Applying QANet to SQuAD 2.0
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Introduction
Machine question answering has been a rising area of research in NLP over the past few years, and at the heart of it is the Stanford Question Answering Dataset (SQuAD), version 2.0. In SQuAD, the model is given a question and a context paragraph, and asked to predict the answer, defined as a span from the paragraph. SQuAD 2.0 added unanswerable questions to the dataset. In this project, we aimed to implement the QANet from Yu et al, one of the top performing models on SQuAD 1.0, and adapt it for for 2.0. QANet focuses on removing the need for sequential processing, instead using a combination of self-attention and convolution to process the input.

Data
We used the official SQuAD dataset, where the training data is taken from the official train set, and our dev and test sets are randomly selected from the official dev set. Additionally, we used pretrained GLoVe word embeddings of dimension 300.

Architecture

Methods
Input Embedding Layer:
1. Concatenate GloVe embeddings for each word with learned character embeddings.
2. Pass through a highway network, the output of which is our embedding

Embedding Encoder Layer (encoder block)
1. Add positional encoding to maintain information lost by convolutions
2. Pass this through convolutional layers with depthwise separable convolutions
3. Pass this through a self-attention layer
4. Pass through a feed-forward layer, which is then output from this block

Context-Query Attention Layer
Computes the attention score between each word in the query and context
1. Compute similarity matrix S and normalize over each row and column to get S’ and S’’ respectively
2. Let C be the matrix of the encoded context, and Q the matrix of the encoded query, the context-to-query attention is A = S’ * Q^T, and the query to context attention is B = S’ * S’’^T * C

Model Encoder Layer:
1. This layer consists 7 encoder blocks chained together
2. Pass the input through the chained blocks 3 times to obtain M_0, M_1, M_2

Output Layer:
1. Find probability distribution of start index by passing M_0, M_2 through a softmax function, and similarly with M_0, M_1 for the end index.
   \[ p^s = \text{softmax}(W_1[M_0; M_1]) \]
   \[ p^e = \text{softmax}(W_2[M_0; M_2]) \]
To handle “No Answer”, we add a special token at the start, and if the model’s prediction of start and end of span is this token, output N/A

Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Dev set EM</th>
<th>F1</th>
<th>Test set EM</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline BiDAF</td>
<td>57.05</td>
<td>60.62</td>
<td>56.298</td>
<td>59.920</td>
</tr>
<tr>
<td>BiDAF with Char Embeddings</td>
<td>61.39</td>
<td>64.84</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>QANet</td>
<td>62.914</td>
<td>66.467</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>QANet convolutional attention</td>
<td>62.527</td>
<td>66.227</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>QANet multi-head attention (2 heads)</td>
<td>64.24</td>
<td>67.67</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>QANet multi-head attention (3 heads)</td>
<td>63.74</td>
<td>67.04</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>BiDAF + QANet ensemble</td>
<td>66.258</td>
<td>69.432</td>
<td>63.956</td>
<td>67.442</td>
</tr>
</tbody>
</table>

Analysis
Our model struggles with many no answer questions, where the query is almost exactly in the context, but there is no answer. In this example, it is likely the model did not properly associate “Triton” with being male, and so incorrectly associated Triton with the “she” in the context.

Conclusion
Our ensemble of BiDAF with 3 different QANets achieved EM of 63.956 and F1 of 67.442 on the test set, good enough for sixth place on the leaderboard. This illustrates that QANet, originally designed with SQuAD 1.0 in mind, works well on the version 2.0 dataset, with only a few simple changes.

In the future, we would ideally have access to a GPU with more memory, as we were memory constrained while training. Additionally, we would train our best model several times with random starts, and ensemble this to test whether or not it would achieve higher performance than the result of single training sessions.

References