Retrospective Reader for Machine Reading Comprehension

Zhuosheng Zhang1,2,3, Junjie Yang2,3,4, Hai Zhao1,2,3,∗
1Department of Computer Science and Engineering, Shanghai Jiao Tong University
2Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, Shanghai Jiao Tong University, Shanghai, China
3MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University, Shanghai, China
4SJTU-ParisTech Elite Institute of Technology, Shanghai Jiao Tong University, Shanghai, China
zhangzs@sjtu.edu.cn, jj-yang@sjtu.edu.cn, zhaohai@cs.sjtu.edu.cn

Abstract

Machine reading comprehension (MRC) is an AI challenge that requires machine to determine the correct answers to questions based on a given passage. MRC systems must not only answer question when necessary but also distinguish when no answer is available according to the given passage and then tactfully abstain from answering. When unanswerable questions are involved in the MRC task, an essential verification module called verifier is especially required in addition to the encoder, though the latest practice on MRC modeling still benefits from adopting well pre-trained language models as the encoder block by only focusing on the “reading”. This paper devotes itself to exploring better verifier design for the MRC task with unanswerable questions. Inspired by how humans solve reading comprehension questions, we proposed a retrospective reader (Retro-Reader) that integrates two stages of reading and verification strategies: 1) sketchy reading that briefly investigates the overall interactions of passage and question, and yield an initial judgment; 2) intensive reading that verifies the answer and gives the final prediction. The proposed reader is evaluated on two benchmark MRC challenge datasets SQuAD2.0 and NewsQA, achieving new state-of-the-art results. Significance tests show that our model is significantly better than the strong ALBERT baseline. A series of analysis is also conducted to interpret the effectiveness of the proposed reader.

1 Introduction

Be certain of what you know and be aware what you don’t. That is wisdom.
Confucius (551 BC - 479 BC)

Machine reading comprehension (MRC) is a fundamental and long-standing goal of natural language understanding (NLU) that aims to teach a machine to answer questions after comprehending a given passage [Hermann et al., 2015; Joshi et al., 2017; Rajpurkar et al., 2018]. It has significant application scenarios such as question answering and dialog systems [Choi et al., 2018; Reddy et al., 2019]. The early MRC systems [Kadlec et al., 2016; Dhingra et al., 2017; Wang et al., 2017; Cui et al., 2017; Seo et al., 2016] are designed on a latent hypothesis that all questions can be answered only according to the given passage (Figure 1-[a]), which is not always true for real-world cases. Thus the recent progress on MRC task has required that the model must be capable of distinguishing those unanswerable questions to avoid giving plausible answers [Rajpurkar et al., 2018]. MRC task with unanswerable questions may be usually decomposed into two subtasks: (1) answerability verification and (2) reading comprehension. To determine unanswerable questions requires a deep understanding of the given text and requires more robust MRC models, making MRC much closer to real-world applications. Table 1 shows an unanswerable example from SQuAD2.0 MRC task [Rajpurkar et al., 2018].

So far, a common reading system (reader) which solves MRC problem generally consists of two modules or building steps as shown in Figure 1-[a]: 1) building a robust language model (LM) as encoder; 2) designing ingenious mechanisms as decoder according to MRC task characteristics. Pre-trained language models such as BERT [Devlin et al., 2018] and XLNet [Yang et al., 2019] have achieved a series of
success on various natural language processing tasks, which broadly plays the role of a powerful encoder. However, it is quite time-consuming and resource-demanding to impart massive amounts of general knowledge from external corpora into a deep language model via pre-training.

Not until recently keep the primary focuses of nearly all MRC readers on the encoder side, i.e., the deep pre-trained LMs (PLMs) [Devlin et al., 2018], as readers may simply and straightforwardly benefit from a strong enough encoder. Meanwhile, little attention is paid to the decoder side\(^1\) of MRC models [Hu et al., 2019; Back et al., 2020], though it has been shown that better decoder or better manner of using encoder still has a significant impact on MRC performance, no matter how strong the encoder (i.e., the adopted pre-trained LM) it is [Zhang et al., 2020a].

For the concerned MRC challenge with unanswerable questions, a reader has to handle two aspects carefully: 1) give the accurate answers for answerable questions; 2) effectively distinguish the unanswerable questions, and then refuse to answer. Such requirements complicate the reader’s design by introducing an extra verifier module or answer-verification mechanism. Most readers simply stack the verifier along with encoder and decoder parts in a pipeline or concatenation way (Figure 1-[b-c]), which is shown suboptimal for installing a verifier.

As a natural practice of how humans solve complex reading comprehension, the first step is to read through the full passage along with the question and grasp the general idea; then, people re-read the full text and verify the answer if not so sure. Inspired by such a reading and comprehension pattern, we proposed a retrospective reader (Retro-Reader, Figure 1-[d]) that integrates two stages of reading and verification strategies: 1) sketchy reading that briefly touches the relationship of passage and question, and yield an initial judgment; 2) intensive reading that verifies the answer and gives the final prediction.\(^2\)

Our major contributions in this paper are three folds:

1. We propose a new retrospective reader design which is capable of sufficiently and effectively performing answer verification instead of simply stacking verifier in existing readers.
2. Experiments show that our retrospective reader can yield substantial improvements on strong baselines and achieve new state-of-the-art results on benchmark MRC tasks.
3. For the first time, we define the significance test for the concerned MRC task and show that our models are significantly better than the baselines.

2 Our Proposed Model

We focus on the span-based MRC task, which can be described as a triplet \(\langle P, Q, A \rangle\), where \(P\) is a passage, and \(Q\) is a query over \(P\), in which a span is a right answer \(A\). Our system is supposed to not only predict the start and end positions in the passage \(P\) and extract span as answer \(A\) but also return a null string when the question is unanswerable.

Our retrospective reader is composed of a sketchy reading module and an intensive reading module to imitate human reading. The sketchy reader first makes a preliminary

\[^{1}\text{We define decoder here as the task-specific part in an MRC system, such as passage and question interaction and answer verification.}\]

\[^{2}\text{Our source codes and models will be publicly available soon.}\]
2.2 Intensive Reading Module

The objective of the intensive reader is to verify the answerability, produce candidate answer spans, and then give the final answer prediction. It employs the same encoding and interaction procedure as the sketchy reader, to obtain the representation $\mathbf{H}$. In previous studies [Devlin et al., 2018; Yang et al., 2019; Lan et al., 2020], $\mathbf{H}$ is directly fed to a linear layer to yield the prediction.

Inspired by previous success of explicit attention matching between passage and question [Kadlec et al., 2016; Dhingra et al., 2017; Wang et al., 2017; Cui et al., 2017; Seo et al., 2016], we are interested in whether the advance still holds based on the strong PLMs. Here we investigate two alternative question-aware matching mechanisms as an extra layer.

**Question-aware Matching** To obtain the representation of each passage and question, we split the last-layer hidden state $\mathbf{H}$ into $\mathbf{H}^Q$ and $\mathbf{H}^P$ as the representations of the question and passage, according to its position information. Both of the sequences are padded to the maximum length in a minibatch. Then, we investigate two potential question-aware matching mechanisms, 1) Transformer-style multi-head cross attention (CA) and 2) traditional matching attention (MA).

- **Cross Attention** We feed the $\mathbf{H}^Q$ and $\mathbf{H}^P$ to a revised one-layer multi-head attention layer inspired by Lu et al. [2019]. Since the setting is $\mathbf{Q} = \mathbf{K} = \mathbf{V}$ in multi-head self attention, which are all derived from the input sequence, we replace the input to $\mathbf{Q}$ with $\mathbf{H}^P$, and both of $\mathbf{K}$ and $\mathbf{V}$ with $\mathbf{H}^Q$ to obtain the question-aware context representation $\mathbf{H}'$.

- **Matching Attention** Another alternative is to feed $\mathbf{H}^Q$ and $\mathbf{H}^P$ to a traditional matching attention layer [Wang et al., 2017], by taking the question presentation $\mathbf{H}^Q$ as the attention to the representation $\mathbf{H}^C$:

$$
\mathbf{M} = \text{SoftMax}(\mathbf{H}^C(\mathbf{W}_p \mathbf{H}^Q + b_p \otimes \mathbf{e}_q)^T),
$$

$$
\mathbf{H}' = \mathbf{M} \mathbf{H}^Q,
$$

where $\mathbf{W}_q$ and $\mathbf{b}_q$ are learnable parameters. $\mathbf{e}_q$ is an all-ones vector and used to repeat the bias vector into the matrix. $\mathbf{M}$ denotes the weights assigned to the different hidden states in the concerned two sequences. $\mathbf{H}'$ is the weighted sum of all the hidden states and it represents how the vectors in $\mathbf{H}^C$ can be aligned to each hidden state in $\mathbf{H}^Q$.

Finally, the representation $\mathbf{H}'$ is used for the later predictions.

**Span Prediction** The aim of span-based MRC is to find a span in the passage as answer, thus we employ a linear layer with SoftMax operation and feed $\mathbf{H}'$ as the input to obtain the start and end probabilities, $s$ and $e$:

$$
p^s \propto \text{SoftMax}(\text{Linear}(\mathbf{H}')).
$$

The training objective of answer span prediction is defined as cross entropy loss for the start and end predictions,

$$
\mathbb{L}^{\text{span}} = - \frac{1}{N} \sum_{i=1}^n (\log p_i^s + \log p_i^e)
$$

Intuitively, our model is supposed to be designed as shown in Figure 1[d]. In the implementation, we find that modeling the entire reading process into two parallel modules is both simple and practicable with basically the same performance, which results in a parallel reading module design at last as the model shown in Figure 1[e].
**Internal Front Verification** We adopted an internal front verifier (I-FV) such that the intensive reader can identify unanswerable questions as well. In general, a verifier’s function can be implemented as either a classification or regression task. The representation $\mathbf{H}$ as input is passed to a fully connected layer to get the classification logits or regression score.

(1) We use cross entropy as loss function for the classification verification:

$$
\mathbb{L}^{\text{ans}} = -\frac{1}{N} \sum_{i=1}^{n} \left[ y_i \log \bar{y}_i + (1 - y_i) \log (1 - \bar{y}_i) \right]
$$

where $\bar{y}_i \propto \text{SoftMax}(\text{Linear}(\mathbf{H}'))$ denotes the prediction and $y_i$ is the target.

(2) For the regression verification, mean square error is adopted as its loss function.

$$
\mathbb{L}^{\text{ans}} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y}_i)^2
$$

where $\bar{y}_i \propto \text{SoftMax}(\text{Linear}(\mathbf{H}'))$ denotes the prediction and $y_i$ is the target.

During training, the joint loss function for RV is the weighted sum of the span loss and verification loss.

$$
\mathbb{L} = \alpha_1 \mathbb{L}^{\text{span}} + \alpha_2 \mathbb{L}^{\text{ans}}
$$

where $\alpha_1$ and $\alpha_2$ are weights.

**Rear Verification** Rear verification (RV) is the combination of predicted probabilities of E-FV and I-FV, which is an aggregated verification for final answer.

$$
v = \beta_1 \bar{y} + \beta_2 \bar{\bar{y}}
$$

where $\beta_1$ and $\beta_2$ are weights.

### 2.3 Answer Prediction

For prediction, given output start and end probabilities $s$ and $e$, and the verification probability $v$, we calculate the has-answer score $\text{score}_{\text{has}}$, and the no-answer score $\text{score}_{\text{na}}$:

$$
\text{score}_{\text{has}} = \max(s_k + e_l), 0 < k \leq l \leq n,
\text{score}_{\text{na}} = \lambda_1 (s_0 + e_0) + \lambda_2 v.
$$

where $\lambda_1$ and $\lambda_2$ are weights. We obtain a difference score between has-answer score and the no-answer score as final score. An answerable threshold $\delta$ is set and determined according to the development set. The model predicts the answer span that gives the has-answer score if the final score is above the threshold $\delta$, and null string otherwise.

### 3 Experiments

#### 3.1 Setup

Our implementation is based on the Pytorch implementation of BERT and ALBERT.\(^5\) We use the pre-trained LM weights in encoder module in our reader, using all the official hyper-parameters.\(^6\) We set the initial learning rate in \{2e-5, 3e-5\} with a warm-up rate of 0.1, and L2 weight decay of 0.01. The batch size is selected in \{32 and 48\}. The maximum number of epochs is set in 2 for all the experiments. Texts are tokenized using wordpieces, with a maximum length of 512.

Hyper-parameters were selected using the dev set. The manual weights are $\alpha_1 = \alpha_2 = \beta_1 = \beta_2 = \lambda_1 = \lambda_2 = 0.5$ in this work.

We use the available PLMs as encoder to build baseline MRC models: BERT [Devlin et al., 2018], and ALBERT [Lan et al., 2020]. For answer verification, we follow the same setting according to the corresponding literatures [Devlin et al., 2018; Lan et al., 2020], which simply adopts the answerable threshold method described in Section 2.3.

#### 3.2 Benchmark Datasets

Our proposed reader is evaluated in two benchmark MRC challenges.

**SQuAD2.0** As a widely used MRC benchmark dataset, SQuAD2.0 [Rajpurkar et al., 2018] combines the 100,000 questions in SQuAD1.1 [Rajpurkar et al., 2016] with over 50,000 new, unanswerable questions that are written adversarially by crowdworkers to look similar to answerable ones. The training dataset contains 87K answerable and 43K unanswerable questions.

**NewsQA** NewsQA [Trischler et al., 2017] is a question-answering dataset on paragraphs of news articles that tend to be longer than SQuAD. The passages are relatively long at about 600 words on average. The training dataset has 20K unanswerable questions among 97K questions.

#### 3.3 Evaluation

**Metrics** Two official metrics are used to evaluate the model performance: Exact Match (EM) and a softer metric F1 score, which measures the weighted average of the precision and recall rate at a character level.

**Significance Test** With the rapid development of deep MRC models, the dominant models have achieved very high results (e.g., over 90% F1 scores on SQuAD2.0), and further advance has been very marginal. Thus a significance test would be beneficial for measuring the difference in model performance.

For selecting evaluation metrics for the significance test, since answers vary in length, using the F1 score would have a bias when comparing models, i.e., if one model fails on one severe example though works well on the others. Therefore, we use the tougher metric EM as the goodness measure. If the EM is equal to 1, the prediction is regarded as right and vice versa. Then the test is modeled as a binary classification problem to estimate the answer of the model is exactly right (EM=1) or wrong (EM=0) for each question.

We now describe the statistical significance tests for our results. According to our task setting, we used McNemar’s test [McNemar, 1947] to test the statistical significance of our results. This test is designed for paired nominal observations, and it is appropriate for binary classification tasks [Ziser and Reichart, 2016]. It is applied to a $2 \times 2$ contingency table, as shown in Figure 2, which tabulates the outcomes of two models on all the evaluated examples. The null hypothesis for...
| Model                  | Dev EM | Dev F1 | Test EM | Test F1 |
|-----------------------|--------|--------|---------|---------|
| **Regular Track**     |        |        |         |         |
| Joint SAN             | 69.3   | 72.2   | 68.7    | 71.4    |
| U-Net                 | 70.3   | 74.0   | 69.2    | 72.6    |
| RMR + ELMo + Verifier| 72.3   | 74.8   | 71.7    | 74.2    |
| **Top results on the leaderboard** |        |        |         |         |
| Human                 | - -    | 86.8   | 89.5    |         |
| XLMNet [Yang et al., 2019] | 86.1  | 88.3   | 86.4    | 89.1    |
| RoBERTa [Liu et al., 2019] | 86.5  | 89.4   | 86.8    | 89.8    |
| UPM†                  | - -    | 87.2   | 90.1    |         |
| XLMNet + SG-Net Verifier++† | - -    | 87.2   | 90.1    |         |
| ALBERT [Lan et al., 2020] | 87.4  | 90.2   | 88.1    | 90.9    |
| ALBERT + DA Verifier† | - -    | 87.8   | 91.3    |         |
| albert+verifier†      | - -    | 88.4   | 91.0    |         |
| ALBERT (+TAV)         | 87.0   | 90.2   | - -     | - -     |
| Retro-Reader over ALBERT | **87.8** | **90.9** | **88.1** | **91.4** |

Table 2: The results (%) from single models for SQuAD2.0 challenge. The results except ours are obtained by the online evaluation server and the corresponding literatures. † refers to the results without a published literature citation. Our model results are in bold face. Our model is significantly better than all the baselines with p-value < 0.05.

This test states that the marginal probability for each outcome (label one or label two) is the same for both algorithms. In other words, when applying both algorithms on the same data, we would expect them to be correct/incorrect, on the same proportion of items.

\[
\chi^2 = \frac{(|b - c| - \gamma)^2}{b + c} \quad (14)
\]

where \(\gamma\) is the correction factor. The p-value is defined as the probability, under the null hypothesis, of obtaining a result equal to or more extreme than what was observed. The smaller the p-value, the higher the significance. A commonly used level of reliability of the result is 95%, written as \(p = 0.05\).

### 3.4 Results

Table 2 compares the leading single models on SQuAD2.0.\(^7\) Retro-Reader over ALBERT denotes our final model (i.e., \(^7\)The results are from the current official leaderboard, https://rajpurkar.github.io/SQuAD-explorer/.

Table 3: Test results (%) for NewsQA dataset. Our model is significantly better than all the baselines with p-value < 0.05.

| Method                  | HasAns EM | HasAns F1 | NoAns EM | NoAns F1 | All EM | All F1 |
|-------------------------|-----------|-----------|----------|----------|-------|--------|
| BERT                    | 78.9      | 85.4      | 77.0     | 77.0     | 78.0  | 81.2   |
| + E-FV                  | 79.1      | 85.7      | 77.4     | 77.4     | 78.2  | 81.5   |
| + I-FV (Class.)         | 77.7      | 84.5      | 79.6     | 79.6     | 78.6  | 82.0   |
| + I-FV (Reg.)           | 78.0      | 84.6      | 78.9     | 78.9     | 78.5  | 81.7   |
| + both FVs (RV)         | 78.0      | 84.0      | 80.7     | 80.7     | 79.3  | 82.4   |
| ALBERT                  | 82.6      | 89.0      | 91.4     | 91.4     | 87.0  | 90.2   |
| + E-FV                  | 82.4      | 88.7      | 92.4     | 92.4     | 87.4  | 90.6   |
| + I-FV (Class.)         | 81.7      | 87.9      | 92.7     | 92.7     | 87.2  | 90.3   |
| + I-FV (Reg.)           | 82.4      | 88.5      | 92.3     | 92.3     | 87.3  | 90.4   |
| + both FVs (RV)         | 83.1      | 89.4      | 92.4     | 92.4     | 87.8  | 90.9   |

Table 4: Results (%) with different answer verification methods on the SQuAD2.0 dev set. Class. and Reg. are short for the classification and regression loss defined in Section 2.2.

Under the null hypothesis, with a sufficiently large number of disagreements between the algorithms, the test statistic \(\chi^2\) has a chi-squared distribution with one degree of freedom.

Our Retro-Reader was submitted to the official SQuAD2.0 official leaderboard for evaluation on Jan. 10th, 2020. The leaderboard updated on Jan. 25th 2020 shows that our submission achieves the first places for both ensemble and single models.

### 4 Ablations

Evaluation on Answer Verification Table 4 presents the results with different answer verification methods. We observe that either of the front verifier boosts the baselines, and integrating both as rear verification works the best.

Our Retro-Reader was submitted to the official SQuAD2.0 official leaderboard for evaluation on Jan. 10th, 2020. The leaderboard updated on Jan. 25th 2020 shows that our submission achieves the first places for both ensemble and single models.

\(^9\)The results except ours are from Tay et al. [2018] and Back et al. [2020].
Table 5: Results (%) with different interaction methods on the dev sets of SQuAD2.0 and NewsQA.

| Method   | SQuAD2.0 EM | SQuAD2.0 F1 | NewsQA EM | NewsQA F1 |
|----------|-------------|-------------|-----------|-----------|
| BERT     | 78.0        | 81.2        | 51.8      | 62.5      |
| + CA     | 78.3        | 81.1        | 52.1      | 62.7      |
| + MA     | 78.3        | 81.2        | 52.4      | 62.6      |
| ALBERT   | 87.0        | 90.2        | 57.1      | 67.5      |
| + CA     | 87.3        | 90.3        | 56.0      | 66.3      |
| + MA     | 86.8        | 90.0        | 55.8      | 66.1      |

Evaluation on Different Interactions

Table 5 shows the results with different interaction methods. We see that adding extra interaction layers after the strong PLMs could only yield marginal improvement, which verifies the PLMs’ strong ability to capture the relationships between passage and question. In contrast, answer verification could still give substantial advance, which shows the potential for future study.

Comparison of Predictions

To have an intuitive observation of the predictions of Retro-Reader, we give a prediction example on SQuAD2.0 from baseline and Retro-Reader in Table 6, which shows that our method works better at judging whether the question is answerable on a given passage and gets rid of the plausible answer.

5 Related Work

The research of machine reading comprehension has attracted great interest with the release of a variety of benchmark datasets [Hill et al., 2015; Hermann et al., 2015; Rajpurkar et al., 2016; Joshi et al., 2017; Rajpurkar et al., 2018; Lai et al., 2017]. The early trend is a variety of attention-based interactions between passage and question, including Attention Sum [Kadlec et al., 2016], Gated attention [Dhingra et al., 2017], Self-matching [Wang et al., 2017], Attention over Attention [Cui et al., 2017] and Bi-attention [Seo et al., 2016]. Recently, well pre-trained language models (PLMs) dominate the encoder design for MRC and achieve great success [Lan et al., 2020], which facilitates us to take PLMs as our backbone encoder.

In the meantime, the study of the decoder mechanisms has come to a bottleneck due to the already powerful PLM encoder. Thus this work focuses on the non-encoder part, such as passage and question attention interactions, and especially the answer verification.

To solve the MRC task with unanswerable questions is though important, only a few studies paid attention to this topic with straightforward solutions. Mostly, a treatment is to adopt an extra answer verification layer, the answer span prediction and answer verification are trained jointly with multi-task learning (Figure 1-[c]). Such an implemented verification mechanism can also be as simple as an answerable threshold setting broadly used by powerful enough PLMs for quickly building readers [Devlin et al., 2018; Zhang et al., 2020b]. Liu et al. [2018] appended an empty word token to the context and added a simple classification layer to the reader. Hu et al. [2019] used two types of auxiliary loss, independent span loss to predict plausible answers and independent no-answer loss to decide answerability of the question. Further, an extra verifier is adopted to decide whether the predicted answer is entailed by the input snippets (Figure 1-[b]). Back et al. [2020] developed an attention-based satisfaction score to compare question embeddings with the candidate answer embeddings (Figure 1-[c]). Zhang et al. [2020c] proposed a verifier layer, which is a linear layer applied to context embedding weighted by start and end distribution over the context words representations concatenated to “[CLS]” token representation for BERT (Figure 1-[c]).

Different from these existing studies which stack the verifier module in a simple way or just jointly learn answer location and non-answer losses, our Retro-Reader adopts a humanoid design based on a comprehensive survey over existing answer verification solutions.

6 Conclusion

As machine reading comprehension tasks with unanswerable questions stress the importance of answer verification in MRC modeling, this paper devotes itself to better verifier-oriented MRC task-specific design and implementation for the first time. Inspired by human reading comprehension experience, we proposed a retrospective reader that integrates both sketchy and intensive reading. With the latest PLM as encoder backbone and baseline, the proposed reader is evaluated on two benchmark MRC challenge datasets SQuAD2.0 and NewsQA, achieving new state-of-the-art results and outperforming strong baseline models in terms of newly introduced statistical significance, which shows the choice of verification mechanisms has a significant impact for MRC performance and verifier is an indispensable reader component even for powerful enough PLMs used as encoder.
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