JaQuAD: Japanese Question Answering Dataset for Machine Reading Comprehension

ByungHoon So\textsuperscript{*} Kyuhong Byun\textsuperscript{*} Kyungwon Kang Seongjin Cho
{byunghoon, khbyun, kangnak, sjcho}@skelterlabs.com

Abstract

Question Answering (QA) is a task in which a machine understands a given document and a question to find an answer. Despite impressive progress in the NLP area, QA is still a challenging problem, especially for non-English languages due to the lack of annotated datasets. In this paper, we present the Japanese Question Answering Dataset, JaQuAD, which is annotated by humans. JaQuAD consists of 39,696 extractive question-answer pairs on Japanese Wikipedia articles. We finetuned a baseline model which achieves 78.92\% for F1 score and 63.38\% for EM on test set. The dataset and our experiments are available at https://github.com/SkelterLabsInc/JaQuAD.

1 Introduction

Question Answering (QA), a.k.a. Reading Comprehension (RC), is a natural language processing task in which a machine understands a given document and a question to find an answer. This task has become popular with the emergence of a large-scale and high-quality QA dataset named SQuAD [17, 16], leading to the release of other datasets such as Natural Questions [10], CoQA [18], and HotpotQA [24]. These datasets contributed impressive progress for English question answering models over the past few years.

Naturally, a variety of studies have emerged for non-English QA. Some researchers made substantial efforts to construct non-English QA datasets. Similar to SQuAD, large-scale and high-quality datasets have been proposed, such as KorQuAD in Korean [27, 26], FQuAD in French [6], and GermanQuAD in German [13]. As a more general solution for non-English QA, other studies proposed multilingual models [11, 5] or techniques transferring a monolingual model to the target language [2]. Although these approaches solved QA without training data of the target language, the reported performance failed to achieve comparable results compared to the performance training with the target language data [26, 6, 13].

To fill the gap for the Japanese language, we propose a Japanese Question Answering Dataset (JaQuAD) to address the need for a large-scale and high-quality Japanese QA dataset. JaQuAD contains 39,696 question-answer pairs annotated by humans and 12,348 contexts which span over one or more paragraphs from 901 Japanese Wikipedia articles. More specifically, the training, development, and test sets of JaQuAD contain 31,748, 3,939, and 4,009 question-answer pairs, respectively.

To evaluate the JaQuAD, we finetuned BERT-Japanese [8], a transformer-based pretrained language model, on JaQuAD. This baseline achieves 78.92\% for F1 score and 63.38\% for EM on test set. It suggests there is plenty of room for improvement in modeling and learning on the JaQuAD dataset.

2 Related work

2.1 Reading comprehension in English

The Reading Comprehension [19, 17] attempts to solve the Question Answering problem by finding the span in one or several paragraphs which answer a given question. In recent years, English Question Answering models made impressive progress. This progress was affected by the release of large and realistic English QA datasets such as SQuAD 1.1 [17], SQuAD 2.0 [16], MS Marco [14], Natural Questions [10], QuAC [3], CoQA [18], and HotpotQA [24]. Among them, SQuAD 1.1 has been one of the most famous reference datasets which consists

\textsuperscript{*}Equal contribution
of Wikipedia documents and question-answer pairs generated by crowd workers. Based on SQuAD 1.1, each of the datasets introduced its subtleties. SQuAD 2.0 introduced unanswerable adversarial questions. MS Marco and Natural Questions contain much larger questions by using Bing and Google search logs, respectively, rather than generated by crowd workers. CoQA and QuAC were built for conversational QA (multi-turn QA) and free-form answers. HotpotQA introduced multi-hop questions where the answer must be found among multiple documents.

### 2.2 Reading comprehension in other languages

There were a few SQuAD format datasets released in non-English languages. Some examples are KorQuAD 1.0 [27], KorQuAD 2.0 [26], KLUE-MRC [15], FQuAD 1.1 [6], GermanQuAD [13], and SberQuAD [7]. KorQuAD 1.0 is a Korean QA dataset that contains over 70k samples. KorQuAD 2.0 is another Korean QA dataset that contains over 100k samples whose contexts are HTML contents from Korean Wikipedia, not plain text contents. KLUE-MRC is a Korean QA dataset that contains over 29k samples which includes unanswerable questions and plausible fake answers. FQuAD 1.1 is a French QA dataset that contains over 60k samples. GermanQuAD is a German QA dataset that contains over 13k samples. SberQuAD is a Russian QA dataset that contains over 50k samples. Table 1 lists some of the available datasets along with the number of question-answer pairs they contain [20]. For comparison, Table 1 also includes some English QA datasets and JaQuAD.

In the case of Japanese, a few Japanese QA datasets were released such as a driving-domain RC-QA dataset [25] and an answerability annotated RC dataset [1]. The driving-domain RC-QA dataset contains over 20k samples. However, the documents of the dataset come from driving-blogs which limits its domain and patterns. The answerability annotated RC dataset contains 12k question-answer pairs over 56k contexts. The question-answer pairs come from buzzer quizzes of the abc/EQIDEN competition and the contexts are paragraphs automatically collected from Wikipedia articles. Later, the answerability score of a context is annotated by crowdsourcing. Thus, this dataset has a shortcoming that the majority of contexts and corresponding questions are contrived, and that they could be biased by the original competition in some ways.

### 3 Dataset Collection

Referencing the data collection of SQuAD 1.1, we collect our dataset in three stages: (1) collecting contexts, (2) generating question-answer pairs on those contexts, and (3) validating collected questions and answers. For stages (2) and (3), human annotators were selected through a qualification test. We asked annotators to generate question-answer pairs from a Wikipedia document and news articles as the qualification test. Then, only the annotators who generated fluent questions and produced answers in a consistent format participated in dataset collection.
### Table 2: Distribution of answer types. For JaQuAD, the distribution was extracted from the entire dataset. For KorQuAD 1.0 and SQuAD 1.1, the distributions are extracted from the random 280 and 192 samples from the development set, respectively. “SQuAD 1.1 except Others type” represents the proportions of the remaining types calculated by taking the remaining 81.9% as the total, excluding the Others type.

| Answer Types (Question interrogatives) | SQuAD 1.1 | SQuAD 1.1 except Others type | KorQuAD 1.0 | JaQuAD |
|----------------------------------------|-----------|------------------------------|-------------|-------|
| Object (What/Which)                    | 49.4%     | 60.3%                        | 55.4%       | 49.4% |
| Person (Who)                           | 10.0%     | 12.2%                        | 23.2%       | 15.5% |
| Date/Time (When)                       | 6.6%      | 8.1%                         | 8.9%        | 19.5% |
| Location (Where)                       | 4.1%      | 5.0%                         | 7.5%        | 14.1% |
| Manner (How)                           | 10.3%     | 12.6%                        | 4.3%        | 0.5%  |
| Cause (Why)                            | 1.5%      | 1.8%                         | 0.7%        | 1.0%  |
| Others                                 | 18.1%     | -                            | -           | 0.0%  |

#### 3.1 Contexts collection

We chose Japanese Wikipedia pages as contexts to cover a wide range of domains. We collected 799 articles from the Japanese Wikipedia pages referencing quality articles [21, 22]. Also, we collected 102 articles in other categories to broaden the domains of our dataset. 901 articles are randomly split to training, development, and test sets which are made up of 691, 101, and 109 articles, respectively.

From each article, we extracted a context consisting of an individual paragraph or consecutive paragraphs without an image, a figure, and a table. As a result, training, development, and test sets are made up of 9,713, 1,431, and 1,479 contexts, respectively.

#### 3.2 Question and answer pairs generation

Human annotators generated multiple question-answer pairs while reading a context. A question had to be answerable using the content of the corresponding context. And an answer must be a span in the context. For the consistency of the answers, all annotators generated answers according to the criteria provided. For example, the answer should be the minimum span corresponding to the question and the basic unit should be included when asked about the number. The details are in Appendix A. Also, we asked annotators to tag the answer types and question types used in KorQuAD 1.0 and gave feedback on balancing the question and answer type to control the distribution of each type. As a result, 39,696 question-answer pairs are generated. Training, development, and test sets have 31,748, 3,939, and 4,009 question-answer pairs, respectively.

#### 3.3 Quality management

For credible evaluation, collected data went through a cross-validation process. During this process, annotators validated not only questions and answers, but answer types and question types. While validating the answer and question types, validators double-checked the logical process of inferring answers. Thus, they naturally validate the answerability of the question in-depth. Ambiguous question-answer pairs were corrected through discussion in the annotator group. During validation, we fixed either question or answer in 4693 question-answer pairs and the question type or answer type of 1807 question-answer pairs.

#### 4 Dataset Analysis

This chapter compares JaQuAD with two datasets in the same format, SQuAD 1.1 and KorQuAD 1.0. Referencing the analyses on SQuAD 1.1 [12] and KorQuAD 1.0 [27], we analyzed questions and answers of JaQuAD. First, we categorized answers by predefined types and measured the distribution of each answer type. Second, we categorized questions according to the required reasoning ability and measured the distribution of each question type. Finally, we measured the distribution of the lengths of contexts and answers.
4.1 Answer type analysis

The first analysis aims to understand the answer types of the dataset. For the answer type analysis, annotators manually labeled the answer types during data collection and validation. We used six answer types used in the analysis of KorQuAD 1.0: Object, Person, Date/Time, Location, Manner, and Cause. Further, we compared JaQuAD with SQuAD 1.1 by matching answer types to corresponding question types of SQuAD 1.1 which are categorized based on interrogative [12]. Among them, the “Others” question type is removed, and “What” and “Which” question types are merged into the “Object” answer type because they are hard to distinguish clearly by answers.

Table 2 shows the distribution of answer types on SQuAD 1.1, KorQuAD 1.0, and JaQuAD. In the Answer Types column, corresponding question types used in SQuAD 1.1 are described in parentheses. Because KorQuAD 1.0 and JaQuAD do not have Others type, we added the column “SQuAD 1.1 except Others type” for direct comparison. This column represents the proportions of the remaining types calculated by taking the remaining 81.9% as the total, excluding the Others type. In SQuAD 1.1 and KorQuAD 1.0, Object type occupies more than half of the dataset. Similarly, Object type occupies the largest proportion in JaQuAD, but it decreases to 49.4%. Compared to the other datasets, the proportion of Date/Time and Location types significantly increased to 19.7% and 14.0%, respectively. The proportion of Person type is 15.4%, similar to that of the SQuAD 1.1. As a result, the proportions of the Person, Date/Time, and Location types are similar. In contrast, the proportion of Manner and Cause types significantly decreases to 0.5% and 1.0%, respectively.

4.2 Question type analysis

The second analysis aims to understand the question types of the dataset. Referencing KorQuAD 1.0, we categorized questions into five question types according to the reasoning ability required to answer the question.
| Types                           | SQuAD 1.1 | KorQuAD 1.0 | JaQuAD |
|--------------------------------|-----------|-------------|--------|
| Syntactic variation            | 64.1%     | 56.4%       | 32.0%  |
| Lexical variation (synonymy)   | 33.3%     | 13.6%       | 16.7%  |
| Lexical variation (world knowledge) | 9.1%     | 3.9%        | 21.2%  |
| Multiple sentence reasoning    | 13.6%     | 19.6%       | 20.2%  |
| Logical reasoning              |           | 3.6%        | 10.0%  |
| Ambiguous                      | 6.1%      | 2.9%        | -      |

Table 4: Distribution of question types. For JaQuAD, the distribution was extracted from the entire dataset. For KorQuAD 1.0 and SQuAD 1.1, we use the values in their paper which are the results of the random 280 and 192 samples from the development set, respectively.

Table 3 shows an example for each question type. *Syntactic variation* implies that a question is made by changing the word order or reorganizing the sentence. *Lexical variation (synonymy)* implies that the keywords in a question are transformed to a synonym compared to the context. *Lexical variation (world knowledge)* implies that world knowledge is required to match keywords in a question and the corresponding words in the context. *Multiple sentence reasoning* implies that reasoning over multiple sentences is required to answer the question. *Logical reasoning* implies that the question requires multi-hop reasoning to find the answer among the multiple options in the context: the answer could be found by matching the condition of the question or actively using the information in parentheses. This type of question often requires comparing features of listed items or using implicit information in the context.

Table 4 shows the proportion of question types of SQuAD 1.1, KorQuAD 1.0, and JaQuAD. The Ambiguous type includes the cases that authors of the paper disagree with annotators’ answers, a question does not have a unique answer, and external knowledge out of the corresponding context is needed to answer a question.

The proportion of Syntactic variation type is almost half compared to SQuAD 1.1 and KorQuAD 1.0. In contrast, the proportions of Lexical variation (world knowledge) and Logical reasoning types are more than double. The proportion of Lexical variation (synonymy) and Multiple sentence reasoning types remains similar to KorQuAD 1.0. These represent JaQuAD requires a higher level of reasoning ability than SQuAD 1.1 and KorQuAD 1.0.

### 4.3 Context and answer length

The third analysis aims to understand the distribution of context and answer lengths. The length represents the number of tokens. We use the tokenizer of BERT-Japanese in the transformers library [23]. The tokenizer first segments a text into morphemes using MeCab tokenizer [4] and the Unidic 2.1.2 dictionary [9]. Then, the tokenizer generates subword tokens from each morpheme. The vocabulary size of BERT-Japanese is 32,000.

Figure 1 shows the distribution of context lengths, question lengths, and answer lengths. In Figure 1a, the context length ranges from 22 to 1,130, and the average is 266.5.0% of contexts are longer than 500 tokens. As the max sequence length of pre-trained models is 512 in general, truncation of these contexts could affect the performance of a model. In Figure 1b, the question length ranges from 5 to 126, and the average is 21.1. As all of the questions are shorter than 128 tokens, we did not truncate a question during training. In Figure 1c, the answer length ranges from 1 to 70, and the average is 3.3. Most of the answers are short, and only 4.1% are longer than 8 tokens. Therefore, JaQuAD has lower coverage for long answers compared to other datasets.

### 5 Dataset Evaluation

We use two evaluation metrics, Exact Match (EM) and F1 score, which are common metrics for evaluating performances of QA models.

**Exact Match (EM).** This metric measures the percentage of predictions that match exactly to the ground truth answer.

**F1 score.** This metric measures the overlap between the prediction and the ground truth answer. We treat the prediction and the ground truth as bags of characters, compute F1 score, and average over all of the questions. Note that although SQuAD used word-level F1 score, we computed character-level F1 score.

Computing F1 in words is not trivial in Japanese because Japanese sentences do not have spaces. We chose a character-level F1 score as an evaluation metric by referring to the use of character-based evaluation metrics.
in Korean QA datasets [27, 26, 15]. Because Japanese uses thousands of kanji (Chinese characters) and each kanji has a meaning, the probability of two phrases coincidentally overlapping by character is low when the two phrases have different meanings. Table 5 shows an example of calculating the character-level F1 score in Japanese and the word-level F1 scores in English. When we translate the ground truth and prediction in English, “treatment problem of German residents” (イツ系住民処遇問題) and “self-determination for treatment problem” (処遇問題に対し民族自決主義) overlap two words in English (‘treatment’ and ‘problem’). No words overlap coincidentally. The comparison in Japanese is similar; ドイツ系住民処遇問題 (treatment problem of German residents) and 処遇問題に対し民族自決主義 (self-determination for treatment problem) overlap five characters (処, 遇, 問, 題, and 民). Only one Japanese character (民), which means people or nation, overlap coincidentally.

Although the evaluation process in SQuAD ignores punctuation and articles (a, an, the), we did not need them because Japanese has no articles, and there is no punctuation in the ground truth answers of JaQuAD. Thus, we could remain consistent with the former approach without any additional filtering.
ヒトラーは、周辺各国のドイツ系住民処遇問題に対し民族自決主義を主張し、ドイツ人居住地域のドイツへの併合を要求した。

 Hitler insisted on self-determination for the treatment problem of German residents in neighboring countries and demanded the merger of German settlements with Germany.

Question: ヒトラーは、周辺各国のどのような問題に対し民族自決主義を主張し、ドイツ人居住地域のドイツへの併合を要求したか？

(For what problems did Hitler insist on self-determination and demand the annexation of German settlements into Germany?)

Table 5: An example of calculating F1 scores in English and Japanese.

| Model        | Model size | Development F1 | Development EM | Test F1   | Test EM   |
|--------------|------------|----------------|----------------|-----------|-----------|
| BERT-Japanese| BERT BASE  | 77.35          | 61.01          | 78.92     | 63.38     |

Table 6: Performance of the baseline on JaQuAD

6 Experiments

6.1 Experimental setup

The baseline model is a Japanese pre-trained language model, BERT-Japanese [8], published in HugginFace’s transformers library [23]. We trained the baseline model on JaQuAD for four epochs with a learning rate of $2 \cdot 10^{-5}$ using AdamW with default settings. The learning rate is linearly increased for the first 10% of steps and linearly decreased to zero afterward. The batch size is set to 32 and a maximum sequence length of 384 tokens. We did not truncate a question, because the longest question has 126 tokens. However, contexts could be truncated to meet the maximum sequence length. All the experiments were carried out with the HuggingFace transformers library [23] and trained with cloud TPUs provided by TPU Research Cloud program 1.

6.2 Model performance

Table 6 shows the performance of the baseline model on the development and the test sets of JaQuAD. The baseline achieves 78.92% for F1 score and 63.38% for EM on test set. Further, we analyzed the performance of the baseline by the question types, answer types, and answer lengths described in Chapter 4.

6.2.1 Performance by answer types

In order to understand the effect of answer types on model performance, we analyzed the model performance according to the answer type. We have explored the answer types and the distribution of them in Chapter 4.1. Figure 2a shows the F1 and EM scores of the baseline for each answer type. The model shows much better performance on Date/Time than the average, followed by Person, Object, and Location types. The model seems to perform better on types with few plausible candidates, such as Date/Time and Person types. Note that the proportions of Manner and Cause types are up to 1%. These types seem to suffer from the lack of training data.

6.2.2 Performance by question types

In order to understand the effect of required reasoning ability on model performance, we analyzed the model performance according to the question type. We have explored the question types and the distribution of them in Chapter 4.2. Figure 2b shows the F1 and EM scores of the baseline for each question type. Syn., Lex.

1https://sites.research.google/trc/
(syn), Lex. (world), Mul. sent., and Logical represent Syntactic variation, Lexical variation (synonymy), Lexical variation (world knowledge), Multiple sentence reasoning, and Logical reasoning types, respectively. The model performed best on Syntactic variation type and performed the second-best on Lexical variation (synonymy) type. The performances on Lexical variation (world knowledge) and Multiple sentence reasoning are similar to the average. As expected, the performance on Logical reasoning type is the lowest of all types, which is more than 20% lower than the average.

6.2.3 Performance by answer lengths

We analyzed the model performance according to the answer lengths. Figure 3 shows the F1 and EM scores of the baseline according to the answer lengths. The model performed best on the answers with length 3-4 tokens, but the f1 score are similar when the answer lengths are 3-8 tokens. The model shows the lower performance when the answer length is 1-2 tokens or 9+ tokens. This result shows that a question with a short answer is not always an easy one.
7 Conclusion

In this paper, we proposed the Japanese Question Answering Dataset, JaQUAD. We collected the contexts from Japanese Wikipedia articles and 39k+ questions were manually annotated by fluent Japanese speakers. JaQUAD has the same format as SQuAD, and the characteristics of the data are generally similar to KorQuAD 1.0. In the experiments, we fine-tuned a Japanese pre-trained language model with JaQUAD as a baseline and achieved 78.92% for F1 score and 63.38% for EM on test set. The baseline reaches promising results, but there is plenty of room for improvement. Extension of the dataset, such as covering longer answers, is left for future work. The dataset and our experiments are available at https://github.com/SkelterLabsInc/JaQuAD.

8 Acknowledgements

This work was supported by TPU Research Cloud (TRC) program. For training models, we used cloud TPUs provided by TRC. We also thanks to anotators who generated and labeled JaQUAD.

References

[1] abc/EQIDEN. 解答可能性付き読解データセット. http://www.cl.ecei.tohoku.ac.jp/rcqa/. [Accessed: 17-January-2022].

[2] M. Artetxe, S. Ruder, and D. Yogatama. On the cross-lingual transferability of monolingual representations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4623–4637, Online, July 2020. Association for Computational Linguistics.

[3] E. Choi, H. He, M. Iyyer, M. Yatskar, W.-t. Yih, Y. Choi, P. Liang, and L. Zettlemoyer. QuAC: Question answering in context. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2174–2184, Brussels, Belgium, Oct.-Nov. 2018. Association for Computational Linguistics.

[4] 京都大学情報学研究科 and 日本電信電話株式会社コミュニケーション科学基礎研究所. MeCab: Yet Another Part-of-Speech and Morphological Analyzer. https://taku910.github.io/mecab/. [Accessed: 17-January-2022].

[5] A. Conneau, K. Khandelwal, N. Goyal, V. Chaudhary, G. Wenzek, F. Guzmán, E. Grave, M. Ott, L. Zettlemoyer, and V. Stoyanov. Unsupervised cross-lingual representation learning at scale. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8440–8451, Online, July 2020. Association for Computational Linguistics.

[6] M. d’Hoffschmidt, W. Belblidia, Q. Heinrich, T. Brendlé, and M. Vidal. FQuAD: French question answering dataset. In Findings of the Association for Computational Linguistics : EMNLP 2020, pages 1193–1208, Online, Nov. 2020. Association for Computational Linguistics.

[7] P. Efimov, A. Chertok, L. Boytsov, and P. Braslavski. SberQuAD - Russian Reading Comprehension Dataset: Description and Analysis. In International Conference of the Cross-Language Evaluation Forum for European Languages, pages 3–15. Springer, 2020.

[8] Inui Laboratory, Tohoku University. Pretrained Japanese BERT models. https://github.com/cl-tohoku/bert-japanese/tree/v1.0, 2019.

[9] A. Kawase, tnakamura1128, T. Ogiso, and yasuden. UniDic. https://osdn.net/projects/unidic/. [Accessed: 17-January-2022].

[10] T. Kwiatkowski, J. Palomaki, O. Redfield, M. Collins, A. Parikh, C. Alberti, D. Epstein, I. Polosukhin, J. Devlin, K. Lee, K. Toutanova, L. Jones, M. Kelcey, M.-W. Chang, A. M. Dai, J. Uszkoreit, Q. Le, and S. Petrov. Natural Questions: A Benchmark for Question Answering Research. Transactions of the Association for Computational Linguistics, 7:452–466, 2019.

[11] P. Lewis, B. Oguz, R. Rinott, S. Riedel, and H. Schwenk. MLQA: Evaluating cross-lingual extractive question answering. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7315–7330, Online, July 2020. Association for Computational Linguistics.
[12] X. Liu, Y. Shen, K. Duh, and J. Gao. Stochastic answer networks for machine reading comprehension. In \textit{Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)}, pages 1694–1704, Melbourne, Australia, July 2018. Association for Computational Linguistics.

[13] T. Möller, J. Risch, and M. Pietsch. GermanQuAD and GermanDPR: Improving Non-English Question Answering and Passage Retrieval. \textit{CoRR}, abs/2104.12741, 2021.

[14] T. Nguyen, M. Rosenberg, X. Song, J. Gao, S. Tiwary, R. Majumder, and L. Deng. MS MARCO: A human generated machine reading comprehension dataset. In \textit{Proceedings of the Workshop on Neural Information Processing Systems (NIPS 2016)}, volume 1773, Barcelona, Spain, Dec. 2016. CEUR-WS.org.

[15] S. Park, J. Moon, S. Kim, W. I. Cho, J. Han, J. Park, C. Song, J. Kim, Y. Song, T. Oh, et al. Klue: Korean language understanding evaluation. \textit{arXiv preprint arXiv:2105.09680}, 2021.

[16] P. Rajpurkar, R. Jia, and P. Liang. Know What You Don’t Know: Unanswerable Questions for SQuAD. In \textit{Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)}, pages 784–789, Melbourne, Australia, July 2018. Association for Computational Linguistics.

[17] P. Rajpurkar, J. Zhang, K. Lopyrev, and P. Liang. SQuAD: 100,000+ questions for machine comprehension of text. In \textit{Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing}, pages 2383–2392, Austin, Texas, Nov. 2016. Association for Computational Linguistics.

[18] S. Reddy, D. Chen, and C. D. Manning. CoQA: A Conversational Question Answering Challenge. \textit{Transactions of the Association for Computational Linguistics}, 7:249–266, 2019.

[19] M. Richardson, C. J. Burges, and E. Renshaw. MCTest: A challenge dataset for the open-domain machine comprehension of text. In \textit{Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing}, pages 193–203, Seattle, Washington, USA, Oct. 2013. Association for Computational Linguistics.

[20] S. Ruder. NLP-progress. \url{https://nlpprogress.com/english/question_answering.html}. [Accessed: 17-January-2022].

[21] Wikipedia Contributors. Wikipedia: 秀逸な記事 (Good articles). \url{https://ja.wikipedia.org/wiki/Wikipedia:秀逸な記事}. [Accessed: 17-January-2022].

[22] Wikipedia Contributors. Wikipedia: 良質な記事 (Featured articles). \url{https://ja.wikipedia.org/wiki/Wikipedia:良質な記事}. [Accessed: 17-January-2022].

[23] T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, P. Cistac, T. Rault, R. Louf, M. Funtowicz, and J. Brew. Huggingface’s transformers: State-of-the-art natural language processing. \textit{CoRR}, abs/1910.03771, 2019.

[24] Z. Yang, P. Qi, S. Zhang, Y. Bengio, W. Cohen, R. Salakhutdinov, and C. D. Manning. HotpotQA: A Dataset for Diverse, Explainable Multi-hop Question Answering. In \textit{Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing}, pages 2369–2380, Brussels, Belgium, Oct.-Nov. 2018. Association for Computational Linguistics.

[25] 高橋憲生, 柴田知秀, 河原大輔, and 黒橋禎夫. ドメインを限定した機械読解モデルに基づく述語項構造解析. In \textit{Proceedings of the Twenty-fifth Annual Meeting of the Association for Natural Language Processing}, pages 3–20, Brussels, Belgium, Oct.-Nov. 2019. Association for Computational Linguistics.

[26] 김영민, 임승영, 이현정, 박소윤, and 김병지. KorQuAD 2.0: 웹문서 기계독해를 위한 한국어 질문응답 데이터셋. \textit{정보과학회논문지}, 47(6):577–586, 2020.

[27] 임승영, 김병지, and 이주열. KorQuAD: 기계독해를 위한 한국어 질문응답 데이터셋. \textit{한국정보과학회 학술발표논문집}, pages 539–541, 2018.
Appendices

A Criteria for choosing answer spans

- Select the minimum answer span corresponding to the question.
- When the answer is proper nouns (e.g. event, book, work name), include parentheses.
- When the answer is a year, use basic calendar year and include ‘年’.
- When the answer is numeric, include the basic unit of measurement (e.g. 人, 円, 点, km).
- When the answer is an approximate value, include the expressions that indicate approximation (e.g. 約, 以上, 弱).
- When the answer is ‘correct answer (explanation)’ form, exclude parentheses except the above cases.