QuACC : Question Answering for Cornell Courses

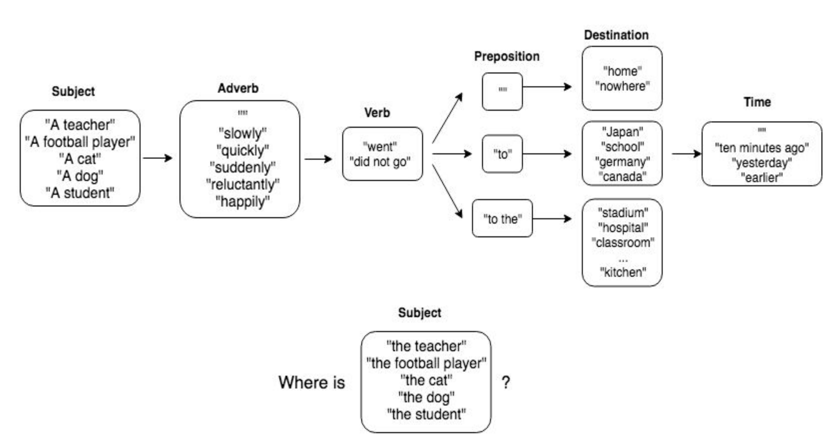
Kenta Takatsu, Yuji Akimoto, Chetan Velivela

Objective

QuACC : Question Answering for Cornell Courses is a deep learning architecture that aims to synthesize information from online resources such as textbooks and syllabi, and respond to questions about those resources. To achieve this long-term goal, we built a reading comprehension model which reads source passages and answers questions about the source passages

Dataset

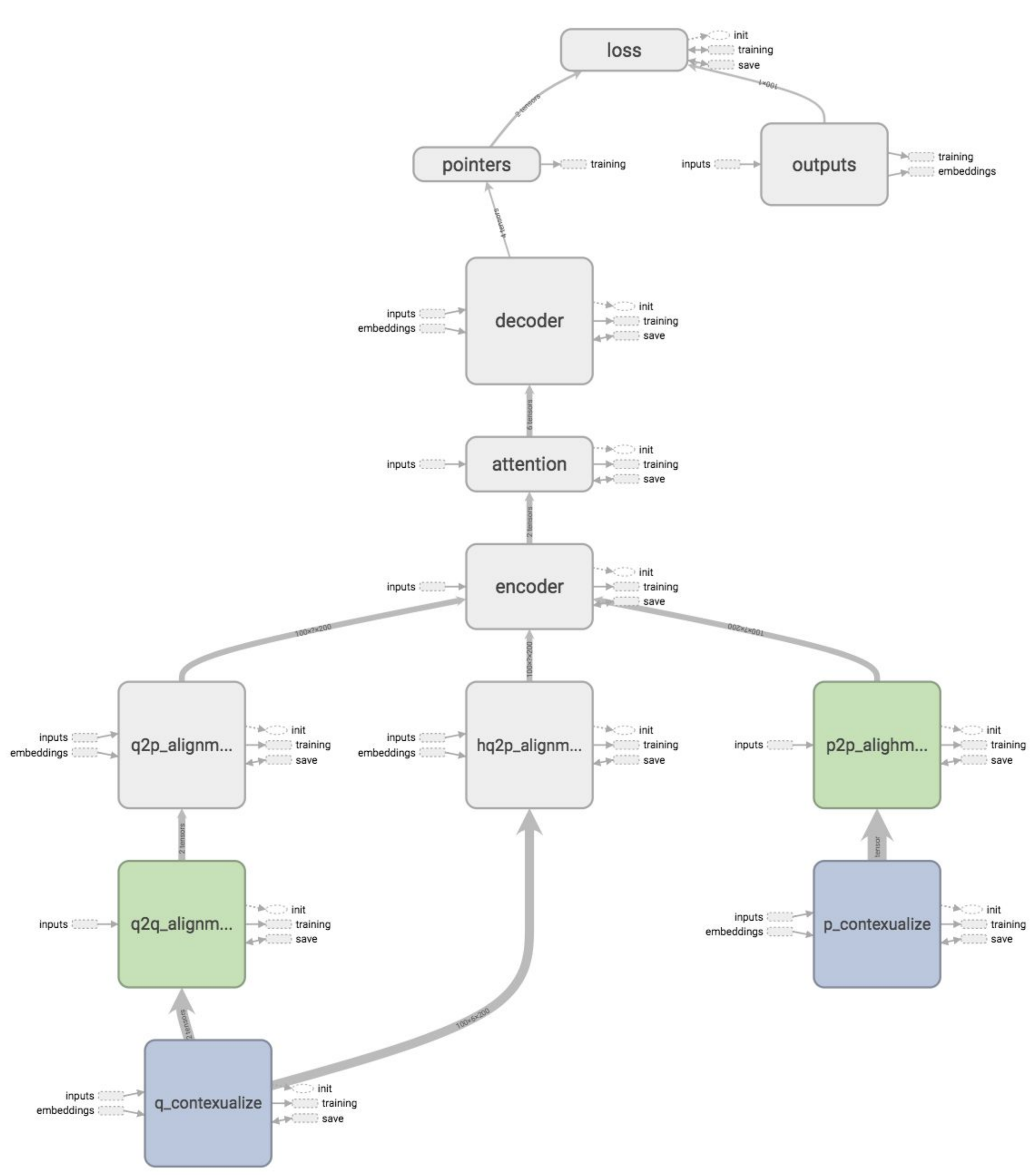
We conducted research with artificially synthesized data, which contains source passages, question sentences and locations of the answer to the question



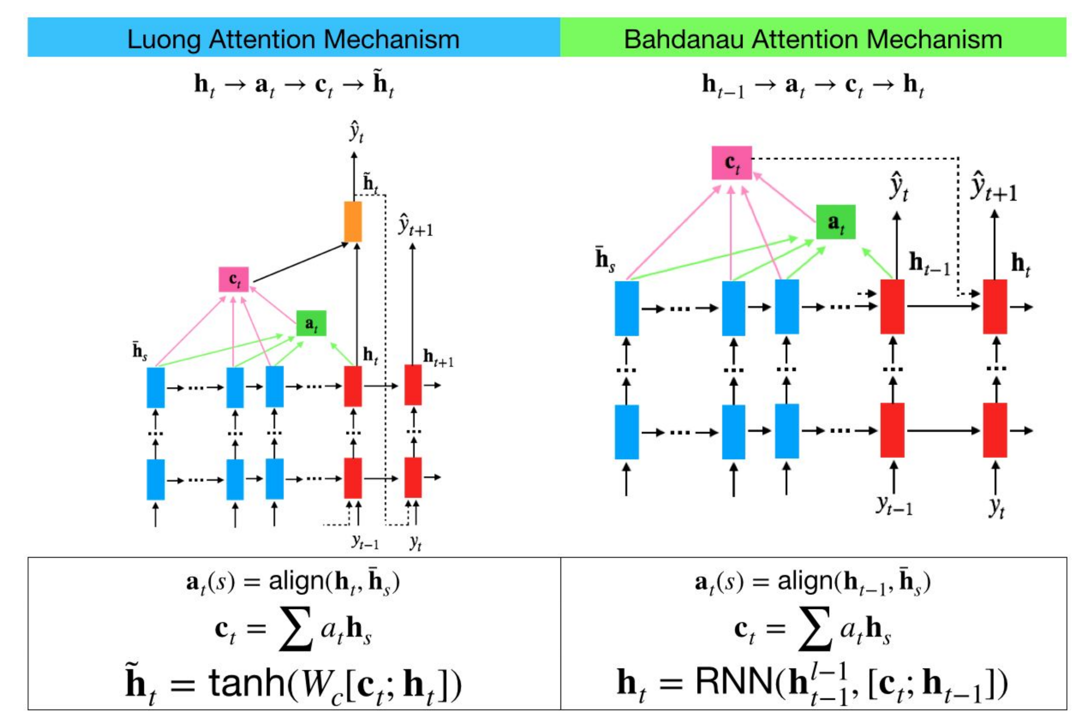
Model Architecture

QuACC takes following steps to perform reading comprehension tasks.

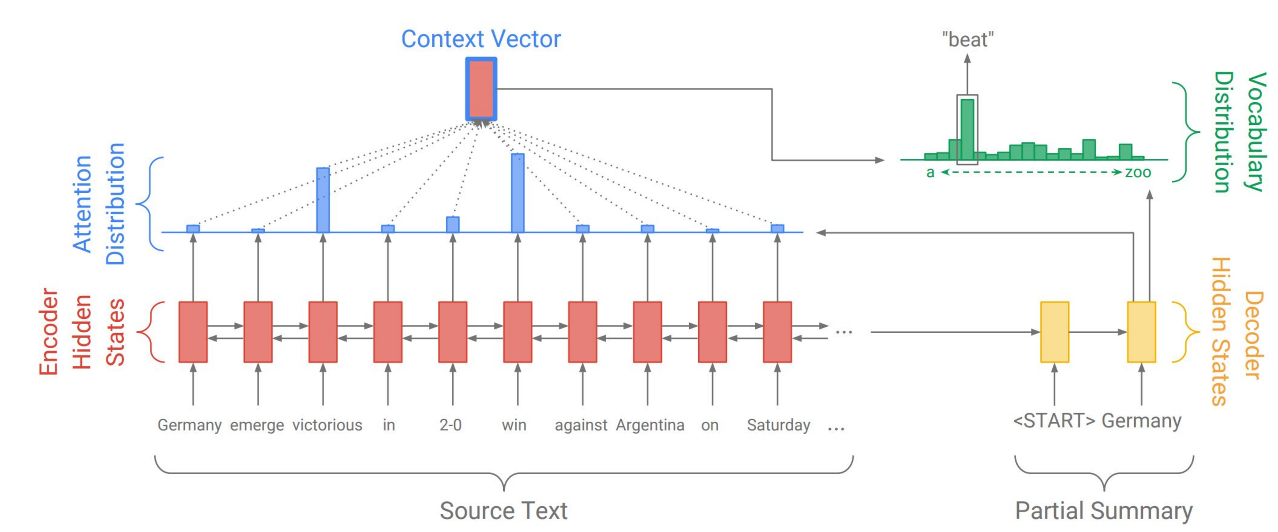
1. Convert each word into high-dimensional vector using GloVe [1]
2. Generate abstract representation of passages
3. Read questions with contextual knowledge of questions (Proofreading)
4. Read passages with contextual knowledge of questions
5. Read abstract representation of passages with contextual knowledge of questions [2]
6. Read abstract representation of passages with knowledge of question-aware representation of passages [3]
7. Find the answer



Attention Mechanisms

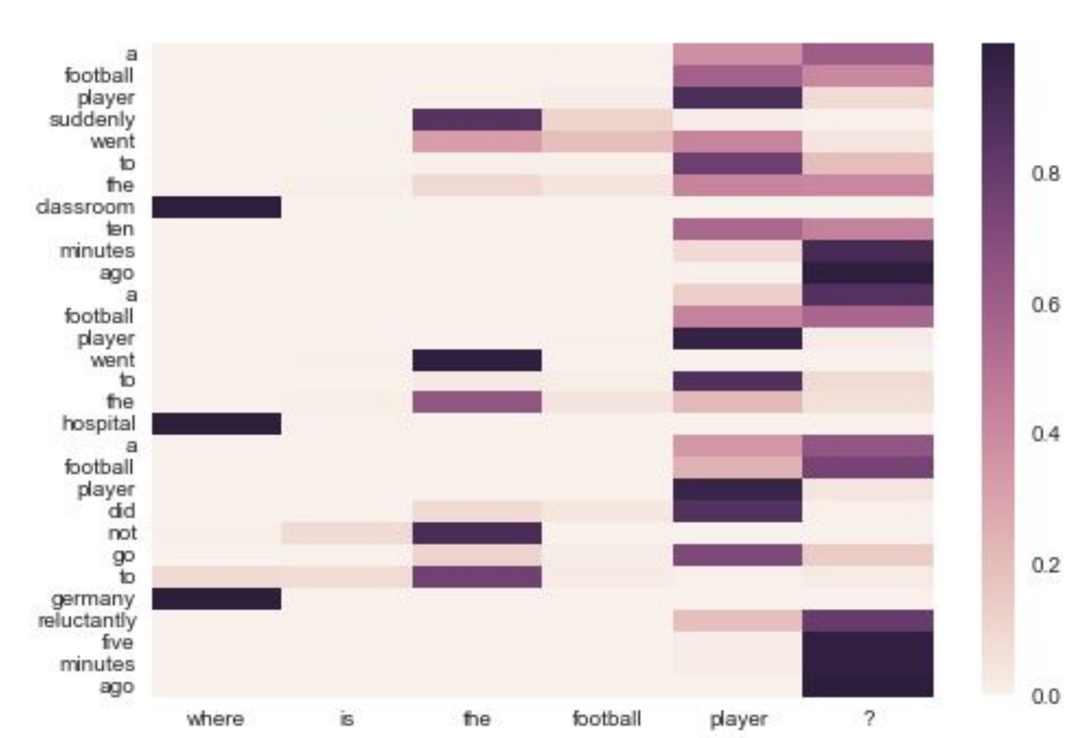


Pointer Net



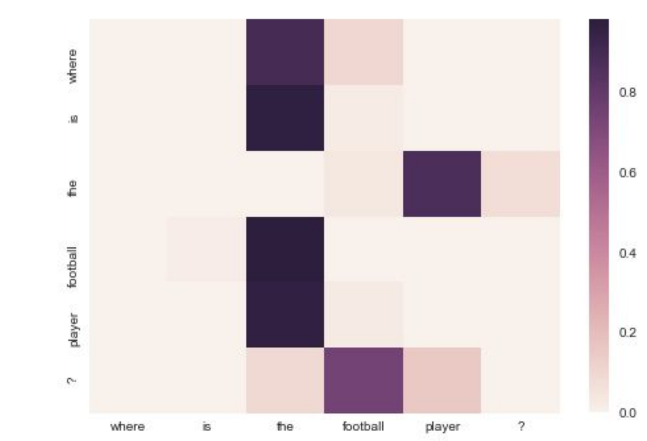
Passage-Question Alignment

Attention mechanisms allow us to conceptually understand the "thought" process of reading comprehension models. The figure below shows the attention weight of each word when the model reads a passage with contextual knowledge of question. We can see how the word "where" corresponds to the location words, and "the" filters out unnecessary words such as adverbs and "not".



Proofreading Layer

Previous models [4,5,6] in question answering did not have the process of "proofreading". We believe that this process will allow faster and more accurate convergence



Training

In order to combat the "vanishing gradient problem", we used Exponential Linear Units as activation [7]. We trained our model with learning rate of 0.0015 and batch size 100. We used GRU Cells with 100 units, dropout rate of 0.3, and single-layer RNNs. The model learned to correctly answer all questions on a test set after 30 epochs.

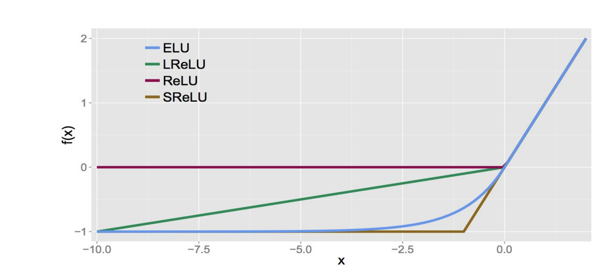
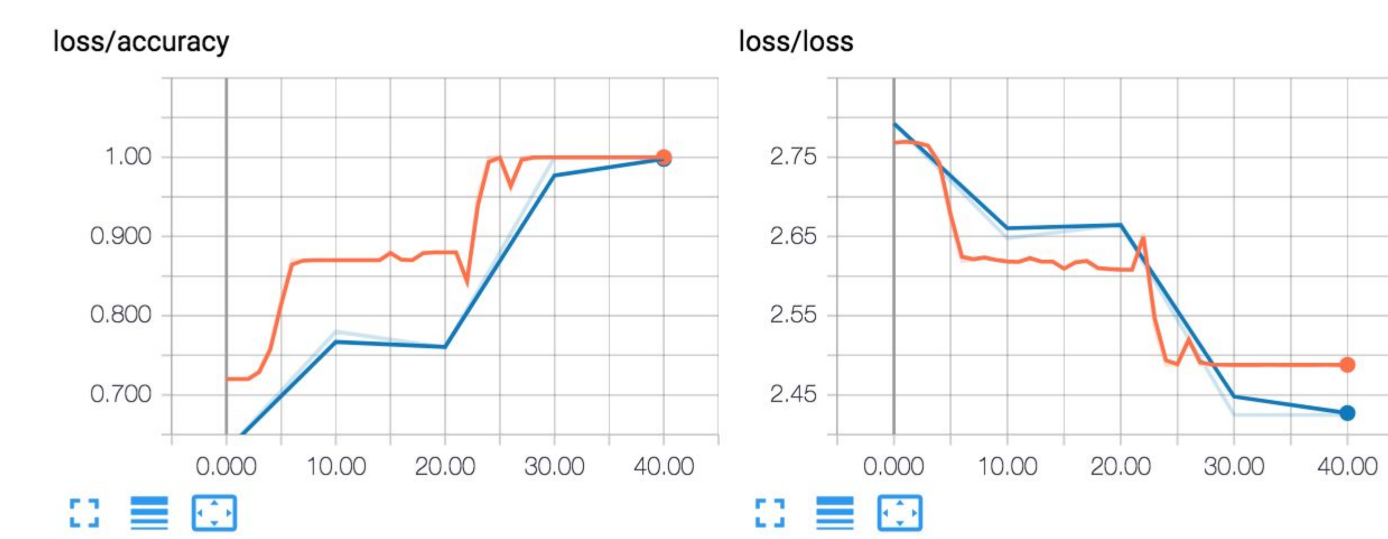


Figure 1: The rectified linear unit (ReLU), the leaky ReLU (LReLU, $\alpha = 0.1$), the shifted ReLUs (SReLUs), and the exponential linear unit (ELU, $\alpha = 1.0$).



Discussion

These experiments demonstrate the feasibility of our long-term goal. Although real-world data has far less consistent structure compared to our synthetic data, these results are promising in the following aspects:

- RNNs are able to keep track of relevant information through multiple sentences and learn the relevant rules.
- The attention mechanisms are able to parse relevant information in an interpretable fashion, even without explicit constraints or data distribution requiring them to do so.

Our next steps are to vary question type before moving on to industry standard tasks such as the SQuAD dataset challenge.

References

[1] *GloVe: Global Vectors for Word Representation*
[2] *Reasoning about Entailment with Neural Attention, arxiv:1509.06664,* 2016
[3] *R-NET: Machine Reading Comprehension With Self-matching Networks,* 2015
[4] Bidirectional Attention Flow for Machine Comprehension, *arxiv:1611.01603,* 2016
[5] *FusionNet: Fusing via Fully-aware Attention with Application to Machine Comprehension,* 2018
[6] Fast and Accurate Deep Network Learning by Exponential Linear Units, *arxiv:1511.07289,* 2015
[9] Pointer Networks, *arxiv:1506.03134,* 2017
[10] Effective Approaches to Attention-based Neural Machine Translation, *arxiv:1508.04025,* 2015