Assignment 2 – Window-based Tagging

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Part 4 – Adding sub-word units

Architecture

- Both tasks implement the same Network: MLP
  - Embedding layer - **sum of word embedding and sub-word embedding**.
  - one hidden layer
  - tanh activation function.
- The way we implemented the sub-word embedding:
  - Assign an embedding vector to each prefix and suffix of 3 letters. (Among the prefixes and suffixes that were observed in the corpus).
  - Then, we represent each word as **the sum of the word vector, the prefix vector, and the suffix vector.**
- The network trained with cross-entropy loss.
- The optimizer is Adam.
- We Experimented with several network configurations and chose the best configuration based on the DEV accuracy using our grid search function.

Best parameters

- **NER:**
  - Hidden layer size: 130
  - Dropout probability: 0.4
  - Batch size: 128
  - Optimizer: Adam (Learning rate: 0.001)
  - Epochs: 5
- **POS:**
  - Hidden layer size: 130
  - Dropout probability: 0.4
  - Batch size: 2048
  - Optimizer: Adam (Learning rate: 0.001)
  - Epochs: 6

Considerations

- The sub-word unit method can be combined with the pretrained embedding so we had to consider all the things we considered in the pretrained part:
  - We handle unseen the same way as in the other parts (with the UNK token).
  - If we used the pre-trained embedding vectors, we transform the training and the dev data to lower case because the embedding vocabulary being lower-case.
  - Because the embedding vocabulary contains special words like “DGDGDGDG”, “DG.DG”, “+DG”, “NNNUMMM”, etc. We treated those words as digit patterns.
  - We padded the sentences with SOS (start of string) and EOS (end of string) at the beginning and end of the sentence.
- If a length of a word is less than 3, we take the whole word as a suffix and prefix.

Results

	POS		NER	
	With pre-trained	Without pre-trained	With pre-trained	Without pre-trained
BATCH	128	2048	128	128
EPOCHS	6	3	5	3
HIDDEN LAYER	130	130	130	130
LR	0.001	0.001	0.001	0.001
DROPOUT	0.2	0.2	0.4	0.4
LOSS	0.145	0.136	0.191	0.158
ACCURACY	95.6	95.84	80.12	78.97

*the results are the best we achieved and aren't the same as we used in the comparison below.

** All used subword

Brief analysis of the results

In order to compare the performance of our model with the different embedding settings combinations [standard/pre-trained & sub-word/sub-word/pre-trained] we had to run them with the same parameters. We used the standard – without both as the baseline.

we run the model for 8 epochs with the following configuration:
{'hidden_layer': 130, 'dropout_p': 0.4, 'batch_size': 128, 'lr': 0.0004}

Tagger	Best DEV Accuracy	conclusion
standard	82.95	Baseline
Pre-trained & Sub-word	79.54	significant difference compared to the **baseline**
Sub-word	79.25	No significant difference compared to **pre trained** and **sub-word**
Pre-trained	77.51	significant difference compared **sub-word**

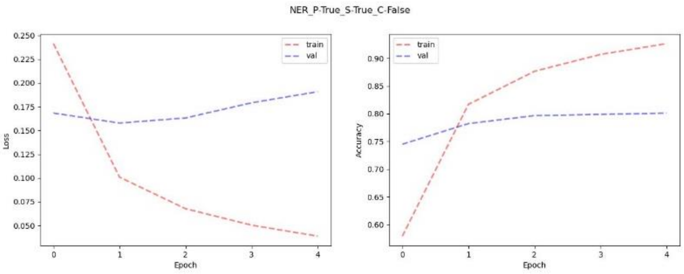
Main points:

- We can see that all of the methods are less optimal than our standard tagger which uses a Xavier initialization for the embedding.
- Although, it seems like the sub-word units are more useful than the pre-trained embedding.
- There is no significant difference in combining them together.
- Prefixes and suffixes can be helpful in two major ways:
  - For POS tagging- can tell the POS for example - ing,ify,ise are usually verbs. For ner not too much.
  - For unknown words that have a common prefix/suffix we get a better representation.
    *We didn't have time to try it but using the prefix/suffix only on unknown words and having all the other words with the Xavier init may result in better performance.

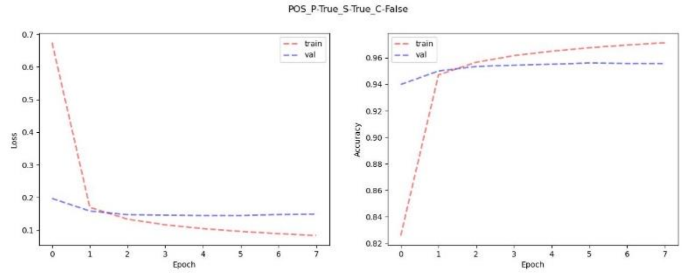
Graphs

With pretrained embedding:

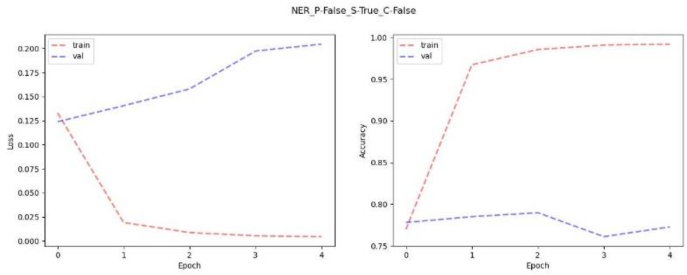
NER with pre-trained & sub-word



POS with pre-trained & sub-word



NER with sub-word only



POS with sub-word only