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HRCA+: An Advanced Machine Reading Comprehension Method

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ABSTRACT

Multiple-choice question answering (MCQA) for machine reading comprehension (MRC) is challenging. It requires a model to select a correct answer from several options related to text passages or dialogue. To select the correct answer, such models must have the ability to understand natural languages, comprehend textual representations, and infer the relationship between options, questions, and passages.

Previous models calculated representations between passages and question-option pairs, thereby ignoring the effect of other relation pairs. This study proposes a human reading comprehension attention (HRCA) model and a passage-question-option (PQO) matrix-guided HRCA model called HRCA+.

The HRCA model updates the information learned from the previous relation pair to the next relation pair. HRCA+ utilizes the information and the interior relation between every two parts in a passage, a question, and the options.

Our proposed method outperforms other state-of-the-art methods. **On the Semeval-2018 Task 11 dataset, our proposed method improved accuracy levels from 95.8% to 97.2%, and on the DREAM dataset, it improved accuracy levels from 90.4% to 91.6% without extra training data, from 91.8% to 92.6% with extra training data.**

OBJECTIVES

Machine reading comprehension (MRC) is a challenging task that involves training a model to comprehend the meaning of documents. MRC has attracted significant attention in the field of artificial intelligence, and it was developed to measure how deeply a machine understands context (Liu et al., 2019a).

MRC requires a model to answer questions based on a specific context. Researchers are expected to train a model to orientate a passage and question pair towards the answer. In this study, we tackle the multiple-choice question answering task.

Multiple-choice tasks require selecting one correct answer among multiple options according to a passage. An example is shown in **Table**. 1

Table 1: An example of multiple-choice MRC task

Passage (dialog form):
W: Tom, look at your shoes. How dirty they are! You must clean them.
M: Oh, mum, I just cleaned them yesterday.
W: They are dirty now. You must clean them again.
M: I do not want to clean them today. Even if I clean them today, they will get dirty again tomorrow.
W: All right, then.
M: Mum, give me something to eat, please.
W: You had your breakfast in the morning, Tom, and you had lunch at school.
M: I am hungry again.
W: Oh, hungry? But if I give you something to eat today, you will be hungry again tomorrow.
Q1 Why did the woman say that she wouldn't give him anything to eat?
A. Because his mother wants to correct his bad habit. ✓
B. Because he had lunch at school.
C. Because his mother wants to leave him hungry.

Previous methods combine questions and options as the entire textual input for their models. **However, candidate options are not always guaranteed to make sense when combined with the question**.

In addition, previous methods consider the relationships between passages, questions, and the candidate options separately. **However, the relationships between every two parts of a passage, a question, and the candidate options are not independent.**

Novelty

The problem of incomplete correspondence

For example, a common option might be "None of the above choices." Combining such an option with a question affects a model's performance.

Previous Method	HRCA
[(Question + Option) pair] Combine **Q** and **O** to a pair (Jin et al., 2020), ignore the incomplete correspondence	**[Question + Option]** Left **Q** and **O** separately, resolved cases where **Q** and **O** may not match

The helping-relationship problem

Determining the relationship between a question and the options helps in the inference of the relationship between a passage and a question, and this aspect applies to other differently related pairs.

Previous Method	HRCA
[Relation pair | Relation pair] Ignore the inter-relation (Zhu et al., 2020)	$\left[\textbf{Relation pair} \xrightarrow{\textit{update}} \textbf{Relation pair}\right]$ Updates information to the next process

PROPOSED METHOD

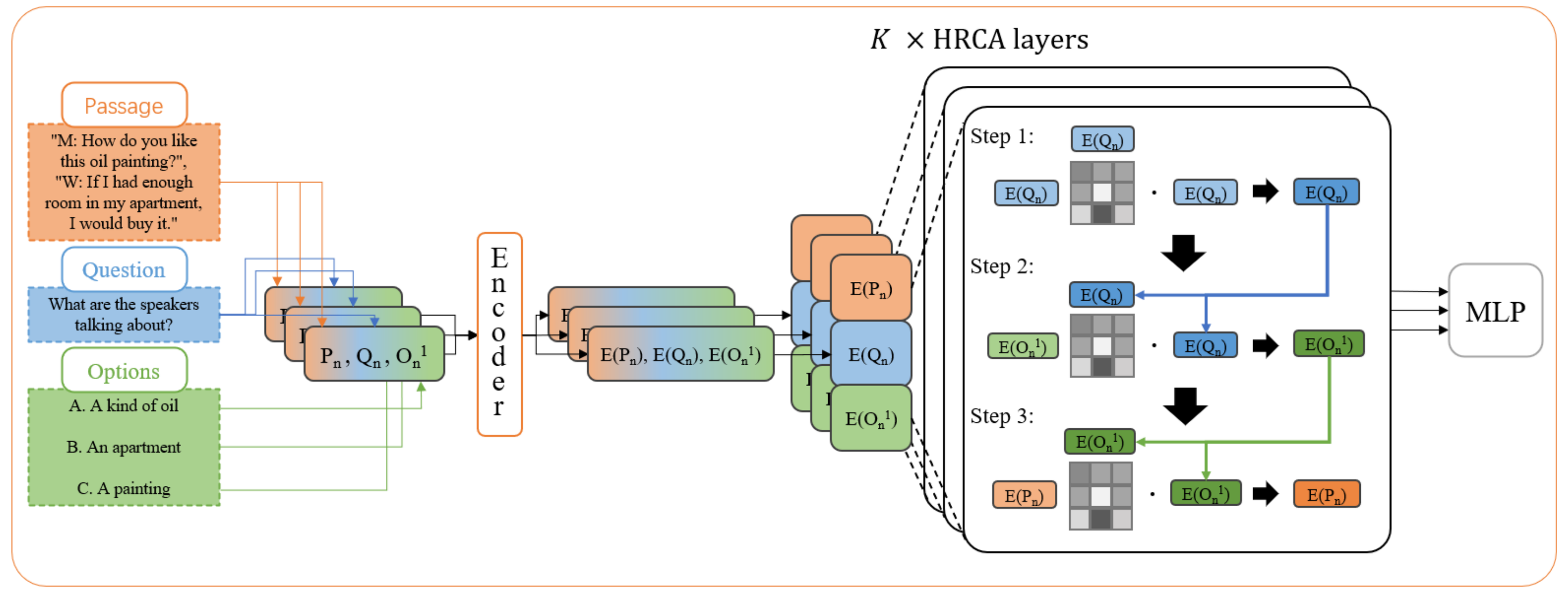

Figure 1: Architecture of HRCA model.

Step 1: We perform multi-head self-attention on the question. This step is aimed to allow the model to confirm the question again.

Step 2: We perform multi-head attention on the option and the updated question presented in Step 1. This step is executed to simulate the understanding of the options after confirming the question.

Step 3: We perform multi-head attention on the passage and the updated options presented in Step 2. This step allows for the model to comprehend the passage with the question and the options after understanding the options.

PQO-Matrix

	Passage	Question	Option
Passage	Self	PtoQ	PtoO (Step 3)
Question	QtoP	Self (Step 1)	QtoO
Option	OtoP	OtoQ (Step 2)	Self

Figure 2: PQO Matrix for calculating the attention

The PQO matrix is a 3 × 3 matrix that includes all the possible combinations of the relationships between passages, questions, and options.

HRCA+

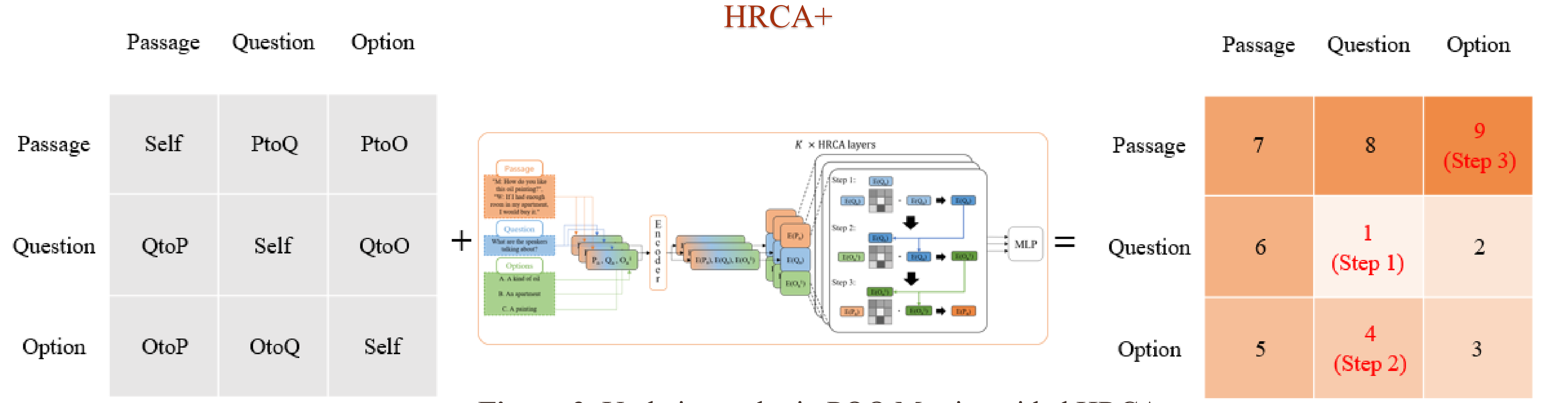

Figure 3: Updating order in PQO Matrix guided HRCA

We extend the operations of the HRCA method to adopt all the passage, question, and option relationships. Therefore, we propose an advanced multi-choice MRC method called HRCA+ to adopt the unused relationships in the proposed HRCA. The number in the PQO matrix represents the updated order of the attention calculation process.

RESULTS

Table 2: Performance in accuracy (%) on DREAM dataset.

MODEL	ACC
RoBERTa-large	85.0
ALBERT-xxlarge	88.5
ALBERT-xxlarge + DCMN (Zhang et al., 2020)	87.8
RoBERTa-large + MMM (Jin et al., 2020)	88.9
(SOTA) ALBERT-xxlarge + DUMA (Zhu et al., 2020)	90.4
(Proposed) ALBERT-xxlarge + HRCA+	**91.6 (+1.2)**
(SOTA) ALBERT-xxlarge + DUMA + Multi-Task Learning (Wan, 2020)	91.8
(Proposed) ALBERT-xxlarge + HRCA+ + Multi-Task Learning	**92.6 (+0.8)**

Table 3: Performance in accuracy (%) on Semeval-2018 Task 11 dataset.

MODEL	ACC
Best score in competition (Ostermann et al., 2018)	84.1
GPT	88.0
RoBERTa-large	94.0
ALBERT-xxlarge	95.4
GPT+Strategies (2×) (Sun et al., 2019b)	89.5
(SOTA) RoBERTa-large + MMM (Jin et al., 2020)	95.8
(Proposed) ALBERT-xxlarge + HRCA+	**96.6 (+0.8)**
(Proposed) ALBERT-xxlarge + HRCA+ + Multi-Task Learning	**97.2 (+1.4)**

Table 4: Ablation experiments for HRCA on DREAM dataset.

MODEL	Steps	ACC
ALBERT-base	-	64.4
+ HRCA	Step1	66.9
+ HRCA	Step1 & Step2	67.8
+ HRCA	Step1 & Step3	67.2
+ HRCA	Step2 & Step3	67.1
+ HRCA	Step1 & Step2 & Step3	68.8

CONCLUSIONS

In this study, we propose a method called human reading comprehension attention (HRCA) for simulating the reading strategies employed by humans. Compared to other state-of-the-art methods, our proposed approach achieves a higher score when tackling multiple-choice comprehension tasks. We further propose a passage-question-option matrix-guided HRCA approach called HRCA+ to fully utilize the information between passages, questions, and the corresponding candidate options extracted using PrLMs. The experiments' results on the DREAM and Semeval-2018 Task 11 datasets show that our proposed method achieves the highest accuracy among other existing state-of-the-art methods.

In our future studies, we shall integrate the applications of our proposed method to tasks in other fields, such as the extraction of relationships between passages and given argument pairs.

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