Attention Mechanisms for Recurrent Neural Networks

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Abstract. We explore the use of an attention mechanism to enhance the standard neural machine translation (NMT) task which uses a recurrent neural network (RNN) with a gated recurrent unit (GRU) The attention mechanism allows the RNN to learn which words of the input sentence are important at each step of translation.

1 Introduction

Given a corpus of written sentences in one language with corresponding sentence translations in another language, we would like to train a deep neural network to learn a model which maps from the original language to the translated language and has generalizing capabilities to translate novel sentences. Translation is difficult for humans, even after years of study and practice, and is often best performed by those who have studied and used the two languages in question from their nativity. Any technology which can quickly and reliably complete this task is highly desirable and can be used in many applications.

One common approach to neural machine translation (NMT) uses a recurrent neural network (RNN) with a gated recurrent unit (GRU). The RNN model is capable of learning patterns in time-series data, like sentences, with variable length. The GRU is an internal component to the RNN which allows the model to persist a memory state between time steps, or words, in the sentence. We apply an attention mechanism, proposed by Bahdanau, et. al.[1], which further enhances the translation process by allowing the RNN to observe data from every time step in the sequence, not just the previous.

2 Background

2.1 RNN Encoder-Decoder

In typical neural machine translation, an encoder-decoder structure is used. In such approaches, the encoder, an RNN, produces a hidden state for each token in the input sequence. At each time step in the sequence, the hidden state is a function of the input token and the hidden state of the previous input token. Then the decoder, another RNN, uses the state vector from the encoder as its initial state to generate new words, updating its state with each new word generation. One chief weakness of this approach is that the way that the hidden states from the original encoding are compressed might not be optimal for each distinct step of the decoding process. In fact, in many implementations, only the final hidden state of the encoder is preserved as the encoding of the entire input. This dramatically limits the length of sequences that can be translated, since in long sentences, signal from early input words might be slowly diluted.

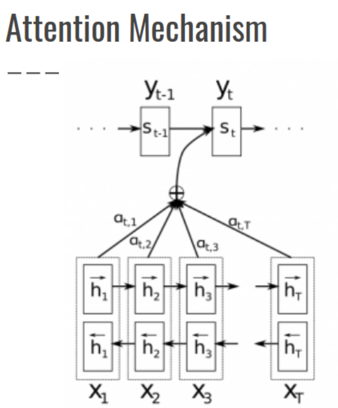
2.2 GRU

At each time step of an RNN, there must be some function to combine any state from the last time step and the input at the current time step. One solution is the gated recurrent unit (GRU)[2]. A GRU takes two inputs, the input data at time t and the output of the GRU at time $t-1$, outputting a single vector. The output becomes a type of memory, updated with the new input of the time series data.

3 Model Architecture

3.1 Attention Mechanism

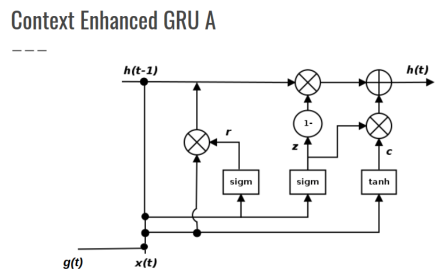
Bahdanau, et. al.[1], propose the use of an attention mechanism to mitigate the bias towards one end of the sequence that is inherent in traditional encoder-decoder RNNs. Instead of using the resultant state vector from the encoder, the decoder is allowed to have input from each time step of the encoder, using an attention mechanism. The attention mechanism is a sub-architecture of the network and a function of the current hidden state of the decoder and the output of each and every encoder time step. This mechanism produces a weight for each output of the encoder, allowing the decoder, as a function of its current state, to learn how to use the encoder outputs. This sub-architecture is a simple fully-connected feedforward neural network. Thus, error signals can be propagated from the decoder back through the attention mechanism and the encoder. Now the decoder, having a full view of the input sequence, can learn which parts of the input sequence are relevant in determining the next output in the output sequence. A diagram of this is shown below.



3.2 GRU Variation

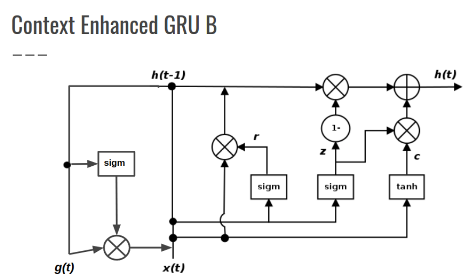
While Bahdanau, et. al.[1] presented the implementation details for the attention mechanism model, they left open to interpretation a way to apply the model. In most encoder-decoder architectures, the time cells in the decoder are only built to handle an input and a previous state, which is often initialized with the encoders output. When we introduced the output of the attention mechanism, which we will refer to as the context, we could no longer pass it in as the initialization of the state, because the context changes at every time step of the decoding process.

We decided to treat the context as an additional type of input to keep it separate from the state, which has a distinct purpose in an RNN. We propose two context-enhanced GRU architectures that incorporate the context as part of the input of our time cell. Cell type A was the simplest alteration we could design.



It involves simply concatenating the context vector to the input and treating the concatenation as a new input. The rest of the cell is identical to a typical GRU.

Cell type B involved passing the state and the context through a fully connected layer and then through a sigmoid, to create a set of gating coefficients through which to pass the context.



This enables the model to filter out the irrelevant portions of the context. The filtered context is then concatenated to the input to create a new input and the remainder of the cell looks like a typical GRU.

4 Experiment

We decided to try our attention mechanism model on an English-to-Spanish NMT task. We selected a canonical NMT dataset, the European Parliament Proceedings corpus[3]. More specifically, we used the subset of this corpus that had aligned English and Spanish sentences. We knew that our model would have a set output vocabulary size and worried that many of the words that appeared in our dataset, things such as diverse world leaders, locations, and organizations, would be too uncommon to be included in our output vocabulary. Therefore, we used Stanfords Named Entity Recognition library[4] (NER) to tag all people, locations, and organizations and replace them with their class name. We further simplified our translation task by pruning our dataset to preserve only sentences of length 30 or less composed only of words in the 3000 most common words of the dataset. We did this for both English and Spanish.

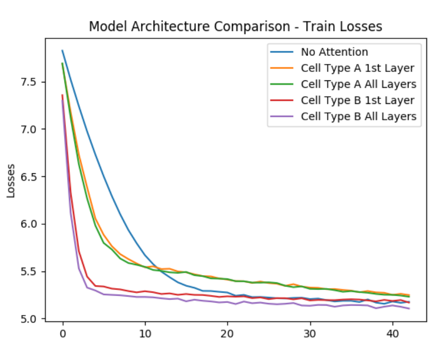
Having simplified our task, we implemented a model that we thought would have sufficient learning capacity. Our encoder was a bidirectional RNN where each direction had 2 layers, hidden states of size 256, and an input size of 300, which was set by the FastText embedding dimension. It output concatenated hidden states of size 512 as embeddings. Our decoder was a forward RNN with 2 layers, hidden states of size 512, and an input size of 300. We used this model size to train 5 different models: a default encoder-decoder model with no attention mechanism, an attention mechanism based model with cell type A at the first layer, one with cell type A at every layer, one with cell type B at the first layer, and one with cell type B at every layer.

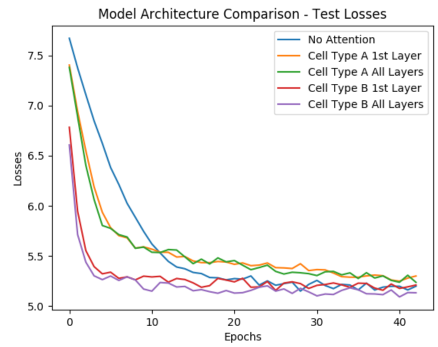
We also trained 2 additional models in order to see if increasing model capacity would improve results. These were an attention mechanism model with cell type B at the first layer and one with cell type B at every layer. However, these models had encoder RNNs with hidden size 512 and a decoder RNN with hidden size 1024. Moreover, both the encoder and decoder had 3 layers.

For our loss function, since we were trying to predict individual words from a set of 3000, we thought that cross entropy loss would be appropriate. Since we were trying to do this for an entire sequence, we averaged cross entropy losses over the entire output sequence and over the batch as well.

5 Results

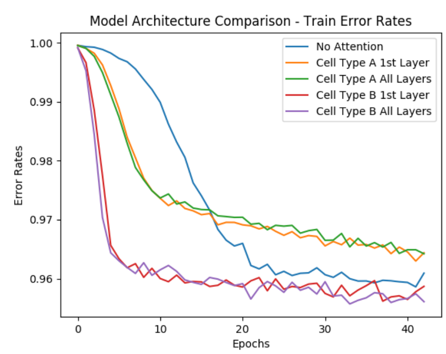
Our models show a clear trend of learning. Consider the train and test loss plots, respectively shown below.





While all models appear to converge to the same minimum, those which use the attention mechanism begin their convergence more quickly. The models which use cell type A, plateau sooner, so the model without the attention mechanism quickly surpasses them. The models with cell type B have better convergence overall.

We also consider a word error rate. This measurement determines what percentage of the words were incorrectly translated. Consider the plots below, containing the word error rates for all the models at both train and test time.



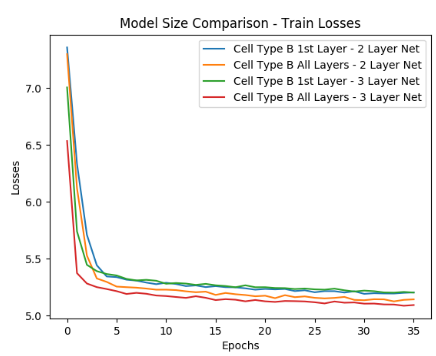
These word error rates correlate highly with the losses, though with more variance between epochs.

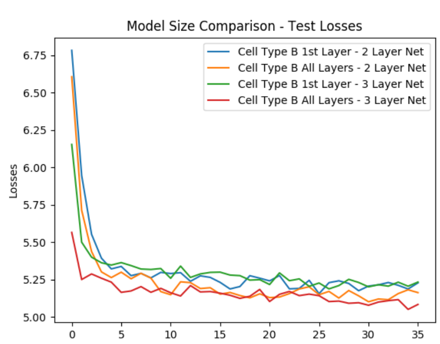
As indicated by our error rate graph, we only achieved a 95% error rate. Our 5% accuracy can likely be explained by our mean sentence length being 20 and the final token always being the end of sentence token. This can be seen in the sample translation below:

Source
i have already mentioned the eastern partnership . EOS
Target
ya he mencionado la organizacin organizacin . EOS
Predicted
el puede podra la ha de dar EOS

While there is a clear indication of learning some mapping between the English and Spanish text, our word error rates are hardly deployable. We attempted to simplify the learning process from the beginning. We applied NER to remove the occurances of rare names, places and organizations. We further reduced the vocab to the most common words.

Attempting to improve our results, we tried altering the model architecture for our two cell type B models. Since the loss plateaued quickly, this seemed a reasonable choice. We doubled our hidden state size and added a layer to increase the model's learning capacity. The loss plots are shown below.





However, changing the hyperparameter settings showed little improvement. There is slight improvement in the capacity of the model when using more layers, as can be expected.

In future iterations, we would consider a couple more variations to lower the word error rate. It is possible that the models could drop out of their local minima given significantly longer training time. Furthermore, a different loss function could ease the task at hand for the models. Currently, the models are only predicting about one word in 20 correctly, or one word per sentence. Our loss function does not consider slight variations in word order that could be allowed by the natural language. We might also reduce our sentence length to simplify the task.

6 Summary

Neural machine translation is a difficult task. A translation dataset requires significant natural language processing techniques. Using an attention mechanism on a traditional RNN allowed us to achieve faster convergence given the same amount of training data, however we underestimated the importance of the loss function.

7 Bibliography

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