Retrospective Reader for Machine Reading Comprehension

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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 most 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 ELECTRA and ALBERT baselines. 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)

Passage:

Computational complexity theory is a branch of the theory of computation in theoretical computer science that focuses on classifying computational problems according to their inherent difficulty, and relating those classes to each other. A computational problem is understood to be a task that is in principle amenable to being solved by a computer, which is equivalent to stating that the problem may be solved by mechanical application of mathematical steps, such as an algorithm.

Ouestion:

What cannot be solved by mechanical application of mathematical steps?

Gold Answer: (no answer)
Plausible answer: algorithm

Table 1: An unanswerable MRC example.

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 ex-

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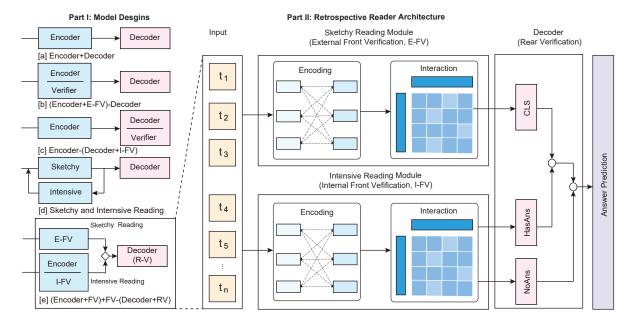


Figure 1: Reader overview. For the left part, models [a-c] summarize the instances in previous work, and model [d] is ours, with the implemented version [e]. In the names of models [a-e], "(·)" represents a module, "+" means the parallel module and "-" is the pipeline. The right part is the detailed architecture of our proposed Retro-Reader.

ample 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 side¹ 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 en-

coder (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 answerverification 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:

¹We define *decoder* here as the task-specific part in an MRC system, such as passage and question interaction and answer verification.

²Our source codes are available at https://github.com/cooelf/AwesomeMRC.

- 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.
- Experiments show that our retrospective reader can yield substantial improvements on strong baselines and achieve new state-of-theart results on benchmark MRC tasks.
- 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 Related Work

The research of machine reading comprehension have 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 multitask 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 the 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.

3 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 two parallel modules: a *sketchy reading module* and an *intensive reading module* to imitate human reading. The sketchy reader first makes a preliminary judgment, whether the question is answerable. Then, the intensive reader is applied to produce candidate answer spans, verify the answerability, and give the final answer prediction. The outputs of both of the modules are aggregated for final decision.³

3.1 Sketchy Reading Module

Embedding The raw text sequences are firstly represented as embedding vectors to feed an encoder (i.e., a PLM). The input sentence is first tokenized to word pieces (subword tokens). Let $T = \{t_1, \ldots, t_n\}$ denote a sequence of subword tokens of length n. For each token, the input embedding is the sum of its token embedding, posi-

³Intuitively, 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].

tion embedding, and token-type embedding. Let $X = \{x_1, \dots, x_n\}$ be the outputs of the encoder, which are embedding features of encoding sentence words of length n. The input embeddings are then fed into the interaction layer to obtain the contextual representations.

Interaction The encoded sequence X is processed to a multi-layer bidirectional Transformer for learning contextual representations. Let $X^l =$ $\{x_1^l, \dots, x_n^l\}$ be the features of the *l*-th layer. The features of the l+1-th layer, x^{l+1} is computed by

$$\tilde{h}_{i}^{l+1} = \sum_{m=1}^{M} W_{m}^{l+1} \left\{ \sum_{j=1}^{n} A_{i,j}^{m} \cdot V_{m}^{l+1} x_{j}^{l} \right\}, \qquad (1)$$

$$\begin{split} & h_i^{l+1} = \textit{LayerNorm}(x_i^l + \tilde{h}_i^{l+1}), \\ & \tilde{x}_i^{l+1} = W_2^{l+1} \cdot \textit{GELU}(W_1^{l+1} h_i^{l+1} + b_1^{l+1}) + b_2^{l+1}, \end{split}$$

$$\tilde{x}_i^{l+1} = W_2^{l+1} \cdot \textit{GELU}(W_1^{l+1}h_i^{l+1} + b_1^{l+1}) + b_2^{l+1}, \tag{3}$$

$$x_i^{l+1} = \textit{LayerNorm}(h_i^{l+1} + \tilde{x}_i^{l+1}), \tag{4} \label{eq:definition}$$

where m is the index of the attention heads, and $A_{i,j}^m \propto \exp[(Q_m^{l+1} x_i^l)^\top (K_m^{l+1} x_j^l)]$ denotes the attention weights between elements i and j in the m-th head, which is normalized by $\sum_{j=1}^n A_{i,j}^m = 1.$ $W_m^{l+1}, Q_m^{l+1}, K_m^{l+1}$ and V_m^{l+1} are learnable weights for the m-th attention head, W_1^{l+1}, W_2^{l+1} and b_1^{l+1}, b_2^{l+1} are learnable weights and biases, respec-

For the following part, we use H $\{h_1,\ldots,h_n\}$ to denote the last-layer hidden states of the input sequence.

External Front Verification After reading, the sketchy reader will make a preliminary judgment, whether the question is answerable given the context. We implement this reader as an external front verifier (E-FV) to identify unanswerable questions. The pooled first token (special symbol, [CLS]) representation $h_1 \in \mathbf{H}$, as the overall representation of the sequence, is passed to a fully connection layer to get classification logits or regression score. We use cross entropy as training objective:

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

where $\hat{y}_i \propto SoftMax(Linear(h_1))$ denotes the prediction and y_i is the target indicating whether the question is answerbale or not. N is the examples.

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 **H**. In previous studies (Devlin et al., 2018; Yang et al., 2019; Lan et al., 2020), 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.4

Question-aware Matching To obtain the representation of each passage and question, we split the last-layer hidden state **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} 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,⁵ which are all derived from the input sequence, we replace the input to **Q** with **H**, and both of **K** and **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} to a traditional matching attention layer (Wang et al., 2017), by taking the question presentation \mathbf{H}^Q as the attention to the representation H:

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

$$\mathbf{H}' = \mathbf{M}\mathbf{H}^Q,$$
 (6)

where \mathbf{W}_q and \mathbf{b}_q are learnable parameters. \mathbf{e}_q is a all-ones vector and used to repeat the bias vector

⁴This part is only used for ablation in Table 5 as a reference for interested readers. We do not use any extra matching part in our submission for test evaluations (e.g., in Tables 2-3) for simplicity as our major focus is the verification.

 $[\]bar{{}^5} \text{In}$ this work, Q,K,V correspond to the items $Q_m^{l+1} x_i^l, K_m^{l+1} x_j^l)$ and $V_m^{l+1} x_j^l,$ respectively.

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} can be aligned to each hidden state in \mathbf{H}^Q .

Finally, the representation \mathbf{H}' is used for the later predictions. If we do not use the above matching like the original use in BERT models, then $\mathbf{H}' = \mathbf{H}$ for the following part.

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:

$$p^s, p^e \propto SoftMax(Linear(\mathbf{H}')).$$
 (7)

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

$$\mathbb{L}^{span} = -\frac{1}{N} \sum_{i}^{N} [\log(p_{y_{i}^{s}}^{s}) + \log(p_{y_{i}^{e}}^{e})]$$
 (8)

where y_i^s and y_i^e are respectively ground-truth start and end positions of example i. N is the number of examples.

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 pooled representation $h_1' \in \mathbf{H}'$, 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:

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

(9)

where $\bar{y}_i \propto SoftMax(Linear(h'_1))$ denotes the prediction and y_i is the target. N is the number of examples.

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

$$\mathbb{L}^{ans} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y}_i)^2$$
 (10)

where $\bar{y}_i \propto SoftMax(Linear(h'_1))$ 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.

$$\mathbb{L} = \alpha_1 \mathbb{L}^{span} + \alpha_2 \mathbb{L}^{ans} \tag{11}$$

where α_1 and α_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.

$$v = \beta_1 \hat{y} + \beta_2 \bar{y} \tag{12}$$

where β_1 and β_2 are weights.

3.3 Threshold-based Answerable Verification

Threshold based answerable verification (TAV) is the previously used heuristic strategy to decide whether a question is answerable according to the predicted answer start and end logits (Devlin et al., 2018; Lan et al., 2020). Given output start and end probabilities s and e, and the verification probability v, we calculate the has-answer score $score_{has}$ and the no-answer score $score_{na}$:

$$score_{has} = \max(s_k + e_l), 0 < k \le l \le n,$$

$$score_{na} = \lambda_1(s_1 + e_1) + \lambda_2 v.$$
 (13)

where λ_1 and λ_2 are weights. We obtain a difference score between *has-answer* score and the *no-answer* score as final score. An answerable threshold δ 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 δ , and null string otherwise.

TAV is used in all our models as the last step for the answerablity decision. We denote it in our baselines with (+TAV) sa default in Table 2-3, and omit the notation for simplicity in analysis part to avoid misunderstanding to keep on the specific ablations.

4 Experiments

4.1 Setup

We use the available PLMs as encoder to build baseline MRC models: BERT (Devlin et al., 2018), ALBERT (Lan et al., 2020), and ELECTRA (Clark et al., 2019). Our implementation is based on the

Pytorch implementation of BERT and ALBERT.⁶ Electra is based on the Tensorflow release.⁷ We use the pre-trained LM weights in encoder module in our reader, using all the official hyperparameters.⁸ We set the initial learning rate in $\{2\text{e-5}, 3\text{e-5}\}$ with a warm-up rate of 0.1, and L2 weight decay of 0.01. The batch size is selected in $\{32 \text{ and } 48\}$. 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

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 §3.3. In the following part, ALBERT (+TAV) is denoted as our baseline for easy reading, which is equivalent to the ALBERT baseline in public literatures.

4.2 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.

4.3 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 McNemars 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 2×2 contingency table, as shown in Figure 2, which tabulates the outcomes of two models on all the evaluated examples. The null hypothesis for 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.

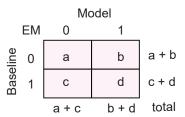


Figure 2: Contingency table.

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

$$\chi^2 = \frac{(|b - c| - \gamma)^2}{b + c} \tag{14}$$

where γ is the correction factor. The *p*-value is defined as the probability, under the null hypothesis,

⁶https://github.com/huggingface/ transformers.

⁷https://github.com/google-research/ electra.

⁸BERT (large); ALBERT(xxlarge); ELECTRA (large).

Madal	Dev		Test	
Model	EM	F1	EM	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 th	e leader	board		
Human	-	-	86.8	89.5
XLNet (Yang et al., 2019)	86.1	-88.8	86.4	89.1
RoBERTa (Liu et al., 2019)	86.5	89.4	86.8	89.8
UPM†	-	-	87.2	89.9
XLNet + 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
ELECTRA	88.0	90.6	88.7	91.4
SA-Net on Electra†	-	-	88.9	91.5
ELECTRA+RL+EV†	-	-	89.0	91.8
albert+KD+transfer+twopass†	-	-	89.1	91.9
ALBERT (+TAV)	87.0	90.2	-	-
Retro-Reader over ALBERT	87.8	90.9	88.1	91.4
ELECTRA (+TAV)	88.0	90.6	-	-
Retro-Reader over ELECTRA	88.8	91.3	89.6	92.1

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. \dagger refers to the results without a published literature citation. Our model is significantly better than all the baselines with p-value < 0.01. TAV: threshold based answerable verification ($\S 3.3$)

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.

4.4 Results

Table 2 compares the leading single models on SQuAD2.0.9 Retro-Reader over ALBERT and Retro-Reader over ELECTREA denote our final model (i.e., our submissions to SQuAD2.0 online evaluation), which are respectively ALBERT and ELECTRA based retrospective reader composed of both sketchy and intensive reading modules without question-aware matching. In terms of powerful enough PLMs like ALBERT, our Retro-Reader not only significantly outperforms the ALBERT baseline with simple threshold-based verifier, but also achieves new state-of-the-art on the SQuAD2.0 challenge.¹⁰ Table 3 compares models on NewsQA, which further verifies the effective-

M. J.1	Dev		Test	
Model	EM	F1	EM	F1
Neural BoW	25.8	37.6	24.1	36.6
BARB	36.1	49.6	34.1	48.2
Match-LSTM	34.4	49.6	34.9	50.0
BiDAF	-	-	37.1	52.3
FastQA	43.7	56.4	41.9	55.7
FastQAExt	43.7	56.1	42.8	56.1
R2-BiLSTM	-	-	43.7	56.7
AMANDA	48.4	63.3	48.4	63.7
DECAPROP	52.5	65.7	53.1	66.3
BERT	-	-	46.5	56.7
BERT + NeurQuRI	-	-	48.2	59.5
ALBERT (+TAV)	57.1	67.5	55.3	65.9
Retro-Reader over ALBERT	58.5	68.6	55.9	66.8

Table 3: Test results (%) for NewsQA dataset. Our model is significantly better than all the baselines with p-value < 0.01.

ness of our reader, achieving new state-of-the-art results. 11

5 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. Note that we show the HasAns and NoAns only for completeness. Since the final predictions are based on the threshold search of answerability scores (§3.3), there exists a tradeoff between the HasAns and NoAns accuracies. Therefore, the final (ALL) is the best way to show the final performance, as the standard measurement for previous BERT-related MRC models. We see that +both FVs shows the best performance, which we select as our final implementation.

Evaluation on Different Interactions Table 5 shows the results with different interaction methods described in §3.2. We see that simply adding extra layers could not bring obvious improvement, which indicates that simply adding more layers and parameters would not substantially benefit the model performance. The results verified 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.

⁹The results are from the current official leaderboard, https://rajpurkar.github.io/SQuAD-explorer/.

¹⁰When our models were submitted (*Jan 10th 2020* for ALBERT-based model, *Apr 05, 2020* for ELECTRA-based model), our Retro-Reader achieved the first place on the SQuAD2.0 Leaderboard for both single and ensemble models.

¹¹The results except ours are from Tay et al. (2018) and Back et al. (2020).

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

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 §3.2.

Method	SQuA	SQuAD2.0		sQA
	EM	EM F1		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

Table 5: Results (%) with different interaction methods on the dev sets of SQuAD2.0 and NewsQA.

Comparisons with Equivalent Parameters

When using sketching reading module for external verification, we have two parallel modules that have independent parameters. For comparisons with equivalent parameters, we add an ensemble of two baseline models, to see if the advance is purely from the increase of parameters. Table 6 shows the results. We see that our model can still outperform two ensembled models. Although the two modules share the same design of the Transformer encoder, the training objectives (e.g., loss functions) are quite different, one for answer span prediction, the other for answerable decision. The results indicate that our two-stage reading modules would be more effective for learning diverse aspects (verification and span prediction) for solving MRC tasks with different training objectives. From the two modules, we can easily find the effectiveness of either the span prediction or answer verification, to improve the modules correspondingly. We believe this is also quite useful for real-world applications.

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 7, which shows that

Method	EM	F1
ALBERT Two-model Ensemble	87.0 87.6	90.2 90.6
Retro-Reader	87.8	90.9

Table 6: Comparisons with Equivalent Parameters on the dev sets of SQuAD2.0.

1	Pa	SSS	age

Southern California consists of a heavily developed urban environment, home to some of the largest urban areas in the state, along with vast areas that have been left undeveloped. It is the third most populated megalopolis in the United States, after the Great Lakes Megalopolis and the Northeastern megalopolis. Much of southern California is famous for its large, spread-out, suburban communities and use of automobiles and highways...

Question

What are the second and third most populated megalopolis after Southern California?

Answer:

Gold: (no answer)

ALBERT (+TAV): Great Lakes Megalopolis and the

Northeastern megalopolis.

BERT baseline and Retro-Reader.

Retro-Reader over ALBERT: $\langle \text{no answer} \rangle$ $score_{has} = 0.03, score_{na} = 1.73, \lambda = -0.98$

Table 7: Answer prediction examples from the AL-

our method works better at judging whether the question is answerable on a given passage and gets rid of the plausible answer.

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 taskspecific 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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