QALD-9-plus: A Multilingual Dataset for Question Answering over DBpedia and Wikidata Translated by Native Speakers

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Abstract—The ability to have the same experience for different user groups (i.e., accessibility) is one of the most important characteristics of Web-based systems. The same is true for Knowledge Graph Question Answering (KGQA) systems that provide the access to Semantic Web data via natural language interface. While following our research agenda on the multilingual aspect of accessibility of KGQA systems, we identified several ongoing challenges. One of them is the lack of multilingual KGQA benchmarks. In this work, we extend one of the most popular KGQA benchmarks – QALD-9 by introducing high-quality questions’ translations to 8 languages provided by native speakers, and transferring the SPARQL queries of QALD-9 from DBpedia to Wikidata, s.t., the usability and relevance of the dataset is strongly increased. Five of the languages – Armenian, Ukrainian, Lithuanian, Bashkir and Belarusian – to our best knowledge were never considered in KGQA research community before. The latter two of the languages are considered as “endangered” by UNESCO. We call the extended dataset QALD-9-plus and made it available online.

I. INTRODUCTION

The core task of a Knowledge Graph Question Answering system is to represent a natural language question in the form of a structured query (e.g., SPARQL) to a knowledge graph (KG). In other words, KGQA systems provide access to the data in KGs via a natural-language user interface, s.t., end users are not required to learn a particular query language for fetching data manually. Obviously, the relevance (or accuracy) of the answers given by such system should strive to human performance and reduce labor costs for learning a particular query language; otherwise, the system is useless. Many researchers are aiming at measuring and increasing the Question Answering (QA) quality or the quality of a particular KGQA sub-tasks, such as named entity linking (e.g., [1]), expected answer type prediction (e.g., [2]), etc. However, the accessibility characteristic of the KGQA systems often stays overlooked. In this context, the perfect accessibility denotes an equivalent experience to all user groups of a particular KGQA system. Hence, such research questions as: “How many people can really take advantage of the high-quality KGQA system?” and “Who are these people?” as well as “How diverse they are?” are often left unnoticed.

In this work, we focus on the multilingual aspect of accessibility. The majority of research activities are dedicated to using the English language, however, there are approximately 7000 languages spoken in the world. Moreover, many languages spoken by hundreds of thousands or even millions of people (e.g., Udmurt, Bashkir, Belarusian) are not considered in the KGQA research to this moment. In the context of the multilingual aspect, increased accessibility provides the opportunity to use a KGQA system effectively for the speakers of different languages (including low-resource and endangered ones). While doing preliminary research, we identified that multilingual KGQA (mKGQA) has several ongoing challenges. One of them is the lack of available benchmarks. To the best of our knowledge, there are only 3 mKGQA datasets in the research community (QALD-9 [3], RuBQ 2.0 [4], and CWQ [5]) and all of them are not fulfilling completely the practical needs of researchers and developers (see Section II). Hence, even if one develops an mKGQA system, there are not so many opportunities for full-fledged evaluation. In this regard, it was decided to extend the well-known QALD-9 dataset in order to enlarge its language coverage and improve the quality of non-English questions. The English questions

\[\text{Figshare:} \ \text{https://doi.org/10.6084/m9.figshare.16864273} \ \text{GitHub:} \ \text{https://github.com/Perevalov/qald_9_plus}\]

\[\text{standards/webdesign/accessibility} \ \text{cf.,} \ \text{http://www.unesco.org/languages-atlas/en/atlasmap.html}\]
from the dataset are considered as a reference. To create the extension, a number of crowd workers were asked to translate the questions into their mother tongue manually (and validate translations by others). As a result, 17 volunteer participants and 290 crowd workers from Amazon Mechanical Turk and Yandex Toloka translated questions into 8 languages, such as: German, Russian, French, Armenian, Belarusian, Lithuanian, Bashkir, and Ukrainian, the latter five of which, to our knowledge, have never been considered in the KGQA context. In addition, the SPARQL queries in the dataset were transformed from DBpedia to Wikidata in order to increase the usability of the dataset. We name the extended dataset as “QALD-9-plus” and plan to continuously extend it over time. Thus, the main contribution of this work is that we introduce the mKGQA benchmark with high-quality translations that covers 9 languages in total (including English) some of that were never covered in the KGQA research community before. Moreover, Belarusian and Bashkir languages are considered as endangered by UNESCO. We value our contribution as a small but very important step towards improving multilingual accessibility of KGQA systems.

This paper is structured as follows: in Section II we describe currently available multilingual KGQA datasets, Section III describes in details the process of creation and analysis of QALD-9-plus. We demonstrate evaluation results of multilingual KGQA systems on QALD-9-plus in Section IV and conclude the paper in Section V.

II. MULTILINGUAL KGQA BENCHMARKS

Today, the research in the field of KGQA is strongly dependent on data, and it suffers from the lack of multilingual benchmarks. To the best of our knowledge, only three KGQA benchmarks exist that tackle multiple languages: QALD, RuBQ, and CWQ.

QALD-9 contains 558 questions incorporating information of the DBpedia knowledge base where for each question the following is given: a textual representation in multiple languages, the corresponding SPARQL query (over DBpedia), the answer entity URI, and the answer type. The dataset has become a benchmark for many research studies in QA (e.g., RuBQ 2.0 is a KGQA dataset over Wikidata that contains 2910 questions. The questions are represented in native Russian language and machine-translated to English language. Additionally, it contains a list of entities, relations, answer entities, SPARQL queries, answer-bearing paragraphs, query type tags.

CWQ is a recently published KGQA dataset over Wikidata that is based on CFQ data. CWQ contains questions in Hebrew, Kannada, Chinese, and English languages. All the non-English questions were obtained using machine translation with several rule-based adjustments. It has a well-detailed structure including: question with highlighted entities, original SPARQL query over Freebase (from CFQ), SPARQL query over Wikidata (introduced in CWQ), textual representations of a question in four aforementioned languages, and additional fields.

Despite the considered benchmarks contain questions in multiple languages, these multilingual representations were either machine-translated (RuBQ 2.0, CWQ) or have doubtful quality (QALD-9, see Section III-A). In contrast, the dataset that we present is covering 9 languages (including English) and was created by native speakers.

III. QALD-9-PLUS BENCHMARK CREATION PROCESS

A. Qualitative Analysis of QALD-9

While working with QALD-9 the following flaws in the data were identified.

Firstly, there is poor translation quality of the majority of questions in languages other than English. The authors, as native speakers of German and Russian, were capable to identify them for the respective languages. The question: “Which subsidiary of TUI Travel serves both Glasgow and Dublin?” has the following translation to Italian: “Quale società sussidiaria di TUI Travel serve sia Dortmund che Dublino?”. While not being a native speaker of Italian, it is obvious that two different cities are used in the original question (Glasgow) and in its translated version (Dortmund). It is worth noting, that the corresponding SPARQL query uses Glasgow, as in the original English question. Additionally, an analysis was performed for the German questions by an English teacher from Germany, rating the quality of the translation from English to German. It scores only 4.09 of 5.00 (5.00 is the highest rating) where 29 question received a rating of 1, 40 a rating of 2 (87 of 3, 97 of 4, and 305 of 5). Hence, this qualitative rating of the questions’ translation to German shows that the translation quality is not sufficient.

Secondly, the meaning of some questions is ambiguous, for example: “How often did Jane Fonda marry?”, here, the actual meaning is probably how many times. Another ambiguous example of a question is: “Who is the heaviest player of the Chicago Bulls?”, in this case, the time span of the question is unclear – the heaviest in the history or currently playing. The corresponding SPARQL query for the question “Give me all films produced by Steven Spielberg with a budget of at least $80 million.” contains the property and the question asks for .

In our work, we focus on the first part of the dataset’s flaws – poor translation quality. The original DBpedia queries were not changed, but were transformed to Wikidata. In the next sections, we describe the translation process and the process of migration of the SPARQL queries from the DBpedia KG to the Wikidata KG.

\[\text{https://www.mturk.com/}\]
\[\text{https://toloka.yandex.com/}\]
\[\text{cf. } \text{http://www.unesco.org/languages-atlas/}\]
\[\text{https://www.dbpedia.org/}\]
\[\text{https://www.wikidata.org/}\]
Fig. 1: An example of different basic graph patterns in DBpedia and Wikidata for question: “When did Finland join the EU?”. Prefixes are omitted (we used the typical RDF prefixes as shown at https://prefix.cc/popular/all).

TABLE I: The number of “gold standard” answer sets computed over DBpedia that have less or equal corresponding intersection rate between QALD-9 and QALD-9-plus, i.e., how many “gold standard” answer sets have the intersection rate less than X%?

|   | ≤ 25% | ≤ 50% | ≤ 75% | ≤ 100% |
|---|-------|-------|-------|--------|
| Train | 183   | 227   | 269   | 408    |
| Test  | 69    | 86    | 98    | 150    |

TABLE II: Overview of the extended QALD-9-plus.

| en | de | fr | ru | uk | lt | be | ba | by | DBpedia | Wikidata | # questions |
|----|----|----|----|----|----|----|----|----|---------|-----------|-------------|
| Train | 408 | 543 | 260 | 1203 | 447 | 468 | 441 | 284 | 80 | 408 | 371 | 408 |
| Test  | 150 | 176 | 26 | 348 | 176 | 186 | 155 | 117 | 20 | 150 | 136 | 150 |

B. Translation of Questions

The translation process was executed in a crowdsourcing manner with the following settings: (1) the crowd workers had to translate the questions from English to their mother tongue, (2) each crowd worker was provided with a prepared subset of questions selected from different parts of the dataset to avoid possible biases (one crowd worker translated at least 10 questions), (3) the usage of machine translation tools was prohibited (only dictionaries were allowed), (4) the crowd workers were not aware of the existing multilingual representations from the QALD-9 dataset, and (5) the crowd workers were not aware of the other’s tasks. In total, 17 volunteers and 290 crowd workers from Amazon Mechanical Turk and Yandex Toloka speaking 8 languages took part in the translation process. The coverage of translations was set to ≥ 2.

After the translations were obtained, the validation process was executed. During the validation, the crowd workers were provided with the original question and two translation options. A crowd worker had to select one of the following options: (1) no translations are correct, (2) first translation is correct, (3) second translation is correct, or (4) both translations are correct.

Despite the volunteers, the tasks to the crowd workers were assigned according to the main country of language’s origin (e.g., one has to be from France to translate from English to French). Thus, the questions were translated by native speakers of these different languages and additionally multiple times validated.

C. Migration from DBpedia to Wikidata

To extend the usability of the dataset, we ported the corresponding QALD-9 queries from DBpedia to the Wikidata KG. This process was carried out and validated in-house by 3 experienced computer scientists. Although semi-automatic scripts for retrieving entity and property mappings were partly used to speed up the process, it was very labor-intensive. In particular, we found that a simple property path in DBpedia is not necessarily simple considering the Wikidata KG, which complicated the transformation process. For example, the DBpedia query for the question “When did Finland join the EU?”, consists of one triple (DBpedia) while three triples are required to fetch the same information from the Wikidata KG (see Figure 1).

Several DBpedia SPARQL queries were not portable to Wikidata due to the absence of the corresponding information (e.g., “How many calories does a baguette have?”). In this regard, 51 queries could not be transferred to Wikidata, since the information available in the DBpedia KG was not available in the Wikidata KG. The “gold standard” answers over Wikidata for the questions were obtained by executing the corresponding SPARQL queries. The updated “gold standard” answers over DBpedia were obtained the same way.

We compared the answer-sets of the SPARQL queries of the old (QALD-9) and the updated (QALD-9-plus) datasets (see Table I). Given the table, nearly half of the “gold standard” answer sets for both train and test splits has less than 50% similarity, while comparing QALD-9 and QALD-9-plus. That is caused by changes in the DBpedia that may occur due to several reasons. For example, historical reasons, such as the change of president, governor etc., play a role, but also the data model has changed over time, or missing information was updated or added. This shows also the importance of the answer sets in the KGQA datasets since they enable comparability between different versions of a knowledge base. The up-to-date information should always be retrieved via the corresponding SPARQL queries.
TABLE III: Comparison of quantitative text features between QALD-9 and QALD-9-plus (both train and test subsets were considered)

| Feature                        | English (not changed) | German       | Russian      | French       |
|--------------------------------|-----------------------|--------------|--------------|--------------|
|                                | QALD-9                | QALD-9-plus  | QALD-9       | QALD-9-plus  | QALD-9       | QALD-9-plus  | QALD-9       | QALD-9-plus  |
| Average syllables per word     | 1.32                  | 1.86         | 1.87         | 2.13         | 2.31         | 1.51         | 1.55         |              |
| Average word length            | 4.77                  | 5.64         | 5.68         | 3.49         | 5.99         | 7.18         | 7.62         |              |
| Average sentence length        | 33.92                 | 35.65        | 39.14        |              |              |              |              |              |
| Average words per sentence     | 7.06                  | 6.32         | 6.89         |              |              |              |              |              |
| Type Token Ratio               | 0.30                  | 0.33         | 0.32         | 0.32         | 0.49         | 0.32         | 0.49         |              |

TABLE IV: Evaluation results on QALD-9-plus with GERBIL system. Only multilingual KGQA systems were used. The first value of a cell corresponds to Micro F1 score, the second one corresponds to Macro F1 score [16].

| QAnswer | English | German       | Russian      | French       |
|---------|---------|--------------|--------------|--------------|
|         | Micro F1 | Macro F1     | Micro F1     | Macro F1     | Micro F1     | Macro F1     | Micro F1     | Macro F1     |
| Wikidata test | 0.1002 | 0.4459       | 0.0291       | 0.3171       | 0.0159       | 0.2143       | 0.1190       | 0.2300       |
| Wikidata train | 0.0566 | 0.4009       | 0.0587       | 0.3009       | 0.0382       | 0.2264       | 0.0926       | 0.2777       |
| DBpedia test | 0.0527 | 0.3059       | 0.0219       | 0.1998       | 0.0153       | 0.0575       | 0.0406       | 0.1506       |
| DBpedia train | 0.1016 | 0.3416       | 0.1102       | 0.1807       | 0.0029       | 0.0436       | 0.0969       | 0.1968       |

DeepPavlov

| QAnswer | German | Russian | French       |
|---------|--------|---------|--------------|
|         | Micro F1 | Macro F1 | Micro F1     | Macro F1     | Micro F1     | Macro F1     |
| Wikidata test | not supported | 0.0011 | 0.1240       | not supported | 0.0005       | 0.0870       | not supported |
| Wikidata train | not supported | 0.0017 | 0.1032       | not supported | 0.0009       | 0.0933       | not supported |

Platypus

| QAnswer | German | Russian | French       |
|---------|--------|---------|--------------|
|         | Micro F1 | Macro F1 | Micro F1     | Macro F1     | Micro F1     | Macro F1     |
| Wikidata test | not supported | not supported | 0.0005       | 0.0870       | not supported |
| Wikidata train | not supported | not supported | 0.0009       | 0.0933       | not supported |

D. Dataset Statistics

The overview of the dataset statistics is present in Table II. We extended the dataset with 4,930 new question translations for different languages. In this regard, the majority of the multilingual representations of QALD-9 were replaced by the new ones. Note that for some languages like Russian we could collect multiple translations for some questions (i.e., 2.9 Russian translations per one question in training set) while for other languages like Armenian, Bashkir, French we provide only a partial converge of the original QALD-9 questions. All translations were carried out by native speakers.

In terms of the SPARQL queries, we extended the dataset with 507 new queries over Wikidata. The queries were manually created by the authors of the paper.

E. Quantitative and Qualitative Question Analysis

We used several language-agnostic quantitative text analysis measures in order to observe the change between QALD-9 and QALD-9-plus textual representations w.r.t. the descriptive statistics. Consequently, we analyzed only those languages that were present in both QALD-9 and QALD-9-plus. To do this, the LinguaF library for Python was used. The results of comparison are demonstrated in Table III.

Given the data, it is obvious, that for all the QALD-9-plus translations longer words were used. In addition, there are more words in the QALD-9-plus translated questions and consequently, the translated question length was increased. The Type-Token Ratio (TTR) that corresponds to the ratio between unique words and total number of words was also increased for Russian and French, and not changed for German. This analysis shows us that the QALD-9-plus multilingual representations are more complex and rich in comparison to the original QALD-9 translations. As the translations were done by native speakers, we consider this results as an implicit

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https://github.com/Perevalov/LinguaF
marker of improved translation quality. Additionally, a well-experienced English teacher from Germany did an evaluation of the translation quality. The original dataset was rated with 4.09 points out of 5. The new German translations of the questions were also evaluated, and only 19 question translations were optimized in the final validation process step (where 4 changes addressed typos and missing quotation marks). Hence, we can also conclude that the new German translations have a very high quality (5 out of 5 according to the previous rating).

F. Impact and Usability

It was decided to keep the QALD-JSON format for the QALD-9-plus as it enables the researchers to reuse their systems for the evaluation (e.g., GERBIL [16]). Hence, researchers and developers are enabled to benchmark and compare their KGQA systems in both mono- and multilingual settings over DBpedia and Wikidata. As there are several alternative translations provided, it is possible to develop techniques for paraphrasing and evaluating machine translation quality. The same is true for the SPARQL queries over DBpedia and Wikidata.

IV. Evaluation of Multilingual KGQA Systems

We evaluated our QALD-9-plus dataset on currently available multilingual KGQA systems: QAnswer [11], DeepPavlov [17] and Platypus [18]. QAnswer supports 11 languages (en, de, fr, it, es, pt, nl, zh, ar, ja, ru) and works over DBpedia and Wikidata, DeepPavlov – 2 languages (en, ru) and works over Wikidata, and Platypus – 2 languages (en, fr) and works over Wikidata. Consequently, we decided to evaluate the systems on the languages that are present in QALD-9-plus and are supported by them natively. The evaluation was done using the GERBIL system, the URIs of the experimental runs with detailed data (see the online appendix) are stored in the README.md file of the dataset. The results are demonstrated in Table V.

From the results we see that QAnswer has strong dominance w.r.t. English and French. DeepPavlov performed better on the Wikidata test subset in Russian, however, QAnswer is better on the corresponding train subset. The results for German language and DBpedia subset are not comparable due to the lack of its support.

Additionally, the original multilingual questions from QALD-9 were used in the evaluation while having updated SPARQL queries from QALD-9-plus (see Table V). For simpler comparability, only languages that were used for the QALD-9-plus were selected (i.e., German, Russian, and French). Given the results, no particular tendencies w.r.t. the quality difference between QALD-9 and QALD-9-plus were identified. Hence, while having a significantly different quantitative text measures between the original and extended translations (see Section II-E), the actual QA quality was not changed significantly. We hypothesize, that such result may be caused by the high robustness of the considered KGQA systems to the grammatical correctness of the questions or the still very keyword-dependent behavior of the considered KGQA systems. Together with the robustness, the systems may also be capable of answering only a particular subset of questions, that might be the reason why the quality values for some experiments did not change. However, this aspect has to be investigated further and is beyond the scope of this paper.

V. Conclusion and Future Work

In this paper, we presented a new benchmark for KGQA called QALD-9-plus. It is based on QALD-9 and was extended by creating translations from its English questions to German, French, Russian, Armenian, Belarussian, Lithuanian, Bashkir, and Ukrainian. The translations were done by native speakers of corresponding languages in a crowdsourcing setting. In addition, the DBpedia SPARQL queries from QALD-9 were transferred to Wikidata to improve the usability of the data. As QALD-9-plus contains multiple text representations for several languages and the questions are multilingual (i.e., parallel corpus), it enables researchers to address the paraphrasing and machine translation tasks. In addition, paraphrasing may be done on the SPARQL query level (i.e., from DBpedia to Wikidata). QALD-9-plus is keeping the QALD-JSON format in order to be reusable by the research community. The quantitative and qualitative comparison of the QALD-9 and QALD-9-plus multilingual question representations illustrated that the quality of the translation was improved. We consider QALD-9-plus as a significant contribution to the multilingual KGQA research community that creates wider possibilities for evaluation of KGQA systems.

By evaluation on three state-of-the-art KGQA systems using QALD-9-plus, we demonstrated that the extension to other KGs, namely Wikidata, and improving the translations gave new insights into these systems’ performance.

In the future, we will increase the coverage of languages (e.g., Bashkir, Armenian, and French) and extend the number of languages in the dataset. We also will enlarge the number of questions in the dataset, extend their meta-information (e.g., expected answer type, named entities etc.), and align SPARQL queries with the newest instance of DBpedia.

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