Improving Lexical Embeddings for Robust Question Answering

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Abstract

Recent techniques in Question Answering (QA) have gained remarkable performance improvement with some QA models even surpassed human performance. However, the ability of these models in truly understanding the language still remains dubious and the models are revealing limitations when facing adversarial examples. To strengthen the robustness of QA models and their generalization ability, we propose a representation Enhancement via Semantic and Context constraints (ESC) approach to improve the robustness of lexical embeddings. Specifically, we insert perturbations with semantic constraints and train enhanced contextual representations via a context-constraint loss to better distinguish the context clues for the correct answer. Experimental results show that our approach gains significant robustness improvement on four adversarial test sets.

1 Introduction

With the help of recent developments in neural networks (Seo et al., 2016; Devlin et al., 2019) as well as the release of high-quality datasets (Rajpurkar et al., 2016; Joshi et al., 2017; Rajpurkar et al., 2018), the QA task has made unprecedented progress. On the famous SQuAD dataset, QA models have achieved higher performance than human. However, the high performances of existing models do not account for the full understanding of language, as models often rely on recognizing the predictive patterns on test sets without learning the deep semantics beneath the language (Rimell et al., 2009; Paperno et al., 2016).

As shown in Figure 1(a), a small perturbation in the question may mislead the model to get the wrong answer. This issue is presented as oversensitivity (Szegedy et al., 2013; Goodfellow et al., 2014), causing models incapable to generalize to semantically invariant text perturbations. Figure 1(b) shows another scenario, where adding one distracting sentence sharing sufficient words with the question but meaningfully changed, is enough to confuse the model to select the distractor as the answer. This issue is described as overstability (Jia and Liang, 2017). Both issues are difficult to be addressed by using superficial lexical representations (e.g., simple word embeddings) which is not always enough for QA models to distinguish the texts containing the correct answer and the distracting context. Existing methods solve these robustness issues mainly by refining kinds of attentions to make models predict precisely (Huang et al., 2018; Hu et al., 2018; Xu et al., 2021a), adversarial training based methods (Miyato et al., 2016; Alzantot et al., 2018; Iyyer et al., 2018), learning the deep mutual information among the paragraph, the question and its answer (Yeh and Chen, 2019; Xu et al., 2021b), or using external knowledge to build adversarial examples to enlarge the training size (Wang and Bansal, 2018; Zhou et al., 2020).

This paper addresses the robustness issues by improving the robustness of lexical embeddings to make them less sensitive to variations. To this end, we propose an ESC approach: 1) We insert per-
We expect the context constraint can precisely rep-
resent the context clues to facilitate QA models
how to react to the context change and thus learn
to apply a simple pattern-match policy. Therefore,
we refer the output of self-attention as contextual repre-
sentation: $C = \{c'_1, ..., c'_K, e'_1, ..., e'_N\}$, which is then
projected together with the word embeddings to
produce the hidden state $H$. Based on the hidden
state, we find the most likely span to answer the
question.

## 2.1 Perturbations with Semantic Constraint

To address the sensitivity of non-robust QA models
to the trivial perturbations in the input question, we
follow the robust training strategies (Belinkov and
Bisk, 2018; Cheng et al., 2018) but insert perturba-
tions with semantic constraint, as such perturba-
tions would potentially improve the generalization
ability of models by slightly changing semantics of
contexts during the training step.

As depicted in Figure 2, we automatically in-
sert perturbations with semantic constraint in the
input sequence to generate an adversarial sample.
Specifically, we randomly select multiple positions
in each input sequence with a probability $\sigma$ and
perturb the corresponding words. For the word $w_i$
chosen to be perturbed, we build a dynamic set $\mathcal{V}_{w_i}$
consisting of $n$ words that have the highest cosine
similarities with $w_i$ (exclude $w_i$). We average the
embeddings of the words in $\mathcal{V}_{w_i}$ to construct the
perturbation for $w_i$.

$$\mathcal{V}_{w_i} = \{w_j \in \mathcal{D}, j \neq i : \top_{n} \cos(e_i, e_j)\}$$

$$e'_i = \frac{1}{n} \sum_{w_j \in \mathcal{V}_{w_i}} e_j$$

where $\mathcal{D}$ is the dictionary, $e_i$ is the word embedding
for $w_i$ and $e'_i$ is the perturbation for $w_i$. We perturb
$w_i$ by replacing $e_i$ with $e'_i$.

## 2.2 Representations with Context Constraint

On the other hand, as Yeh and Chen (2019) argued,
QA models tend to choose a span after the word
that existing in the question. We find that the con-
textual representations fail to extract decisive clues
to determine the answer, which causes the model
to apply a simple pattern-match policy. Therefore,
we utilize the adversarial samples generated with
semantic constraint in Sec. 2.1 to teach the model
how to react to the context change and thus learn
the contextual representations to better represent
the context clues. As shown in Figure 2, the origi-
nal input and the adversarial sample go parallelly
in ESC. We keep the contextual representations of
the adversarial sample as similar as those of the

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**Figure 2:** The architecture of ESC. The black solid
lines indicate the original path of BERT, while the red
dotted lines for adversarial input.
original input by a Context Constraint Loss (CCL), which teaches ESC to pay less attention to the word itself and retain most context clues of the current position.

Formally, let $C_l$ and $C'_l$ be the output of self-attention in the $l$-th BERT layer for the original input and the adversarial sample respectively. The CCL for each layer is

$$
L_{ccl}^l = ||C_l - C'_l||^2
$$

Note that the above two constraints are mutually beneficial. On the one hand, the semantic constraint creates an adversarial sample, which works as a teacher to guide the contextual representations learning. On the other hand, the context constraint provides the supervision ($C_l$) for the adversarial sample, preventing it from shifting too much. We demonstrate it in Table 3.

### 2.3 Training

Both the original input and the adversarial sample go parallelly in our ESC model. At each layer, we calculate the CCL using $C_l$ and $C'_l$. We finally use the last layer hidden state of the original input to predict the answer span (See Figure 2).

As there are 12/24 (base/large) layers in BERT, to prevent the CCLs slowing down the training speed and overfitting, we only sample $k$ ($k < 12/24$) CCLs to update in each iteration. The final CCL can be written as

$$
L_{ccl} = \frac{1}{k} \sum_{l \in S} L_{ccl}^l,
$$

where $S$ contains $k$ sampled layer indexes to be updated.

The final training objective $L$ is the combination of QA answer span prediction loss $L_{span}$ and CCL. $\lambda$ is the weighting parameter for CCL.

$$
L = L_{span} + \lambda L_{ccl}
$$

### 3 Experimental Settings

We evaluate the effectiveness of ESC on four challenging adversarial test sets – ADDSENT, ADDONESENT, Para-Q and Adv-Q. The two adversarial test sets, ADDSENT and ADDONESENT, are constructed by Jia and Liang (2017) based on SQuAD. In ADDSENT, they add an adversarial sentence to each paragraph that makes QA models give the worst answer. In ADDONESENT, only a randomly adversarial sentence is added. These two are to evaluate the model’s robustness on adversarial attack.

Gan and Ng (2019) construct another two adversarial test sets: Para-Q and Adv-Q. In Para-Q, they use a paraphrasing model to paraphrase the questions based on PPDB (Pavlick et al., 2015). While in Adv-Q, they manually paraphrase the questions. These two are to evaluate the model’s ability on generalization.

As ADDSENT and ADDONESENT add distracting sentences in paragraphs and Para-Q and Adv-Q paraphrase only the questions, we build three variants of our model, where the ESC approach is added to paragraph words (ESC-P), question words (ESC-Q), and both words (ESC). Detailed implementations can be found in the Appendix A.1.

### 4 Results and Analysis

Table 1 shows the results on ADDSENT, ADDONESENT, and the original development set. We implement our ESC on strong baselines BERT(B) and BERT(L) and compare with the approaches without using extra data, including QANet (Yu et al., 2018), GQA (Lewis and Fan, 2019), FusionNet (Huang et al., 2018), QAInfomax (Yeh and Chen, 2019), AT+VAT (Yang et al., 2019), and Liu et al. (2020) to make the improvements of our ESC approach more convincing.¹

¹For a fair comparison, we do not compare with Wang and Bansal (2018); Zhou et al. (2020); Wang et al. (2021), as their works rely on external knowledge in addition to the original SQuAD dev set. Highest scores are bolded.

| Model          | Original | ADDSENT | ADDONESENT |
|----------------|----------|---------|------------|
| QANet          | 83.8     | 45.2    | 55.7       |
| GQA            | 83.7     | 47.3    | 57.8       |
| FusionNet      | 83.6     | 51.4    | 60.7       |
| QAInfomax (B)  | 88.6     | 54.5    | 64.9       |
| Liu et al.     | 90.4     | 63.1    | -          |
| AT/VAT (L)     | 92.4     | 65.5    | 72.5       |
| **Our Approaches** |         |         |            |
| BERT (B)       | 87.3     | 52.9    | 63.4       |
| + ESC-P        | 88.4     | 55.2    | 65.5       |
| + ESC-Q        | 87.4     | 54.4    | 65.0       |
| + ESC          | 88.5     | 57.0    | 67.1       |
| BERT (L)       | 93.3     | 67.8    | 76.5       |
| + ESC-P        | 92.9     | 69.9    | 78.3       |
| + ESC-Q        | 92.3     | 69.1    | 76.1       |
| + ESC          | 91.8     | 69.8    | 76.9       |

Table 1: F1 scores on three test sets (B refers to BERT base model; L: refers to BERT large model). Original is the original SQuAD dev set. Highest scores are bolded.

Table 2: F1 scores on Para-Q and Adv-Q and their corresponding original test sets.

Performance on both adversarial test sets with the improvements of 4.1 and 3.7 of F1 against the BERT(B), respectively. All three variants improve over the baseline BERT significantly, while ESC-P is better than ESC-Q on these test sets. The results are within expected as ESC-P is specifically designed to handle and evaluate the performance of the model in this scenario where an adversarial sentence is present in the paragraph texts. By extending the model to handle adversarial attack on the question, ESC still exceeds or maintains its performance on both ADDSENT and ADDONESENT.

**Performance against Paraphrasing** Column 2\textsuperscript{nd} and 3\textsuperscript{rd} of Table 2 show the results on Para-Q with its original test set Para-Orig.\textsuperscript{2} We compare ESC with the latest approaches: DrQA (Chen et al., 2017), BiDAF (Seo et al., 2016), and the baseline BERT. The results indicate that ESC improves the robustness on adversarial test sets with 1.0 and 0.5 of F1 on BERT(L) and BERT (B), respectively. Column 4\textsuperscript{th} and 5\textsuperscript{th} of Table 2 show the results on Adv-Q with its original test set Adv-Orig. Since Adv-Q only contains 56 samples, the performance on this test set may not fully reflect the model’s capability to deal with question paraphrasing. We can see that the performance fluctuates since the test set is small. Nevertheless, both results on BERT (B) and BERT (L) show that overall ESC is effective and improves the baseline by 4.2 and 1.3 F1 respectively. The results demonstrate that enhancing the lexical embeddings in both paragraph and question texts helps to improve the robustness of the question answering.

**Ablation Study** We conduct an ablation study on the two constraints described in Sec. 2. Table 3 shows that both constraints improve over the BERT baseline independently, where +Semantic performs better on Para-Q, and +Context performs better on ADDSENT and ADDONESENT. This is in line with our motivation to use semantic and context constraints to address the robustness issue. We also notice that +Both gains more improvement than +Semantic or +Context especially on ADDSENT and ADDONESENT. It implies that lexical embeddings and contextual representation affect each other and improving their robustness bring greater benefit and synergy to QA models.

**Effect of Dynamic Set Size** We look into the dynamic set size $n$ to see how it affects the model stability in Figure 3. The curves are quite stable and consistent where a size of around 4 achieves the best performance among all three test sets.

5 Conclusion

This paper presents a novel approach, ESC, to address the robustness issues for QA models. We insert perturbations with a semantic constraint to improve the lexical embeddings and enhance context representations via a context constraint loss to make the model more generalizable. To verify the effectiveness of our approach, we compare it with strong approaches on four challenging adversarial test sets. Experimental results show that ESC can significantly improve the robustness of QA models with regards to adversarial sentences in paragraph.
and question paraphrasing.

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A Appendix

A.1 Hyper-parameter Settings

We use PyTorch re-implementation of BERT\(^3\). The BERT related hyper-parameter setting remains the same as released for SQuAD1.1 training. For other new hyper-parameters, we perform grid search to find optimal values, where $\sigma$ is selected from $\{0.05, 0.1, 0.2\}$, $\lambda$ is selected from $\{0.1, 0.5, 1, 2\}$, $n$ is selected from $\{1, 2, 3, 4, 5\}$ and $k$ is selected from $\{1, 2, 3, 4, 5\}$. The learning rate is set to $3e^{-5}$ and ADAM (Kingma and Ba, 2014) optimizer is used for parameters optimization with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We apply ESC approach both on BERT\textsubscript{Base} and BERT\textsubscript{Large} backbones. Each Base model is trained on one GeForce GTX 1080 Ti card and it takes 10 hours to complete 3 epochs. Each Large model is trained on one TITAN RTX card and it takes 8 hours to complete 3 epochs with fp16 enabled.

A.2 Detailed Results on Para-Q and Adv-Q

In addition to Table 2, we show the EM scores along with the F1 scores of different approaches on Para-Q (Table 4) and Adv-Q (Table 5) in this section.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|}
\hline
Model & EM & F1 & Orig-Q & Para-Q \\
\hline
\textbf{Existing Approaches} & & & \\
DrQA & 67.3 & 65.3 & 76.3 & 74.3 \\
BiDAF & 67.8 & 63.8 & 76.9 & 73.5 \\
\hline
\textbf{Our Approaches} & & & \\
BERT (B) & 80.4 & 76.8 & 88.0 & 85.3 \\
+ESC-P & 80.0 & 77.9 & 87.9 & 85.8 \\
+ESC-Q & 80.2 & 78.4 & 88.0 & 86.2 \\
+ESC & 82.0 & 78.5 & 88.9 & 86.3 \\
BERT (L) & 86.6 & 83.8 & 93.3 & 91.0 \\
+ESC-P & 86.8 & 84.6 & 93.1 & 91.3 \\
+ESC-Q & 88.3 & 86.0 & 93.6 & 91.3 \\
+ESC & 87.7 & 85.3 & 93.2 & 91.5 \\
\hline
\end{tabular}
\caption{EM and F1 scores on the original questions (Orig-Q) compared to the paraphrased questions (Para-Q).}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|}
\hline
Model & EM & F1 & Orig-Q & Adv-Q \\
\hline
\textbf{Existing Approaches} & & & \\
DrQA & 71.4 & 39.3 & 81.0 & 48.9 \\
BiDAF & 75.0 & 30.4 & 81.6 & 38.3 \\
\hline
\textbf{Our Approaches} & & & \\
BERT-S (B) & 82.1 & 51.8 & 88.9 & 56.6 \\
+ESC-P & 83.9 & 53.5 & 90.3 & 59.6 \\
+ESC-Q & 82.1 & 58.9 & 90.4 & 65.5 \\
+ESC & 82.1 & 53.6 & 88.5 & 60.8 \\
BERT-S (L) & 87.5 & 75.0 & 92.5 & 79.6 \\
+ESC-P & 87.5 & 75.0 & 91.2 & 79.3 \\
+ESC-Q & 85.7 & 73.2 & 91.1 & 78.0 \\
+ESC & 87.6 & 75.0 & 92.8 & 80.9 \\
\hline
\end{tabular}
\caption{EM and F1 scores on the original questions (Orig-Q) compared to the adversarial paraphrased questions (Adv-Q).}
\end{table}

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\(^3\)Available at https://github.com/huggingface/transformers.