

# BiRdQA: A Bilingual Dataset for Question Answering on Tricky Riddles

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## Abstract

A riddle is a question or statement with double or veiled meanings, followed by an unexpected answer. Solving riddle is a challenging task for both machine and human, testing the capability of understanding figurative, creative natural language and reasoning with commonsense knowledge. We introduce BiRdQA, a bilingual multiple-choice question answering dataset with 6614 English riddles and 8751 Chinese riddles. For each riddle-answer pair, we provide four distractors with additional information from Wikipedia. The distractors are automatically generated at scale with minimal bias. Existing monolingual and multilingual QA models fail to perform well on our dataset, indicating that there is a long way to go before machine can beat human on solving tricky riddles. The dataset has been released to the community<sup>1</sup>.

## 1 Introduction

Question Answering (QA) is a challenging task in the field of Natural Language Processing (NLP). Existing literature on QA has addressed various kinds of questions, including extractive questions (Rajpurkar et al. 2016; Minjoon Seo and Hajishirzi 2017), multi-hop questions (Yang et al. 2018; Pan et al. 2021a), commonsense questions (Talmor et al. 2019; Yasunaga et al. 2021) and logical questions (Liu et al. 2020b; Huang et al. 2021). While there is a trend that question answering involves more complicated reasoning, the community overlooks the importance of *understanding* the question itself before *reasoning* for the answer. Understanding language requires both linguistic knowledge and commonsense knowledge (LoBue and Yates 2011). However, existing QA datasets are commonly sourced from Wikipedia (Yang, Yih, and Meek 2015; Rajpurkar et al. 2016) and news articles (Trischler et al. 2017), inevitably leading to the creation of superficial, literal questions, which are easy to comprehend. In order to find more challenging questions with diverse linguistic styles and rich commonsense knowledge, we turn to riddles for help.

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<sup>1</sup><https://github.com/yunx-z/BiRdQA>

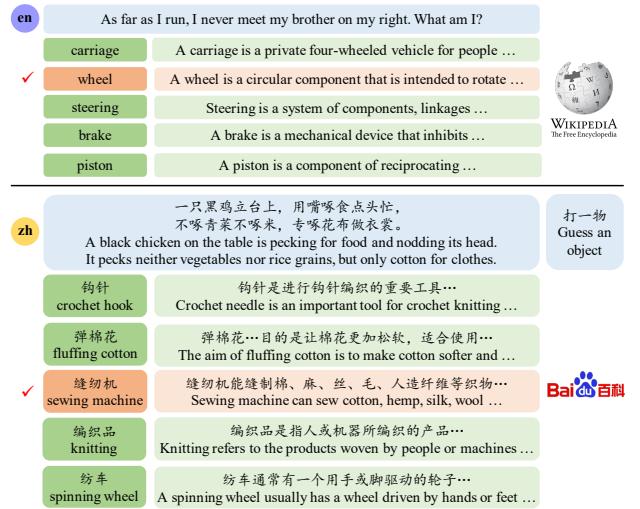


Figure 1: Examples from the English (the upper one) and Chinese (the lower one) part of BiRdQA. There are four distractors and one correct answer for a riddle and an introduction from English Wikipedia or Chinese Baidu Baike is provided for each candidate. Note that Chinese riddles have additional hints. The checkmark indicates the correct answer.

A riddle is a traditional verbal expression which contains one or more descriptive elements, a pair of which may be in opposition; the referent of the elements is to be guessed (Georges and Dundes 1963). As a classical form of guessing game, riddle has been a popular part of folk literature across many countries. One of the most wide-spread riddles appears in Sophocles’s play *Oedipus the King* (Sophocles 1994), where Oedipus is tasked with saving the city of Thebes from a Sphinx by solving her riddle, “*What goes on four legs in the morning, on two legs at noon, and on three legs in the evening? – human*”. While it is a matter of life and death for Oedipus to answer the riddle correctly, it is interesting to investigate the potential of AI for solving riddle, given the rise of deep learning and pretraining based methods in NLP.

Consider the English riddle shown in Figure 1, “*As far as I run, I never meet my brother on my right. What am I? – wheel*”. When people initially come across the word

“brother”, they naturally think of a living creature such as human or animal. But if they think deeper about the description of the brother’s location (“on my right”) and the reason why it “never meets” its “brother”, they will realize that the riddle may be talking about an inanimate object. In fact, it is a wheel that runs in parallel with its counterpart on the opposite side of a vehicle. This typical example shows the following properties of riddle which make it challenging:

- **Figurative.** A common trick of riddles is personification, which gives everyday objects human characteristics. Other types of figurative language used in riddles include metaphor, pun, and hyperbole (Senderovich 2016). The usage of various figurative devices can fox existing QA models (Abulaish, Kamal, and Zaki 2020).
- **Misleading.** Hard riddles are meant to play a trick on readers with an apparently irreconcilable contradiction or incongruity (Georges and Dundes 1963). Aristotle commented on this characteristic of riddle in the *Poetics* (Kenny 2013) that “the very nature indeed of a riddle is this, to describe a fact in an impossible combination of words”. Commonsense reasoning and creative thinking (Schank and Kass 1987) are required in order to develop a valid explanation for the seemingly impossible description of riddling object.

We believe that riddles, as a thought provoking challenge for human, can help sharpen deeper language understanding and reasoning abilities of machines as well. On the one hand, the figurative property of riddle enables communication of far richer meanings than factual question and thus it is beneficial to introduce Figurative Language Processing (FLP) into the field of QA. On the other hand, the misleading nature of riddle puts obstacle in the way of commonsense reasoning.

Riddle is an universal art, since it exists in hundreds of different cultures (Taylor 1977). Besides, many riddles and riddle objects (i.e., the object that a riddle describes) are internationally widespread (Aarne 1918). Given the recent progress in multilingual QA (Jing, Xiong, and Yan 2019; Lewis et al. 2020), we conduct a cross-lingual study of riddles in English and Chinese due to easy access to a large amount of available riddles online in these two primary languages. We present BiRdQA (**Bilingual Riddle Question Answering**), a collection of 6614 English riddles and 8751 Chinese riddles. BiRdQA is a multiple-choice question answering dataset, as we provide a correct answer and four distractors for every riddle. In this way, it is easy and fair to adopt accuracy as evaluation metrics to compare the performance of different QA models on our dataset. Our proposed method for automatic distractor generation allows for robust multiple-choice dataset creation at scale with minimal human effort and sufficient quality. To bring in more commonsense knowledge for reasoning, we also provide a brief introduction of each candidate, which is collected from Wikipedia article. Note that BiRdQA is a *non-parallel* bilingual dataset, because it is extremely difficult and sometimes impossible to correctly translate riddles between different languages<sup>2</sup>. Figure 1 shows two selected examples of our

dataset, one in English and the other in Chinese.

To assess the difficulty of BiRdQA, we conduct experiments on several baseline models. Results show a significant gap between machine and human performance, indicating that there is a lot of headroom for improvement. We also evaluate multilingual pretrained models in zero-shot cross-lingual transfer and multilingual training settings.

The contributions of our work are summarized as follows:

- We construct a large challenge dataset BiRdQA in a non-trivial way. The dataset can be used for testing the question answering ability on tricky riddles. The dataset will be released and contribute to the QA and NLP community.
- We conduct thorough analysis on the BiRdQA dataset and benchmark the performance of pretraining based QA models on BiRdQA. Results show a significant gap between machine and human performance.

## 2 Dataset Collection

We cast solving riddle as a five-way multiple choice task instead of open-ended format, to allow efficient and fair evaluation of the knowledge proficiency of a model (Zellers et al. 2019; Qiu, Wu, and Fan 2020). Given a question with five candidates and their introductions, a model should select one as the correct answer. We create BiRdQA in three steps, for English and Chinese riddles independently: collecting riddles, generating distractors and collecting introductions for candidates<sup>3</sup>. We dub English part of our dataset “BiRdQA-en” and Chinese part “BiRdQA-zh”. We aim to maintain symmetry between the two languages with similar formats and standards of data, and comparable methods of dataset creation.

### 2.1 Riddle Collection

We crawl 16,000+ English riddle-answer pairs from several websites<sup>4</sup> where uniquely crafted, high-quality riddles are in abundance. We also crawl 12,000+ Chinese riddles and their answers from a single website<sup>5</sup>. Different from English riddles, every Chinese riddle contains a hint in parenthesis (e.g., “打一物” in Figure 1) and we separate it as an additional field. We devise rules to remove noisy and duplicated riddles.

### 2.2 Distractor Generation

It is quite challenging to obtain high-quality distractors at scale. Asking humans to write distractors for each correct answer is expensive and time-consuming (Gierl et al. 2017; Zellers et al. 2019), especially for a large-scale dataset.

is never alone? – pear”, the answer makes sense because “pear” sounds like “peer”, which means “never alone”. However in Chinese or other languages, “pear” and “peer” do not sound similarly.

<sup>3</sup>From now on, we use the term “answer” for the correct solution to a riddle, “distractors” for the four wrong choices of a question, and “candidates” for the union of “answer” and “distractors” of a riddle.

<sup>4</sup>e.g., [www.riddlesandanswers.com](http://www.riddlesandanswers.com), [www.riddles.com](http://www.riddles.com)

<sup>5</sup><http://www.cmiyu.com/>

<sup>2</sup>For example, for the riddle “what do you call a fruit that

Moreover, it may suffer from *spurious correlation*, also called *annotation artifacts*: subtle patterns become prediction rules that work for the majority examples but do not hold in general (Gururangan et al. 2018; Poliak et al. 2018; Tu et al. 2020). Therefore, our motivation is that a high-quality distractor generated in an automated fashion should

- be close enough to the correct answer (Goodrich 1977) to make it more plausible and adversarial, so long as it does not become another valid answer.
- be robust to candidate-only bias (Si et al. 2019; Yu et al. 2020), disincentivizing models from leveraging shortcuts to directly predict the correct answer without reading the question.<sup>6</sup>

Now we describe our distractor generation method in detail. Our goal is to generate four distractors for each correct answer. Two of them are designed to be similar to the correct answer in terms of the cosine distance of word embedding<sup>7</sup>, which we refer to as *global distractors*. The other two distractors are drawn from the correct answers of other questions (Zellers et al. 2019), so as to overcome the issue of candidate-only bias. We use *local distractors* to refer to these two distractors. For example, for the two riddles in Figure 1, “carriage”, “brake”, “弹棉花” (fluffing cotton), and “纺车” (spinning wheel) are local distractors, while the rest are global ones.

**Global Distractor** For each English riddle, we use the correct answer as the query and retrieve the top-2 most similar words or phrases from the pretrained Sense2Vec (Trask, Michalak, and Liu 2015; Pan et al. 2021b). For each Chinese riddle, we use the word embedding provided by Song et al. (2018).

**Local Distractor** For each language, we build an answer pool with all distinct correct answers of riddles. For each riddle, we obtain the top-2 most similar correct answers from that answer pool. The similarity is also measured by the cosine distance of word embedding and the choices of pretrained embedding for English and Chinese are the same as *global distractors*.

**Invalid Distractor Replacement** To avoid the case that the generated distractor becomes another correct answer or repeats with other distractors, we define rules to ensure that the distractor has less lexical overlap with the correct answer (Pan et al. 2021b) and other distractors of the same riddle. Specifically, two candidates are considered as lexically overlapped if they share at least a same word in English (e.g., “horse” and “wild horse”) or a same character in Chinese (e.g., “蘑菇” and “平菇”). We iteratively replace the problematic distractor with the next best (i.e., most similar

<sup>6</sup>While it is also important for the distractors to be consistent with the semantic context of the question (Gao et al. 2019), our proposed method is effective enough for distractor generation on this dataset, which is demonstrated empirically in Section 5 later. As a result, we do not take that point into account for simplicity.

<sup>7</sup>If the correct answer of a riddle does not have pretrained embedding, we simply remove this riddle.

to correct answer) generated one until it is valid. We generate local distractors before global ones because the larger search space of global distractors allows more alternatives for replacement. We provide a detailed quality analysis of the generated distractors in Section 3.

### 2.3 Candidate Introduction Collection

Wikipedia has been widely used as an important knowledge source for Question Answering (Yang, Yih, and Meek 2015; Chen et al. 2017; Liu et al. 2020a) and Commonsense Reasoning (Storks, Gao, and Chai 2019; Lv et al. 2020). We provide a brief Wikipedia-based introduction of each candidate to help models solve riddles with commonsense knowledge. For Chinese riddles we use Baidu Baike<sup>8</sup>, the Chinese equivalent to Wikipedia, because it has richer Chinese entries<sup>9</sup>. We match each candidate to its corresponding Wikipedia entry and use the introductory part of the article (i.e., the content before the first section) as its introduction. We define that a candidate is matched to a Wikipedia entry if its name is same as the title of the Wikipedia entry or can be redirected to that entry (e.g., “stone” → “Rock (geology)”).<sup>10</sup> To resolve disambiguation issues (e.g., “nail” may refer to “Nail (anatomy)”, “Nail (beak)”, etc.), we select the entry whose introduction has the highest similarity with the question. We calculate the similarity with Sentence-BERT (Reimers and Gurevych 2019). Specially, if the correct answer of a riddle does not have Wikipedia entry, we simply remove this riddle. If a generated distractor does not have linked Wikipedia entry, we iteratively replace it with the next best (i.e., most similar to correct answer) generated one until it has one. In this way, we ensure that all candidates in our dataset are accompanied by introductions. We evaluate the quality of collected Wikipedia introductions in Section 3.

Overall, we collect 6614 English and 8751 Chinese riddles with their answers, distractors and introductions. We observe that there are multiple riddles describing the same object in different ways and thus sharing identical answer (Section 3). If they appeared in both training and development/test set, the machine might memorize the correct answer rather than reason it out (Zellers et al. 2019; Talmor et al. 2019). Therefore, when splitting the dataset into training/development/test set, we ensure that each of the three sets has disjoint correct answers.

## 3 Dataset Analysis

Table 1 describes the key statistics of BiRdQA. Tokens in Chinese are referred to as words segmented by jieba<sup>13</sup> toolkit. Generally speaking, English riddles and candidate introductions are much longer than Chinese ones, while Chinese riddles have more diverse tokens in questions and can-

<sup>8</sup><https://baike.baidu.com/>

<sup>9</sup>We use the word “Wikipedia” to refer to both English Wikipedia and Baidu Baike (Chinese online encyclopedia) hereafter.

<sup>10</sup>[https://en.wikipedia.org/wiki/Rock\\_\(geology\)](https://en.wikipedia.org/wiki/Rock_(geology))

<sup>11</sup>[https://en.wikipedia.org/wiki/Nail\\_\(anatomy\)](https://en.wikipedia.org/wiki/Nail_(anatomy))

<sup>12</sup>[https://en.wikipedia.org/wiki/Nail\\_\(beak\)](https://en.wikipedia.org/wiki/Nail_(beak))

<sup>13</sup><https://github.com/fxsjy/jieba>

| Measurement                 | BiRdQA-en | BiRdQA-zh |
|-----------------------------|-----------|-----------|
| # Training examples         | 4093      | 5943      |
| # Validation examples       | 1061      | 1042      |
| # Test examples             | 1460      | 1766      |
| # Total examples            | 6614      | 8751      |
| # Avg question tokens       | 29.74     | 8.23      |
| # Distinct question tokens  | 15043     | 18298     |
| # Distinct hints            | N/A       | 690       |
| # Distinct answers          | 3057      | 4750      |
| # Distinct candidate tokens | 6593      | 14944     |
| # Avg introduction tokens   | 231.64    | 90.93     |

Table 1: Statistics of BiRdQA.

| Answer    | # en | # zh | Answer   | # en | # zh |
|-----------|------|------|----------|------|------|
| BiRdQA-en |      |      |          |      |      |
| water     | 45   | 0    | moon     | 30   | 0    |
| clock     | 43   | 3    | sun      | 29   | 0    |
| shadow    | 38   | 0    | heart    | 26   | 0    |
| egg       | 33   | 0    | tree     | 26   | 0    |
| fire      | 30   | 0    | candle   | 25   | 10   |
| BiRdQA-zh |      |      |          |      |      |
| 玉米        | 9    | 36   | 公鸡       | 8    | 25   |
| corn      |      |      | rooster  |      |      |
| 蜻蜓        |      |      | 蚊子       |      |      |
| dragonfly | 0    | 30   | mosquito | 6    | 24   |
| 老鼠        |      |      | 棉花       |      |      |
| mouse     | 9    | 27   | cotton   | 2    | 22   |
| 青蛙        |      |      | 狗        |      |      |
| frog      | 9    | 27   | dog      | 11   | 21   |
| 燕子        |      |      | 猫        |      |      |
| swallow   | 1    | 25   | cat      | 15   | 20   |

Table 2: Frequencies of 10 most common answers and their counterparts in English and Chinese riddles of BiRdQA.

dicates. The hints in Chinese riddles do not vary a lot, because they only tell the category of the answer. We randomly sample a set of 100 English and 100 Chinese riddles from the development set to perform the following analyses.

**Quality of Distractors** Although we have reduced lexical overlap between the correct answer and distractors, we cannot completely avoid the problem that the automatically generated distractor becomes another correct answer for the riddle coincidentally (i.e., multiple candidates are equally valid). For example, in a Chinese riddle, the distractor “润色先生” (inkstone) is just another name for the answer “砚” (inkstone). Similarly, in an English riddle, the distractor “acne scar” has the same meaning as the answer “zit”. However, we observe that such coincidences due to synonym rarely happen: among the 100 English and 100 Chinese samples, we only observe 2 such cases for each group respectively. Therefore, we leave them as noise in the dataset. This

| Figure of Speech | # en | # zh |
|------------------|------|------|
| Hyperbole        | 3    | 3    |
| Metaphor         | 6    | 12   |
| Personification  | 18   | 11   |
| Pun              | 11   | 16   |
| Used             | 31   | 44   |

Table 3: Figures of Speech and their frequencies in 100 English and 100 Chinese sampled riddles.

shows that eliminating lexical overlap between generated distractors and the correct answer is an effective strategy to ensure distractor quality.

**Quality of Introductions** We manually check whether the Wikipedia introduction of a correct answer actually matches the answer itself<sup>14</sup> by inspecting the random samples. We only observe 3 and 6 such cases, respectively, mainly due to the lack of corresponding Wikipedia entries. As Wikipedia introduction only serves as an auxiliary source of information in our dataset, we consider this quality as acceptable.

**Distribution of Answers** We notice that there are multiple riddles describing the same object from different perspective within a language or even across languages and thus sharing the same answer (Taylor 1977)<sup>15</sup>. For example, for the riddles “I’m often running yet I have no legs. You need me but I don’t need you. What am I?” and “When it rains, I never get any wetter. What am I?”, both of them have “water” as their answers. Table 2 shows the frequencies of the most common answers in BiRdQA. We observe that common answers in English have higher frequencies than Chinese, and English riddles have less distinct answers (Table 1). This indicates that Chinese answers are more diverse than English. It is also interesting that common answers for Chinese riddles are mostly living things such as animals, while non-living things are more popular in English riddles. The overlap of the riddle objects between English and Chinese makes it easier for models to learn riddles in one language and transfer the knowledge to another language, which is further described in the cross-lingual setting in Section 4.

**Figures of Speech in Riddles** An important property of the riddle is the usage of figures of speech (Section 1). We manually identify the existence and types of figures of speech in the random samples. As each example can be annotated with multiple figures of speech, the total frequency in Table 3 does not sum to “Used”, which means that a riddle uses at least one type of figure of speech. Table 3 shows that a significant proportion of riddles in English and Chinese leverage figurative devices to confuse readers about their true meanings.

<sup>14</sup>We do not check the matching quality for the distractor introductions because the ambiguous Wikipedia entries for a distractor are still wrong for the question.

<sup>15</sup>They are not duplicate riddles, which have been removed.

## 4 Methods

We conduct experiments with multiple pretraining models on BiRdQA under monolingual, cross-lingual and multilingual settings (Jing, Xiong, and Yan 2019).

- **Monolingual.** We use data in the same language for training and evaluating models (i.e., en → en, zh → zh).
- **Cross-lingual.** We test performance in zero-shot cross-lingual transfer learning, where a multilingual pretrained model is fine-tuned on one source language and evaluated on a different target language (i.e., en → zh, zh → en).
- **Multilingual.** We directly mix training instances of the two languages into a single training set and build a single QA model to handle bilingual riddles in BiRdQA (i.e., en+zh → en, en+zh → zh).

We also conduct additional experiments to investigate the influence of adding introductions (“w/ introduction”) or hints (“w/ hint”), removing questions from inputs (“w/o question”), and transfer learning with CommonsenseQA (Talmor et al. 2019) (“Train + CQA”, “Train = CQA”) on one or multiple settings, which are detailed in Section 5 later<sup>16</sup>.

### 4.1 Baseline Models

Below we describe the specific English models and Chinese models for monolingual setting, as well as the multilingual models for cross-lingual and multilingual settings.

**English Models** We test the performance of BERT (Devlin et al. 2019) and its variants, RoBERTa (Liu et al. 2019) and ALBERT (Lan et al. 2019). Following the standard multiple-choice QA setup for pretrained language models (Devlin et al. 2019), we treat the question as *A* and each candidate as *B*, before further linearizing them into [CLS] *A* [SEP] *B* [SEP] for encoding. The [CLS] token embedding is used to produce a score for each candidate, which is then passed through a softmax layer for final prediction. We also experiment with UnifiedQA (Khashabi et al. 2020), the state-of-the-art QA model for many QA benchmarks. We feed the question and all five candidates together to UnifiedQA so that it can choose among the candidates instead of judging them independently like BERT.

**Chinese Models** We experiment with popular Chinese pretrained models, including Chinese BERT (Devlin et al. 2019), BERT-wwm, RoBERTa-wwm (Cui et al. 2019) and ERNIE (Sun et al. 2019). BERT-wwm and RoBERTa-wwm are models pretrained with Whole Word Masking (WWM). ERNIE incorporates knowledge graphs (KGs) to enhance language representation with external knowledge. We adopt the fine-tuning procedure similar to English BERT.

**Multilingual Models** Multilingual pretrained language models are able to perform cross-lingual zero-shot learning on multilingual QA datasets such as MLQA (Lewis et al. 2020). We test the performance of multilingual BERT (mBERT) (Devlin et al. 2019) and XLM-R (Conneau et al. 2019) on BiRdQA. We adopt the fine-tuning procedure similar to English BERT.

<sup>16</sup>To clarify, we only use introductions and hints in additional experiments.

**Input Format** For additional experiments regarding the influence of adding introduction/hint, the *B* in [CLS] *A* [SEP] *B* [SEP] for BERT-style input is instead the concatenation of the candidate and its introduction/hint, while the *A* is still the question.

### 4.2 Evaluation Metric

We evaluate the model performance with two metrics, accuracy and mean reciprocal rank (MRR), which show how well the model makes inference and ranks the candidates, respectively. The model ranks the candidates by their softmax prediction probabilities, except for UnifiedQA. Because UnifiedQA is an end-to-end generative model, we cannot apply MRR metric to it.

### 4.3 Experimental Setup

We use Huggingface (Wolf et al. 2020) implementations for all the baseline models. Due to limitation of computational resource, we restrict the input length to 256 tokens for all models except 150 for UnifiedQA. All hyper-parameters are decided by the model performance on the development set. For cross-lingual experiment, model selection is constrained to be strictly zero-shot, using only source language development data to pick hyperparameters (Lewis et al. 2020). To keep symmetric input formats of English and Chinese riddles, we do not use the hints in Chinese riddles because they do not exist in English riddles. We further investigate the effect of adding hints with additional experiments.

### 4.4 Human Performance Evaluation

We evaluate human performance on BiRdQA under monolingual setting. We employ three bilingual post-graduate students to independently answer 100 Chinese riddles and 100 English riddles randomly sampled from the test sets. They are instructed not to directly search for the answers of riddles online. We then calculate the average accuracy of the three human workers as the final human performance on our dataset.

## 5 Results

Tables 4 and 5 show monolingual experiment results on BiRdQA-en and BiRdQA-zh, respectively. Table 6 describes cross-lingual and multilingual results. The human accuracy is 81.33% for English and 87.67% for Chinese<sup>17</sup>, which indicates that it is not difficult for human testees to distinguish the correct answer from other distractors, though human may struggle to answer the riddles “from scratch” (i.e., no candidates are provided). In contrast, all of the evaluated QA models perform much worse than human, indicating that these methods are relatively weak in solving riddle and that there is ample room for improvement in future.

<sup>17</sup>Because human performances are evaluated on a subset of 100 random samples from the test set, they cannot be strictly compared with the model performances evaluated on the whole test set.

| Model                | BiRdQA-en      |                       |
|----------------------|----------------|-----------------------|
|                      | Dev            | Test                  |
| Random Guess         | 20.00 / 0.4567 | 20.00 / 0.4567        |
| BERT-Base            | 48.82 / 0.6834 | 41.92 / 0.6404        |
| w/ introduction      | 51.46 / 0.6949 | 44.38 / 0.6609        |
| w/o question         | 29.59 / 0.5519 | 21.44 / 0.4835        |
| Train + CQA          | 46.56 / 0.6771 | 44.86 / 0.6599        |
| Train = CQA          | 42.41 / 0.6463 | 38.29 / 0.6164        |
| BERT-Large           | 46.65 / 0.6735 | 44.25 / 0.6519        |
| RoBERTa-Large        | 47.31 / 0.6749 | 45.21 / 0.6653        |
| ALBERT-XXL           | 63.52 / 0.7856 | 58.70 / 0.7590        |
| Train + CQA          | 67.11 / 0.8045 | <b>64.79 / 0.7978</b> |
| UnifiedQA (T5-Large) | <b>67.20</b>   | 62.60                 |
| Human                | -              | 81.33                 |

Table 4: Results (accuracy/MRR) of English models on the development and the test data of BiRdQA-en. CQA means CommonsenseQA (Talmor et al. 2019). Human performance is tested on a subset of 100 random samples.

**English vs. Chinese** In monolingual setting, the best performance on BiRdQA-en is 62.60% by UnifiedQA (without additional data), higher than that on BiRdQA-zh, which is 59.29% by ERNIE. However, English results are almost worse than the corresponding Chinese results for the same type of model (e.g., BERT-Base vs. BERT-base-chinese). We also observe similar trends in the multilingual setting. However, this does not necessarily mean that English riddles are generally harder than Chinese riddles, since there are less training samples for English riddles and also English answers are less diverse than Chinese ones (Section 3). In another word, models tend to learn less knowledge in English. In future, we plan to increase diversity of English riddle and make the dataset more balanced between the two languages.

**Monolingual vs. Multilingual** In monolingual training setting, monolingual model (BERT) can outperform its multilingual counterpart (mBERT), which is called *the curse of multilinguality* (Conneau et al. 2019). We also observe that the multilingual training (e.g., en+zh → en) substantially improves the performance comparing with the monolingual training (e.g., en → en), especially for English riddles. It shows that multilingual models are able to transfer knowledge from source language to improve performance on different target language on our dataset.

**Comparing Different QA Models** In monolingual English setting (Table 4), UnifiedQA performs the best (without additional data) since it can see all the candidates in the input sequence at the same time rather than consider them independently like BERT. Another possible reason is that UnifiedQA has been pretrained on other QA dataset, making it possible to transfer external knowledge and skills to BiRdQA. In monolingual Chinese setting (Table 5), ERNIE achieves the best accuracy surprisingly, given that it has

| Model                 | BiRdQA-zh             |                              |
|-----------------------|-----------------------|------------------------------|
|                       | Dev                   | Test                         |
| Random Guess          | 20.00 / 0.4567        | 20.00 / 0.4567               |
| BERT-base-chinese     | 53.45 / 0.7099        | 55.10 / 0.7210               |
| w/ introduction       | 55.95 / 0.7244        | 54.08 / 0.7102               |
| w/o question          | 28.79 / 0.5413        | 22.48 / 0.4954               |
| w/ hint               | 54.32 / 0.7162        | 54.08 / 0.7139               |
| BERT-wwm-ext          | 58.25 / 0.7421        | 57.02 / 0.7353               |
| RoBERTa-wwm-ext-large | 60.17 / <b>0.7563</b> | 58.04 / 0.7415               |
| ERNIE                 | <b>60.65</b> / 0.7550 | <b>59.29</b> / <b>0.7479</b> |
| Human                 | -                     | 87.67                        |

Table 5: Results (accuracy/MRR) of Chinese models on the development and the test data of BiRdQA-zh. Human performance is tested on a subset of 100 random samples.

less parameters than RoBERTa-wwm-ext-large. The difference of the domains of pretraining text may account for this phenomenon. ERNIE is trained on larger data other than Wikipedia, including text from online forum, which will be more useful on casual text like riddles (Cui et al. 2019). We note that higher accuracy does not necessarily mean higher MRR, especially when accuracies of two models are very close to each other. For example, in Table 5, ERNIE beats RoBERTa on accuracy but is left behind on MRR, which shows that RoBERTa is better at ranking candidates. We also observe that larger models consistently perform better than smaller models. In cross-lingual setting, mBERT is the best one for zero-shot transfer, which is different from the case on MLQA (Lewis et al. 2020). While in multilingual setting, XLM-R-Large outperforms other models on both English and Chinese test sets.

**Influence of Additional Information** Wikipedia introductions and hints (only for Chinese riddles) are auxiliary information in our dataset and they may be useful to models. We evaluate the impact of appending Wikipedia introduction to each candidate for input. We find that adding Wikipedia introduction (“w/ introduction” in Tables 4 and 5 and 6) can boost performance on English riddles across the three experimental settings, but cannot improve performance on Chinese ones, unexpectedly. We conjecture that this is because solving Chinese riddles requires deeper information of candidates, such as the meaning of each character<sup>18</sup>, rather than factual/literal descriptions from Wikipedia. We also observe that using hints in Chinese riddles (“w/ hint” in Table 5) does not lead to higher performance, indicating that they do not carry a lot of useful information. For example, if all five candidates are animals, the hint “打一动物” (guess an animal) will be useless. This is also correlated to the fact that the hint is a less diverse feature in our dataset – Table 1 shows that there are only 690 distinct hints across all Chinese riddles.

<sup>18</sup>Unlike English, each Chinese character has its own meaning and the combination of character meanings does not necessarily equal to the word meaning.

| Setting                  | Cross-lingual                    |   |                                  |   | Multilingual                     |                                  |
|--------------------------|----------------------------------|---|----------------------------------|---|----------------------------------|----------------------------------|
|                          | en                               |   | zh                               |   | en+zh                            |                                  |
| Train                    | en                               | zh                                      | zh                               | en                                      | en                               | zh                               |
| mBERT<br>w/ introduction | 36.30 / 0.6003<br>42.40 / 0.6467 | <b>40.60 / 0.6188</b><br>30.12 / 0.5521 | 50.17 / 0.6845<br>47.85 / 0.6677 | 38.97 / 0.6144<br><b>41.23 / 0.6359</b> | 40.14 / 0.6246<br>43.08 / 0.6505 | 50.51 / 0.6906<br>48.75 / 0.6771 |
| XLM-R-Base               | 28.77 / 0.5408                   | 31.20 / 0.5552                          | 46.49 / 0.6646                   | 25.21 / 0.5181                          | 33.77 / 0.5783                   | 48.41 / 0.6769                   |
| XLM-R-Large              | 39.73 / 0.6249                   | 33.01 / 0.5651                          | 57.25 / 0.7319                   | 38.15 / 0.6099                          | <b>43.97 / 0.6591</b>            | <b>57.13 / 0.7335</b>            |

Table 6: Results (accuracy/MRR) of multilingual models under cross-lingual and multilingual settings of BiRdQA. We only mark the best performances in cross-lingual (en → zh, zh → en) and multilingual (en+zh → en/zh) experiments as bold.

**Investigating Candidate-only Bias** We conduct ablation experiments to measure candidate-only bias by removing question from input (“w/o question” in Table 4 and 5). We observe that models can only make nearly random guess (20%) without the question, demonstrating the effectiveness of local distractors (Section 2.2) to prevent machine from learning spurious correlations between distractors and correct answers.

**Transfer Learning with CommonsenseQA** BiRdQA-en is similar to CommonsenseQA (Talmor et al. 2019) in terms of commonsense reasoning. We conduct transfer learning experiments to gauge the degree of overlap of necessary knowledge between these two datasets. We append the training set of CommonsenseQA to BiRdQA (“Train + CQA” in Table 4), and observe an improvement of performance from 41.92% to 44.86% on BERT-Base model and achieve the highest performance so far (64.79%) on ALBERT-XXL. Besides, we fine-tune a model on the data of CommonsenseQA only (“Train = CQA” in Table 4), and achieve a zero-shot transfer performance of 38.29% with BERT-Base on BiRdQA-en, which indicates that there exists an overlap in terms of commonsense knowledge for solving problems in both BiRdQA and CommonsenseQA.

## 6 Related Work

To the best of our knowledge, RiddleSense (Lin et al. 2021) is the most similar dataset to ours. It contains 5.7k English riddles and also comes in a multiple-choice format. However, we argue that our work is different in that 1) BiRdQA contains bilingual riddles and thus can facilitate a cross-lingual study of riddles 2) BiRdQA provides Wikipedia introduction for each candidate to promote future research on commonsense reasoning for riddles 3) We generate distractors in an automated fashion with quality guarantee and less human efforts. It can work for English, Chinese and other languages as long as pretrained word embeddings are available 4) The bias in BiRdQA-en is much weaker than RiddleSense. A BERT-Base model simply achieves an accuracy of 42.21% even without question input on RiddleSense, compared with only 21.44% on BiRdQA-en.

Tan et al. (2016) has studied on the solution and generation of Chinese *character* riddle, which present challenge regarding the structure of Chinese character rather than the meaning of the answer. But BiRdQA-zh explicitly excludes

this type of Chinese riddle.

There are also commonsense-based QA datasets such as COSMOS QA (Huang et al. 2019) and CommonsenseQA (Talmor et al. 2019). However, solving riddle requires more than just commonsense knowledge. While normal commonsense questions navigate the readers to the right direction for the answer, riddles tend to mislead them on purpose. Besides, the machine needs to understand the figurative and ambiguous effect of the riddle language. Therefor, riddle is a great benchmark for higher-order understanding of natural language and broader intelligence.

There is a trend for multilingual QA in recent years, with the release of BiPaR (Jing, Xiong, and Yan 2019), XQuAD (Artetxe, Ruder, and Yogatama 2019), MLQA (Lewis et al. 2020) and other cross-lingual QA datasets. While translation from English dataset is a common approach to the creation of multilingual dataset, we build BiRdQA independently yet symmetrically in English and Chinese, due to the difficulty of riddle translation.

## 7 Conclusion

In this paper, we introduce BiRdQA, a large-scale, bilingual multiple-choice question answering dataset to facilitate the development of QA systems capable of solving tricky riddles. The huge gap between the human and machine leaves much room for improvement. In future work, we plan to extend BiRdQA with riddles in other languages and incorporate figurative language understanding into riddle solving. We hope that BiRdQA will stir more research for question answering on riddles.

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