Assignment 5

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1 Character-based convolutional encoder for NMT

(a) Explain one reason why the embedding size used for character-level embeddings is typically lower than that used for word embeddings

When using character-level embeddings the size of the vocabulary is smaller than the size of the word-level vocabulary and multiple character embeddings are combined together to build a word. As such the size of each embedding can be smaller.

(b) Total number of parameters

For character-level embeddings the number of parameters is

$$N_{char} = V_{char} * e_{char} + e_{word} * e_{char} * k + e_{word} + 2 * (e_{word} * e_{word} + e_{word})$$

For word-level embeddings the number of parameters is

$$N_{word} = V_{word} * e_{word}$$

For $k = 5$, $V_{word} = 50000$ and $V_{char} = 96$ and given that $e_{word} \approx 5 * e_{char}$ the approximate number of parameters are

$$N_{char} = 96 * e_{char} + e_{word}^2 * e_{char} + e_{word}^2 \approx e_{word}^2 * e_{char}$$

$$N_{word} = 50000 * e_{word}$$

The ratio is

$$\frac{N_{word}}{N_{char}} = \frac{50000}{e_{word} * e_{char}}$$

For $e_{word} = 256$ and $e_{char} = 50$ there are **four times as many parameters in the word embeddings as in the character embeddings**.

(c) One advantage of using a convolutional architecture rather than a recurrent architecture for the character based embedding models

When a 1d convnet computes features from character embeddings the features are given the same importance no matter where the original characters are placed in the world. This allows the convnet to focus on subwords/n-grams and learn the most relevant sections of the word. In contrast an RNNs always look at the whole world which makes it hard to discard the prefix, for example. Therefore for longer words convnets are more likely to extra the more relevant sub-word which could be specially for languages with joined words.

(d) Compare max-pooling and average pooling

TODO

(h) Testing for highway network

In order to test my highway implementation I wrote the `unittest` based `test/highway_test.py` to validate the following use cases

- We validated the projection path by setting gate weights to 10.0 - when passed through the `sigmoid` this will set the gate to ≈ 1.0 and disable the skip connection. We used two value for the linear projection weights to 0.3 and 20.0, without bias. We validated that when passing 1.0 as input the output is equal to the projection parameter.
- We validated the skip connection by keeping the projection path as above and setting the gate weights to -10. The expected output in this case is 1.0 (equal to the input). Note that we had to reduce the precision from $1e-5$ to $1e-3$.
- We tested training of part of the network. For this we adapted the `polynomial` subproject from the pytorch examples to validate that I can train part of the network - removed the `relu` layer and setup the gate to positive numbers as above. See the `run-highway.py` file. The output is

```
==> Actual function: y = +10.86 x^4 +5.07 x^3 -3.35 x^2 -3.40 x^1 -7.35
==> Learned projection: y = +10.93 x^4 +5.11 x^3 -3.37 x^2 -3.40 x^1 -7.42
==> Learned gate: y = +1.37 x^4 +4.08 x^3 +2.22 x^2 +3.64 x^1 +4.41
```

The one interesting fact is that the gate parameters remained relatively high after the training, otherwise comparing the learned function with the actual one would have been a bit useless.

2 Character-based LSTM decoder for NMT

BLEU score:

3 Analyzing NMT Systems