very large semantic nets that integrate various and heterogeneous information sources to represent knowledge about certain domains of discourse” [16].

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Over the last decade, creating and especially maintaining large KGs have gained attention (e.g., Amazon Product Knowledge Graph [11], Bing Knowledge Graph, eBay’s Product Knowledge Graph, Google’s Knowledge Graph [30]). KGs provide structured data for customers’ applications such as search engines, personal assistants, and question answering systems. However, KGs inevitably have inconsistencies, such as duplicates, wrong assertions, missing values, and more. The presence of such issues may compromise the outcome of business intelligence applications. Hence, it is crucial and necessary to explore efficient and effective semi-automatic methods and tools for tackling the curation of KGs. In other words, we need a curation framework for KGs that can well balance between ensuring correctness and completeness of knowledge graphs.

To face this challenge, we proposed a practical framework for improving the quality of KGs. Our approach involves (1) assessing the status of KGs based on quality dimensions and metrics, (2) detecting and correcting wrong assertions, and (3) enriching the KGs by adding new statements. Furthermore, we discuss our findings.

There have been approaches proposed to curate KGs. In this paper, we review methods and tools for knowledge curation. We found out that most of them focus on one specific task, either assessing the quality, detecting wrong assertions, or correcting those wrong assertions. However, curation of KGs usually implies a trade-off between correctness and completeness, which is tackled and assessed differently in each knowledge graph [16, 32, 51]. Therefore, we propose a practical knowledge curation framework, which is based on a process model for knowledge graph generation proposed by [16], that tackles the assessment, correctness, and completeness of KGs. In addition, we take into account the user perspective to define a degree of importance (i.e., weights) when curating KGs, e.g., the degree of importance determines KGs’ utility in specific application scenarios.

This paper is structured as follows. Section 2 presents a practical framework for curation of KGs. In Section 3 we list some interesting findings. Finally, we conclude in Section 4, by summarizing the conclusions and future work plans.

2 KNOWLEDGE GRAPH CURATION FRAMEWORK
While a lot of effort is being invested in the deployment of KGs, new issues arise, such as the verification and validation of knowledge (i.e., knowledge cleaning tasks), the increasing coverage of KGs (i.e., knowledge completeness task), and the quality assurance (i.e., knowledge assessment task). These tasks are of utmost importance as the KGs grow to billions of statements [30].

The Knowledge Curation Framework follows the workflow described in Figure 1. Before start, we assumed that a KG has been created and hosted in advance. First, the workflow starts with the
assessing component that receives as input a mapped and indexed knowledge graph (KG), afterwards the assessing process starts triggered by the definition of the quality metrics and weights of importance for each of the quality metrics, later the outcome of the assessment is stored, so the information can be used in other components. Second, at this point, either the cleaning or enrichment component can be started. We proceed with the cleaning component, which mainly deals with (a) the verification of the KG against a set of constraints and (b) the validation of each statement in the KG. The outcomes of this component are the verification and validation report. Third, the enrichment component aims to detect duplicates in the KG. Therefore, it runs the instance matching process helped with a configuration learning module, which tries to find a tuned configuration. The resulting duplicates report triggers the entity fusion process supported by fusion strategies based on the assessment report of the KGs. Finally, after having curated a KG, it is possible to repeat the curation process of the KG.

We start this section by introducing quality dimensions for KG assessment (Section 2.1). Later, we describe the KG cleaning (Section 2.2) tasks, as well as KG enrichment (Section 2.3) tasks.

2.1 Knowledge Graph Assessment

Assessing the status of KGs is the first step to curate KGs. In recent years, several KGs have been created and released as open (e.g. DBpedia, Wikidata) or proprietary (e.g. Amazon Product Knowledge Graph). We observe that these KGs widely vary in their quality, from manually curated KGs to automatically extracted KGs. Therefore, a data consumer needs to face the challenge to define a useful data source for specific tasks (i.e. "fitness for use"). There are a number of studies, which have identified data quality dimension into various categories [5, 6, 15, 16, 33, 48, 49, 51] with the aim of measuring the usefulness of knowledge sources. For instance, [5] describe a comparative analysis of methodologies and strategies of data quality dimensions, and [15] adopt some of these criteria to compare several data sources such as Freebase, OpenCyc, Wikidata, and YAGO.

Based on the analysis of the works mentioned above related to data quality assessment, we summarize 20 quality dimensions to consider on assessing the status of a Knowledge Graph (KG):

1. **Accessibility** implies that the KG must be available, provide a public SPARQL endpoint, retrievable in RDF format, support content negotiation, and describes a licence.
2. **Accuracy** defines the syntactic and semantic validity of assertions contained in the KG.
3. **Appropriate amount** evaluates whether the KG contains knowledge for specific use case scenarios.
4. **Believability** or trustworthiness measures whether the KG proves provenance information, and it is verifiable.
5. **Completeness** in terms of schema and instance level for a specific use case.
6. **Concise representation** evaluates the use of blank nodes and reification.
7. **Consistent representation** detects the existence of disjoint inconsistencies of classes and schema restrictions in the KG.
8. **Cost-effectiveness** measures the degree to which accurate data is necessary.
9. **Ease of manipulation** evaluates the existence of documentation for manipulating the knowledge contained in the KG.
10. **Ease of operation** refers to the possibility of updating, downloading, and integrating the KG.
11. **Ease of understanding** evaluates whether self-descriptive URIs are used and knowledge is presented in more than one language.
12. **Free-of-error** refers to the total number of wrong and missing assertions contained in the KG.
13. **Interoperability** evaluates whether the KG re-uses standard vocabularies and complies with Linked Open Data 5 Star.
14. **Objectivity** defines the degree to which the KG is unbiased and impartial.
15. **Relevancy** evaluates the level of applicability in terms of domain coverage, of the KG to a specific use case.
16. **Reputation** measures whether exist explicit trust ratings to the KG or there exist qualifiers on KG’s statements.
17. **Security** evaluates the degree to which the KG uses a digital signature and verifies the identity of the publisher.
18. **Timeliness** measures the frequency of updates occurring in the KG and the validity period of its statements.
19. **Traceability** evaluates the degree to which the KG provides provenance information and keeps a log of edits and changes.
20. **Variety** refers to the degree to which the KG contains knowledge from different sources and various domains.

The approach provides a practical framework for effectively assessing the status of KGs. Additionally, different quality dimensions may have different degrees of importance for different application scenarios. For instance, the Timeliness dimension may be very important in a domain that has predominantly dynamic data. Therefore, we let users define the weight of importance for each quality dimension. The tools proposed in [16, 32, 40, 46] can be used for measuring the proposed quality dimensions in this paper.

2.2 Knowledge Graph Cleaning

This task aims to improve the correctness of the KGs, which may contain a significant amount of syntax and semantic errors. For that, we distinguish between the verification and validation of KGs. The first aims to evaluate schema conformance and integrity constraints of KGs. The second one checks whether KGs accurately describe or represent the so-called "real" world.

2.2.1 Verification. It is the process of evaluating KGs with formal specifications of integrity constraints. In a heterogeneous environment of structured data like KGs, there is not necessarily a unique constraint language for verifying KGs. We distinguish three categories:

- **Query-based approaches**, such as Schemarama [28] that applies the XPath method and uses SquisQL language, and SPARQL Query Language¹, Simple Application-Specific Constraints [39], SPARQL Inferencing Notation (SPIN), RDFUnit [24], Shape Expressions (ShEx), and Shapes Constraint

¹https://www.w3.org/TR/sparql11-query/
Knowledge Graph Curation: A Practical Framework

We have presented constraint languages for verifying KGs. We noticed that some constraints are easier to write in one syntax (e.g., ShEx) than in others (e.g., SHACL). Furthermore, we distinguished between query-based, inference-based, and structural language approaches. These approaches can be used for the verification of KGs.

2.2.2 Validation. It is a critical task to provide accurate, correct, and reliable knowledge. The knowledge validation task in KGs evaluates whether an assertion (e.g., “Bill Gates is 64 years old”) from a KG is semantically correct or not and whether it corresponds with the so-called “real” world. We surveyed methods for validating KGs, we distinguish them according to the data used by them:

i Internal approaches rely on statements or triples that exist within a KG. For instance, some methods identify statements as pieces of evidence to support a particular statement [23, 25, 37, 38, 44]. Moreover, there exist approaches that use outlier detection techniques to evaluate whether a property value is out of the assumed distribution [44, 45, 50] and approaches that use embedding models [26]. Furthermore, we can mention some tools, like COPAAI [44] and KGTIm [23] that evaluate possible interesting relationship between entity pairs (subject, object) within a KG.

ii External approaches use external sources like the Freebase source to validate a statement. For example, there are approaches that use websites information [10, 20, 41], Linked Open Data datasets [43], Wikipedia pages [14, 31], and DBpedia knowledge base [22, 35]. Furthermore, there are methods that use topic coherence [2] and information extraction [41] techniques to validate KGs. The proposed tools are DeFacto [20], ExFaKT [18], Leopard [41], FactCheck [43], and FacTify [14], which rely on the Web and/or external knowledge sources like Wikipedia.
The reviewed approaches are mostly focused on validating well-disseminated knowledge than factual knowledge, e.g. Wikipedia is the most frequently used by external approaches. The approaches mentioned above can validate KGs.

2.3 Knowledge Graph Enrichment

Enriching KGs is a process of high practical relevance to improve the completeness of KGs, and there is a need for effective\(^2\) and efficient\(^1\) frameworks to tackle the problem. For doing that, we identified two tasks:

- **Identifying and resolving duplicates** is identifying where two or more records in a single or various KGs are referring to the same entity and linking those. The tools found during the review of the literature are ADEL [34], DDaaS [40], Dedupe [7], DuDe [13], Duke [19], Legato [1], LIMES [29], SERIMI [3], and Silk [47].

- **Resolving conflicting property value assertions** or data fusion refers to handle for example situations such as the pair of duplicated entities have a different value for the same property, the state-of-the-art tools for tackling this task are FAGI [21], Sieve [27], and SLIPO Toolkit [4].

Most of the tools mentioned above need a previous configuration to start working, such as Silk and Sieve. Also, most of the approaches focus on an individual type of use case (e.g. FAGI focuses on geospatial data). We also notice that these tools are mostly focused on the detection of duplicates rather than on the resolution of the conflicting property values. It is important to note that when we resolve property value conflicts from different KGs, we need to assess them in order to know which KG is reliable and suitable for the task at hand. Besides, the identification of new relevant KGs must be done in advance.

3 DISCUSSION AND FINDINGS

From the description of our framework in Section 2, we can notice that there are numerous approaches proposed for improving the quality of KGs, either for assessing the status of KGs, for detecting and correcting errors, or for detecting duplicates and perform knowledge fusion. We discuss our findings as follows:

- **Automation.** Various quality dimensions can hardly be fully automated for a technical or operational reason. Furthermore, it is desirable to allow users to create a semi-automatic mapping (or schema alignment [12]) between their KG and another KG.

- **Cost-effectiveness.** Validating KGs may lead to a high cost of deployment, due to its dependency on proprietary services (e.g., search engines). This can be overcome, to a certain level, if a validation framework uses open corpora (e.g. Wikipedia) but its performance lows down.

- **Dynamic data.** We should add the complexity of dynamic data (i.e., fast-changing data) since statements can be represented differently over a period of time. For instance, the telephone number of a restaurant can change.

- **Prevention.** Fixing syntactic and semantic errors can be caught during the creation and hosting of KGs. For instance, checking whether the input data conform to a specific schema. Furthermore, we have observed that the expressivity of constraint languages is directly related with the expressivity of SPARQL.

- **Reproducibility.** On one hand, most of the tools provide vast documentation, on the other hand, we notice usability issues of tools, e.g., complex to apply in different domains. Also, many of them were abandoned in their GitHub repositories and no longer maintained.

- **Re-usability.** Knowledge assessment frameworks may help to identify reliable and trustworthy KGs, to which user’s KG can be interlinked, e.g., the quality assessment may help to define to which extent a KG can be used for interlinking entities. Furthermore, most of the duplicate detection frameworks offer only simple similarity metrics, however in complex cases, complex metrics are needed.

- **User-in-the-Loop.** Users can define the degree of importance of a quality dimension (i.e. weights), for assessing a KG, according to the task at hand. For instance, knowledge assessment can help to decide which KG is best for resolving conflicting property values.

- **Scalability.** Existing frameworks are still lacking scalability to large KGs. For instance, applying a genetic algorithm can automatically tune a configuration for duplicate detection (i.e. Configuration learning process).

- **Trade-off between completeness and correctness.** Most of the approaches only detect errors or missing values but leave the correction part completely to users.

Our framework described in Section 2 aims to provide a practical curation framework that can be used for improving the quality of KGs. Above, we listed our findings that one can consider on the development of future curation frameworks.

4 CONCLUSION AND FUTURE WORK

Although our paper has presented methods and tools, improvement suggestions, and workflow in knowledge graph curation, we believe that there is still work to do in this field. This work aimed to fill this gap and facilitate future research in KGs curation domain. Twenty dimensions of KG quality were explored, several tools were listed for the cleaning and enrichment of KGs. Furthermore, this paper presents building modules that KGs architects can take into account in the development of future knowledge graph curation frameworks.

In the following, we point out our future work and open research questions. Firstly, our next steps involve the development of the KG curation framework to tackle the assessment, cleaning, and enrichment of KGs. Moreover, we will evaluate the performance of the framework and conduct surveys from domain experts and KG researchers to evaluate and improve the proposed knowledge curation framework.

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