

# Advancing with Adversaries: Comparing LSTMs Across Adversarial Inputs

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## Problem

Recently, more effort has been made to increase robustness against adversarial examples in reading comprehension systems. Robust systems are suggested to have "real language understanding abilities" [1] and are more transferrable to real-world question answering tasks (e.g. social media posts). Modern approaches attempt to model more complex relationships between the question and context [2] or encourage the identification of an adversarial example. We look to explore these approaches in more detail.

## Data/Task

We will train and evaluate our model on the SQuAD 2.0 dataset. SQuAD 2.0 contain examples that have unanswerable questions.

#### Example:

**Paragraph:** King David I of Scotland, whose elder brother Alexander I had married Sybilla of Normandy, was instrumental in introducing Normans and Norman culture to Scotland, part of the process some scholars called the "Davidian Revolution." **Question:** What did Sybilla of Normandy

introduce to Scotland?

#### Answer: N/A

**Model Predicts:** Normans and Norman culture

Using non-PCE models, we want to improve on the baseline QA system. The baseline QA model predicts non-existent answers on passages that don't contain an answer to a given question. By improving upon no-answer conditions, our goal is to improve our baseline QA scores.

## Approach

**Character embeddings:** added using CNN's to better capture the internal structure of words and predict OOV words better

**Reattention:** to capture more complex interactions between the question and context, we modify BiDAF attention to a reattention mechanism, a multi-round alignment architecture:

$$\begin{split} \tilde{E}_{ij}^t = & \text{softmax}(E_{i:}^{t-1}) \cdot \text{softmax}(B_{:j}^{t-1}) \\ E_{ij}^t = & f(v_i^t, u_j^t) + \gamma \tilde{E}_{ij}^t \end{split}$$

 $\tilde{B}_{ij}^{t} = \operatorname{softmax}(B_{i}^{t-1}) \cdot \operatorname{softmax}(B_{i}^{t-1})$ 

 $B_{ij}^t = \mathbb{1}_{(i \neq j)} \left( f(h_i^t, h_j^t) + \gamma \tilde{B}_{ij}^t \right)$ 



## Results

Model	EM	F1
BiDAF	56.298	59.920
BiDAF + Char Embed	58.394	62.413
BiDAF + Char Embed + Reattn	59.121	62.979

## Analysis

In order to analyze the effect of reattention, we compare the full model's performance with the character embeddings-only model. In general, the full model is able to model complex interactions between question and context better:

#### Question: How did peace start?

**Context:** The war was fought primarily along the frontiers between New France and the British colonies, from Virginia in the South to Nova Scotia in the North. It began with a dispute over control of the confluence of the Allegheny and Monongahela rivers, called the Forks of the Ohio, and the site of the French Fort Duquesne and present-day Pittsburgh, Pennsylvania. The dispute erupted into violence in the Battle of Jumonville Glen in May 1754, during which Virginia militiamen under the command of 22-year-old George Washington ambushed a French patrol. **Answer:** N/A

Char Embed Prediction: with a dispute over control of the confluence of the Allegheny and Monongahela rivers Reattn Prediction: N/A

However, the full model did not do any better in terms of adversarial input (i.e. unanswerable questions)

#### **Future Work**

*Adversarial evaluation.* Adversarial data available for SQuAD 1.1; would be useful to evaluate models on updated data sets.

*Improving on unanswerable questions.* Predicting no-answer will improve performance on adversarial data; can implement a no-answer reader or a modified objective loss function.

#### References

[1] R. Jia and P. Liang. 2017. Adversarial Examples for Evaluating Reading Comprehension Systems. In *Empirical Methods in Natural Language Processing (EMNLP)* 2017.

[2] M. Hu, Y. Peng, Z. Huang, X. Qiu, F. Wei, and M. Zhou. 2018. Reinforced Mnemonic Reader for Machine Reading Comprehension. In 27th International Joint Conference on Artificial Intelligence (IJCAI).