MMQA: A Multi-domain Multi-lingual Question-Answering Framework for English and Hindi

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Abstract
In this paper, we assess the challenges for multi-domain, multi-lingual question answering, create necessary resources for benchmarking and develop a baseline model. We curate 500 articles in six different domains from the web. These articles form a comparable corpora of 250 English documents and 250 Hindi documents. From these comparable corpora, we have created 5,495 question-answer pairs with the questions and answers, both being in English and Hindi. The question can be both factoid or short descriptive types. The answers are categorized in 6 coarse and 63 finer types. To the best of our knowledge, this is the very first attempt towards creating multi-domain, multi-lingual question answering evaluation involving English and Hindi. We develop a deep learning based model for classifying an input question into the coarse and finer categories depending upon the expected answer. Answers are extracted through similarity computation and subsequent ranking. For factoid question, we obtain an MRR value of 49.10% and for short descriptive question, we obtain a BLEU score of 41.37%. Evaluation of question classification model shows the accuracies of 90.12% and 80.30% for coarse and finer classes, respectively.

Keywords: Multi-lingual Question answering, Answer extraction, Neural network, Question classification

1. Introduction
Question answering (QA) is an important area with a wide range of applicability in various Natural Language Processing (NLP) tasks, such as information retrieval, information extraction etc. The aim of a QA system is to automatically extract/generate the answer(s) for a given question from the data repository (e.g., web, document etc.). In a QA system questions are formulated in natural languages and answers are also dealing with natural languages. Unlike search engine instead of extracting information, here a QA system usually focus on extracting relevant and precise answer(s). In other words, we can say QA system is the extended modification in the search engine. For achieving QA system, usually three subprocesses are followed i) question classification ii) document(s)/passage(s) extraction and iii) appropriate answer(s) extraction. Most of the existing works focus on retrieving answers in the same language in which the questions are posed. However, with the rapid growth of multilingual contents on the web, it is necessary to build an automated system that retrieves information from the documents written in multiple languages.

Posing questions in multiple languages and retrieving answers accordingly is known as Multilingual Question Answering (MQA), which has emerged as an interesting research area in QA. This enables the situation where the question could be in a different language from the language of documents where the answer(s) lie. This allows users to interact in their native languages, facilitating multilingual information access, which is immensely useful in a country like India. MQA system can contribute to conserving the endangered languages which are losing their existence and prestige as mentioned in (Knott et al., 2001). Hindi is a widely spoken language in India, and in terms of native speakers, it ranks fourth all over in the world. In India, a sum of 53.60% of total population speak Hindi as compared to English (12.18%). English, on the other hand, is used for all kinds of official communications. There is often need to exchange information from Hindi to the other popular language(s) such as English.

In recent years, several multilingual and cross-lingual QA systems have been built. These systems are seeking to overcome the issue of accessing and retrieving information in multiple languages. The majority, however, are based on translating relevant sections of the question – usually with the aid of machine translation system - which is used to access to a collection containing relevant information. The basic goal of MQA framework is to set up a common system to evaluate both bilingual and cross-lingual question answering that process queries in either Hindi or English language and retrieve answer in either language from documents in Hindi or English. The main motivations and/or contributions of the current work are as follows:

1. Most of the existing works are in resource-rich languages such as the English. Indian languages are resource-scarce, and developing a multi-lingual QA system involving English and Hindi has the benefit of utilizing resources and tools available for the resource-rich language like English.

2. Creating a benchmark setup for multi-lingual QA involving Indian languages will be beneficial for multilingual information access. To the best of our knowledge, this is the very first attempt in this direction.

3. Question classification is an important step in Question-Answering (QA). We propose a method based on deep Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) for question classification.
Table 1: An example of comparable articles from English and Hindi and set of question-answer pairs created from the given articles.

Table 2: The set of possible reasoning types with the corresponding question-answer pair example and descriptions. Reasoning types show the difficulty of the question in terms of finding their answer. The answer in answer sentence has been shown in bold font.

Problem Definition

Given a natural language question $Q$ (factoid or short descriptive) in either language, English or Hindi. The QA system should return the answer $A$ for the given question $Q$ from the comparable English and Hindi documents. The returned answer should be in the same language as the question $Q$.

2. Related Work

In literature, we found a very few existing works related to question-answering (QA) in Hindi or English (Sekine and Grishman, 2003; Kumar et al., 2005; Sahu et al., 2012; Stalin et al., 2012). However, none of these focuses on multilingual QA. (Kumar et al., 2005) implemented the Hindi search engine. The task of the search engine is to retrieve relevant passages from the collection of the passages. In the proposed architecture various modules were introduce. Automatic Entity Generator module identified domain related entities from which user can ask questions. Question classification module has several categories of question. An answer extraction module extracts the answer. By using ranking, answer selection module selects the answer among the candidate answers.

(Sahu et al., 2012) discussed an approach for question answering system for the Hindi language. This work deals with four types of questions when, where, how many and what time. For given question, the answer was retrieved from Hindi text. Each sentence in the text was analyzed to understand its meaning. In this work, they represent the questions using query logic language(QLL) which is a subset of Prolog. For identification of the noun, verb and question word Hindi shallow parser was used.

(S Stalin et al., 2012) implemented the web based Hindi question answering system. In this work the question and answer deal with only Hindi language, if the answer was not presented in Hindi document then it was retrieved from Google.

(Sekine and Grishman, 2003) proposed a question answering system for Hindi and English. The questions were created in Hindi language and the answers retrieved from Hindi newspaper in the Hindi language. These answers were then converted into the English language. In this work, an English Hindi bilingual dictionary was used to find top 20 Hindi articles which were used to find candidate answers.

(Reddy and Bandyopadhyay, 2006) proposed question answering system in the Telugu language. The system was dialogue based and railway specific domain. The architecture was based on the keyword approach. The query analyzer generates the tokens and keywords. From tokens, SQL statements were generated. Using SQL query the answer was retrieved from the database.

(Reddy and Bandyopadhyay, 2006) develop the question answer system in English and Punjabi language. In this work a pattern and matching algorithm was introduced to retrieve the most relevant appropriate answer from multiple sets of answers for a given question.

3. Resource Creation

We create QA dataset MMQA (Multi-domain Multilingual Question Answering) in Hindi and English languages covering multiple domains. We focus on creating factoid and
3.3. Validation

Validation stage is performed to ensure that we obtain a high quality datasets at the end. We ask two other annotators to verify the questions and answers generated in both the languages. Annotators were given a free hand to correct the answers to some extent, or by eliminating the question-answer pairs, if found not fitting. The validation stage is applicable for the question-answer pair of both the languages.

3.4. Analysis

We analyze the questions and answers of the proposed MMQA dataset. It is required to understand its property and usefulness as a multilingual dataset. Our analysis focuses on studying the difficulty level of questions and diversity of answers. We provide some examples in Table 3 to give some ideas about the difficulty levels associated. For better understanding and thorough analysis of various answer types, similar to Rajpurkar et al. (2016) and Trischler et al. (2016), we categorize the answers of factoid questions into 8 entities and phrases. Statistics of the answer types for English and Hindi QA pairs are provided in Table 4.

An example of QA pairs formulated from a comparable article is given in Table 5. Some examples of short descriptive QA pair from our dataset are given in Table 6. The direct comparison of our dataset with the Cross-Language Evaluation Forum (CLEF) datasets (Pamela et al., 2010) is not possible because we have created question answers pair in both language (MQA) in contrast the CLEF dataset have the question and answer pair in the different languages. However, we have shown the comparison in various terms as shown in Table 7.

### 4. Evaluation: Proposed Approach

We develop a translation based approach for multilingual QA. As English is a resource-rich language, we translate Hindi question and articles into English. Our proposed model comprises of Knowledge Source Preparation, Question Processing and Answer Extraction, We describe the details of each component in the following.

#### 4.1. Knowledge Source Preparation

In this step, an information source (articles) from which answers are to be derived was set-up. We translate Hindi questions and articles into English by Google Translate. The complete English articles are indexed at passage level using inverted indexing mechanism. We use the Lucene implementation of inverted indexing.

#### 4.2. Question Processing:

The question processing (QP) step is responsible for analyzing and understanding the questions posed to the QA system. We perform question classification with the question classes proposed by Li and Roth (2002). Question class provides us the semantic constraint on the sought-after answer. We propose a deep learning based question classification

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Table 3: Statistics of comparable English and Hindi articles from various domains.

| Domains   | # Articles | # Paragraphs | # Sentences | # Words |
|-----------|------------|--------------|-------------|---------|
| Tourism   | 112/112    | 1,560/1,586  | 5,078/7,799 | 92,222/79,363 |
| History   | 68/68      | 563/597      | 2,518/2,224 | 40,368/46,418 |
| Diseases  | 31/31      | 441/298      | 1,932/1,717 | 33,787/28,128 |
| Geography | 16/16      | 85/171       | 304/520     | 8,915/9,443  |
| Economics | 13/13      | 146/144      | 667/477     | 10,633/10,875 |
| Environment| 10/10    | 64/54        | 290/272     | 5,319/6,109  |
| Total (EN/HI) | 250/250 | 2,864/2,450  | 10,788/8,463 | 189,244/172,836 |
| Total (EN/HI) | 500      | 5,314        | 19,231      | 302,080     |

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2Tourism (EN): www.india.com/travel

2Tourism (HI): https://hindi.nativeplanet.com

Diseases (EN, HI): https://simple.wikipedia.org/wiki/List_of_diseases

Rest of the domains are curated from http://www.jagranjosh.com/1

1The annotators are equally proficient in both the languages

2Total of 7120 questions (English+Hindi) for which the answer exists in either of two language documents.

3https://translate.google.com

4https://lucene.apache.org/
Table 4: Statistics of QA pairs for factoid and short descriptive questions in English and Hindi.

| Domains     | QA pair in only English (Fact/Desc) | QA pair in only Hindi (Fact/Desc) | QA pair in Both Languages (Fact/Desc) | Total QA pair (Fact/Desc) | Total QA pair |
|-------------|-------------------------------------|-----------------------------------|--------------------------------------|--------------------------|---------------|
| Tourism     | 456/14                              | 403/5                             | 422/10                               | 1,281/29                 | 1,310         |
| History     | 110/75                              | 126/78                            | 1,118/588                            | 1,354/741                | 2,095         |
| Diseases    | 81/54                               | 33/26                             | 48/40                                | 162/120                  | 282          |
| Geography   | 55/7                                | 29/10                             | 174/202                              | 258/219                  | 477          |
| Economics   | 25/4                                | 14/5                              | 682/218                              | 721/227                  | 948          |
| Environment | 9/3                                 | 2/1                               | 226/142                              | 237/146                  | 383          |
| Total       | 736/157                             | 607/125                           | 2,670/1,200                          | 4,013/1,482              | 5,495         |

Table 5: Examples of short descriptive QA pairs from the dataset.

| Question (English): Why did Alexander marched back in 325 BC? | Answer (English): After Alexander’s last major victory in India as his forces refused to go any further. They were too tired to carry on with the Alexander’s expedition and wanted to return home. Moreover, the might of Magadhan Empire (the Nanda Rulers) also dissuaded them. Alexander marched back in 325 BC after making necessary administrative arrangement for the conquered territories. He died at the age of 33 years when he was in Babylon. |
| Question (Hindi): अलेक्जेंडर किस वर्ष में इसकी बड़ी जीत कर ली? | Answer (Hindi): आखरीक ताजक क्वां हुई शेयर उसके सेना ने इसके बाद अपने जाने से इनकार कर दिया था। वे सिंकर के अभियान के साथ जाने से काफी श्क गए थे और वापस दाओ से घूम लॊना चाहते थे। इसके अलावा, महाधिन्य समाज (नंदा शासक) की ताकत से भी वे भयभीत थे। वे इसका दर 325 ईसा पूवों वापस चले गया। |

• Question embedding layer: It is responsible for obtaining the sequence of dense, real-valued vectors, $E = [v_1, v_2, \ldots, v_T]$ of a given question having $T$ tokens. We keep the maximum size of token $T = 15$ in this layer. The distributed representation $v_i \in \mathbb{R}^k$ is the $k$-dimensional word vector. The distributed representation $v$ is looked up into the word embedding matrix $W$. In our experiment we have used the pre-trained word embedding matrix by Mikolov et al. (2013).

• Convolution layer: This layer performs convolution operation. Similar to Xiao and Cho (2016) and Kim (2014) we obtain convolution feature $c_t$ at given time $t$. Then we generate the feature vectors $C = [c_1, c_2, \ldots, c_T]$. The convolution operations are performed with the filter size of 3, 4 and 5.

• Recurrent layer: This layer performs recurrent operations over the convolution output $c$ at given time $t$. Similar to Xiao and Cho (2016) we obtained the forward and backward hidden states at every step $t$ using the gated recurrent unit (GRU) (Cho et al., 2014). Xiao et al. (2016) have used LSTM unit, however we have employed GRU (Cho et al., 2014) due to its less complex architecture compared to long short term memory (LSTM).

\[
\begin{align*}
    z_t &= \sigma(W_zc_t + V_zh_{t-1} + b_z) \\
    r_t &= \sigma(W_rc_t + V_rock_{t-1} + b_r) \\
    c_t &= \tanh(W_c(c_t + V_r(k_t \odot h_{t-1}) + b) \\
    h_t &= z_t \odot h_{t-1} + (1 - z_t) \odot c_t 
\end{align*}
\]

7https://code.google.com/archive/p/word2vec/
where $z_t$, $r_t$, and $c_t$ are update gate, reset get and new memory content, respectively. $c_t$ is the convolution output at time $t$. The final output of recurrent layer $h_t$ is obtained as the concatenation of the last hidden state of forward and backward hidden states.

1. Softmax classification layer: Finally, the fixed-dimensional vector $h_t$ is fed into the softmax classification layer to compute the predictive probabilities for all the question classes (coarse or fine).

### 4.2. Query Formulation

In order to form the query, we remove all the stop word, punctuation symbol from the question. We tag the question with Stanford PoS tagger (Toutanova et al., 2003). Then we concatenate all the noun, verb and adjective in the same order in which it appears in the question.

### 4.3. Passage Retrieval

The candidate passage that contains the answer(s) to the given question(s) are extracted in this stage. We exploit the Lucene’s text retrieval functionality to retrieve passage. It retrieves and ranks the passages using a combination of a Boolean model and the BM25 vector space model (Zaragoza et al., 2004). The query obtained from the question processing stage, serve as an input to the scorer module. The most relevant 30 passages were retrieved for subsequent processing.

### 4.4. Candidate Answer Extraction

This depends on the output of question classification. For factoid question, the coarse class and finer class guide this stage to extract the appropriate entities from the candidate passage(s). We tag the candidate passage with Stanford named entity tagger (Finkel et al., 2005). We utilize the coarse class and finer class of a question to extract the suitable candidate answers. For a descriptive question, candidate answers are extracted by segmenting the relevant passage.

### 4.5. Answer Scoring and Ranking

Each candidate answer is assigned a score using the candidate answer extraction phase. We segment the candidate passage into several candidate answer sentences. Thereafter, we calculate the score for each of the candidate answer sentences.

1. **Term coverage (TS):** It calculates the number of query terms appearing in the candidate answer sentence. This is normalized w.r.t the number of terms present in the given query.

2. **Proximity score (PS):** It calculates the length of the shortest span that covers the query contained in the candidate answer sentence. This is again normalized in the same way.

3. **N-Gram coverage score (NS):** We compute the n-gram coverage till $n = 4$. Finally, the $n$-gram score between a query ($q$) and a candidate answer sentence ($S$) is calculated based on the following formula.

$$
NGCoverage(q, S, n) = \frac{\sum_{n_g \in S} Count_{common}(n_g)}{\sum_{n_g \in q} Count_{query}(n_g)}
$$

$$
NGScore(q, S) = \sum_{i=1}^{n} NGCoverage(q, S, i)
$$

4. **Semantic Similarity Score (SS):** Query and candidate answer are represented using the semantic vectors. Cosine similarity is then computed between the query and candidate answers.

$$
VEC(X) = \frac{\sum_{t_i \in X} VEC(t_i) \times tf-idf_i}{\text{number of look-ups}}
$$

where $X$ is query or candidate answer sentence $S$, $VEC(t_i)$ is the word vector of word $t_i$, $\text{number of look-ups}$ represents the number of words in the question for which pre-trained word embeddings are available.

5. **Pattern matching score (MS):** This score is used in the descriptive question only. We design a set of patterns similar to the (Joho, 1999) to match a query against the candidate answers. We setup a score for each pattern according to their importance. For factoid and descriptive questions the weighted aggregate score for each candidate answer ($A$) is calculated as:

$$
S_f(Q, A) = W_f^1 \times TC + W_f^2 \times PS + W_f^3 \times NS + W_f^4 \times SS
$$

$$
S_d(Q, A) = W_d^1 \times TC + W_d^2 \times PS + W_d^3 \times NS
= W_d^4 \times SS + W_d^5 \times MS
$$

Table 6: Comparison of our dataset with the various released Cross-Language Evaluation Forum (CLEF) dataset.

| Purpose | Type of questions | No. of questions | Collection | Our data |
|---------|-------------------|------------------|------------|----------|
| Document Snippet Paragraph Document | 200 Factoid | 200 | News 1994 + News 1995 | + Wikipedia Nov. 2006 | JRC-Acquis Web |
| Supporting info. | | 500 | | | 7120 |

| Type of questions | No. of questions | Collection | Target lang. | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 |
|-------------------|------------------|------------|--------------|------|------|------|------|------|------|------|
| Factoid | 200 | News 1994 | + | 3 | 7 | 8 | 9 | 10 | 11 | 9 |
| Descriptive | | | | | | | | | | 2 |

8https://code.google.com/archive/p/word2vec/
model is used to classify the incoming questions while we train, we use three datasets classification model. We obtain the accuracies of the questions using the model discussed in Section 4.1. Question Classification

Hindi dataset can be categorized in two-fold: English question classification and answer extraction.

We perform 5-fold cross-validation to evaluate the question

We perform the experiment on coarse and fine class set of

We obtain the lowest scores for the domains D-Diseases

Here, $W^f_k$ and $W^d_k$ are the learning weights for factoid and descriptive question, respectively. Optimal values are determined through the validation data. For factoid question, the candidate having the maximum score is returned as an answer to the given question. Answers to the descriptive questions may sometimes cover multiple sentences. At first, we consider the sentence having the maximum score, and then include the other sentences which have scores closer to the highest one.

5. Experiments, Result and Analysis

The experiments performed on the benchmark English-Hindi dataset can be categorized in two-fold: English question classification and answer extraction.

5.1. Question Classification

We perform the experiment on coarse and fine class set of the questions using the model discussed in Section 4.1. For training, we use three datasets

1. A dataset of 5,452 questions collected from Hovy et al. (2001), TREC 8 and TREC 9 questions dataset,
2. A dataset of 500 questions from TREC 10,
3. We also manually label 1,022 questions at coarse and finer labels with the taxonomy guidelines provided by Li and Roth (2002). These questions were randomly taken from the set of curated questions.

We perform 5-fold cross-validation to evaluate the question classification model. We obtain the accuracies of 90.12% and 80.30% for question classification under coarse (i.e. 6 classes) and fine classes (i.e. 63 classes), respectively. This model is used to classify the incoming questions while we perform answer extraction.

Network Training and Hyper-parameters

We have applied the rectified linear units (ReLu) as the activation function in our experiment. We use the development data to fine-tune the hyper-parameters. In order to train the network, the stochastic gradient descent (SGD) over mini-batch is used and Backpropagation algorithm is used to compute the gradients in each learning iteration. In order to prevent the model from over-fitting, we employed a dropout regularization (set to 50%) proposed by Srivastava et al., 2014 on the penultimate layer of the network. We have used cross-entropy loss as the loss function.

5.2. Answer Extraction

We perform experiments for the factoid and descriptive questions using the model proposed in Section 4.1. We use 10% of the total dataset of factoid and descriptive QA pairs, shown in Table 4 as the validation dataset to fine-tune the weight parameters. Mean reciprocal rank (MRR) and exact match (EM) (Trischler et al., 2016) are used to evaluate the model performance on factoid question. For descriptive questions, we use the well-known machine translation evaluation metrics like BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004). While evaluating we translate Hindi answer to English and create a gold answer set by combining the actual English answer and the translated English answer for each question. Performance of the system is reported in Table 4.

For factoid questions, we obtain the maximum MRR value of 65.72 for the domain Environment. We obtain the lowest EM and MRR values for the domain Diseases. One possible reason could be that most of the factoid answers are the phrases and the PoS tagger could not extract these correctly. The system achieves the maximum BLEU of 48.51 and ROUGE-L of 45.72 scores for the domains Diseases and History, respectively. Our model could not perform well for the descriptive questions of the domain Tourism. However, it is to be noted that Tourism contains only a few (29) short descriptive questions. Our close analysis reveals that the system suffers due to the errors encountered in the linguistic components such as PoS tagger and named entity (NE) tagger. The NE tagger could not detect some of the

| Answer type       | Proportion (English/Hindi) | Examples (English/Hindi)                      |
|-------------------|----------------------------|----------------------------------------------|
| Person            | 12.22 / 14.28              | Krishna (Tulasidas)                          |
| Location          | 17.26 / 14.89              | Madurai (bhubaneswar)                       |
| Organization      | 7.69 / 8.96                | International Monetary Fund/ Tata Mulbhut Amusandhan Sansthan |
| Noun Phrase       | 23.79 / 24.57              | Hotel Apsara / Steel plant                   |
| Verb Phrase       | 2.58 / 1.57                | planned economic development/ Tanav se Chhutkara |
| Adjective Phrase  | 1.98 / 1.02                | Smiling Buddha / 14 pramukh bhartiya bank    |
| Date / Numbers    | 32.43 / 33.17              | 580 / 7 kilo                                 |
| Other             | 2.05 / 1.54                | at least two / सापुत्रा का मनलब हैं नामगी का जास। (Saputra ka matlat hai `Nagon ka vas`) |

Table 7: Set of various answer type categories (only for factoid questions) from the dataset with their proportion (in %) for English and Hindi answer.

optimal weights for factoid (0.31, 0.18, 0.39, 0.12)

optimal weight for descriptive (0.21, 0.09, 0.23, 0.19, 0.28)

http://cogcomp.org/Data/QA/QC/

http://cogcomp.org/Data/QA/QC/TREC_10.label
Table 8: Performance (in %) of the proposed model for factoid and descriptive questions

| Domains | Factoid | Descriptive |
|---------|---------|-------------|
| EM      | MRR     | BLEU        | ROUGE-L    |
| Environment | 39.13   | 65.72       | 45.81      | 42.56      |
| History | 29.53   | 57.19       | 42.84      | 45.72      |
| Geography | 35.55   | 52.27       | 43.02      | 44.61      |
| Diseases | 23.29   | 34.78       | 48.51      | 39.19      |
| Economics | 26.28   | 46.89       | 45.12      | 44.77      |
| Tourism | 27.68   | 37.79       | 22.96      | 24.29      |
| Total   | 30.24   | 49.10       | 41.37      | 40.19      |

In this paper, we propose a new multilingual QA dataset: MMQA. The dataset has wide coverage of various entities as the answer. It can be used to build a monolingual (EN: English, HI: Hindi), cross-lingual (EN → HI, HI → EN) and multilingual (EN ↔ HI) QA system. We have collected 5,105 QA pairs from 500 articles covering various domains. Our analysis yields divers answer types and a significant proportion of questions that require some reasoning ability to solve. We expect that MMQA will facilitate research in multilingual QA, involving Indian languages. We have also built a deep CNN-RNN based model for question classification. Our scoring based answer extraction module will serve as a useful baseline for future research. In future, we would like to extend the dataset by adding more QA pairs from various languages and different types of questions such as list and complex questions. We would also like to propose an end-to-end model for multilingual QA in the near future.

6. Conclusion

In this paper, we propose a new multilingual QA dataset: MMQA. The dataset has wide coverage of various entities as the answer. It can be used to build a monolingual (EN: English, HI: Hindi), cross-lingual (EN → HI, HI → EN) and multilingual (EN ↔ HI) QA system. We have collected 5,105 QA pairs from 500 articles covering various domains. Our analysis yields divers answer types and a significant proportion of questions that require some reasoning ability to solve. We expect that MMQA will facilitate research in multilingual QA, involving Indian languages. We have also built a deep CNN-RNN based model for question classification. Our scoring based answer extraction module will serve as a useful baseline for future research. In future, we would like to extend the dataset by adding more QA pairs from various languages and different types of questions such as list and complex questions. We would also like to propose an end-to-end model for multilingual QA in the near future.

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