DRCD: a Chinese Machine Reading Comprehension Dataset

Chih Chieh Shao and Trois Liu and Yuting Lai and Yiying Tseng and Sam Tsai
{cchieh.shao,trois.liu,yuting.lai,yiying.tz,i-sam.tsai}@deltaww.com
Delta Research Center
Delta Electronics, Inc.

Abstract

In this paper, we introduce DRCD (Delta Reading Comprehension Dataset), an open domain traditional Chinese machine reading comprehension (MRC) dataset. This dataset aimed to be a standard Chinese machine reading comprehension dataset, which can be a source dataset in transfer learning. The dataset contains 10,014 paragraphs from 2,108 Wikipedia articles and 30,000+ questions generated by annotators. We build a baseline model that achieves an F1 score of 53.78%. F1 score of Human performance is 93.30%. The dataset is available at https://github.com/DRCSolutionService/DRCD

1 Introduction

Machine reading comprehension (MRC) is the task of understanding paragraphs, and integrating it with what the human reader already knows. MRC systems can read documents written for humans and answer questions about the contents of such documents. In today’s business world, all parties expect fast response times and easy access to information. For example, customers are often impatient to obtain answers to critical questions about products before purchasing. Novice workers look for timely support from experienced staff to help them solve problems. In the above cases, MRC can fill in for human experts and answer most questions immediately.

Although rule-based approaches to MRC have been developed and applied, the high labor cost of rule maintenance and the difficulty handling variations on the same questions limit the applications of rule-based MRC. Machine-learning-based approaches can mitigate these two problems. However, they require large enough datasets for training of RC models.
Thanks to advances in and widespread adoption of deep learning and natural language processing, several large-scale MRC datasets have been compiled (Lai et al. 2017; Hermann et al. 2015; Cui et al. 2016; Rajpurkar et al. 2016; Nguyen et al. 2016; He et al. 2017), providing sufficient training data for deep learning MRC. These datasets have different research purposes and different task definitions, but they can be classified into four types by answer types: multiple choice, cloze-style, span-based, and user-log, we will describe more in Session 2. Multiple-choice datasets provide answer candidates and answers of cloze-style datasets were constrained to be a single word. Therefore, both of them are inappropriate for search scenario. Span-based and user-log datasets are more suited to our goal. There are two main abilities required in a search scenario, search, and comprehension. Models apply to user-log datasets need to learn both of the abilities. However, the state-of-the-art results of user-log datasets (e.g. MSMARCO) are still far behind human performance. It still remains a challenging problem in research. Furthermore, we want to test the ability of our model to comprehend text separately instead of learning both abilities at the same time. Therefore, we choose span-based datasets as our research target.

Most existing MRC datasets are in English, and a few exist in simplified Chinese. However, to the best of our knowledge, no large-scale traditional Chinese MRC dataset has been compiled yet. In this paper, we introduce DRCD, an open domain RC dataset, consisting of 10,014 paragraphs from 2,108 Wikipedia articles and 33,941 question-answer pairs.

2 Related Work

Recently, many RC datasets have been constructed for different tasks and with different methods. Here we describe the four types of RC dataset and give examples of each.

Multiple-choice: Multiple-choice MRC formulates the RC task as an option selection problem. Multiple-choice datasets can easily be adapted from school examinations without much human labeling. Many previous works like Khashabi et al. (2016), Shibuki et al. (2014), Penas et al. (2014), Rodrigo et al. (2015) compiled RC datasets from various levels of multiple-choice tests. Richardson et al. (2013) created MCTest, which contains 660 stories, 2,640 questions (4 per story) and 10,560 answer choices (4 per question) designed for 7-year-old children. Lai et al. (2017) constructed RACE, which contains 27,933 passages and 97,687 questions written for middle and high school students from 12–18 years old. But Lai et al. (2017) also indicate that multiple-choice MRC datasets are often far from sufficient for the training of advanced data-driven MRC models because of the expensive data-generation process by human experts.
**Cloze-style:** Cloze-style MRC formulates reading comprehension as the prediction of missing words in a sentence. Since cloze-style datasets can be constructed without human labeling, it is more practicable to compile one large enough for a data-demanding approach like deep learning. In English, Hermann et al. (2015) created a corpus from CNN and Daily Mail news summaries, and Hill et al. (2015) built the Children’s Book Test. In Chinese, Cui et al. (2016) constructed a cloze dataset from the People’s Daily news articles and another consisting of children’s fairy tales. Though many deep learning models have been applied to these public datasets with impressive results, Chen et al. (2016) showed that cloze-style datasets require less reasoning and inference than previously assumed. This may be because the answers to cloze questions are single words or entities, which are relatively easier to guess than the answers to span-based dataset.

**Span-based dataset:** Span-based MRC assumes that the answer to each question can be found in the reference document. Rajpurkar et al. (2016) constructed the first span-based dataset, SQuAD, which has over 100,000 questions. Joshi et al. (2017) proposed TriviaQA, which includes 95,000 question-answer pairs from 14 trivia and quiz league websites. According to their analysis, TriviaQA has relatively complex, compositional questions compared with other large-scale datasets. Another difference between SQuAD and TriviaQA is that each question in SQuAD refers to only one evidence document, while questions in TriviaQA refer to multiple documents.

| Question Type | Percent (%) | Example keywords |
|---------------|-------------|------------------|
| how           | 5.30        | 如何             |
| what          | 28.42       | 什麼             |
| when          | 13.59       | 何時             |
| where         | 4.98        | 哪裡             |
| which         | 30.96       | 何種             |
| who           | 10.46       | 誰               |
| why           | 0.27        | 為何             |
| other         | 5.97        | X                |

Table 1: Question types of DRCD.

**User log dataset:** User log datasets are constructed from real-world search logs. Nguyen et al. (2016) released the MSMARCO dataset with 100,000 queries and answers. In MSMARCO, all questions are real anonymized user queries from the Bing search engine, and the evidence documents used as context passages are real web documents in Bing’s index. He et al. (2017) constructed a Chinese user log dataset, DuReader, from the Baidu search engine and Baidu Zhidao, a question answering community site. Their dataset contains 200,000 questions, over 1 million documents, and over 420,000 human-generated answers.

### 3 Dataset Collection

In this work, we follow the method proposed by Rajpurkar et al. (2016) to collect Wikipedia data in three stages: passage curation, question-answer collection, and additional answer selection.

**Passage curation.** To select more informative pages, we determined the top 10,000 articles in Chinese Wikipedia \(^1\) using Project Nayuki’s internal PageRank tool. These pages were

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\(^1\) The Chinese Wikipedia dump is obtained in the data 2017/03/20
randomly assigned to annotators, who then selected paragraphs from 250 to 1500 characters in length for creating questions. In total, 10,014 paragraphs were selected from 2,108 pages.

**Question-answer collection.**

In this stage, annotators were asked to read the whole article and then generate 3 to 5 questions. The answer to each question must be found in the given paragraph. Annotators were asked to paraphrase as much as possible and avoid direct quotations in their questions. Additionally, we encouraged annotators to create complex questions whose answers are not just entities.

We also asked annotators to create specific questions with only one concrete answer. For example, if one asks, “Where did Obama live?” the paragraph might contain multiple answers like Hawaii or Washington, D.C. We suggested that annotators add more information to make questions more specific. For example, “Where did Obama live in 2018?” would be a better-phrased question.

To verify if the MRC model is able to infer the correct answer, not just perform information extraction, we asked annotators to label the sentences each answer is based on so that the model not only provides answers to questions but also indicates the sentences they refer to.

We divide our dataset into three parts: the training set contains 26,936 questions in 8,014 paragraphs, the development set contains 3,524 questions in 1,000 paragraphs, and the test set contains 3,485 questions in 1,000 paragraphs.

**Additional answer collection.** To evaluate human performance on our dataset, we obtained one additional answer to each question in the development and test sets. Annotators were shown only questions and paragraphs and then asked to select the shortest span in the paragraph that could answer the question.

**4 Dataset Analysis**

We analyzed the training and development sets, including paragraph length, question type, answer type, and the difficulty of DRCD.

**Question type:** To investigate the distribution of question types in DRCD, we sampled 660 questions randomly and constructed a keyword list for each question type. Then, we classified all questions into 7 types according to this keyword list. See Table 1 for keyword samples and distribution of each question type.

**Answer type:** We categorized the answers automatically into three types, numeric, entity, and description. First, we separated description and non-description answers. If the length of the answer was larger than 6 characters, the answer was categorized as description type. Then, we further split non-description answers into numeric and entity. The answers containing only numbers, Chinese numbers, and Chinese measure words were categorized as numeric. The remaining answers were categorized as entity type. According to our statistics, the breakdown of answer types is 18.03% numeric, 70.45% entity, and 11.50% description.

**Statistics on Length:** On average, the length of paragraphs, questions, and answers are 435.8, 21.07 and 4.86 Chinese character respectively. We
also examine SQuAD dataset. The average document length is 116.63 words and the average length of questions and answers are 10.06 and 3.16. Paragraphs in DRCD are much longer than previous dataset due to the reason that we ask annotator to separate paragraph by the topic of the paragraph instead of automated separate by period.

5 Experiment

In this section, we implement MRC systems with two state-of-the-art models, R-Net and BiDAF. F1 score and exact match from Rajpurkar et al. (2016) are used as the evaluation metrics. Both metrics ignore punctuations. In F1 score metric, we consider predictions and ground truth as bag of character.

**Human Performance:** We assess human performance on development set and test set of DRCD. For each paragraph in development set and test set, we involve another annotator different from the one that constructs the paragraph and question-answer pair to answer the question and treat the answer as human prediction. The resulting human performance score on the test set is 80.43% for exact match metric, and 93.30% for F1.

**Baseline Systems:** We implement one basic method and two state-of-the-art models as the baseline. we use EternalFeather project to process wikidump data, translate the text into traditional Chinese using OpenCC. We use EternalFeather project to train a CBow word embedding with 300 dimensions on the processed wiki text. We use this pre-trained word embedding in R-Net and BiDAF model.

**TF-IDF:** We count TF-IDF of every sentence in paragraph and question. For each question, we find the most similar sentence in the related paragraph using cosine similarity and take it as answer.

**R-Net:** Wang et al. (2017) proposed R-net, which is a widely used MRC model. We adjust Yereval Project to process Chinese character.

**BiDAF:** We use BiDAF which is implemented by He et al. (2017). We use pre-trained word embedding instead of randomly initialize. The other hyper-parameters remain the same.

6 Conclusion and Future Work

We introduce DRCD, a new MRC dataset, which is first large-scale reading comprehension dataset in traditional Chinese. The dataset contains 10,014 paragraphs and 40,410 question-answer pairs from 2,108 Wikipedia articles. We aim to use this dataset to be the source dataset in transfer learning.

In future work, we will focus on industrial data, which is our goal field to make next-generation search engine and question answering system. We expect we can improve annotation process and further adjust our task based on feedback from the community. We hope this dataset can promote the

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1. [https://github.com/EternalFeather/Word2Vec-on-Wikipedia-Corpus](https://github.com/EternalFeather/Word2Vec-on-Wikipedia-Corpus)
2. [zhwiki-20180320-pages-articles.xml.bz2](https://github.com/EternalFeather/Word2Vec-on-Wikipedia-Corpus)
3. [https://github.com/BYVoid/OpenCC](https://github.com/BYVoid/OpenCC)
4. [https://github.com/YerevaNN/R-NET-in-Keras](https://github.com/YerevaNN/R-NET-in-Keras)
research in traditional Chinese reading comprehension. Our long-term goal is to apply different techniques in the applications that can be used in industry. Reading comprehension for search engine and question answering system is our first target.

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