Assignment 2 – Window-based Tagging

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Part 5 – Convolution-based sub-word units

Architecture

- Both tasks implement the same Network:
  - CNN
    - Embedding layer
    - 1d Conv
    - Maxpooling
  - MLP with:
    - Embedding- word embedding concat to char embedding (from the CNN).
    - one hidden layer
    - tanh activation function.
- The Convolution-based sub-word units' architecture is the following:
  - each word is represented as a **max-pooled vector** over the vectors resulting from a **convolution over the word's characters**.
  - The pre-trained word-vectors and the character-based CNN vectors are combined via concatenation.
- The network trained with cross-entropy loss.
- We Experimented with several network configurations and chose the best configuration based on the DEV accuracy.
- The optimizer is Adam.
  - It achieved faster run times and better results than the optimizer described at the paper.

Best parameters

- NER:
  - Hidden layer size: 130
  - Dropout probability: 0.4
  - Batch size: 128
  - Optimizer: Adam (Learning rate: 0.0002)
  - Epochs: 4
  - CNN filters: 30
  - CNN embedding dimension: 30
  - CNN kernel size: 3
  - CNN padding size: 2
  - CNN dropout: 0.5
- POS:
  - Hidden layer size: 130
  - Dropout probability: 0.2
  - Batch size: 2048
  - Optimizer: Adam (Learning rate: 0.0001)
  - Epochs: 8

- CNN filters: 30
- CNN embedding dimension: 30
- CNN kernel size: 3
- CNN padding size: 2
- CNN dropout: 0.5

Considerations

- The Convolution-based sub-word units' method can be combined with the pretrained embedding so we had to consider all the things in the pretrained part:
  - We handle words that appear in the training file but not in the embedding file as we handle those words in part1 (words that don't appear in dev file), we assign them 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 digits patterns.
  - We padded the sentences with SOS (start of string) and EOS (end of string) at the beginning and end of the sentence.
- The Convolution-based sub-word units cannot be combined with the sub-word unit's method, so we prevent this from happening.
- Compared to what we implemented in Part 4 (sub-word units) this method got much better results which were quite close to our naïve tagger with the Xavier init.

  Testing different CNN parameters on the NER task:

Window size	Number of filters	embed dim	result
3	10	30	81.98
3	30	30	82.19
5	30	20	81.15
5	50	30	81.91

*MLP parameters: parameters: {'hidden_layer': 130, 'dropout_p': 0.4, 'batch_size': 128, 'lr': 0.002}

Results

MLP parameters: {'hidden_layer': 130, 'dropout_p': 0.4, 'batch_size': 128, 'lr': 0.001}

CNN parameters: {number of filters: 10, embed dim: 20, window size =3}

- NER:
  - Loss validation: 0.127
  - Accuracy validation: 81.98%
- POS:
  - Loss validation: 0.22
  - Accuracy: 94.71%

Brief analysis filters & Embedding layers.

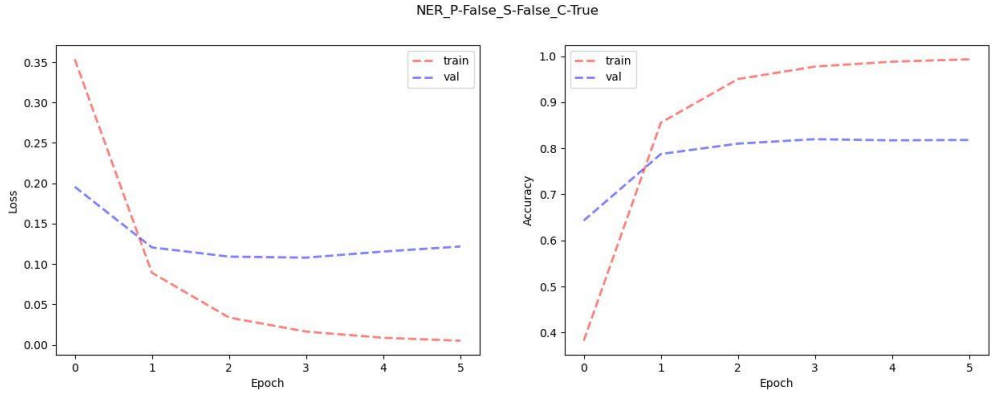
Just by looking at the filters and the embedding layers we couldn't find interesting patterns.

We tried finding similarities between embedding vectors to another, and between filters.

In addition, to show it in a visual way we can do some kind of dimension reduction like PCA.

Graphs

NER



POS