Abstract
Multilingual question answering tasks typically assume answers exist in the same language as the question. Yet in practice, many languages face both information scarcity—where languages have few reference articles—and information asymmetry—where questions reference concepts from other cultures. This work extends open-retrieval question answering to a cross-lingual setting enabling questions from one language to be answered via answer content from another language. We construct a large-scale dataset built on questions from TyDi QA lacking same-language answers. Our task formulation, called Cross-lingual Open-Retrieval Question Answering (XOR QA), includes 40k information-seeking questions from across 7 diverse non-English languages. Based on this dataset, we introduce three new tasks that involve cross-lingual document retrieval using multi-lingual and English resources. We establish baselines with state-of-the-art machine translation systems and cross-lingual pretrained models. Experimental results suggest that XOR QA is a challenging task that will facilitate the development of novel techniques for multilingual question answering. Our data and code are available at https://nlp.cs.washington.edu/xorqa.

1 Introduction
Information-seeking questions—questions from people who are actually looking for an answer—have been increasingly studied in question answering (QA) research. Fulfilling these information needs has led the research community to look further for answers: beyond paragraphs and articles toward performing open retrieval on large-scale document collections (Chen and Yih, 2020). Yet the bulk of this work has been exclusively on English. In this paper, we bring together for the first time information-seeking questions, open-retrieval QA, and multilingual QA to create a multilingual open-retrieval QA dataset that enables cross-lingual answer retrieval.

While multilingual open QA would benefit the many speakers of non-English languages, there are several pitfalls to consider in designing such a dataset. First, a multilingual QA dataset should include questions from non-English native speakers to represent real-world applications. Questions in most recent multilingual QA datasets (Lewis et al., 2020b; Artetxe et al., 2020b; Longpre et al., 2020) are translated from English, which leads to English-centric questions—such as questions about American sports, cultures and politics. Second, it is important to support retrieval across large multilingual document collections (Chen and Yih, 2020).
ing answers in languages other than the original language due to information scarcity of low-resource languages (Miniwatts Marketing Group, 2011). Moreover, questions strongly related to entities from other cultures are less likely to have answer content in the questioner’s language due to cultural bias (information asymmetry, Callahan and Herring, 2011). For example, Fig. 1 shows that the Japanese Wikipedia article of an American politician, Ron Paul, does not have information about his college degree perhaps because Japanese Wikipedia editors are less interested in the educational background of American politicians.

In this paper, we introduce the task of cross-lingual open-retrieval question answering (XOR QA) which aims at answering multilingual questions from non-English native speakers given multilingual resources. To support research in this domain, we construct a dataset (called XOR-TyDi QA) of 40k annotated questions and answers across 7 typologically diverse languages. Questions in our dataset are inherited from TyDi QA (Clark et al., 2020) and answers are augmented with our annotation process, adding 20k new answer annotations. All questions are written by native speakers, but a large collection of questions are originally unanswerable due to the information scarcity and asymmetry issues.

XOR-TyDi QA is constructed with an annotation pipeline that allows for cross-lingual retrieval from large-scale Wikipedia corpora (§2). Unanswerable questions in TyDi QA are first translated into English using a professional translation service. Then, annotators find answers to the English query given English Wikipedia using our new model-in-the-loop annotation framework designed to minimize crowdworker annotation errors. Finally, answers are verified and translated back to the target languages.

Building on the dataset, we introduce three new tasks in the order of increasing complexity (§2): XOR-Retrieve, XOR-ENGLISHSPAN, and XOR-Full. In XOR-Retrieve, a system retrieves paragraphs from English Wikipedia that contain information to answer the question posed in the target language. XOR-ENGLISHSPAN takes one step further and finds a minimal answer span from the retrieved English paragraphs. Finally, XOR-Full expects a system to generate an answer end to end in the target language by consulting both English and the target language’s Wikipedia.

We provide baselines that extend state-of-the-art open-retrieval QA systems (Asai et al., 2020; Karpukhin et al., 2020) to our multilingual retrieval setting. Our best baseline achieves 17.1 F1 on XOR-Full. This result indicates that XOR-TyDi QA poses unique challenges which we need to tackle to build a real-world open-retrieval QA system for diverse languages. We further provide detailed analysis for several languages to guide future studies. To summarize, our contributions are:

- We introduce XOR QA, a new task framework that involves cross-lingual retrieval and question answering with three sub-tasks, to overcome the low answerability issues in multilingual open-retrieval QA.
- We construct XOR-TyDi QA, a dataset with 40k newly annotated question-answer pairs across 7 languages built upon TyDi QA.
- We introduce several strong baseline systems with experimental results, showing that there is much room for improvement in this area.
- We demonstrate how XOR-TyDi QA serves to evaluate three crucial tasks: query and answer translation, multilingual machine reading, and cross-lingual retrieval.

2 The XOR-TyDi QA Dataset

Our XOR-TyDi QA dataset comprises questions inherited from TyDi QA (Clark et al., 2020), and answers augmented with our annotation process across 7 typologically diverse languages. Here we focus on cross-lingual retrieval from English Wikipedia because in our preliminary investigation we were able to find answers to a majority of the questions from resource-rich English Wikipedia, and experienced annotators were readily available via crowdsourcing.

2.1 XOR-TyDi QA Collection

Our annotation pipeline consists of four steps: 1) collection of realistic questions that require cross-lingual references by annotating questions from TyDi QA without a same-language answer (§2.1.1); 2) question translation from a target language to the pivot language of English where the missing information may exist (§2.1.2); 3) answer
span selection in the pivot language given a set of candidate documents (§2.1.3); and 4) answer verification and translation from the pivot language back to the original language (§2.1.4). Fig. 2 shows an overview of the annotation pipeline.

2.1.1 Question Collection
We randomly sample 5,000 questions without any passage answer annotations (unanswerable questions) from the TyDi QA train data, and split it into training (4,500) and development (500) sets. We use the development data from TyDi QA as our test data, since the TyDi QA’s original test data is not publicly available. We choose 7 languages with varying amounts of Wikipedia data out of the 11 languages: Arabic, Bengali, Finnish, Japanese, Korean, Russian and Telugu, removing Thai, Swahili, and Indonesian in TyDi QA based on the cost and availability of translators.

2.1.2 Question Translation
We use a professional translation service, Gengo, to translate all collected questions into English. Since named entities are crucial for QA, we instruct translators to carefully translate them by searching for common English translations from English Wikipedia or other external sources. For the quality assessment, we perform manual assessment by native speakers on 50 translation samples, finding that more than 95% are correct. Note that while these translations are a part of the annotation procedure (due to the inherently cross-lingual nature of this task), these translations are not provided to models during evaluation.

2.1.3 Answer Retrieval in English
We use Amazon Mechanical Turk to retrieve answers to translated English questions given English Wikipedia articles. Annotators are instructed to select passage answers (gold paragraphs) and minimal answer spans.

Open-retrieval annotation desiderata Open-retrieval QA annotation comes with unique challenges. In article-oriented QA such as SQuAD (Rajpurkar et al., 2016), all labels are with regard to a single document and a single human can indeed read the whole document. In open-retrieval QA, answers can be retrieved from millions of documents. Because exhaustively reading so much content is impossible for humans, the notion of “human performance” must be reconsidered in this context. This is why we only evaluate questions having answers in the open-retrieval setting and discard those where no answer was found—it is difficult to prove an answer does not exist in the millions of documents.

Limits of traditional annotation In addition to fundamental problems of information scarcity and asymmetry in multilingual QA, questions can be labeled as unanswerable simply because of annotation errors. Annotation procedures for information-seeking QA data usually have each annotator read a single Wikipedia article retrieved by a search engine and label the correct answer span or label the question as not answered by the article (Kwiatkowski et al., 2019; Clark et al., 2020). In this procedure, the answer coverage is underestimated when the search engine fails to retrieve relevant articles (retrieval miss) or the annotator overlooks answer content from the selected article (annotation miss) (Asai and Choi, 2020).

Figure 2: Overview of the annotation process for XOR-TYDi QA.
Importantly, these two types of annotation errors present a tradeoff: if we retrieve many articles, retrieval misses will be reduced at the expense of annotation misses because annotators have to find answer context among many candidate articles. An annotation procedure that misses too many answers will lead to an artificially small dataset.

Collaborative model-in-the-loop. We introduce a collaborative model-in-the-loop framework that uses Google Search and a state-of-the-art paragraph ranker to find the middle ground. We first run Google Search to retrieve as many as 10 Wikipedia articles, which translates to 387 paragraphs on average. We score them with Path Retriever (Asai et al., 2020) and present the five highest scoring paragraphs. Annotators are asked to read these five paragraphs first; if they cannot find any answer content from the initial set, they are asked to skim the rest of the paragraphs, where the Wikipedia section headings help to quickly guide their reading. We found that about 70% of the answers from the 5 paragraphs and 30% from the rest of the paragraphs in the top 10 articles. This means that while our paragraph ranking was effective, the annotators did not fully rely on it, thereby mitigating the influence of the passage ranking model on the dataset. See Appendix §A.1 for annotation interface details.

2.1.4 Answer Verification and Translation

Answer verification We trained undergraduate students who are native English speakers to verify the annotated paragraphs and short answers. Only 8% of the answers were marked as incorrect through the verification phase and were later corrected by our pool of high-quality crowdworkers who yielded less than 1% annotation error.

Answer translation We again use Gengo to translate answers from English back to the original languages. We give translators further instructions to normalize answers such that they are consistent with answers in TYDI QA. For example, some languages use their own unique set of numerals rather than Arabic numerals to represent numeric answers (e.g., Bengali numerals, Chinese numerals in Japanese text). The details of the answer translation process are described in Appendix §A.3.

| %       | Ar | Bn | Fi | Ja | Ko | Ru | Te | All |
|---------|----|----|----|----|----|----|----|-----|
| TYDI QA | 82 | 42 | 57 | 50 | 29 | 69 | 28 | 50  |
| XOR-TYDI QA | 92 | 82 | 83 | 77 | 68 | 83 | 44 | 72  |
| Improvement | 10 | 40 | 26 | 27 | 39 | 14 | 16 | 22  |

Table 1: Percentage of the questions with short answers (answerable questions) in the original TYDI QA dataset (dev) and XOR-TYDI QA. The third row (Improvement) represents how many of the questions become answerable by searching the English articles in addition to the target language.

| Cross-lingual | In-language |
|--------------|-------------|
| Train | Dev | Test | Train | Dev | Test |
| Ar | 2574 | 351 | 137 | 15828 | 357 | 1133 |
| Bn | 2582 | 312 | 128 | 2428 | 116 | 141 |
| Fi | 2088 | 362 | 530 | 7680 | 253 | 1197 |
| Ja | 2288 | 296 | 449 | 5527 | 140 | 869 |
| Ko | 2469 | 299 | 647 | 1856 | 74 | 512 |
| Ru | 1941 | 255 | 235 | 7349 | 313 | 1125 |
| Te | 1308 | 238 | 375 | 5451 | 113 | 712 |

Table 2: Dataset size of the XOR-TYDI QA corpus (answered data). Cross-lingual data comes from our re-annotated questions that did not originally have same-language answers in TYDI QA. In-language data are taken directly from answerable questions in TYDI QA. During evaluation, we exclude the questions for which we cannot find any minimal answer annotations.

2.2 The XOR-TYDI QA corpus

Dataset statistics Table 1 shows the percentages of the questions annotated with short answers in the original TYDI QA and our XOR-TYDI QA, and Table 2 shows statistics of our dataset. As shown in Table 1, cross-lingual retrieval significantly increases the answer coverage in all languages by up to 45% absolute (Korean), and consequently we found answers for more than 50% of the original information-seeking questions in 6 out of 7 languages, confirming the effectiveness of searching multilingual document collections to improve the answer coverage of a multilingual QA system. Detailed statistics of the number of long

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6We found in the Telugu data, certain types of questions are very frequent (e.g., what is the pin code of X mandal?). These questions often ask some specific information of local administration districts, and are often unanswerable because (a) they are typically not described in English Wikipedia and (b) the overall coverage of Telugu Wikipedia is quite low. This results in overall low answer coverage in the Telugu set.
Table 3: Examples newly annotated for Korean (Ko) and Russian (Ru) questions. The bottom example is an answerable question from TYDi QA for which only Japanese Wikipedia includes the correct answer.

| L | Original Question | Passage Answer | Minimal Answer | Final Answer |
|---|-------------------|----------------|----------------|-------------|
| Ko | 1993년 프랑스 총리는 누구인가요? (Who was the French Prime Minister in 1993?) | Mayor of Neuilly-sur-Seine from 1983 to 2002, he was Minister of the Budget under Prime Minister Édouard Balladur (1993–1995). | Édouard Balladur | 에두아르 발라뒤르 |
| Ru | Какая средняя зарплата в Краснодаре на сегодняшний день? (What is the average wage in Krasnodar?) | Krasnodar has the lowest unemployment rate among the cities of the Southern Federal District at 0.3% of the total working-age population. In addition, Krasnodar holds the first place in terms of highest average salary—21,742 rubles per capita. | 21,742 rubles | 21,742 рубля |
| Ja | 速水堅曹はどこで製糸技術を学んだ？ (Where did Kenso Hayami learn the silk-reeling technique?) | 滝宮前橋製糸所を前橋に開設。カスパル・ミュラーから直接、器楽製糸技術を学び (he founded Hanei Maebashi Silk Mill and learned instrumental silk reeling techniques directly from Caspal Müller) | – | 滝宮前橋製糸所 (Hanei Maebashi Silk Mill) |

Table 4: Comparison with recent multilingual QA datasets.

| Dataset | Asked by native speakers | Open-retrieval | Cross-lingual |
|---------|--------------------------|----------------|--------------|
| TYDi QA | ✓ | × | ✓ |
| MLQA | × | ✓ | ✓ |
| XQuAD | × | × | ✓ |
| MKQA | × | WikiData | ✓ |
| MLQA-R | × | 21k sents | ✓ |
| XQuAD-R | × | 13k sents | ✓ |
| XOR-TYDi QA | ✓ | Wikipedia | ✓ |

Qualitative examples Table 3 shows some example questions in our dataset to showcase that finding relevant articles from multilingual document collections is important to answer questions asked by users with diverse linguistic and cultural backgrounds. The first question is unanswerable in Korean Wikipedia, but there is a clear description about who was the prime minister of France at the time in English Wikipedia. The second example shows how English Wikipedia contains rich information about a target language-specific topic (e.g., economy in Krasnodar, a city in Russia). Those examples show the effectiveness of searching for answers in another language with more abundant knowledge sources. The last question in Table 3, on the other hand, shows an example where only the Wikipedia of the target language can provide the answer. XOR QA allows for both retrieval paths.

Comparison with other datasets Table 4 compares XOR-TYDi QA and existing work. XOR-TYDi QA has three key properties that are distinct from recent multilingual QA benchmarks. Firstly, since all questions are inherited from TYDi QA, they are information-seeking questions written by native speakers that better reflect native speaker’s interests and their own linguistic phenomena. This distinguishes our dataset from translation-based datasets such as MLQA (Talmor and Berant, 2019) and MKQA (Longpre et al., 2020). Secondly, our dataset requires cross-lingual retrieval unlike other multilingual datasets such as TYDi QA or XQuAD (Artetxe et al., 2020b), which focus on same-language QA. Lastly, questions in XOR-TYDi QA require open retrieval from Wikipedia, whereas MLQA-R and XQuAD-R (Roy et al., 2020) limit the search space to matching each question with one of the predetermined 21k and 13k answer sentences.

3 XOR QA Tasks and Baselines

We introduce three new tasks (Fig. 3): XOR-RETRIEVE, XOR-ENGLISHSPAN, and XOR-FULL with our newly collected XOR-TYDi QA...
dataset. The first two tasks pose a novel challenge of large-scale cross-lingual retrieval and question answering for information-seeking questions. The final task adds several more challenges (e.g., finding evidence without knowing in advance which languages we can find answers, presenting answers in the users’ languages) that are crucial when we deploy a QA system in real-world applications. For each task, we construct strong baselines. We denote target languages as $L_i$ and their collection as $L = \{L_1, L_2, \ldots, L_i, \ldots, L_N\}$, where $N$ is the number of the target languages. We denote the English Wikipedia collection as $W_{eng}$, the Wikipedia collection in each target language $L_i$ as $W_i$, and the whole collection as $W = \{W_1, W_2, \ldots, W_i, \ldots, W_N\}$.

### 3.1 XOR-RETRIEVE: Cross-lingual Paragraph Retrieval

**Task** Given a question in $L_i$ and English Wikipedia $W_{eng}$, the task is to retrieve English paragraphs that can answer the question. Finding evidence paragraphs from large-scale document collections like Wikipedia is a challenging task, especially when a query and documents are in different languages, and systems cannot perform simple lexical matching.

**Evaluation** Different open-retrieval QA models use different units for retrieval: DPR (Karpukhin et al., 2020) retrieves 100-token segments while Path Retriever (Asai et al., 2020) selects paragraphs. To make fair comparisons across various models, we measure the recall by computing the fraction of the questions for which the minimal answer is contained in the top $n$ tokens selected. We evaluate with $n = 2k, 5k$: R@2kt and R@5kt (kilo-tokens).

**Translate Baselines** Here we first translate queries into English, and then paragraphs are retrieved in a monolingual way. For query translation, we train transformer machine translation models on publicly available corpora for easy replication. Additionally, we run Google’s online machine translation service (GMT). Note that online translators are not completely reproducible as these systems get constantly updated; nor do we know what model and training data they use. Because of this, we encourage the community to experiment with open MT systems such that system details can be fully understood. For retrieval, we explore three approaches: term-based retrieval (BM25, Robertson and Zaragoza 2009), term-based retrieval followed by neural paragraph ranking (Path Retriever, Asai et al. 2020), and end-to-end neural retrieval (DPR, Karpukhin et al. 2020).

**Multilingual Baselines** Alternatively, we can directly apply a multilingual pretrained model to retrieve paragraphs. We apply DPR to the multilingual setting by finetuning with multilingual BERT (Devlin et al., 2019).

### 3.2 XOR-ENGLISHSPAN: L-to-English Open-Retrieval QA

**Task** Given a question in $L_i$ and English Wikipedia $W_{eng}$, a system retrieves paragraphs from $W_{eng}$ and extracts an answer. This setting closely mirrors existing open-retrieval QA tasks (Chen et al., 2017), except that the query is not written in English. This task involves challenging cross-lingual retrieval and question an-
swering on the target language $L_i$ query and English evidence paragraphs.

**Evaluation** We use Exact Match (EM) and F1 over the annotated answer’s token set as in SQuAD (Rajpurkar et al., 2016), following previous practice in English open-retrieval QA.

**Baselines** Our pipeline uses a machine reading model to find a minimal span that answers the question given paragraphs selected from the previous XOR-RETRIEVE step. In particular, for the translate baselines, we use an approach similar to state-of-the-art models (Asai et al., 2020; Karpukhin et al., 2020) that jointly predict a span and a relevance score of each paragraph to the question. For the multilingual baseline where queries are not automatically translated during evaluation, we build a reader model with multilingual BERT and finetune it with data from Natural Questions and XOR-TyDi QA.

### 3.3 XOR-FULL: Round Trip

**Task** Given a question $q$ in target language $L_i$ and Wikipedia in both English and $L_i$ ($W_{eng}$ and $W_i$), a system is required to generate an answer in $L_i$. In this setting, a system does not know a priori in which language we can find information that the user is seeking; this task is closest to real-world applications.

**Evaluation** We use F1 and EM scores as well as token-level BLEU (Papineni et al., 2002) scores over a ground-truth token set. The same tokenizer is applied to ground-truth and predicted answers to compute token-level F1 and BLEU.

**Baselines** We apply monolingual retriever (BM25) and machine reading models in the target language, in addition to XOR-ENGLISHSPAN baselines. We finally translate selected answer spans into the target language if they are extracted from English articles.

## 4 Experiments

We present results from the baselines discussed above. We find that the three XOR QA tasks present challenges even for the strong models.

### 4.1 Experimental Setup

For training, we first finetune the retrieval and machine reading models with Natural Questions data (Kwiatkowski et al., 2019) and then further finetune on our XOR-TyDi QA data, starting from the bert-base-uncased models. For the BM25 retrieval baseline, we use ElasticSearch to store and search documents using BM25 similarities. For both Path Retriever and DPR, we run the official open-source code. For our MT systems, we train base-sized autoregressive transformers (Vaswani et al., 2017) on parallel corpora from OPUS (Tiedemann and Nygaard, 2004), MultiUN (Ziemski et al., 2016), and WMT19 (Barrault et al., 2019). All data are encoded into subwords by BPE (Sennrich et al., 2016) or SentencePiece (Kudo and Richardson, 2018). We use the fairseq library (Ott et al., 2019). Additional experimental details and full lists of hyperparameters are available in Appendix §B.

### 4.2 XOR-RETRIEVE Experiments

Table 5 shows the R@5kt (as defined in §3.1) for different retrieval and query translation systems. The table also reports the performance with the human English translations of the questions used during the dataset collection as an upper bound of translate baselines.

The best R@5kt macro-averaged over the 7 languages comes from running DPR on human translations: 70.3. Machine translation systems achieve averages of 65.6 (GMT) and 48.5 (our MT) again with DPR. The discrepancy between human and machine translation suggests that even state-of-the-art translation systems struggle to translate questions precisely enough to retrieve an evidence paragraph. The translate baselines generally outperform the multilingual approach apart from Telugu. The Telugu translation model suffers from small training data (114k sentences), suggesting that a multilingual approach performs better when we do not have sufficient translation training data.

The term-based retrieval of BM25 substantially underperforms both DPR and Path Retriever across the board. DPR generally achieves similar performance, if not better, compared to Path Retriever despite the fact that Path Retriever was substantially improved over the bert-base-uncased models.
multilingual approach that bypasses the
retriever and BM25 respectively. The rightmost column is a multilingual approach that bypasses the query translation step (§3.1).

Table 5: R@5kt (§3.1) on the test data in the XOR-RETRIEVE setting. PATH and BM denote Path Retriever and BM25 respectively. The rightmost column is a multilingual approach that bypasses the query translation step (§3.1).

used in our annotation (§2.1.3). Since we found that these patterns continued in all the following experiments, we will only report results with DPR.

4.3 XOR-ENGLISHSPAN Experiments

Table 6 shows the performance of the baseline models for XOR-ENGLISHSPAN. The average macro F1 score when the query is translated by a human translator is 31.2, substantially higher than that of machine translation-based models: 27.0 and 17.0 F1 points for GMT and our MT respectively. This suggests that errors in automatic query translation affect later layers in the pipeline. Nonetheless, the multilingual approach consistently outperforms translation-based methods, similarly to XOR-RETRIEVE. Similar to the original TyDi QA dataset, the performance on XOR-ENGLISHSPAN varies across languages, which can be partially explained by the differing sets of questions (Clark et al., 2020); the best baseline achieves 31.3 in Arabic compared to 19.3 F1 points in Japanese. This gap may come from differences in question difficulty as well as how the multilingual model represents each language.

Table 6: Performance on XOR-ENGLISHSPAN. The rightmost Multi. section is a multilingual approach without query translation (§3.1).

and can use both English $W_{en}$ and the target language Wikipedia $W_{i}$ corpora. We first describe the full set up which uses both document collections (first row block), and then describe single Wikipedia settings, which use only $W_{en}$ or only $W_{i}$ as the document collection.

The pipelined model, which applies GMT for query and answer translation and Google Search (GS) and DPR retrieval from $W_{en}$ and $W_{i}$, yields the best average performance: 17.1 F1, 10.1 EM, and 15.3 BLEU points. As an oracle experiment, this suggests that systems like GMT and Google Search, which are typically trained on large data, are very effective. However, we encourage the community to experiment on top of open systems such that all experimental details can be fully reported and understood. Replacing GMT with our MT (second row) results in a large performance drop in Bengali (8.0 vs. 16.7 F1 points) and Telugu (2.8 vs. 9.5). Further replacing GS with BM25 retrieval in the target languages (third row) causes a large performance drop in all languages (e.g., 9.4 vs. 19.1 in Korean). Consistent with the previous tasks, the multilingual approach shown in the forth row underperforms the translation-based counterpart (13.1 vs. 17.1 F1 points on average). These results illustrate the complex, multi-dimensional challenges posed by XOR-FULL task.

4.4 XOR-FULL Experiments

Results Table 7 presents results on the XOR-FULL task. For this task, each model should output the answer in the original query language $L_{i}$,
| Wiki Corpus | Translation Query | Answer | Retrieval $L_i$ | Target Language $L_i$ | Macro Average |
|-------------|------------------|--------|----------------|----------------------|---------------|
|             | Wiki            | Eng.   |                | F1       | EM   | BLEU |
| $W_{i,eng}$ | GMT            | GMT    | GS  | DPR       | 30.9 | 16.7 | 16.7 | 7.7 | 19.1 | 19.7 | 9.5 | 17.1 | 10.1 | 15.3 |
|             | Our MT         | Our MT | GS  | DPR       | 29.7 | 8.0  | 15.3 | 7.1 | 15.4 | 19.1 | 2.8 | 13.2 | 5.6  | 11.9 |
|             | Our MT         | Our MT | BM25 | DPR       | 12.0 | 8.1  | 9.1  | 5.3 | 9.4  | 7.4  | 2.0 | 9.1  | 5.6  | 8.4  |
|             | GMT            | GMT    | GS  | DPR       | 29.7 | 5.5  | 12.8 | 6.8 | 16.0 | 18.9 | 3.6 | 13.3 | 8.6  | 12.0 |
| $W_{eng}$   | GMT            | GMT    | –   | DPR       | 20.4 | 16.2 | 18.9 | 17.6 | 14.1 | 13.0 | 9.0 | 15.6 | 9.2  | 12.6 |
|             | Our MT         | Our MT | –   | DPR       | 11.0 | 7.4  | 14.7 | 10.1 | 5.9  | 7.4  | 2.0 | 8.4  | 4.0  | 6.9  |
|             | –              | –      | G8  | –         | 28.9 | 7.9  | 9.4  | 6.1 | 13.7 | 18.5 | 0.8 | 11.2 | 7.4  | 9.6  |
| $W_i$       | –              | –      | BM25 | –         | 12.0 | 8.1  | 9.1  | 5.3 | 9.4  | 7.3  | –  | –    | –    | –    |

Table 7: Performance on XOR-FULL (test data F1 scores). “GS" denotes Google Search retrieval. The forth row is a multilingual method that avoids query translation for searching $W_{eng}$. The bottom section shows results from the single Wikipedia baselines. ElasticSearch (BM25) does not support Telugu.

configuration that uses both $W_{eng}$ and $W_i$: 15.6 vs. 17.1 F1 points on average. Similarly, the $W_i$ only setting generally underperforms the best $W_{i,eng}$ pipeline. These results demonstrate the importance of searching multilingual collections.

5 Analysis

In this section, we conduct a detailed analysis to understand what remains as challenges for state-of-the-art models, with a focus on the effect of translation models as well as a subset of the questions where retrieval is particularly hard.

Effects of translation performance on overall QA results

Translating queries into the pivot language of English is a competitive approach for cross-lingual modeling, and a powerful machine translation system may boost the final performance. On the other hand, standard metrics such as BLEU may not always reflect an MT system’s competitiveness in XOR QA. In Table 8, we compare the BLEU scores and the final QA F1 performance on XOR-ENGLISHSPAN of the translate-based baseline with three different MT systems: GMT, Our MT, and Helsinki (Tiedemann and Thottingal, 2020). It is noteworthy that high BLEU scores do not always lead to better QA performance. In Bengali, while Helsinki achieves considerably better BLEU scores than our MT (33.0 vs. 30.8), our MT shows 1.4 points better F1 scores. In Japanese, Helsinki and our MT show almost equivalent BLEU scores while our MT systems yields more than 2 points higher F1 scores. See Appendix §C.1 for an example of translation errors that caused final QA errors. Those results suggest that the BLEU score is not always indicative of the final XOR QA performance and that evaluating MT performance in the context of XOR QA would be important for further improvements of multilingual systems in the real world. This finding is consistent with recent work (Sun et al., 2020) that found cross-lingual information retrieval with synthetic data is better correlated with human judgements than BLEU.

Per-difficulty retrieval performance

In our collaborative annotation framework, we first show the paragraphs selected by the BERT retriever and annotators read additional paragraphs when those pre-selected paragraphs do not include sufficient information to answer given questions (§2.1.3). We split our data by difficulty, i.e., whether or not a gold paragraph is selected by the BERT retriever used during annotation. As shown in Table 9, there is a large performance gap between the easy and hard subset in all models, suggesting that the questions from the hard subset are clearly more challenging than the ones from the easy subset. We found that in the hard subset, the gold paragraphs often require some reasoning and include limited lexical overlap with the question.

6 Related Work

Multilingual QA

Recently, much effort has been made to create non-English QA datasets to overcome the data scarcity in non-English languages. We already discussed primary differences between our XOR-TyDi QA and existing multilingual QA datasets in §2.2. MLQA (Lewis et al., 2020a) and XQuAD (Artetxe et al., 2020b) were created by translating questions from SQuAD (Rajpurkar et al., 2016) to several languages to pro-
Table 8: F1 scores on XOR-ENGLISH-SPAN and the BLEU scores of the target language to English on the dev set. All configurations use DPR for paragraph retrieval. Telugu is excluded since Helsinki does not support it as of October, 2020.

Table 9: Macro-averaged retrieval recall on the development easy and hard subsets. All configurations use DPR for retrieval. The Multilingual model avoids query translation.

Cross-lingual Information Retrieval
Cross-lingual Information Retrieval (CLIR) is the task of retrieving relevant documents when the document collection is in a different language from the query language (Hull and Grefenstette, 1996). The retrieval component in XOR QA is closely related to CLIR, but differs in several critical ways. Firstly, since the end goal of XOR QA is QA, XOR QA queries always take question forms rather than key words for search. Further, while CLIR typically retrieves documents from a single (low-resource) language (Zhang et al., 2019), XOR QA considers documents from both English and the query language. In many applications, we do not know a priori in which language we can find information that the user is seeking for. Lastly, our document collection is orders of magnitude bigger than typical CLIR benchmarks (Sasaki et al., 2018; Zhang et al., 2019).

7 Conclusion
We presented the task of XOR QA, in which a system retrieves and reads documents across languages to answer non-English information-seeking questions. We introduce a new large-scale XOR QA dataset, XOR-TYDI QA, with 40k newly annotated open-retrieval questions that cover seven typologically diverse languages. Our experiments showed that XOR-TYDI QA is a challenging benchmark that can benefit from further effort in the research community.
Acknowledgments

This research was supported by gifts from Google, ONR N00014-18-1-2826, DARPA N66001-19-2-403, the NSF (IIS1252835, IIS-1562364), an Allen Distinguished Investigator Award, the Sloan Fellowship, and the Nakajima Foundation Fellowship. We thank Sewon Min, Kristina Toutanova, David Wadden, and the members of the UW NLP group for their insightful feedback on this paper, Nancy Li, Xun Cao, Hitesh Boinpally, Samek Mulepati, Casey Zhao, Vitaly Nikolaev, Soumyadip Sengupta, Bindita Chaudhuri, and Aditya Kusupati for their help on our annotations and dataset proofing, and Nelson Liu and Pradeep Dasigi for their suggestions on the annotation interface and Amazon Mechanical Turk crowdsourcing.

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Appendix

A Additional Details of Dataset Creation

A.1 Annotation Interface

In this section, we describe the details of the annotation interface we used for answer annotation in English (§2.1.3). The annotation interface can be seen in Figs. 4 and 5. To maximize the answer coverage for open-retrieval questions, we first rank paragraphs from top articles retrieved by Google Search. During this paragraph ranking process, we only consider top 5 paragraphs and exclude the articles ranked from top 6 to 10. Increasing the number of the initial articles introduces more noise and confuses our paragraph ranking model, while human annotators sometimes found that those low-ranked articles relevant and retrieve answers from them as discussed in §2.1.3. In the annotation interface, we first present those top 5 paragraphs first (the ones highlighted in light blue in Fig. 4). When annotators do not find answers in the pre-selected top 5 paragraphs, they will explore more paragraphs and articles by expanding originally collapsed articles as in Fig. 5.

Figure 4: Annotation interface (expanded). The blue highlighted paragraphs are ranked high by the BERT paragraph ranker, and the orange highlighted paragraph is the one clicked by an annotator.

Figure 5: Annotation interface (collapsed). Annotator can choose to read full articles or collapse articles.

and English we recruited independently. Once we confirm that the translation results are generally consistent with the ones translated by our bilingual speakers, we request the full translation. In our preliminary experiments, we found that some translators heavily rely on open-source machine translation services, and failed to even correct errors from those tools. We closely collaborated with Gengo and filtered out those erroneous translators from our pool.

Quality control for QA annotation To control the QA annotation quality, we recruit workers with a high approval rate (≥ 96%) located in English-speaking countries and conducted a rigorous qualification procedure. In our qualification stage, we post small calibration batches and evaluate the workers’ performance by expert judgements and agreement with other annotators. To keep the high quality of annotations, we randomly sample qualified workers weekly and manually monitor their annotations by comparing them with gold annotations by authors. We remove qualifications when we detect too many incorrect annotations (e.g., label a paragraph about a different person as a gold paragraph) and remove the annotations done by those disqualified annotators, which are later re-annotated by a qualified worker. Over 200 annotators participated in our calibration tasks. About 40 workers are qualified with 24 actively working on the final dataset. Each HIT contains 5 questions with a reward ranging from 1.5 to 2.5 USD. A qualified annotators generally spends 1-2 min-

A.2 Quality Control

Quality control for question translation We first ask Gengo translators to translate 20 sample questions from each language into English, and compare the translated results with the ones translated by bilingual speakers in the target language.
utes to answer each question.

A.3 Answer Translation Instructions
During answer translation, we asked annotators to follow the instructions listed below:

- Translators need to use metric units by default, instead of imperial units.
- If the original answers are expressed in an imperial unit, translators are encouraged to convert them into a metric unit (e.g., Height 5’3” → Hauteur 160 cm).
- When translating proper nouns, translators are asked to use an official translation if it is available in Wikidata; otherwise they are encouraged to transliterate them.

We also specify some language-specific instructions to make the translated answers format consistent with the ones in the original TyDi QA dataset.

- For Japanese and Korean, translators do not need to spell out the numbers (e.g., 1954 → 千九百五十四) as people usually use Arabic numerals.
- For Bengali, we expect the numbers will be spelled out in Bengali numerals as Bengali speakers rarely use Arabic numerals.
- For Japanese and Korean, translators use appropriate measure words (e.g., 1867년 57歳) if those measure words are commonly added in those languages.
- For the languages where the date needs to be expressed in some rigid format, translators need to translate the date following the format.

A.4 Full Data Statistics

Seen in Table 10 are full data statistics of cross-lingual data of XOR-TyDi QA. Among the questions with “Long” answer annotations are some questions without any short answers as in Natural Questions or TyDi QA. We do not include those “Long answer only” examples in our XOR-TyDi QA evaluations.

B Training details

We describe the details in training our baselines to facilitate easy replication of our results.

B.1 Machine Translation Models

Table 11 lists hyperparameters for training our transformer machine translation models. We generally follow the hyperparameters for the base-sized transformer (Vaswani et al., 2017). For each language direction, all data are encoded into subwords by Moses tokenization (Koehn et al., 2007, for ar, fi, and ru) and BPE (Sennrich et al., 2016) or SentencePiece (Kudo and Richardson, 2018, for bn, ja, ko, and te). We train a base-sized transformer (Vaswani et al., 2017) with the fairseq library (Ott et al., 2019).

B.2 Retrieval Models

Training DPR and Path Retriever

To train an English DPR and Path Retriever, we first initialize the parameters of the models with the ones trained on Natural Questions Open data, available on their repository. During finetuning on XOR-TyDi QA, we use the human translated questions with the annotated gold paragraph data. The selection of positive and negative examples is crucial to train competitive neural retriever models (Karpukhin et al., 2020). To train DPR, we use the original gold paragraphs (long answers) annotated by MTurkers as positive passages, while we randomly sample one negative paragraph per question from the top 5 paragraphs pre-selected by our paragraph re-ranking model in §2.1.3. We also reuse the in-batch negative paragraphs as discussed in (Karpukhin et al., 2020). Regarding the training of Path Retriever, we randomly sample top 50 paragraphs from the top 10 articles retrieved for annotations and use them as negative paragraphs. We also use the annotated long answers as positive paragraphs. We follow the hyperparameters used in the original papers (Karpukhin et al., 2020; Asai et al., 2020).

Implementation Details of BM25 Retrievers

To implement BM25-based retrievers for 7 languages, we use ElasticSearch’s python client (Python Elasticsearch Client).11 We apply the default tokenizers and analyzers for Arabic, Bengali, Finnish and Russian. Japanese and Korean are not supported by the default ElasticSearch language analyzers, so we use Kuromoji12 and Nori plug-
| $L_i$ | **Train (1 way)** | **Dev (2 way)** | **Test (2 way)** |
|------|-------------------|-----------------|-----------------|
|      | Total | Long (%) | Short (%) | Total | Long (%) | Short (%) | total | Long (%) | Short (%) |
| Arabic | 4500 | 2862 (63) | 2574 (57) | 500 | 357 (71) | 351 (70) | 235 | 144 (61) | 137 (58) |
| Bengali | 4500 | 2822 (63) | 2582 (57) | 500 | 330 (66) | 312 (62) | 185 | 131 (70) | 128 (69) |
| Finnish | 4500 | 2454 (55) | 2088 (46) | 500 | 372 (74) | 362 (72) | 800 | 556 (69) | 530 (66) |
| Japanese | 4500 | 2557 (57) | 2288 (51) | 500 | 320 (64) | 296 (60) | 779 | 477 (69) | 449 (58) |
| Korean | 4500 | 2674 (59) | 2469 (55) | 500 | 314 (63) | 299 (60) | 1177 | 684 (58) | 647 (55) |
| Russian | 4500 | 2178 (48) | 1941 (43) | 500 | 270 (34) | 255 (51) | 470 | 252 (53) | 235 (50) |
| Telugu | 4500 | 1515 (33) | 1308 (29) | 500 | 258 (52) | 238 (47) | 1752 | 394 (22) | 375 (21) |

Table 10: Dataset statistics of the resulting XOR QA corpus (cross-lingual data). “Long” denotes the questions with paragraph answer annotations, and “Short” denotes the questions with short answer annotations. During evaluation, we disregard the questions without short answer annotations.

| Hyperparameter | Value |
|----------------|-------|
| label smoothing | 0.1 |
| # max tokens | 4096 |
| dropout rate | 0.3 |
| encoder embedding dim | 512 |
| encoder ffn dim | 2048 |
| # encoder attn heads | 8 |
| decoder embedding dim | 512 |
| decoder ffn dim | 2048 |
| # decoder attn heads | 8 |
| max source positions | 10000 |
| max target positions | 10000 |
| Adam lrate | $5 \times 10^{-4}$ |
| Adam $\beta_1$ | 0.9 |
| Adam $\beta_2$ | 0.98 |
| lr-scheduler | inverse square |
| warm-up lr | $1 \times 10^{-7}$ |
| # warmup updates | 4000 |
| # max updates | 300K |
| length penalty | 1.0 |

Table 11: Hyperparameters for our transformer machine translation models.

ins\textsuperscript{13} for Japanese and Korean respectively.

### B.3 Machine Reading Models

#### The choice of negative and positive examples

For the Path Retriever and BM25 baselines’ reader, we sample three negative paragraphs per annotated question-gold paragraph pair and train a model that jointly predicts an answer span and relevance score of each paragraph to the question, following Asai et al. (2020). In DPR, the training examples are retrieved by the trained retriever, and we train the reader with 24 negative paragraphs and distant supervision (Karpukhin et al., 2020). We use human translated English questions to train English reader models, and use the original questions in $L_i$ to train a multilingual reader model.

### C Additional Results

**XOR-Rетrievе results** We present the R@2kt scores of the retrieval baselines in Table 12. We also present R@2kt and R@5kt of our DPR based models on our development set in Table 13.

**XOR-EnglishsPаn results** Table 14 shows the F1 and EM scores of our DPR-based models on the development data in the XOR-EnglishsPаn setting.

**XOR-Full results** We present BLEU and EM scores for XOR-Full in Tables 15 and 16.

\textsuperscript{13}https://www.elastic.co/guide/en/elasticsearch/plugins/7.9/analysis-nori.html
| GMT R@2kt R@5kt | Our MT R@2kt R@5kt | Multi. R@2kt R@5kt |
|-----------------|---------------------|-------------------|
| Ar 59.2 70.2 | 41.7 50.8 | 31.3 42.1 |
| Bn 72.0 78.3 | 51.3 59.9 | 44.5 55.5 |
| Fi 54.5 61.8 | 51.6 60.8 | 38.3 45.9 |
| Ja 53.9 61.4 | 39.0 47.3 | 29.0 35.4 |
| Ko 56.5 65.3 | 47.0 54.4 | 35.3 43.2 |
| Ru 51.5 58.6 | 32.9 39.2 | 33.8 39.6 |
| Te 70.6 76.0 | 41.7 29.4 | 42.4 50.4 |
| Av 59.7 66.9 | 41.0 48.8 | 36.4 44.6 |

Table 13: R@5kt (§3.1) of DPR-based models (Translate DPR and Multilingual DPR) on the development data in the XOR-RETRIEVE setting.

| GMT F1 EM | Our MT F1 EM | Multi. F1 EM |
|-----------|--------------|--------------|
| Ar 30.1 11.8 | 18.7 13.7 | 11.5 8.5 |
| Bn 34.6 29.2 | 20.5 17.3 | 14.0 8.5 |
| Fi 28.9 20.7 | 27.2 20.2 | 16.5 10.8 |
| Ja 25.6 22.3 | 19.7 16.6 | 10.1 8.4 |
| Ko 29.7 21.1 | 22.3 15.1 | 13.4 8.7 |
| Ru 27.1 20.8 | 13.0 9.0  | 16.1 12.9 |
| Te 37.0 29.4 | 2.5 1.7  | 10.8 8.0 |
| Av 30.4 23.7 | 17.7 13.4 | 13.2 9.7 |

Table 14: F1 and EM scores of our DPR-based models (Translate DPR and Multilingual DPR) on the development data in the XOR-ENGLISHSPAN setting.

C.1 Qualitative Analysis on Translation Errors

One primary challenge in question translation is precisely translating key words (e.g., entities, year); our MT correctly translates a Japanese question, アーモンドアイはいつ生まれた? (When was Almond Eye born; Almond Eye is a Japanese popular race horse)\(^\text{14}\) while Helsinki (Tiedemann and Thottingal, 2020) translates it as “When was almond born?” This resulted in retrieval errors, and Wikipedia articles related to almonds were selected. Intrinsic metrics such as BLEU would not penalize for those cases much.

\(^{14}\)https://en.wikipedia.org/wiki/Almond_Eye
| Wiki Corpus | Translation Query | Answer | Retrieval | Target Language $L_i$ | Ar | Bn | Fi | Ja | Ko | Ru | Te |
|-------------|-------------------|--------|-----------|----------------------|----|----|----|----|----|----|----|
| $W_{i,\text{eng}}$ | GMT | GMT | GS | DPR | 21.7 | 10.1 | 11.9 | 2.1 | **14.6** | **10.8** | 5.4 |
| | Our MT | Our MT | GS | DPR | 21.0 | 2.9 | 10.6 | 2.0 | 11.8 | 10.7 | 1.9 |
| | Our MT | Our MT | BM25 | DPR | 7.7 | **12.4** | 6.1 | 1.2 | 6.5 | 3.8 | 1.1 |
| | – | GMT | GS | DPR | 20.9 | 5.4 | 9.0 | 1.7 | 12.4 | 10.3 | 2.4 |
| $W_{\text{eng}}$ | GMT | GMT | – | DPR | 11.1 | 9.3 | **13.5** | **10.4** | 9.8 | 5.9 | 4.7 |
| | Our MT | Our MT | – | DPR | 5.0 | 2.2 | 8.9 | 4.8 | 3.3 | 2.5 | 1.4 |
| | – | – | GS | – | 20.5 | 10.0 | 9.0 | 1.5 | 11.0 | 10.3 | 0.8 |
| $W_{i}$ | – | – | BM25 | – | 7.7 | **12.4** | 6.1 | 1.2 | 6.5 | 2.8 | – |

Table 15: Performance on XOR-FULL task (EM scores on the test data). “GS” denotes Google Search retrieval. The bottom section shows results from the single Wikipedia baselines. ElasticSearch for BM25 does not support Telugu.

| Wiki Corpus | Translation Query | Answer | Retrieval | Target Language $L_i$ | Ar | Bn | Fi | Ja | Ko | Ru | Te |
|-------------|-------------------|--------|-----------|----------------------|----|----|----|----|----|----|----|
| $W_{i,\text{eng}}$ | GMT | GMT | GS | DPR | 28.9 | 17.1 | **15.2** | 1.9 | **12.8** | **17.5** | **11.4** |
| | Our MT | Our MT | GS | DPR | 27.8 | 7.2 | 11.9 | 1.8 | 11.0 | 17.2 | 2.1 |
| | Our MT | Our MT | BM25 | DPR | 12.7 | **19.5** | 6.5 | 1.2 | 6.7 | 7.1 | 1.4 |
| | – | GMT | GS | DPR | 27.8 | 7.0 | 13.9 | 1.8 | 11.3 | 17.0 | 5.3 |
| $W_{\text{eng}}$ | GMT | GMT | – | DPR | 20.7 | 16.4 | 12.6 | **4.7** | 8.0 | 10.4 | 11.1 |
| | Our MT | Our MT | – | DPR | 11.5 | 6.9 | 13.9 | 4.0 | 4.6 | 6.5 | 1.4 |
| | – | – | GS | – | 17.2 | 10.7 | 9.6 | 1.3 | 10.6 | 16.5 | 0.7 |
| $W_{i}$ | – | – | BM25 | – | 12.7 | **19.5** | 5.4 | 1.2 | 6.6 | 7.1 | – |

Table 16: Performance on XOR-FULL task (BLEU scores on the test data). “GS” denotes Google Search retrieval. The bottom section shows results from the single Wikipedia baselines. ElasticSearch for BM25 does not support Telugu.