Abstract

Existing question answering systems can only predict answers without explicit reasoning processes, which hinder their explainability and make us overestimate their ability of understanding and reasoning over natural language. In this work, we propose a novel task of reading comprehension, in which a model is required to provide final answers and reasoning processes. To this end, we introduce a formalism for reasoning over unstructured text, namely Text Reasoning Meaning Representation (TRMR). TRMR consists of three phrases, which is expressive enough to characterize the reasoning process to answer reading comprehension questions. We develop an annotation platform to facilitate TRMR’s annotation, and release the \( R^3 \) dataset, a Reading comprehension benchmark Requiring Reasoning processes. \( R^3 \) contains over 60K pairs of question-answer pairs and their TRMRs. Our dataset is available at: http://anonymous.1

1 Introduction

The ability to understand and perform reasoning over natural language is an ultimate goal of artificial intelligence. The machine reading comprehension task provides a quantifiable and objective way to evaluate systems’ reasoning ability, where an answer is sought for question given one or more documents. To this end, many high-quality and large-scale reading comprehension datasets have been released (Rajpurkar et al., 2016; Yang et al., 2018; Reddy et al., 2019; Dua et al., 2019), which lay a good data foundation for QA systems in different scenarios. In turn, various neural models have also emerged recently (Seo et al., 2017; Yu et al., 2018; Huang et al., 2018; Hu et al., 2019), which approach or even surpass human-level performance.

Nonetheless, we may overestimate the ability of current QA systems to understand natural language (Sugawara et al., 2018). Recent analysis suggests that current models can predict gold answers even when original questions are replaced with nonsensical questions (Feng et al., 2018), and that higher accuracy does not ensure more robustness or generalization (Jia and Liang, 2017; Wallace et al., 2019). We argue that one root cause of these problems is that most current QA tasks only require models to predict gold answers. But metrics, which only depend on answers, are hard to capture our utmost desiderata of these systems, i.e., the ability to understand and reason over natural language (Lipton, 2018; Arrieta et al., 2019). Inspired by human beings, giving the reasoning process shows the examinee’s abilities more elaborately and comprehensively than just giving the final answer. We argue it is more accurately evaluate systems capabilities by requiring them to explicitly give the reasoning process.

In this work, we propose a novel task of reading comprehension over unstructured text, in which a model is required to provide final answers and reasoning processes to demonstrate its ability to understand natural language. To this end, we construct a large-scale dataset \( R^3 \), a Reading comprehension benchmark Requiring Reasoning processes. \( R^3 \) contains 60k QA pairs, each of which is labeled with an reasoning process.

Annotating reasoning processes precisely across diverse problems is a challenging task even for humans. To alleviate the difficulty and reduce the cost, we choose to annotate the existing dataset DROP (Dua et al., 2019), which requires Discrete Reasoning Over the content of Paragraphs. To do well in DROP, a system must resolve references in a question, perhaps to multiple input positions, and perform discrete reasonings over them (such as addition, counting, ...
Passage
[1] The Rams drew first blood in the first quarter with a 48-yard field goal from Greg Zuerlein to take a 3-0 lead for the only score of that quarter. [2] The Rams responded with a 29-yard field goal from Zuerlein as they came up within a point 7-6 before on the Lions' next possession. [3] The Lions then responded with Jason Hanson kicking a 41-yard field goal to shorten the Rams’ lead to 13-10 at halftime.

Question: How many field goals over 40 yards were made?

Problem Parsing
count(filter(over 40 yards, field goals))

Information Retrieval
1. field goals -> 48
2. field goals -> 29
3. field goals -> 41

Answer Derivation
filter
1. 48 > 40
2. 29 < 40
3. 41 > 40
answer: {48, 41}
count
1. {48, 41}
answer: 2

Figure 1: An example from $R^3$. Each passage-question pair in $R^3$ is annotated with text reasoning meaning representation (TRMR). The corresponding TRMR is presented, with text spans of passages or questions involved in reasoning colored in orange and in blue for clarity.

or sorting). These operations force models to understand comprehensively the content of paragraphs. Furthermore, we propose a formalism for reasoning over unstructured text, namely Text Reasoning Meaning Representation (TRMR), and develop a software to facilitate the annotation task at large scale.

TRMR is inspired by the problem-solving process of human reading comprehension. When a question needs to be answered, humans first determine the steps required according to the information of passages and questions; then find out the information elements required for the solution; finally, the elements are processed according to the aforementioned determined steps to derive the final answer. An example of TRMR is shown in Figure 1. Formally, each TRMR contains three steps:

1. Problem Parsing converts questions into atomic operation sequences, where each atomic operation answers sub-questions of the original questions. For the question “How many field goals over 40 yards were made?” in Figure 1, it is converted into two predefined atomic operations: “filter” and “count”.

2. Information Retrieval retrieves the items needed to answer those simple questions. For above example, the yards of field goals are retrieved by this step.

3. Answer Derivation deduces the final answer according to the reasoning process of “problem decomposition”, the retrieved items of “information retrieval” and/or answers given by intermediate operations.

Based on the above formalism, we annotate DROP to construct a large-scale reading comprehension dataset, namely $R^3$. We make DN publicly available at http://anonymous.

2 Text Reasoning Meaning Representation

In this section, we define the Text Reasoning Meaning Representation (TRMR). TRMR aims to characterize the reasoning process when the system answers questions over diverse natural language: determine the problem-solving steps according to passages and questions, find the information needed to answer the questions, and perform operations or reasoning to arrive at the final answer.

TRMR Definition Formally, given a passage $P = [w_1, w_2, \cdots, w_{n-1}, w_n]$ and a question $Q = [w_1, w_2, \cdots, w_{l-1}, w_l]$, its TRMR contains three parts: problem parsing, information retrieval and answer derivation. The “problem parsing” consists of some predefined operations and the arguments required for these operations, formed as $op_1(op_2(arg_1, arg_2, \cdots), op_3(arg_1, arg_2, \cdots), \cdots)$. Table 1 shows these pre-defined operations. For simplicity, we restrict these arguments to spans of the question or operations. Next, “information retrieval” presents the passage spans needed to answer questions, formed as $arg_1 \rightarrow span_1, arg_2 \rightarrow span_2, \cdots$, where $span_1, span_2, \cdots$ are spans from passages. Finally, “answer derivation” details how to perform operations on the retrieved information based on different operations from “problem parsing”. An example of TRMR is shown in Figure 1.

3 Data Collection

In this section, our annotation pipeline for generating $R^3$ is presented, which consists of three phases. First, we collection question-answer pairs
| Type   | Template / Signature | Question                                                                 | Problem Parsing       |
|--------|----------------------|--------------------------------------------------------------------------|-----------------------|
| more   | more($S_1$, $S_2$)   | How many more people were there than households?                         | more(people, households) |
| more-select | more-select($S_1$, $S_2$) | Who has more people in it, Iraq or Iran?                                 | more-select(Iraq, Iran) |
| less   | less($S_1$, $S_2$)   | How many less households were there compared to housing units?           | less(households, housing units) |
| less-select | less-select($S_1$, $S_2$) | Which gender group is smaller: females or male?                         | less-select(females, male) |
| cu     | cu($S_1$)            | How many percent of people were not white?                               | cu(white)             |
| completion-more | completion-more($S_1$) | How many points were the Bears winning by at halftime?                  | completion-more(Bears) |
| completion-less | completion-less($S_1$) | How many points did the Lions lose the game by?                         | completion-less(Lions) |
| after  | after($S_1$, $S_2$)  | How many days after the stamps arrived were they placed on sale?        | after(stamps arrived, they placed on sale) |
| after-select | after-select($S_1$, $S_2$) | What happened second: Poeymirau and Freydenberg launched attacks or significant riots? | after(Poeymirau and Freydenberg launched attacks, significant riots) |
| before | before($S_1$, $S_2$) | How many days before the Italians invaded Trieste was the fleet of the Austro-Hungarians destroyed? | before(Italians invaded Trieste, fleet of the Austro-Hungarians destroyed) |
| before-select | before-select($S_1$, $S_2$) | Which happened first, the Battle of Vittorio Veneto or the Armistice of Villa Giusti? | before-select(Battle of Vittorio Veneto, Armistice of Villa Giusti) |
| sum    | sum($S_1$, $S_2$, ...) | How many percents of the racial makeup of the county was either Asian or Pacific Islander? | sum(Asian, Pacific Islander) |
| count  | count($S_1$)         | How many times did Manning throw to Clark?                               | count(times did Manning throw to Clark) |
| time-span | time-span($S_1$)       | How many years did Micheal Tippets The Knot Garden use a classical guitar? | time-span(Micheal Tippets The Knot Garden use a classical guitar) |
| span   | span($S_1$)          | What event finalized the Lordship of Dernbach being transferred to nassau? | span(finalized the Lordship of Dernbach being transferred to nassau) |
| sort   | sort($S_{superlative}$, $S_1$) | Which racial group made up the smallest percentage of the population? | sort(smallest, racial group) |
| filter | filter($S_{condition}$, $S_1$) | Which groups in percent are larger than 21%?                           | filter(larger than 21%, groups) |

Table 1: The predefined operators in TRMR’s “proble parsing”. 

from existing dataset DROP, a reading comprehension benchmark requiring discrete reasoning over paragraphs. Second, we crowdsource the TRMR annotation of these question-answer pairs. Finally, we validate the worker annotations in order to maintain their quality.

**Question-Answer Collection** The passages and questions in $R^3$ are all based on training and validation sets in the existing dataset DROP, while the test set portion of this dataset is hidden. To encourage annotators to ask complex questions, passages from DROP generally have a narrative sequence of events, and often involve many numbers. They are usually National Football League (NFL) game summaries and history articles. As for the quality of questions in DROP, (Dua et al., 2019) present to works with example questions and workers are only allowed to submit questions that a neural QA model could not solve. By these settings, questions in DROP are generally difficult, which usually requires complex linguistic understanding and discrete reasoning. We allow interested readers to read Dua et al. (2019).

**TRMR annotation** Annotation TRMRs precisely across diverse problems can be a challenging and time consuming tasks for humans. To facilitate annotation and standardize the annotation process, we design and develop an annotation platform. Our platform has the following properties: (a) corresponding to TRMR, the system frames annotation processes into three steps and enforces the annotators to perform annotation step by step. (b) to reduce human input errors and improve annotation efficiency, it automatically calculate the position of spans in questions or passages and generate (possible) answer derivation steps. (c) it employs quality control strategies.

**Annotation Platform** The annotators are provided with a passage, a question and an answer. They are required to annotate the corresponding TRMR, i.e. “problem parsing”, “information retrieval” and “answer derivation” in turn.

- **Problem Parsing** The annotators are instructed to parse questions into reasoning processes according passages and questions. To prevent having noisy parsing, they can only choose operations from the pre-defined operation sets or select spans in questions as valid arguments.

- **Information Retrieval** After parsing the questions, the list of arguments of operations, i.e., spans in question are presented to annotators. They need to retrieve information from the passage to arrive at answers. Similarly, they are only allowed to annotate the text spans in the passage, rather than manually entering information to avoid errors.

- **Answer Derivation** To improve the annotation efficiency, the system automatically generate the “answer derivation” part based on existing problem parsing and retrieved information. Annotators can make modifications on this basis to reduce manual error.

**Worker Validation** To ensure worker quality, we initially train and dynamically evaluate annotators through a collection of quality-control strategies. First, we train our annotators to ensure they understand our annotation principles and how to use the annotation platform. In addition, they are evaluated through a pre-defined set of test questions. If their accuracy does not reach a certain threshold, they have to be retrained to continue their annotation.

To further evaluate the quality, we conduct random validation to check whether the TRMR annotation are valid or not. According to this strategy, at least 2 out of 3 validators should assign the TRMR annotation as valid for it to be selected. The validation accuracy is 95.92% across different operations.

4 Related Work

**Question Answering Dataset** In recent years, there have been more and more large-scale reading comprehension datasets proposed. Among them, the most well-known is the Stanford Question Answering Dataset (SQuAD) (Rajpurkar et al., 2016), which is constructed based on Wikipedia and through crowdsourcing annotation. Recently, more data sets have been proposed to evaluate the performance of QA systems in specific scenarios. CoQA (Reddy et al., 2019) and QuAC (Choi et al., 2018) are introduced to evaluate how reading comprehension models aggregate information and answer questions in the context of a conversation. Zheng et al. (2019) propose a large-scale Chinese reading comprehension dataset, ChiD, to study the comprehension a unique language phenomenon in Chinese. Besides, recent works like
HotpotQA (Yang et al., 2018), RACE (Lai et al., 2017), WikiHop (Welbl et al., 2018), etc., require the ability of multi-step reasoning. In addition, some datasets require models that can handle common sense (Zhang et al., 2018; Talmor et al., 2019), understand multiple languages (Cui et al., 2019), or have the ability to apply specialized knowledge (Zhong et al., 2019). The emergence of these data sets lays the data foundation for the design of data-hungry models, such as neural networks, and also provides a public benchmark for evaluating QA systems in different scenarios.

In contrast, our data set is annotated based on DROP (Dua et al., 2019), which focuses on examining the numerical reasoning capabilities under complex language phenomena. Besides, unlike most previous work, which uses metrics such as EM or F1 to evaluate the final answer, we require the model to explicitly output the reasoning process in order to force them better understanding the document.

**Explainable Question Answering** Although neural network models have achieved promising results on many reading comprehension tasks (Seo et al., 2017; Yu et al., 2018; Huang et al., 2018; Hu et al., 2019), some research work points out that we may overestimate the ability of models to understand or reason. Jia and Liang (2017) shows that reading comprehension models are susceptible to adversarial samples. Kaushik and Lipton (2018) have pointed out that using only passages or questions, reading comprehension models can perform surprisingly well. Min et al. (2019a) reveals that even highly compositional questions can be answered with a single hop if they target specific entity types, or the facts needed to answer them are redundant. These results show that it is difficult to construct a reading comprehension dataset that really requires multi-step inference and accurately evaluate the performance of the model.

Since our work is based on the DROP dataset, which requires models to perform symbolic reasoning on numbers, we argue that it is easier to avoid models to solve problems by matching. However, DROP only judges the performance of the model based on the metrics of F1/EM, which may be not enough to fully describe the model’s understanding or reasoning ability (Arrieta et al., 2019). Therefore, when evaluating models, we not only ask them to give the final answer, but more importantly, to express the intermediate reasoning process explicitly.

**Question Decomposition** Multi-step reasoning in reading comprehension has been a key challenge in QA. To solve this challenge, some models decompose a compositional question into simpler sub-questions that can be answered by off-the-shelf single-hop reading comprehension models (Talmor and Berant, 2018; Min et al., 2019b; Perez et al., 2020). This decomposition technique can not only improve model performance, but also provide some explainable evidence for its decision making in the form of sub-questions. Most recently, Wolfson et al. (2020) introduce a Question Decomposition Meaning Representation (QDMR) for questions and release the BREAK dataset. Our annotation data (problem analysis part) can be easily converted into a problem decomposition format. Different to BREAK, we also provide inference processes that reach the final answers.

## 5 Conclusion

In this work, we present $R^3$, a large-scale reading comprehension dataset in which a QA system is required to give answers to questions over diverse natural language, but also needed to present the reasoning processes. We hope this dataset can facilitating the development of explainable QA systems.

## References

Alejandro Barredo Arrieta, Natalia Díaz Rodríguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, Salvador García, Sergio Gil-Lopez, Daniel Molina, Richard Benjamins, Raja Chatila, and Francisco Herrera. 2019. Explainable artificial intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI. *CoRR*, abs/1910.10045.

Eunsol Choi, He He, Mohit Iyyer, Mark Yatskar, Wen-tau Yih, Yejin Choi, Percy Liang, and Luke Zettlemoyer. 2018. Quac: Question answering in context. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 2174–2184.

Yiming Cui, Wanxiang Che, Ting Liu, Bing Qin, Shijin Wang, and Guoping Hu. 2019. Cross-lingual machine reading comprehension. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International
Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 1586–1595.

Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. 2019. DROP: A reading comprehension benchmark requiring discrete reasoning over paragraphs. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 2368–2378.

Shi Feng, Erica Wallace, Alvin Grissom II, Mohit Iyyer, Pedro Rodriguez, and Jordan L. Boyd-Graber. 2018. Pathologies of neural models make interpretation difficult. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 3719–3728.

Minghao Hu, Yuxing Peng, Zhen Huang, and Dongsheng Li. 2019. A multi-type multi-span network for reading comprehension that requires discrete reasoning. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 1596–1606.

Hsin-Yuan Huang, Chenguang Zhu, Yelong Shen, and Weizhu Chen. 2018. Fusionnet: Fusing via fully-aware attention with application to machine comprehension. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings.

Robin Jia and Percy Liang. 2017. Adversarial examples for evaluating reading comprehension systems. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP 2017, Copenhagen, Denmark, September 9-11, 2017, pages 2021–2031.

Divyansh Kaushik and Zachary C. Lipton. 2018. How much reading does reading comprehension require? A critical investigation of popular benchmarks. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 5010–5015.

Guokun Lai, Qizhe Xie, Hanxiao Liu, Yiming Yang, and Eduard H. Hovy. 2017. RACE: large-scale reading comprehension dataset from examinations. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP 2017, Copenhagen, Denmark, September 9-11, 2017, pages 785–794.

Zachary C. Lipton. 2018. The mythos of model interpretability. Commun. ACM, 61(10):36–43.

Sewon Min, Eric Wallace, Sameer Singh, Matt Gardner, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2019a. Compositional questions do not necessitate multi-hop reasoning. In Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28-August 2, 2019, Volume 1: Long Papers, pages 4249–4257.

Sewon Min, Victor Zhong, Luke Zettlemoyer, and Hannaneh Hajishirzi. 2019b. Multi-hop reading comprehension through question decomposition and rescoring. In Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28-August 2, 2019, Volume 1: Long Papers, pages 6097–6109.

Ethan Perez, Patrick Lewis, Wen-tau Yih, Kyunghyun Cho, and Douwe Kiela. 2020. Unsupervised question decomposition for question answering. CoRR, abs/2002.09758.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100, 000+ questions for machine comprehension of text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, EMNLP 2016, Austin, Texas, USA, November 1-4, 2016, pages 2383–2392.

Siva Reddy, Danqi Chen, and Christopher D. Manning. 2019. Coqa: A conversational question answering challenge. TACL, 7:249–266.

Min Joon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. 2017. Bidirectional attention flow for machine comprehension. In 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings.

Saku Sugawara, Kentaro Inui, Satoshi Sekine, and Akiko Aizawa. 2018. What makes reading comprehension questions easier? In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 4208–4219.

Alon Talmor and Jonathan Berant. 2018. The web as a knowledge-base for answering complex questions. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers), pages 641–651.

Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. 2019. Commonsenseqa: A question answering challenge targeting commonsense knowledge. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 4149–4158.
Eric Wallace, Yizhong Wang, Sujian Li, Sameer Singh, and Matt Gardner. 2019. Do NLP models know numbers? probing numeracy in embeddings. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 5306–5314.

Johannes Welbl, Pontus Stenetorp, and Sebastian Riedel. 2018. Constructing datasets for multi-hop reading comprehension across documents. TACL, 6:287–302.

Tomer Wolfson, Mor Geva, Ankit Gupta, Matt Gardner, Yoav Goldberg, Daniel Deutch, and Jonathan Berant. 2020. Break it down: A question understanding benchmark. CoRR, abs/2001.11770.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W. Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. 2018. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 2369–2380.

Adams Wei Yu, David Dohan, Minh-Thang Luong, Rui Zhao, Kai Chen, Mohammad Norouzi, and Quoc V. Le. 2018. Qanet: Combining local convolution with global self-attention for reading comprehension. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings.

Sheng Zhang, Xiaodong Liu, Jingjing Liu, Jianfeng Gao, Kevin Duh, and Benjamin Van Durme. 2018. Record: Bridging the gap between human and machine commonsense reading comprehension. CoRR, abs/1810.12885.

Chujie Zheng, Minlie Huang, and Aixin Sun. 2019. Chid: A large-scale chinese idiom dataset for cloze test. In Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers, pages 778–787.

Haoxi Zhong, Chaojun Xiao, Cunchao Tu, Tianyang Zhang, Zhiyuan Liu, and Maosong Sun. 2019. JEC-QA: A legal-domain question answering dataset. CoRR, abs/1911.12011.