Character CNN and Self-Attention for SQuAD

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Abstract

The Stanford Question Answering Dataset (SQuAD) and challenge is for researchers to develop reading comprehension and question answering models. The task is to correctly answer a question given a paragraph of context. This paper discusses the use of a character-level convolutional neural network and self-attention layer in tackling this challenge, as well as accompanying memory and performance optimizations.

1 Introduction

The SQuAD [1] challenge is to develop a model that is capable of answering a question given a paragraph of context text containing the answer. The dataset contains around 100K of crowdsourced question-answer pairs. The model is evaluated on its accuracy in selecting the correct span of text within the context paragraph for each question as either an exact match (EM) or partial match (F1) score.

The intended[1] overall approach to this problem was to first experiment with a few independent model enhancements. These would then be combined and optimized through a hyperparameter search. To operate within available computing resources as well as to facilitate faster experimentation, this paper also discusses some performance optimizations for memory usage and processing time for training.

2 Background/Related Work

Character-level convolutional neural networks (CNN) are an increasingly popular mechanism for a variety of natural language processing (NLP) tasks [4]. Character-level embeddings are also commonly used in SQuAD solutions [2][3] although these are typically of secondary importance to boost the final task performance.

Attention methods are a heavily researched area for tackling SQuAD, with many different variants explored [2][3] and regarded a key component of most high-performing models. This is logical for the SQuAD challenge given that the key task is to find the span in the context which attends to the question. Given that the answer is a continuous span of text, it further makes sense to pick an attention method which naturally supports this such as [3].

3 Approach

First, a character-level CNN was implemented similar to [2], where characters are embedded into vectors and fed as 1D inputs in a moving window to a CNN. The CNN output is max-pooled to

[1] Please see Additional Information document for more details.

Table 1: Batch training times with and without variable input length modification.

Architecture	Average Batch Time
Char CNN, Batch size 100	2.02s
+Variable input length	1.44s

produce a fixed size vector for each word, which is then concatenated with the pre-trained word embedding vector. This concatenation is then fed to the baseline bi-directional GRU encoder layer. The character embeddings are not pre-trained, but trained together with the model. The character vocabulary is assembled from all the words loaded from the GloVe embeddings. The input matrix of each batch of training data fed to the CNN was large due to the explosion of having a vector for each character instead of just each word. A memory optimization was implemented to subdivide each training batch processed by the CNN and recombine the results by concatenation.

It was observed that the default context and question length of 600 and 30 respectively was abundant in most cases, which added to training time unneccessarily. Variable context and input length was implemented to reduce this with the primary intention of speeding up iterative experiments for hyperparameter search later on. Being able to better handle contexts and questions longer than the default was a secondary benefit. This was done by setting the context and question lengths on a maximum-per-batch basis, as well as being the smallest possible product of the number of subdivisions configured for the CNN memory optimization. The latter is necessary for equal splitting to work as the last batch used before refilling may not have the same factors as a normal batch. For example, if the CNN subdivisions was set to 4 and the longest context in a particular batch was 102, the context length for the batch would be set as 104 which is the smallest product of 4 that is also larger than 102. All the other questions in the same batch would be padded to 104 words. This helped to reduce the training time required by around 29% as can be seen from Table 1; the table figures were calculated from averaging the processing times from batches 2-500 (omitting batch 1 time as it includes initialization overheads).

Next, a self-attention mechanism was added in reference to [3]. This is done by first adding a gate on the baseline attention layer output by multiplying the attention output with a trainable weight matrix and sigmoid activation. This is then fed into a self-attention layer. In [3], the self-attention layer is additive, i.e.:

$$\mathbf{e}_i = \mathbf{v}^T tanh(\mathbf{W}_1\mathbf{h}_i + \mathbf{W}_2\mathbf{s})$$

However due to memory limitations, the implementation in this paper uses multiplicative attention, i.e.:

$$\mathbf{e}_i = \mathbf{s}^T\mathbf{W}\mathbf{h}_i$$

The output of the self-attention layer is fed into another gate similar to the one used after the baseline attention layer, before being concatenated with the context hidden states as a blended representation and fed into a bi-directional GRU. The additional self-attention and RNN layers are configured to use the same dropout regularization rate as in the baseline GRU encoder and attention layers. Finally, this is passed into the baseline fully-connected layer and softmax function to generate the start and end answer locations. Figure 1 gives an overview of the full architecture.

4 Experiments

On their own, the character CNN and variable input length does not have any significant impact on the task performance. This is not unexpected as out-of-vocabulary (OOV) words have not been observed to be a major issue in the SQuAD dataset and the number of questions or answers exceeding the default fixed length is small. Due to the memory and speed improvements mentioned earlier, it was still possible to run training with a batch size of 100 at a comparable speed to the baseline.

After introducing self-attention, which significantly increased the number of trainable parameters, it was necessary to reduce the batch size to 50 to keep within memory limits. This yielded a significant

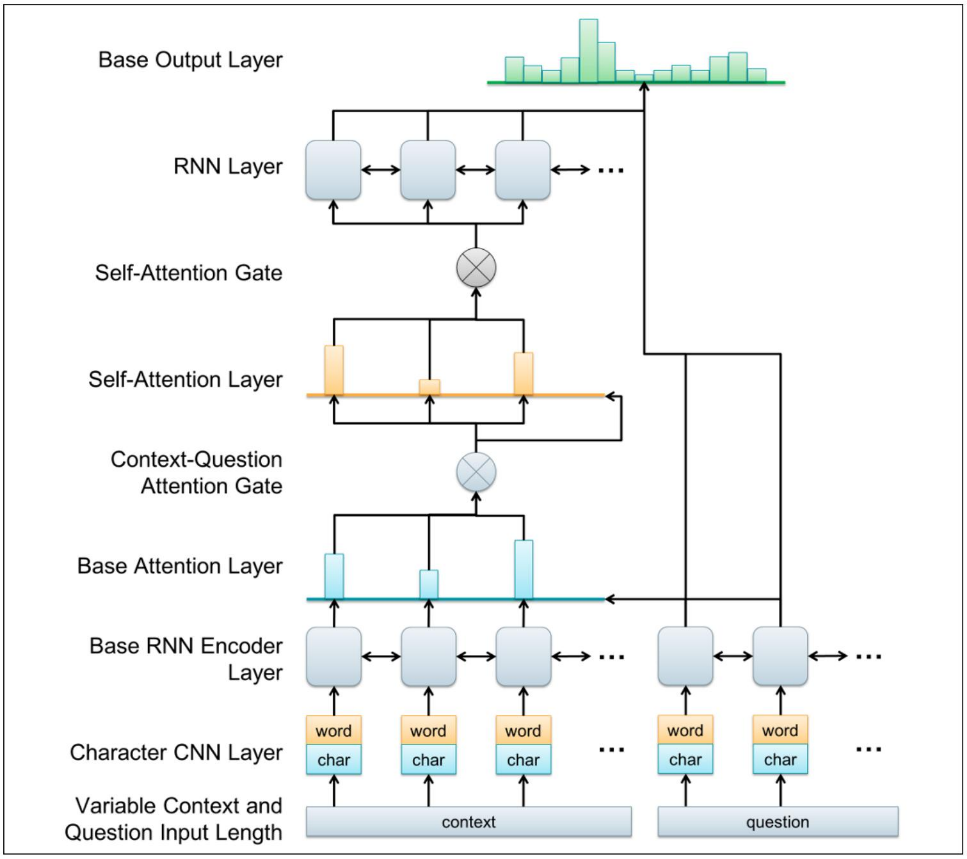


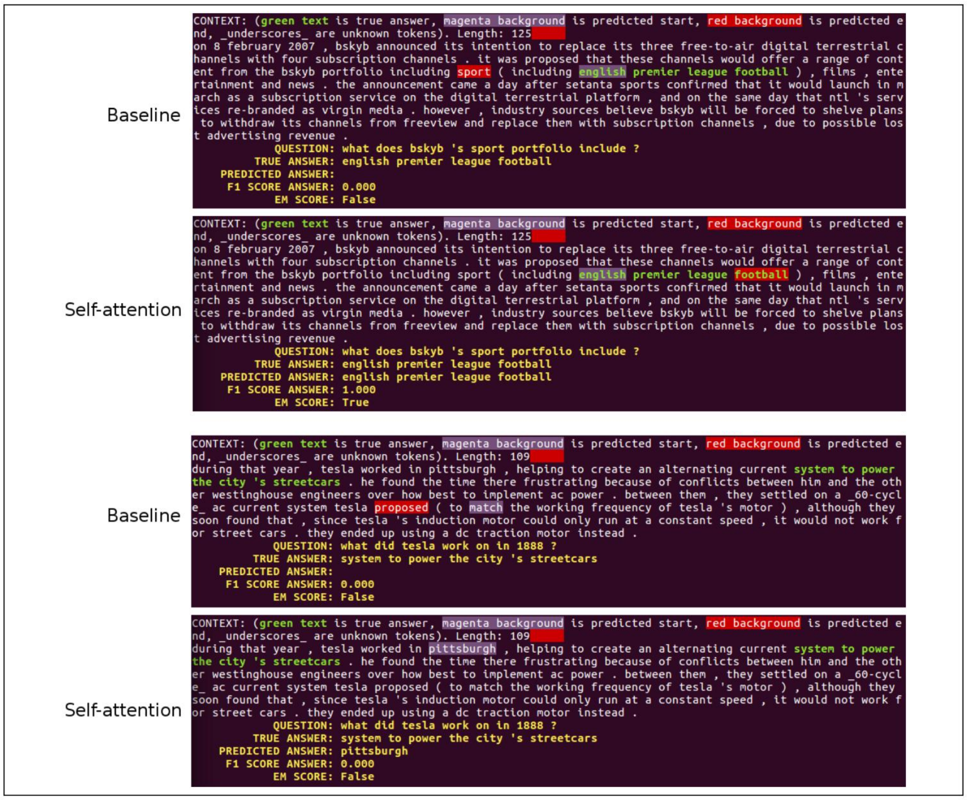
Figure 1: Model architecture.

Table 2: Dev dataset results

Architecture	F1 Score	EM Score
Baseline	43.982	34.683
+Char CNN, +Variable input length	43.721	34.437
+Self-attention, -Batch size 50	**69.024**	**58.666**
+Hidden size 256	68.084	57.275
+GloVe 300D, -Hidden size 150	67.837	57.171

improvement in task performance (Table 2). Examining the sample output of this model compared to the baseline, it is observed that self-attention does not suffer from incorrect answers where the end point is predicted behind the start point (Figure 2). Similarly, self-attention avoids selecting large spans of text as the answer, as seen in Figure 3; even though the self-attention answers in these examples are still wrong, they are arguably more coherent choices than in the baseline. Both these scenarios are consistent with the intuition discussed in [3] that self-attention expands upon the narrow context of basic context-question attention to find other relevant information.

From the tensorboard plots of this model (Figure 4), the dev loss does not increase greatly after the dev performance begins to plateau. This might suggest that the model is not overfitting that aggressively and there may be more headroom to increase the model expressiveness. This was thus the approach for the hyperparameter search. One experiment was to increase the hidden state size from 200 to 256, and another to use the largest GloVe embeddings of size 300 but reduce the hidden state size to 150. In both cases the parameters were empirically chosen to fit within available GPU memory limits. However, these were not successful in improving the task performance (Table 2).



```
CONTEXT: (green text is true answer, magenta background is predicted start, red background is predicted e
nd, _underscores_ are unknown tokens). Length: 125
on 8 february 2007 , bskyb announced its intention to replace its three free-to-air digital terrestrial c
hannels with four subscription channels . it was proposed that these channels would offer a range of cont
ent from the bskyb portfolio including sport ( including english premier league football ) , films , ente
rtainment and news . the announcement came a day after setanta sports confirmed that it would launch in m
arch as a subscription service on the digital terrestrial platform , and on the same day that ntl 's serv
ices re-branded as virgin media . however , industry sources believe bskyb will be forced to shelve plans
 to withdraw its channels from freeview and replace them with subscription channels , due to possible los
t advertising revenue .
            QUESTION: what does bskyb 's sport portfolio include ?
         TRUE ANSWER: english premier league football
    PREDICTED ANSWER:
     F1 SCORE ANSWER: 0.000
            EM SCORE: False
```

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t advertising revenue .
            QUESTION: what does bskyb 's sport portfolio include ?
         TRUE ANSWER: english premier league football
    PREDICTED ANSWER: english premier league football
     F1 SCORE ANSWER: 1.000
            EM SCORE: True
```

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CONTEXT: (green text is true answer, magenta background is predicted start, red background is predicted e
nd, _underscores_ are unknown tokens). Length: 109
during that year , tesla worked in pittsburgh , helping to create an alternating current system to power
the city 's streetcars . he found the time there frustrating because of conflicts between him and the oth
er westinghouse engineers over how best to implement ac power . between them , they settled on a _60-cycl
e_ ac current system tesla proposed ( to match the working frequency of tesla 's motor ) , although they
soon found that , since tesla 's induction motor could only run at a constant speed , it would not work f
or street cars . they ended up using a dc traction motor instead .
            QUESTION: what did tesla work on in 1888 ?
         TRUE ANSWER: system to power the city 's streetcars
    PREDICTED ANSWER:
     F1 SCORE ANSWER: 0.000
            EM SCORE: False
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soon found that , since tesla 's induction motor could only run at a constant speed , it would not work f
or street cars . they ended up using a dc traction motor instead .
            QUESTION: what did tesla work on in 1888 ?
         TRUE ANSWER: system to power the city 's streetcars
    PREDICTED ANSWER: pittsburgh
     F1 SCORE ANSWER: 0.000
            EM SCORE: False
```

Figure 2: Example results showing improvements in not predicting an end point behind the start point.

Table 3: Test dataset results

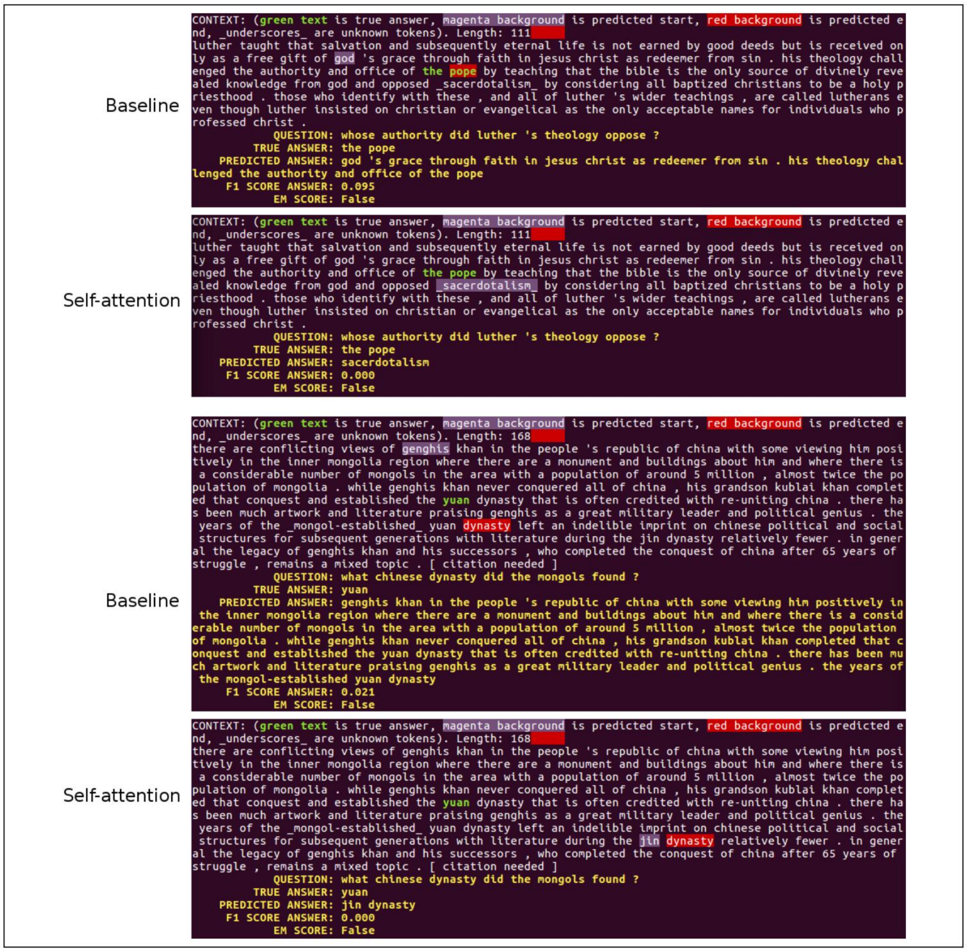
Architecture	F1 Score	EM Score
+Char CNN, +Variable input length, +Self-attention, -Batch size 50	69.637	59.761

Thus for the final test, the self-attention model with batch size 50, hidden size 200 and GloVe embedding size 100 was submitted, achieving the results shown in Table 3.

5 Conclusion

This project has been a useful exercise on many fronts. I learnt about the importance of strategizing the approach to deep learning problems. Under time and resource constraints it is helpful to identify key areas for improvement in order to prioritise work for the greatest performance gains. For instance, if I were to restart the challenge on my own, I would probably not have looked into character CNN so early. Strategizing also applies to knowing which methods work well with each other and how much additional work is required for integration. The variable input length required some effort to integrate with both already-implemented and subsequent model enhancements, but was likely still worth the time investment given the training time savings.

It was also a great learning experience to think about and experiment with all the different levers to pull (to borrow from bandit problem terminology) while considering the training graph plots, training time and memory limits. Especially regarding the latter two points, I have learned about the importance of building efficient models since simply using brute force was not an option.



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CONTEXT: (green text is true answer, magenta background is predicted start, red background is predicted e
nd, _underscores_ are unknown tokens). Length: 111
luther taught that salvation and subsequently eternal life is not earned by good deeds but is received on
ly as a free gift of god 's grace through faith in jesus christ as redeemer from sin . his theology chall
enged the authority and office of the pope by teaching that the bible is the only source of divinely reve
aled knowledge from god and opposed _sacerdotalism_ by considering all baptized christians to be a holy p
riesthood . those who identify with these , and all of luther 's wider teachings , are called lutherans e
ven though luther insisted on christian or evangelical as the only acceptable names for individuals who p
rofessed christ .
            QUESTION: whose authority did luther 's theology oppose ?
         TRUE ANSWER: the pope
    PREDICTED ANSWER: god 's grace through faith in jesus christ as redeemer from sin . his theology chal
lenged the authority and office of the pope
     F1 SCORE ANSWER: 0.095
            EM SCORE: False
```

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rofessed christ .
            QUESTION: whose authority did luther 's theology oppose ?
         TRUE ANSWER: the pope
    PREDICTED ANSWER: sacerdotalism
     F1 SCORE ANSWER: 0.000
            EM SCORE: False
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```
CONTEXT: (green text is true answer, magenta background is predicted start, red background is predicted e
nd, _underscores_ are unknown tokens). Length: 168
there are conflicting views of genghis khan in the people 's republic of china with some viewing him posi
tively in the inner mongolia region where there are a monument and buildings about him and where there is
 a considerable number of mongols in the area with a population of around 5 million , almost twice the po
pulation of mongolia . while genghis khan never conquered all of china , his grandson kublai khan complet
ed that conquest and established the yuan dynasty that is often credited with re-uniting china . there ha
s been much artwork and literature praising genghis as a great military leader and political genius . the
 years of the _mongol-established_ yuan dynasty left an indelible imprint on chinese political and social
 structures for subsequent generations with literature during the jin dynasty relatively fewer . in gener
al the legacy of genghis khan and his successors , who completed the conquest of china after 65 years of
struggle , remains a mixed topic . [ citation needed ]
            QUESTION: what chinese dynasty did the mongols found ?
         TRUE ANSWER: yuan
    PREDICTED ANSWER: genghis khan in the people 's republic of china with some viewing him positively in
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ch artwork and literature praising genghis as a great military leader and political genius . the years of
 the mongol-established yuan dynasty
     F1 SCORE ANSWER: 0.021
            EM SCORE: False
```

```
CONTEXT: (green text is true answer, magenta background is predicted start, red background is predicted e
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there are conflicting views of genghis khan in the people 's republic of china with some viewing him posi
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     F1 SCORE ANSWER: 0.000
            EM SCORE: False
```

Figure 3: Example results showing improvements in not selecting very large spans of text.

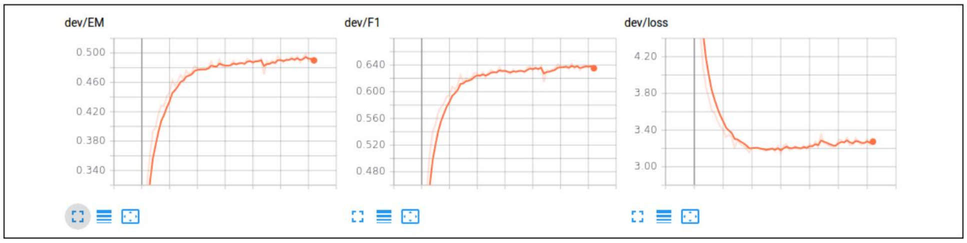

Figure 4: Tensorboard plots for dev performance and loss for self-attention model.

For further work, it should be worth experimenting with pre-trained character embeddings for the character CNN. In [4], this gave marginally better results on a variety of NLP tasks over randomly initialized ones which were trained together with the task, even before tuning the pre-trained vectors for the specific task. This would remove the uncertainty of the character vector training being effective as a factor in the overall SQuAD performance. Another possible improvement is to replace other baseline components such as the final output layer with the Answer Pointer model [5].

References

[1] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text. CoRR, abs/1606.05250, 2016.

[2] Minjoon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. Bidirectional attention flow for machine comprehension. arXiv preprint arXiv:1611.01603, 2016.

[3] Natural Language Computing Group, Microsoft Research Asia. R-net: machine reading comprehension with self-matching networks, 2017.

[4] Yoon Kim. Convolutional neural networks for sentence classification. arXiv: 1408.5882v2, 2014.

[5] Shuohang Wang and Jing Jiang. Machine comprehension using match-lstm and answer pointer. arXiv preprint arXiv:1608.07905, 2016.