Native Chinese Reader: A Dataset Towards Native-Level Chinese Machine Reading Comprehension

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Abstract

We present Native Chinese Reader (NCR), a new machine reading comprehension (MRC) dataset with particularly long articles in both modern and classical Chinese. NCR is collected from the exam questions for the Chinese course in China's high schools, which are designed to evaluate the language proficiency of native Chinese youth. Existing Chinese MRC datasets are either domain-specific or focusing on short contexts of a few hundreds of characters in modern Chinese only. By contrast, NCR contains 8390 documents with an average length of 1024 characters covering a wide range of Chinese writing styles, including modern articles, classical literature and classical poetry. A total of 20477 questions on these documents also require strong reasoning abilities and common sense to figure out the correct answers. We implemented multiple baseline models using popular Chinese pretrained models and additionally launched an online competition using our dataset to examine the limit of current methods. The best model achieves 59% test accuracy while human evaluation shows an average accuracy of 79%, which indicates a significant performance gap between current MRC models and native Chinese speakers. We release the dataset at https://sites.google.com/view/native-chinese-reader/.

1 Introduction

Machine reading comprehension (MRC) is one of the fundamental tasks in natural language understanding, which requires a machine to read a document to correctly answer questions based on the context. MRC has attracted significant efforts from both academia and industry with continuous development of MRC datasets [15, 23, 19, 26, 28, 33], which also keeps pushing the frontier of MRC models and learning algorithms [11, 22, 20, 8] to eventually bridge the gap between AI systems and human readers.

In addition to the advances in English MRC, researchers have also made substantial progresses in Chinese MRC challenges with many high-quality Chinese MRC datasets released. These MRC datasets focus on a variety of domains of Chinese understanding, such as fact extraction [8, 7], dialogue understanding [34], common sense [14], idiom selection [43] and exam questions used in language proficiency tests [14, 15].

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However, all these datasets provide particularly limited challenges for the purpose of building MRC models with the same language proficiency as native Chinese speakers. There are 3 major dataset limitations. First, the length of reading materials are short. For example, C3M [34], a multiple-choice MRC dataset with the longest documents, has merely 180 characters per document on average. Even in the cloze-based datasets, the longest average document length is just around 500 characters. Second, the questions are not sufficiently difficult. Most existing datasets are either extractive or domain-specific (e.g., focusing on idiom or simple facts). Although C3M [34] provides exam-based free-form multiple-choice questions, they are designed for non-native speakers and therefore do not require native-level reasoning capabilities and common sense knowledge to answer the questions. More importantly, none of existing datasets consider reading comprehension on classical Chinese documents, such as classical literature and poetry. Classical Chinese, as a writing style used in almost all formal writing until early 20th century [39], plays a critical role in Chinese culture and has led to numerous idioms and proverbs. Even today, classical literature and poetry are still widely taught and examined in China’s education system.

We developed a new general-form multiple-choice Chinese MRC dataset, Native Chinese Reader (NCR), towards building a native-level Chinese comprehension system. The NCR dataset contains 8390 documents with over 20K questions collected using the exam questions for the Chinese course in China’s high schools, which are designed to evaluate the language proficiency of native Chinese youth. Therefore, NCR naturally overcomes the limitations of existing datasets with sufficiently challenging questions and long documents in an average length of 1024 characters over both modern and classical Chinese writing styles (see Table 1).

We provided in-depth analysis of NCR and implemented baselines using popular pretrained models. To further examine the limit of current MRC methods, we additionally launched an online competition using NCR. The best model we obtained achieves an average test accuracy of 59%, which is far below human evaluation result of 79% accuracy. This suggests a significant gap between current MRC model capabilities and the native-level Chinese language proficiency. We hope that NCR could serve as a milestone for the community to benefit future breakthroughs in Chinese natural language understanding.

2 Related Work

English Datasets: Machine Reading Comprehension tasks require a machine to answer a question based on the content in the given document. Early MRC datasets are primarily cloze/span-based, where the answer is simply a span in the document or a few words to be filled in the blank, including CNN/Daily Mail [15], LAMBADA [29], CBT [16], BookTest [2], Who-did-What [24] and CLOTH [41]. The famous SQuAD dataset [27, 26] for the first time introduces human-generated free-form questions, which requires the machine to understand natural language to select the correct span in Wikipedia pages. Similar datasets follow this trend of using free-form questions and adopt reading documents from a variety of sources, such as news articles [37, 17] and dialogues [18, 28, 4].

In addition to these datasets where the answers can be directly extracted from the document, another popular type of datasets, i.e., abstractive datasets, ask the reader to generate an answer that may not be found in the given context [23, 12]. Abstractive datasets further require the reader to perform non-trivial reasoning over the facts in the document as well as common sense knowledge to produce answers. However, since the answer itself is a natural language, evaluation for abstractive datasets can be tricky. Multiple-choice datasets overcome the evaluation difficulty in abstractive datasets by simply asking the reader to select the correct answer from the candidate options. Representative datasets, such as RACE [19] and DREAM [33], utilize exam questions collected from standard English proficiency tests, which are generated by language teachers to evaluate a variety of language capabilities of non-native English speakers.

Chinese Datasets: The development of Chinese MRC datasets follow a similar trend of English ones. Early cloze-based datasets, such as People Daily news (PD) dataset and Children’s Fairy Tale (CFT) dataset [9], utilize a sentence with a repeated noun removed as the question and ask the reader to predict the removed noun. As Chinese counterparts to the SQuAD dataset, DRCD [31], CMRC2017 [8] and CMRC2018 [7] datasets adopt human-generated questions and ask the reader to extract spans in the given documents as answers. DuReader [14], a representative abstractive dataset collects natural questions and answers from Baidu search data, which are in the same style
Table 1: Comparison between NCR and related Chinese MRC datasets. NQ is short for free-form natural question.

| Dataset   | #Que. Source of Doc. | Que. type | Ans. Type   | Doc. # Token Class. Avg. | Classical Chinese |
|-----------|----------------------|-----------|-------------|-------------------------|-------------------|
| PD        | 877K News            | cloze     | extractive  | 379                     | No                |
| CFT       | 3.5K Stories         | cloze     | extractive  | 139                     | No                |
| DRCD      | 34K Wiki             | NQ        | extractive  | 437                     | No                |
| CMRC 2017 | 364K Wiki            | NQ        | extractive  | 486                     | No                |
| CMRC 2018 | 18K Wiki             | NQ        | extractive  | 508                     | No                |
| DuReader  | 200K Baidu           | NQ        | abstractive | 82                      | No                |
| CMRC 2019 | 100K Story           | cloze     | multiple choice | 557                 | No                |
| ChID      | 729K News&Stories    | cloze     | multiple choice | 159                 | No                |
| C3-D      | 9.6K Exam (Non-Native)| NQ       | multiple choice | 76                   | No                |
| C3-M      | 10K Exam (Non-Native)| NQ       | multiple choice | 180                 | No                |
| NCR       | 20.4K Exam (Native)  | NQ        | multiple choice | 1024                | Included          |

as the English MS-MARCO dataset [23], CMRC2019 dataset [10] and ChID dataset [43] combine cloze-based questions and multiple-choice answer options. In CMRC2019, a few sentences are masked in each document and the reader is asked to match each option sentence to the corresponding blank in the document. ChID focuses on traditional Chinese idioms by asking the reader to select the correct idiom based on the given story context. Recently, the C3 dataset [34] was released, which contains both free-form questions and multiple-choice answer options. C3 is collected using the exam questions for Chinese-as-a-second-language tests and consists of two sub-datasets, C3-D focusing on normal documents and C3-M on dialogues, which can be viewed as the Chinese counterparts of RACE [19] and DREAM [33] respectively.

Position of NCR: We developed Native Chinese Reader (NCR), a exam-question-based MRC dataset with free-form questions and multiple-choice answer options, which aims to push the frontier of building native-level Chinese MRC models. The high-level statistics of NCR and all the aforementioned datasets are summarized in Table 1. C3 is perhaps the most related work to ours. However, C3 are collected from Chinese-as-a-second-language tests, so its questions are much easier than NCR for three reasons. First, documents, questions and answers in NCR are substantially longer than C3. Second, a quarter of the documents in NCR are written in classical Chinese, which is a critical component of Chinese language but largely ignored by existing works. We remark that although the answers in ChID dataset [43] are idioms, which is a restricted form of classical Chinese, the documents in ChID remain in modern Chinese. Lastly, the questions in NCR are collected from the exams for China’s high-school students and require native-level reasoning capabilities using the background knowledge of Chinese history and culture. In-depth comparisons on the question types between C3 and NCR can be found in Sec. 3.4 with example questions shown in Table 6. In addition, we highlight that a lot of questions in NCR require choosing one incorrect option out of 4 options (i.e., three other are correct; see Table 6 and 7 for examples). We count the questions containing “不正确” (“incorrect”), “不符合” (“incompatible”) or “不恰当” (“inappropriate”), 56.49%, 57.63%, and 56.14% of questions fall into this category in training/validation/test sets respectively. This requires the capability of understanding and reasoning with negations.

Finally, we remark that, in addition to Chinese and English, there are also other datasets developed in other languages like Japanese [32, 56], Russian [13] and cross-lingual scenarios [1, 21], which are of parallel interest to our project.

3 Native Chinese Reader (NCR) Dataset

In this section, we provide detailed analysis of the documents and questions in our NCR dataset, including overall statistics, document styles, major challenges as well as studies on question types.

3.1 Task Format and Collection Methodology

In NCR, each document is associated with a series of multiple-choice questions. Each question has 2 to 4 options, of which exactly one is correct. The task is to select the correct option based on the
document and the question. Both questions and options are expressed in natural language covering a wide range of question types (more details discussed below).

All the questions and documents are collected from online open-access high-school education materials. After data cleaning, 8315 documents followed by 20284 questions are obtained. We randomly split the dataset at the document level, with 6315 for training, 1000 for validation and 1000 for testing. Furthermore, to make sure our test set has sufficient novel questions that never appear online, we also invited a few high-school Chinese teachers to manually generate 193 questions for a total of 73 additional documents to augment the test set. Finally, NCR consists of 6315 documents with 15419 questions for training, 1000 documents with 2443 questions for validation and 1073 documents with 2615 questions for testing.

Table 2: The overall statistics of different Chinese multi-choice MRC datasets. ChID and CMRC2019 are cloze-based without questions. * means statistics are collected over validation and test set only.

| Datasets       | Len. of Doc. | Len. of Que. | Len. of Opt. | #Opt. per Que. | #Que. per Doc. |
|---------------|--------------|--------------|--------------|----------------|----------------|
| ChID          | 159.1 / 581  | N/A          | 4 / 4        | 7 / 7.0 / 7    | 1 / 1.2 / 12   |
| CMRC 2019     | 557.3 / 688  | N/A          | 13.8 / 29    | 5 / 10.6 / 15  | 0 / 9.9 / 15   |
| C3-M          | 180.2 / 1,274| 13.5 / 57    | 6.5 / 45     | 2 / 3.7 / 4    | 1 / 1.9 / 6    |
| C3-D          | 76.3 / 1,540 | 10.9 / 34    | 4.4 / 31     | 3 / 3.8 / 4    | 1 / 1.2 / 6    |
| C3            | 116.9 / 1,540| 12.2 / 57    | 5.5 / 45     | 2 / 3.8 / 4    | 1 / 1.5 / 6    |
| NCR Classical only* | 521.5 / 1,258| 25.7 / 178   | 36.8 / 130   | 2 / 4.0 / 4    | 1 / 2.2 / 5    |
| NCR Modern only* | 1207.8 / 4,640| 24.4 / 276   | 44.1 / 152   | 2 / 4.0 / 4    | 1 / 2.5 / 5    |
| NCR All       | 1023.7 / 4,640| 24.5 / 352   | 43.0 / 256   | 2 / 4.0 / 4    | 1 / 2.4 / 5    |

3.2 Dataset Statistics

We summarize the high-level statistics of our NCR dataset and other related multi-choice Chinese MCR datasets in Table 2. In addition, we also measure the statistics of classical and modern documents from the validation and test set, where we can observe that modern Chinese articles are more than twice longer than classical Chinese literature. Comparing with other Chinese MRC datasets, NCR is an order of magnitude longer, even including those very concise classical Chinese documents. Besides documents, NCR also contains much longer questions and answer options. Particularly for the option length, NCR is almost an order of magnitude longer except the CMRC2019 dataset. We remark that CMRC2019 is a cloze-style dataset with a completely different question style from NCR: CMRC2019 options are original document texts while the reader only needs to match the options to the corresponding blank in the document. Overall, NCR has substantially longer articles, questions and options with diverse document styles, which suggests a much higher comprehension difficulty than existing datasets.

Table 3: Statistics of document length over NCR validation set and test set. Classical Chinese articles (including poetry) are much shorter than modern Chinese articles.

| Style      | count | min | avg | max  |
|------------|-------|-----|-----|------|
| Modern     | 1493  | 47  | 1208| 4640 |
| Classical  | 580   | 24  | 522 | 1258 |
| Poetry     | 63    | 24  | 156 | 668  |

3.3 Document Style and Challenges

We manually annotated the writing styles of the documents in validation set and test set with summarized statistics in Table 3. Almost a quarter of the documents are in classical Chinese. We remark that most documents are collected from online open-access resources. This indicates that classical Chinese indeed plays a critical role in China’s Chinese class, which, however, is often ignored in previous Chinese MRC studies. Table 4 presents two example documents, one in classical Chinese (D1) and one in modern Chinese (D2), with associated questions. In the following content, we will discuss the major challenges in NCR with respect to different document writing styles.
Table 4: Example documents and questions (left) with English translation (right). Top (D1): a classical Chinese poem; Bottom (D2): an excerpt of a modern Chinese article. * denotes the correct option for each question (Q).

| D1 | Form of Xiang-Juan Huan | Li Yu |
|----|-------------------------|------|
| Q1 | "In "The lone parasol tree locks the clear autumn in the deep courtyard."
   | "Locks" means |
| A. | The lock B. Gold lock C. Lock up D. Unlock |
| Q2 | The incorrect option for the appreciation and analysis of this poem is |
| A. | The scenery is fixed in the first half, including the west tower, moonlight, parasol tree, deep courtyard, and clear autumn, the picture of which is cold and quiet. |
| B. | The sentence "The lone parasol tree locks the clear autumn in the deep courtyard" says that the courtyard with the parasol tree is very quiet, rendering the atmosphere of autumn. |
| C. | The second half turns to express feelings and writes about author's unreliable feeling when he secretly worry about life. |
| D. | The whole poem visualizes abstract emotions and expresses the author's suffering in leaving his hometown and the capital. |

D2 In the Restaurant (Excerpt) Lu Xun ...(2) I never guessed that here of all places I should expectedly meet a friend – if such he would still let me call him. The newcomer was an old class mate who had been my colleague when I was a teacher, and although he had changed a great deal I knew him as soon as I saw him. Only he had become much bigger in his movements, very unlike the nimble and active Lu Wei-fu of the old days. (11) "As soon as I came back I knew I was a fool". Holding his cigarette in one hand and the wine cup in the other, he spoke with a bitter smile. "When I was young, I saw the way bees or flies stopped in a small circle. If they were frightened they would fly but after flying in a small circle they would come back again to stop in the same place; and I thought this really very foolish, as well as pathetic. But I didn’t think that I would fly back myself, after only flying in a small circle. And I didn’t think you would come back either. Couldn’t you have flown a little further?" (20) "Are you teaching that?" I asked in astonishment (21) "Of course. Did you think I was teaching English? First I had two pupils, one studying the Book of Songs, the other Mencius. Recently I have got another, a girl, who is studying the Canon for Girls. I don’t even teach mathematics; not that I wouldn’t teach it, but they don’t want it taught." (22) "I could really never have guessed that you would teach such books!" (23) "Their father wants them to study these. I’m an outsider so it’s all the same to me. Who cares about such futile affairs anyway There’s no need to take them seriously..." (24) "Then what do you mean to do in future?" (25) "In future? I don’t know. Just think: Has any single thing turned out as we hoped of all we planned in the past? I’m not sure of anything now, not even of what I will do tomorrow, or even of the next minute..."

Q3 What is the author’s attitude towards Lu Wei-fu’s life? A. "Only he had become much bigger in his movements, very unlike the nimble and active Lu Wei-fu of the old days." indicates a high-level overview of Lu Wei-fu’s mental state, highlighting his sluggish decadence. B. "If they were frightened they would fly but after flying in a small circle they would come back again to stop in the same place." reveals the cruel reality of life squeezes the soul, human can only wear out their lives in depression. C. From Lu Wei-fu’s narration of the content and reasons of his current teaching career, it can be seen that he has violated his original ideals, has become stubborn, and yielded to the current stubborn feudal forces. D. The article tells readers through Lu Wei-fu’s experience that Lu Wei-fu’s life tragedy is the representative of the tragedy of countless intellectuals in that era, and behind the personal tragedy is the tragedy of the entire era.

Classical Chinese: Classical Chinese literature is substantially more than modern Chinese documents due to its conciseness and flexible grammar. Most classical Chinese words are expressed in a single character and therefore are not restrictively categorized into parts of speech: nouns can be used as verbs, adjectives can be used as nouns, and so on. For example, the character “东” only means “east” in modern Chinese. However, in the classical Chinese sentence, “顺流而东也” (advance eastward along the river), it actually means “advance eastward”. Classical Chinese also has distinguishing sentence patterns from nowadays, such as changing the order of characters and often dropping subjects and objects when a reference to them is understood.
Furthermore, an important sub-category in classical Chinese is poetry, which is typified by certain traditional poetic forms and rhythms. About 10% of the classical documents in NCR are poetry. Table 4 shows a famous classical Chinese poem from Song dynasty, which is particularly short and abstract in order to satisfy the poetic form of “相见欢” (Xiang-Jian-Huan). This poem describes a scene where the poet stands on a tower staring at the moon. However, in order to correctly understand the sentiment and meaning of the poem, the reader needs to leverage imagery and symbolism in classical Chinese culture (e.g., moon and autumn mean sadness) as well as the personal background of the poet (e.g., Li Yu was a captured emperor).

Modern Chinese: For the modern Chinese documents in NCR, in addition to the challenge due to longer average length, the associated questions also focus more on the high-level metaphors and the underlying thoughts, which often require non-trivial reasoning with historical and cultural knowledge. Table 4 shows an excerpt from a long article (the full document in NCR has about 2000 characters) written by a famous Chinese author, 路 (Lu Xun). The article describes a scene where the author unexpectedly met one of his old friends not seen for a long time and had a meal together. The associated question (Q3) primarily asks about the high-level thoughts expressed by the author, which has to be inferred from the entire article and requires the readers to have strong knowledge of the author’s personal experiences and the background of the era.

In addition to human annotation, we found that sentences in classical documents are usually shorter than in modern documents, which can be used as a simple criterion to categorize writing style. In detail, we split each document into sentences, compute the proportion of sentences with a length greater than 10, and denote it as $p(s>10)$. We plot the histogram of $p(s>10)$ in Figure 1 and 2. We remark that in validation and test sets, 98% of the classical documents have $p(s>10) < 0.2$ while 96% of the modern documents have $p(s>10) \geq 0.2$. This suggests an approximate yet effective categorization criterion, i.e., $p(s>10) < 0.2$, for classifying document style over the training set.

3.4 Question Type

To perform fine-grained analysis of the questions in NCR, we conduct human annotations for a sampled batch of 300 questions from the test set. The label of each question is on the consensus of 3 annotators. The questions are categorized into 5 different categories:

Matching questions ask about a fact that has been explicitly described in the document. The correct answer can be directly obtained from a short span or a single sentence from the document. Note that different options can refer to different spans.
Semantic questions ask about the semantic meanings of words or characters in a sentence, including antonym, synonymy, rhetoric and word segmentation. Q1 in Table 4 belongs to this category. We find that semantic questions are usually associated with classical Chinese documents.

Summary questions require the readers to understand all the facts stated throughout the entire document in order to choose a desired option, which presents a correct or incorrect fact summary.

Reasoning questions require the reader to perform non-trivial reasoning to infer a conclusion not explicitly stated in the document. A reasoning question in NCR often requires the reader to strong background knowledge and common sense. Q3 in Table 4 and Q1 in Table 6 belong to this category.

Sentiment questions ask about the implicit sentiment that the author expressed in the document. Sentiment questions in NCR typically require knowledge of imagery, symbolism and even the author’s sociopolitical perspective. Q2 in Table 4 belongs to this category.

The annotations are summarized in Table 5. We can observe that NCR has very few matching questions, which indicates that most NCR questions require non-trivial comprehension of the documents.

As a comparison, we also sampled a total of 600 questions from $C^3$ dataset, another exam-question-based MRC dataset, with 300 from $C^3_M$ and 300 from $C^3_D$ respectively, and annotated the sampled questions with the same standard and annotation process. The statistics are summarized in Table 5. We can observe that $C^3$ contains a large portion of matching questions and much fewer summary and sentiment questions. Despite the fact that NCR and $C^3$ has about the same percentage of reasoning questions, we remark that reasoning questions in NCR are significantly harder than those in $C^3$. This is not only because the documents in NCR are longer (so that fact extraction will be harder) but also because the reasoning questions in NCR typically require reasoning over a combination of document-level facts and background knowledge of both Chinese history and culture. To better illustrate the difference between NCR and $C^3$, we select two example reasoning questions in Table 6, with one from $C^3$ and one from NCR respective.

4 Experiment

In this section, we conduct quantitative study as well as human evaluation on our NCR dataset.

4.1 Baseline Methods

Trivial Baselines: We consider random guess and deterministic choice as trivial baselines. Deterministic choice always selects the same option ID.

Fine-Tuning of Pretrained Model: We utilize the MRC model architecture from the BERT paper [11] and perform fine-tuning with NCR. We consider the fine-tuned performance of 7 popular Chinese pretrained models, including BERT-Chinese [11], ERNIE [35], BERT-wwm, BERT-wwm-ext, RoBERTa-large-Chinese [6], MacBERT-base and MacBERT-large [5]. We also investigate the effectiveness of data augmentation by additionally collecting 6000 documents and 13K exam questions for China’s primary-school Chinese course. We combine these primary-school exam questions and the NCR training data as an augmented dataset to further boost the final performance. All the model and training details can be found in appendix B.

Competition: To examine the limit of current MRC methods, we organized a 3-month-long online competition using NCR with training and validation set released. Participants are allowed to use any open-access pretrained model or any open-access unlabeled data. Use of any external MRC

| Type       | NCR | $C^3_M$ | $C^3_D$ | $C^3$ |
|------------|-----|---------|---------|-------|
| Matching   | 0.33% | 47.0%   | 48.6%   | 47.8% |
| Semantic   | 20.0% | 1.7%    | 2.3%    | 2.0%  |
| Summary    | 38.3% | 15.3%   | 4.3%    | 9.8%  |
| Reasoning  | 28.3% | 29.3%   | 36.7%   | 33.0% |
| Sentiment  | 13.0% | 6.7%    | 8.0%    | 7.4%  |
which results in a 20% performance margin over the best baseline MRC model. Human performance will be released at our project website.

Table 7. Pretrained models are substantially better than trivial baselines. Particularly, the MacBERT-The performance of different baseline methods as well as human volunteers are summarized in Table 6: Examples of reasoning questions from NCR (top) and C3 (bottom) with Chinese (left) and English translation (right). We defer the NCR document to Table 2 in Appendix C. * denotes the correct option. In order to correctly answer Q1 from NCR, the reader not only needs to comprehend the texts in D1 describing the scene where Jun-tu meets the author’s mother but also needs to understand the cultural meaning of (madam).

| NCR                                      | D1: 故乡（节选）鲁迅                                      | D1: My old home (excerpt) Lu Xun | Q1: Select the incorrect analysis of middle-aged Jun-tu’s image. |
|------------------------------------------|----------------------------------------------------------|---------------------------------|---------------------------------------------------------------|
| Q1: 选出与下文段中有关中学生形象分析不恰当的一项  | A. 他称“我”“母亲为“老太太平”，表现了他有意讨好“我”母亲。*  | A. He called my mother the “madam”, which shows his intention to please my mother. *  |
|                                          | B. 他称自己少年时的好友为“老爷”，说明了他受封建等级观念影响很深。  | B. He called his former good friend “master”, which shows that he was deeply influenced by the feudal concept of hierarchy.  |
|                                          | C. 从他的对话中可以看出他的生活情况非常不好，他是当时下层人民形象的缩影。  | C. From his dialogue, we can see that the situation of his life is very bad, and he is the epitome of the image of the lower class at that time.  |
|                                          | D. 宏儿和水生就像当年的“我”和闰土一样，彼此之间没有隔阂。  | D. Hung-eth and the Shui-sheng are just like me and Jun-tu at that time, they are not estranged from each other.  |

| C3                                      | Q2. What is the most likely relationship between them?     |                                               |
|------------------------------------------|----------------------------------------------------------|------------------------------------------------|
| Q2: 他们最可能是什么关系？          | A. 夫妻  C. 老师和学生  D. 销售员和顾客*                   | A. Husband and wife  C. Teacher and student    |
|                                          | B. 同事                                                   | B. Colleagues                                    |

supervision is forbidden, since a portion of the test questions are possibly accessible online. This aims to prevent human annotations overlapping with our held-out data for a fair competition. There are a total of 141 participating teams and the best submission model with the highest test accuracy is taken as the competition model. The team is from an industry lab. They first pre-trained an XLNet-based model on a company-collected large corpus. For each question, they use an information retrieval tool Okapi BM25 to extract the most relevant parts from the document and then run this pre-trained model for answer selection based on the extracted texts.

Human Evaluation: We randomly sample 50 documents with 120 questions from the annotated subset of test data in NCR and send these questions to 30 sophomore college students. All the students are native Chinese speakers majored in computer science, who have not taken any Chinese course during the recent 2 years after college admission. Therefore, we believe they have reasonable reading comprehension capabilities close to typical China’s high school students. Each question is completed by at least 3 students to get an accurate performance estimation.

4.2 Results

4.2.1 Overall Performance

The performance of different baseline methods as well as human volunteers are summarized in Table 7. Pretrained models are substantially better than trivial baselines. Particularly, the MacBERT-large model produces the highest fine-tuning test accuracy of 0.4780 while the use of external data augmentation further boost the test performance to 0.5021, which suggest the effectiveness of data augmentation. The best model comes from the participants of the online competition. The best competition model achieves a test accuracy of 0.5985, which is much higher than the best fine-tuning model that authors obtained. However, the human volunteers achieves an average accuracy of 0.7917, which results in a 20% performance margin over the best baseline MRC model. Human performance is averaged per question over three annotators. To measure the inter-agreement, we calculate the agreement ratios. 60.83% of the questions have the same answer from all the 3 students, and 96.67% of the questions have the same answers from at least 2 students.

Unfortunately, the company disagreed to release their internal pretraining data but the final trained model will be released at our project website.
Table 7: Validation and test accuracy of different MRC methods on NCR. * Human evaluation is only conducted over a subset of test questions.

| Method               | Val.   | Test  |
|----------------------|--------|-------|
| Random Guess         | 0.2505 | 0.2511|
| Deterministic Choice | 0.2951 | 0.2613|
| BERT-Chinese         | 0.3930 | 0.3946|
| ERNIE                | 0.4445 | 0.4252|
| BERT-wwm             | 0.4310 | 0.4272|
| BERT-wwm-ext         | 0.4814 | 0.4451|
| MacBERT              | 0.4736 | 0.4597|
| RoBERTa-large-Chinese| 0.4666 | 0.4642|
| MacBERT-large        | 0.5051 | 0.4780|
| MacBERT-large (data aug.) | 0.5199 | 0.5021|
| Competition          | 0.5831 | 0.5985|

Table 8: Test accuracy of human and AI w.r.t. different document writing styles. FT is the best model finetuned by ourselves and CMP is the best competition model.

| Document Style          | Human  | FT     | CMP    |
|-------------------------|--------|--------|--------|
| Modern                  | 0.7489 | 0.5257 | 0.6151 |
| Classical (w/o poetry)  | 0.8632 | 0.4502 | 0.5671 |
| Poetry only             | 0.9167 | 0.3462 | 0.4179 |

4.2.2 Fine-Grained Analysis

We measure the performance of the MRC models, i.e., the best fine-tuned model (FT) and the competition model (CMP), and human on the test questions w.r.t. different factors, including writing style, document length and question type. We remark that the model accuracy are measured over the entire test set except the study on question type, which are over the annotated subset only.

Writing style: Table 8 illustrates the performance of MRC models and human on different document styles. The performance of AI significantly drops on classical Chinese documents, particularly on poetry. By contrast, we observe an opposite phenomena for humans, who perform the best on poetry, the most abstract form of classical Chinese literature. We remark that in China’s Chinese exams, questions on modern and classical texts may often have different examination focuses. Questions on classical Chinese are more biased towards understanding the meaning of characters, words, and sentences (see Table 4, Q1), which may not be intrinsically difficult for native Chinese students who have been well trained. While modern Chinese questions are often more general and require in-depth understanding of the entire document (see Table 4, Q3), which can be challenging for humans. This is because Chinese documents are much longer and reading and remembering facts under long documents can easily make a human distracted.

We also investigate whether a AI model purely trained on modern Chinese can directly transfer to classical texts. Since we do not have ground truth annotations on training set, we following the filtering process in section 3.3 as a rough categorization, which yields 4507 documents. We fine-tune the MacBERT-large on this filtered training set (without data augmentation) and show the testing results in Table 8. We can observe that the performance on classical documents drops significantly with classical documents filtered out, while the performance on modern documents remains unchanged. Hence, we argue that classical Chinese training data can be critical. This also suggests an important direction for improving Chinese pre-trained models.

Document Length: Table 10 summarizes the performance of human and AI on documents with various lengths. For classical Chinese documents, the most challenging documents are those shortest ones, which are most likely poetry. For modern articles, human performance drops for particularly long articles. For AI, the hierarchically-structured competition model performs the worst on relatively short articles while the fine-tuning model has the most difficulties in documents with a moderate length, i.e., from 300 to 600 characters. This suggests possible enhancements on model architecture.
Table 9: Test accuracy of MacBERT-large fine-tuned on complete and filtered training set.

| Training set | Modern (w/o poetry) | Classical (w/o poetry) | Poetry |
|--------------|--------------------|-----------------------|--------|
| Complete     | 0.5039             | 0.3871                | 0.3582 |
| Filtered     | 0.5060             | 0.2970                | 0.2836 |

Table 10: Test accuracy of human and AI w.r.t. different document lengths in both classical and modern Chinese. Human data are only presented when at least 5 documents can be collected from the annotated subset.

| Len.       | FT  | CMP  | Human |
|------------|-----|------|-------|
| [0,100]    | 0.3014 | 0.2192 | N/A |
| (100,300]  | 0.5505 | 0.5046 | 0.8333 |
| (300,600]  | 0.4162 | 0.6069 | 0.7333 |
| >600       | 0.4203 | 0.6116 | 0.8958 |

Moreover, although the performance gap between human and machine becomes less significant on particularly long documents, the accuracy of AI systems remains unsatisfying in general. We also want to remark that even those relative short documents in NCR are substantially longer and more sophisticated than existing datasets of the similar question types like C3.

Table 11: Test accuracy of human and AI w.r.t. different question types. We ignore matching questions since they are too infrequent.

| Question Type | Human | FT  | CMP  |
|---------------|-------|-----|------|
| Semantic      | 0.9047| 0.5000 | 0.5833 |
| Summary       | 0.7976| 0.5431 | 0.5603 |
| Reasoning     | 0.7179| 0.6000 | 0.6588 |
| Sentiment     | 0.6333| 0.5641 | 0.5128 |

**Question Type:** We also compare the performance of human and AI on different question types in Table 11. To our surprise, sentiment questions, which are the most challenging for humans, yield the smallest performance margin. While the largest gap is on semantic questions, which we believe the easiest for human. This indicates that a pretrained model is capable of capturing high-level sentiment information but still lacks word/character-level reasoning abilities. In addition, we also observed that the hierarchical competition model performs much worse than the fine-tuned model on sentiment questions, which suggests that running a retrieval model first may result in a loss of document-level global information which can be critical for sentiment analysis. This raises an open challenge for building more effective hierarchical models for processing long texts.

5 Conclusion

We present a novel Chinese MRC dataset, Native Chinese Reader (NCR), towards building native-level Chinese MRC models. Experiments on NCR indicate a significant gap between current MRC methods and human performance, which suggests great opportunities for future research, and, hopefully, pushes the frontier of Chinese natural language understanding.

**Remark:** Our dataset primarily consists of open-access exam questions or generated ones with teacher permission. All the documents are all public teaching materials. The released models are permitted by the online competition participants. Annotations and human evaluation results are completed by PhD students and interns that are all paid according to our institute regulation. Hence, we believe that our project will not lead to any legal or ethical issues.
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Supplementary Materials

A Project Statement

Dataset: All the materials are collected from online education materials or generated by qualified high-school teachers. All the documents are manually verified by the authors so that they all follow the China’s Chinese education standard, which does not contain any sensitive or inappropriate content for high school students. Language of the dataset is written by Mandarin Chinese in the simplified script per China’s education system regulation, including the classical Chinese literature. A detailed dataset instruction as well as a full dataset statement can be found at our project website, https://sites.google.com/view/native-chinese-reader/.

Accessibility: The dataset, related models as well as our human annotations are all kept at Google drive with links at our project website. All of our authors promise to keep the best efforts to keep them accessible. Our project website also has a detailed introduction to the online competition we organized. We include the requirement that all the participating teams should release their model in our competition agreement, so the release of models are permitted by all the participants.

Human Accuracy: Note that each problem requires non-trivial reasoning and reading a long article. To ensure the students treat the problems seriously, we leave this task as a bonus homework in our deep learning course for second-year college students at Tsinghua university. We also make sure that each student will be assigned no more than 10 articles for a reasonable workload. We also make sure each problem is at least answered by 3 students to get an accurate estimate.

Licence: This dataset is released under the CC BY-SA 4.0 license for general research purpose.

B Model Details

Our our code can be found at our project website and are released under the MIT license.

The baseline model of this article is based on pre-trained BERT, with some modifications made to the input layer and output layer.

The input of this task consists of three parts, which are articles, questions, and options. There are 2-4 options for each question, we fill the questions into 4 options. For convenience, we denote the document as D, the question as Q, and the answer options as $A_1$, $A_2$, $A_3$, $A_4$. For the $i$-th option, we construct an input sequence as \[\text{[CLS]} \ D \ \text{[SEP]} \ Q \ \text{[SEP]} \ A_i \ \text{[SEP]}\]. We truncated the documents by dropping the end part to ensure that the input sequences are not longer than the maximum positions of the pre-trained models.

We fine-tuned several commonly used Chinese pre-trained models as baselines, including Google’s BERT-chinese, Baidu’s ERNIE, HFL’s BERT-wwm, BERT-wwm-ext, and MacBERT \[^{[1]}{[6]}{[5]}\]. These 5 base models have a similar model structure with 12-layer of Transformer Encoder \[^{[38]}\] and 12 attention heads, the hidden size is 768. We also tried two large models, Roberta-large and MacBERT-large, both of which have 24 layers and 16 attention heads, hidden size is 1024.

We compared the results of the 7 baseline models in section 4.2. The BERT-based model will generate a 768-dimensional hidden state for each token of the input sequence. We take the output vector of [CLS] token and map it to a one-dimensional logit through a trainable vector. The logit means to what extent $A_i$ may be the correct option. In the same way, we can get the logit of the other 3 options, and employ Softmax to compute the probability of the 4 options. The training objective is to minimize the four-class cross-entropy. In the inferring stage, we just select the option with the highest probability.

All baseline models are trained on 8 Tesla V100 GPU with 32G memory. We set the same hyper-parameters for all base models and large models, separately. For base models, we set epoch as 10, batch size as 64, learning rate as 5e-6. For large models, we set epoch as 10, batch size as 32, learning rate as 2e-6. Regarding data augmentation, we first use the primary school dataset for 5 epoch and then turn to NCR dataset for 5 epochs. All the codes are implemented based on Hugging
Face transformers \cite{40}. It takes about 5 minutes to run one epoch for base model and 20 minutes for large model.

The best competition model applied a similar structure. However, they cut the document into several chunks and utilize an information retrieval tool Okapi BM25 to extract the most relevant chunk according to the question as to the actual passage, which reduce the super long document to a reasonable length. The document segment, question and the options are then input to XLNet-based classifier to predict the correct answer. Compared to our baseline model, their IR tool can effectively keep the most informative segment of the document while reducing to a reasonable sequence length.

C Surface pattern in options

We investigate some special patterns and predict the answer based on these patterns. In Table \ref{12} we focus on several absolute quantifiers including “只能” (“can only”), “必然”, “必定”, “必须”, (“must”), “只可能”, (“may only”), “绝对” (“absolute”). For each pattern, We keep the questions where only one option contains this pattern or only one option doesn’t contain this pattern and choose the special option as the predicted answer. The results are aggregated from the whole dataset with a total of 20477 questions. “combination” represents a combination pattern that including all the aforementioned patterns. We can observe that there are not many questions meeting the requirements, and the accuracy is indeed higher than random but also still very low.

Table 12: Predict the answer based on special patterns. The results are aggregated from the whole dataset with a total of 20477 questions. “combination” represents a combination pattern that including all the aforementioned patterns.

| Pattern | 只能 | 必然 | 必定 | 必须 | 只可能 | 绝对 | combination |
|---------|------|------|------|------|--------|------|-------------|
| # Question |
| 291 | 308 | 52 | 658 | 5 | 101 | 1296 |
| Accuracy |
| 0.3470 | 0.2825 | 0.3077 | 0.2903 | 0 | 0.2673 | 0.2994 |

D Additional Examples

Limited by space, we show some additional examples in this section. The example in Table \ref{13} is a classical Chinese with a question of sentiment. It described a dialogue between the author and his friend, which reflects the author’s inner contradictions and complex feelings. The author quoted predecessors’ (曹操 Cao Cao) verses and the allusions to the Battle of Chibi (赤壁之战) to express his feelings. The question requires the readers to analyze the document from different perspectives, including the author’s sentiment, writing techniques, and rhyme.

In Table \ref{14} we present the document of question in Table 6 of the main paper with its English translation, which is a excerpt from Lu Xun’s famous article My old home (sometimes it is translated to Hometown)
篇文章的句子和理解分析。理解分析的句子是：

Q 下列对文段的理解和分析不正确的—项是
A. 作者通过多组对比，揭示出“尽”的原因。文中既写了曹孟德一世之雄的兴亡之悲，也写了由宇宙无穷与人生短暂的对比所生之悲，还写了现实与理想的矛盾所生之悲。
B. 作者以江水明月作比，说明世间万物和人生既有变的一面，也有不变的一面，阐述了自然万物变化与永恆的哲理，表现出了作者无奈消极的人生态度。
C. 作者以江水明月作比，说明世间万物和人生既有变的一面，也有不变的一面，阐述了自然万物变化与永恆的哲理，表现出了作者无奈消极的人生态度。
D. 文段句式繁散结合，结构、句法、韵律都相对自由，大量对偶句的使用使文章参差错落，整齐简约，极富声韵之美。

Q Choose one from the following options which is incorrect understanding and analysis of the document.
A. The content of the dialogue between the author and his friend is actually a reflection of the author’s inner contradictions and complex feelings. The use of question-and-answer methods can make the writing ups and downs, swaying, and fully demonstrate the author’s thoughts and feelings.
B. The author reveals the cause of “sorrow” through multiple groups of comparisons. The article not only writes the tragedy of the rise and fall of Cao Cao, but also the tragedy born from the contrast between the infinity of the universe and the short-lived life, and the tragedy born from the contradiction between reality and ideal.
C. The author uses the river, water and the moon as a comparison to illustrate that everything in the world and life has both a changeable side and an unchanging side. He expounds the change and eternal philosophy of all things in nature, showing the author’s helpless and passive attitude towards life. *
D. The paragraphs and sentences are combined with parallel and prose, and the structure, syntax, and rhythm are relatively free. The use of a large number of antithetical sentences makes the article jumbled, neat and simple, and full of beauty of rhyme and rhyme.

Table 13: An example of document in Classical Chinese with questions (left) and English translation (right), * is the correct option. And this question is an example of sentiment
故 乡 (节 选) 我 这 时 很 兴 奋，但 不 知 道 怎 么 说 才 好，只 是 说："阿！闰土哥，——你 来 了？……" 我 接 着 便 有 许 多 话，要 求 连 珠 一 般 涌 出： 角 鸡， 童 鱼 儿， 贝 壳， 狐…… 但 又 总 体 被 什 么 所 定 似， 单 在 脑 里 回 旋， 咕 咕 不 出 口 外 去。他 站 住 了， 脸 上 现 出 欢 喜 和 凄 凉 的 神 情； 开 着 嘴 巴， 却 没 有 作 声。他 的 态 度 终 于 恭 敬 起 来 了， 分 明 的 叫 道："老 爷！……" 我 似 乎 打 了 一 个 寒 嚳； 我 就 知 道， 我 们 之 间 已 经 有 了 一 层 可 悲 的 障 碍 存 在。也 说 不 出 话。他 回 过 头 去 说，"水 生， 给 老 爷 蹲 儿，" 便 拖 出 躲 在 背 后 的 孩 子 来， 这 正 是 一 个 十 年 前 的 闰 土， 只 是 黄 瘦 些， 爪 子 上 没 有 银 球 罢 了。"这 是 第 五 个 孩 子， 没 有 见 过 世 面， 躲 躲 闪 闪……" 母 亲 和 宏 兄 下 楼 来 了， 他 们 大 约 也 听 到 了 声 音。"老 太 太。 信 是 早 收 到 了， 我 实 在 喜 欢 的 了 不 知 道 老 爷 回 来……" 闰 土 说。"阿， 你 怎 的 这 样 客 气 起 来。 你 们 先 前 不 是 哥 弟 称 呼 么？ 还 是 照 旧： 闰 土，" 母 亲 高 兴 的 说， "阿 呀， 老 太 太 真 是…… 这 正 是 什 么 规 矩。 那 时 是 孩 子， 不 知 事，……" 闰 土 说 着， 又 叫 水 生 上 来 打 拱， 那 孩 子 却 害 羞， 紧 紧 的 只 贴 在 他 背 后。"他 就 是 水 生？ 第 五 个？ 都 是 他 人， 怕 生 也 难 怪 的； 还 是 宏 儿 和 他 去 走 走，" 母 亲 说。 宏 兄 听 这 话， 稍 微 一 招 水 生， 水 生 却 松 松 爽 爽 同 他 一 路 出 去 了。 母 亲 叫 宏 兄 坐， 他 迟 疑 了 一 回， 终 究 就 了 坐， 将 长 烟 管 靠 在 桌 旁。

Translation:

My old home (excerpt) Lu xun Delighted as I was, I did not know how to express myself, and could only say: "Oh! Jun-tu—so it's you..." After this there were so many things I wanted to talk about, they should have poured out like a string of beads: woodcocks, jumping fish, shells, zha... But I was tongue-tied, unable to put all I was thinking into words. He stood there, mixed joy and sadness showing on his face. His lips moved, but not a sound did he utter. Finally, assuming a respectful attitude, he said clearly: "Master!..." I felt a shiver run through me; for I knew then what a lamentably thick wall had grown up between us. Yet I could not say anything. He turned his head to call: "Shui-sheng, bow to the master." Then he pulled forward a boy who had been hiding behind his back, and this was just the Jun-tu of twenty years before, only a little paler and thinner, and he had no silver necklace. "This is my fifth," he said. "He's not used to company, so he's shy and awkward." Mother came downstairs with Hung-erh, probably after hearing our voices. "I got your letter some time ago, madam," said Jun-tu. "I was really so pleased to know the master was coming back..." "Now, why are you so polite? Weren't you playmates together in the past?" said mother gaily. "You had better still call him Brother Hsun as before." "Oh, you are really too... What bad manners that would be. I was a child then and didn't understand." As he was speaking Jun-tu motioned Shui-sheng to come and bow, but the child was shy, and stood stock-still behind his father. "So he is Shui-sheng? Your fifth?" asked mother. "We are all strangers, you can't blame him for feeling shy. Hung-erh had better take him Out to play." When Hung-eth heard this he went over to Shui-sheng, and Shui-sheng went out with him, entirely at his ease. Mother asked Jun-tu to sit down, and after a little hesitation he did so; leaning his long pipe against the table.

Table 14: The document (top) of example in Table 6 and its English translation. (bottom)