Enhancing Multilingual Accessibility of Question Answering over Knowledge Graphs

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ABSTRACT

There are more than 7000 languages spoken in the world today. Yet, English dominates in many research communities, in particular in the field of Knowledge Graph Question Answering (KGQA). The goal of a KGQA system is to provide natural-language access to a knowledge graph. While many research works aim to achieve the best possible QA quality over English benchmarks, only a small portion of them focuses on providing these systems in a way that different user groups (e.g., speakers of different languages) may use them with the same efficiency (i.e., accessibility). To address this research gap, we investigate the multilingual aspect of the accessibility, which enables speakers of different languages (including low-resource and endangered languages) to interact with KGQA systems with the same efficiency.

CCS CONCEPTS

• **Information systems** → **Question answering**; *Multilingual and cross-lingual retrieval.*

KEYWORDS

question answering, knowledge graphs, multilingual question answering, kgqa, accessibility, digital language divide

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1 INTRODUCTION

The Web is the most used source of knowledge for a large share of people worldwide. Most of the Web content (63.2%) is published exclusively in English[1]. Consequently, only people who are capable of using English properly have access to the major part of the Web. However, according to recent statistics,[2] only 1.35 billion of people worldwide speak English natively or as a second language (which is around 17.4% of the population worldwide). Given that the languages people are able to speak significantly affect their experience on the Web, the numbers above induce an effect often dubbed the *digital language divide*[3].

The bias towards English language is also present in many research communities. For example, the distribution of the languages across the datasets used in the field of Natural Language Processing (NLP) is highly imbalanced towards English.[4] The same applies if the research sub-field is narrowed down to Question Answering (QA) [2]. This work focuses on Question Answering over Knowledge Graphs (KGQA). KGQA systems provide users with a natural-language interface to structured data such that they do not need to learn a structured query language (e.g., SPARQL, Gremlin) to access said data. As the Semantic Web [3] can be conceived of as a giant Knowledge Graph (KG), *KGQA systems are key to providing (lay) users with an (user-friendly) access to knowledge available on the Semantic Web. Hence, these systems are considered an important technology for better knowledge search.*

Problem statement. While many research works in the KGQA field aim to achieve the best possible QA quality on particular benchmarks (mainly in English) [15] or achieve higher results on particular KGQA sub-tasks [12, 18, 21], the multilingual accessibility[5] of KGQA systems is often stays overlooked. Hence, questions such as: "How many people can really take advantage of the high-quality KGQA system?", "Who are these people?", and "How diverse are they?" are currently not answered by the research community.

Importance. The multilingual accessibility of the KGQA systems described in this work resonates with the famous citation of Tim Berners-Lee: "The power of the Web is in its universality. Access by everyone regardless of disability is an essential aspect,"[6]. Together with the main statement, that *the multilingual accessibility is bridging the gap between the least supported languages and the knowledge of the Web*, there are many more positive effects of its development. For example, better technological inclusion on the Web, more general computer-linguistic and machine learning algorithms targeted on NLP, and helping to avoid the extinction of endangered languages.

The following *research questions* are set in this work: (1) Is it possible to provide comparable QA quality for different languages?

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[1]https://w3techs.com/technologies/overview/content_language, retrieved 2021-10-21

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[2]https://www.statista.com/statistics/266808/the-most-spoken-languages-worldwide
[3]http://labs.theguardian.com/digital-language-divide/
[4]See the data published on the Papers with Code website at https://paperswithcode.com/datasets?mod=texts
[5]The ability for different user groups to have an equivalent experience while using a system.
[6]https://www.w3.org/Press/IPO-announce

Table 1: Multilingual KGQA systems overview over the past 10 years

Name	Year	Languages	Online Demo	API	Source code
Freitas A. et al. [7]	2011	not reported	no	no	no
QALL-ME [25]	2011	en, de, it, es	no	no	yes
Aggarwal N. [1]	2012	not reported	no	no	no
XKnowSearch! [23]	2016	en, de, zh	yes	no	no
UTQA [16]	2016	en, es, fs	no	no	no
BreXearch [22]	2017	en, de, es	no	no	no
AMUSE [8]	2017	en, de, es	no	no	yes
DeepPavlov [4]	2018	en, ru	no	no	yes
Platypus [19]	2018	en, fr, es	yes	no	no
QAnswer [6]	2018	en, de, fr, it, es, pt, nl, zh, ar, ja, ru	yes	yes	no
Zhou Y. et al. [24]	2021	en, fa, de, ro, it, ru, fr, nl, es, hi_IN, pt	no	no	no

(2) What is the influence of languages on the QA quality? (3) What KGQA sub-tasks (e.g., Named Entity Linking, Relation Detection) are influenced mostly? (4) Which are efficient ways to adapt an out-of-the-box KGQA system to a new language? (5) What patterns are utilized by users while asking questions to a QA system? (6) Do users utilize different question patterns in native/non-native language while using a QA system? (7) What are the suitable metrics for evaluation the QA system's accessibility w.r.t. the multilingual aspect?

This paper is structured as follows: in Section 1 the introduction, problem statement, importance, and research questions are described. Thereafter, related work is presented in Section 2. The approach and the methodology of the work are described in Section 3. In Section 4 current results of the work are presented. The paper is concluded in Section 5.

2 RELATED WORK

2.1 Multilingual Benchmarks

Today, the research in the field of KGQA is strongly dependent on data, and it suffers from a pronounced lack of multilingual benchmarks [10, 11]. To the best of our knowledge, only three benchmarks exist that tackle multiple languages: (1) QALD-9 [20] contains 558 questions in 10 languages over the DBpedia knowledge graph[7]; (2) RuBQ 2.0 [17] is a KGQA dataset over Wikidata[8] that contains 2910 questions [17] in Russian language and machine-translated English language; (3) CWQ [5] is a recently published KGQA dataset over Wikidata that is based on CFQ data [9]. CWQ contains questions in the Hebrew, Kannada, Chinese, and English languages. All the non-English questions were obtained using machine translation with several rule-based adjustments.

2.2 Multilingual Knowledge Graph Question Answering (mKGQA)

Table 1 contains mKGQA systems that were developed in the last 10 years, the languages they support and their availability in terms of online demos, APIs and source code. Both papers authored by Freitas et al. [7] and Aggarwal [1] propose similar vocabulary independent approach that consists of entity linking, semantic parsing, and relatedness search. The QALL-ME system [25] represents a context-aware (location and time) architecture that incorporates a set of language-dependent components and language identifiers at the very beginning of the QA pipeline. The XKnowSearch! [23] and BreXearch [22] systems use keyword matching and enrichment of multilingual content with means of KG to retrieve content that is relevant to a user's query. The UTQA [16] uses a QA pipeline of several language-dependent components, such as keyword extraction and type identification, entity linking, and answer extraction. The AMUSE system employs a compositional approach including creation of a question's dependency tree and tree nodes linking to a KB. The DeepPavlov KBQA system[9] [4] works based on a set of large language-dependent deep learning models that perform such tasks as: query type prediction, entity detection, relation detection and path ranking. Platypus [19] transforms a natural-language question into a custom logical representation using a language-dependent grammatical analyzer and set of predefined rules. The QAnswer system [6] executes a four-step QA pipeline to answer a question: question expansion, query construction, query ranking, and answer decision. The pipeline is KG-independent and easily portable to a new language. The recent publication of Zhou et al. [24] combines bilingual lexicon induction (BLI) method and multilingual pre-trained language models for answering questions over a knowledge graph.

3 APPROACH AND METHODOLOGY

The *approach* for improving multilingual accessibility of KGQA systems employed in this work is based on enabling such systems to work agnostic to an input/output language or be easily adaptable to the new languages, with a focus on the low-resource and endangered languages while preserving the QA quality.

The research *methodology* consists of the following steps: systematizing existing models and methods for multilingual KGQA, creating multilingual or language-agnostic resources (s.t., benchmarks, language models) and developing a language-agnostic framework for KGQA systems.

[7]https://www.dbpedia.org/
[8]https://www.wikidata.org
[9]http://docs.deeppavlov.ai/en/master/features/models/kbqa.html

4 RESULTS

4.1 Multilingual benchmark QALD-9-Plus

As the KGQA field lacks of high-quality multilingual datasets for evaluation, a new benchmark for KGQA called QALD-9-Plus [14] was created[10]. It is based on the widely used QALD-9 [20] and was extended by creating translations from its English questions to German, French, Russian, Armenian, Belarusian, Lithuanian, Bashkir, and Ukrainian. The translations were carried out by native speakers of corresponding languages in a crowd-sourcing 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 keeps the QALD-JSON format to be reusable by the research community. *QALD-9-Plus is a significant contribution to the multilingual KGQA research community that creates wider possibilities for evaluation of KGQA systems.*

4.2 Machine translation for monolingual KGQA

The experimental results shown in Table 2 and reported in [13] suggest that machine translation (MT) improves the QA quality in most cases if a source language is translated to English as the English language strongly dominates w.r.t. the QA quality for all the systems. The translation impact on the QA quality is weakly dependent on the source language. At the same time, a target language strongly influences the quality. In this case, the improvement or decrease of the QA quality is depending on how precise a system can handle questions in a given target language.

It was identified that the MT quality (BLEU, NIST) has either a small or moderate positive correlation with QA quality. However, we believe that ordinary MT quality metrics are not the only feature that correlates with the QA quality. In the future, it is worth investigating different aspects of machine translation that are play a central role for QA. For example, we would like to determine how precisely named entities in a question are translated (as they play a very important role in a QA process). This is motivated by ongoing research, in which we observed several examples where a failed translation of named entities led to questions that could not be answered by QA systems.

Finally, *it is possible to effectively adapt a KGQA system to an unsupported language by using MT*, s.t., , the accessibility of information on the Web for non-English speakers can be strongly improved. Given current results, the best strategy is obviously to translate a source language to English, which is still de-facto dominating w.r.t. the QA quality. However, research is required to identify the best possible component combinations.

4.3 KGQA leaderboard

The evaluation of a KGQA system is an important step towards comparing its ability to answer the questions with similar systems. Recently, the centralized data-repositories (leaderboards) that collect evaluation results for different research fields became popular. Such leaderboards are enabling researchers to form a global view on the corresponding research field.

To the best of the authors knowledge, no leaderboards for KGQA exist. Thus, it was decided to create the Knowledge Graph Question Answering Leaderboard [15] by gathering the evaluation results for the majority of KGQA benchmarks, analyzing it and publishing online[11]. The current state of the work covers 100 publications and 98 systems from the last decade. The analysis of the data has demonstrated several valuable insights. For example, the authors of 72% papers did not include all the evaluation results from other publications in their comparison that were already available at a particular point of time; the evaluation values across the publications are mostly consistent because the results are not reproduced but cited; only 16.8% of the results are tackling languages other than English. The leaderboard will be continuously updated in order to keep track of the state-of-the-art results in KGQA.

5 CONCLUSIONS AND FUTURE WORK

The initiative on multilingual accessibility described in this work has been started with extending existing KGQA benchmark by involving native speakers of different languages in a crowd-sourcing setting. Another research contribution pertained to studying the applicability of the machine translation approach to monolingual KGQA systems, s.t., the systems could be easily adapted to new languages and side effects of this approach can be identified. The creation of KGQA leaderboard clearly demonstrated the missing inclusion of languages other than English in the research field. Additionally, this work is focused on the language-independent KGQA pipelines. In particular, the multilingual EAT classification component was designed and implemented.

The long-term research agenda of this work is not only focused on the individual contributions of the authors but also is targeted on raising the problems of multilingual accessibility of KGQA systems as well as the Semantic Web to the whole research community.

The following tasks are set for the future work: extend mKGQA benchmarks w.r.t. the number of questions and languages, make a systematic review on the current methods on mKGQA, develop vocabulary-independent KGQA pipelines.

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[10] https://github.com/Perevalov/qald_9_plus

[11] https://kgqa.github.io/leaderboard/

Table 2: Evaluation results for the machine translated questions.

Source	Target	MT Tool	QAnswer			DeepPavlov			Platypus		
			Precision	**Recall**	**F1 score**	**Precision**	**Recall**	**F1 score**	**Precision**	**Recall**	**F1 score**
en	**Native⋆**		**0.5046**	**0.4484**	**0.4459**	**0.1765**	**0.113**	**0.124**	**0.1589**	**0.1526**	**0.1503**
	de	Yandex	0.3491	0.3518	0.3283	not supported by the system			not supported by the system		
		Helsinki NLP	0.349	0.35	0.3374						
	ru	Yandex	0.2284	0.2161	0.2107	0.0735	0.0699	0.0711	not supported by the system		
		Helsinki NLP	0.2238	0.2063	0.2041	0.0882	0.0735	0.0784			
	fr	Yandex	0.3216	0.2949	0.2886	not supported by the system			0.0894	0.101	0.0892
		Helsinki NLP	0.3076	0.2819	0.2757				0.0821	0.0936	0.0819
de	**Native**		**0.3305**	**0.3244**	**0.3171**	not supported by the system					
	en⋆	Yandex	0.4136	0.3871	0.3649	0.1985	0.1259	0.1392	0.1227	0.1160	0.1144
		Helsinki NLP	0.4095	0.3811	0.3657	0.1618	0.0983	0.1093	0.1521	0.1434	0.1426
	ru	Yandex	0.2233	0.2014	0.2033	0.0882	0.0737	0.0763	not supported by the system		
		Helsinki NLP	no model provided								
	fr	Yandex	0.3105	0.2823	0.2771	not supported by the system			0.1227	0.116	0.1144
		Helsinki NLP	0.2832	0.2621	0.2521				0.0591	0.0662	0.0593
ru	**Native**		**0.2102**	**0.2055**	**0.2006**	**0.0956**	**0.0833**	**0.087**	not supported by the system		
	en⋆	Yandex	0.4409	0.3979	0.3898	0.1691	0.1054	0.1161	0.1613	0.1527	0.1511
		Helsinki NLP	0.3912	0.3602	0.3463	0.1324	0.0793	0.0879	0.1324	0.0793	0.0879
	de	Yandex	0.292	0.2988	0.2717	not supported by the system			not supported by the system		
		Helsinki NLP	no model provided								
	fr	Yandex	0.2982	0.2734	0.2662	not supported by the system			0.0784	0.0919	0.0781
		Helsinki NLP	0.216	0.2044	0.1972				0.0664	0.0735	0.0667
fr	**Native**		**0.221**	**0.2188**	**0.1904**	not supported by the system			**0.0526**	**0.0526**	**0.0526**
	en⋆	Yandex	0.4211	0.3504	0.3657	0.3158	0.2202	0.2273	0.2105	0.2105	0.2105
		Helsinki NLP	0.4211	0.3504	0.3657	0.2105	0.1667	0.1729	0.2105	0.2105	0.2105
	de	Yandex	0.3301	0.3582	0.3101	not supported by the system			not supported by the system		
		Helsinki NLP	0.2774	0.3056	0.2574						
	ru	Yandex	0.1158	0.1574	0.1228	0.1053	0.1053	0.1053	not supported by the system		
		Helsinki NLP	0	0	0	0.1053	0.1053	0.1053			
lt	en	Yandex	0.4196	0.3919	0.393	0.1739	0.1094	0.1173	0.1739	0.1522	0.1594
		Helsinki NLP	no model provided								
	de⋆	Yandex	0.3894	0.366	0.3734	not supported by the system			not supported by the system		
		Helsinki NLP	0.4573	0.3935	0.3949						
	ru	Yandex	0.1732	0.1739	0.1735	0.0435	0.0435	0.0435	not supported by the system		
		Helsinki NLP	0.1413	0.1522	0.1449	0.0435	0.0435	0.0435			
	fr	Yandex	0.3326	0.2832	0.2916	not supported by the system			0.1359	0.1522	0.1256
		Helsinki NLP	0.3036	0.2628	0.2642				0.1304	0.1304	0.1304
uk	en⋆	Yandex	0.4315	0.4135	0.3917	0.1691	0.1018	0.1137	0.1497	0.1435	0.1417
		Helsinki NLP	0.3267	0.3301	0.3038	0.1691	0.1024	0.1118	0.1422	0.1344	0.1348
	de	Yandex	0.3186	0.3032	0.2882	not supported by the system			not supported by the system		
		Helsinki NLP	0.2948	0.2732	0.2713						
	ru	Yandex	0.2265	0.2253	0.2202	0.0735	0.0699	0.0711	not supported by the system		
		Helsinki NLP	0.2464	0.2397	0.2319	0.0662	0.0625	0.0637			
	fr	Yandex	0.3085	0.2807	0.2727	not supported by the system			0.0968	0.1066	0.0953
		Helsinki NLP	0.2268	0.2352	0.2076				0.0775	0.0846	0.0765
be	en⋆	Yandex	0.5455	0.4554	0.4562	0.0909	0.0455	0.0606	0.0909	0.0909	0.0909
		Helsinki NLP	no model provided								
	de	Yandex	0.3654	0.2747	0.2746	not supported by the system			not supported by the system		
		Helsinki NLP	no model provided								
	ru	Yandex	0.1818	0.1818	0.1818	0.0909	0.0909	0.0909	not supported by the system		
		Helsinki NLP	no model provided								
	fr	Yandex	0.4091	0.2281	0.2441	not supported by the system			0.0909	0.0909	0.0909
		Helsinki NLP	no model provided						no model provided		
hy	en⋆	Yandex	0.2632	0.2188	0.2253	0.2105	0.1149	0.1221	0.1579	0.1579	0.1579
		Helsinki NLP	no model provided								
	de	Yandex	0.2774	0.3495	0.295	not supported by the system			not supported by the system		
		Helsinki NLP	no model provided								
	ru	Yandex	0.0526	0.0526	0.0526	0.1053	0.1053	0.1053	not supported by the system		
		Helsinki NLP	no model provided								
	fr	Yandex	0.1684	0.1662	0.1378	not supported by the system			0.0526	0.0526	0.0526
		Helsinki NLP	no model provided						no model provided		

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