

Report

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1. DESCRIPTION

In this homework, I have implemented a word sense disambiguation model using the neural approach. The architecture of the neural network is represented in 3 layers: the first layer contains the embedding layer (I used the Glove embeddings with 100 dimensions); the second layer contains a bidirectional LSTM, and the last layer is the softmax layer. I create a function that parses the semcor training set and exploits 2 dictionaries: the first one is the lemma dictionary which associates to each lemma a unique id, and the second one is the sense dictionary, this dictionary associates to each lemma/synset a unique id in this way: for each word in the given sentence, if the word has a synset, then will be associated the synset with a unique id, otherwise will be associated the respective lemma with a unique id; the function returns the formatted train set, the sense dictionary and the reversed sense dictionary. The formatted train set is represented as a matrix that contains for each row many pairs (lemma_id, sense_id). In order to generate a good train set, I have implemented also padding technique, in which each sentence will have same dimension (according to the *window_size* parameter), if the sentence is shorter than the window size, many zeros will be added.

2. TEST RESULTS

To train the BLSTM I choose the following parameters:

Batch size	LSTM hidden size	Window size	Optimizer	Learning rate
16	100	20	AdaDelta	0.03

After the training phase, I have obtained with 45 epochs the following F1 (Macro) scores for the development set:

Senseval2	Senseval3	SemEval07	SemEval13	SemEval15
32,4 %	30,1 %	26%	28,9%	26,4%

3. PREDICTION TECHNIQUE

I created a function that parses the development set and returns a dictionary which groups the development data by the respective *Senseval*/*SemEval* dataset, in order to calculate for each dataset the F1 score, which is calculated using *scikit-learn* library. The prediction phase is computed as follow: each sentence of the development set will be preprocessed similarly to the training phase and will be given in input to the trained neural network, which returns a matrix of the scores. For each word for which we must predict the meaning, if the word has associated senses S , the function returns the sense s with the maximum score (with $s \in S$), otherwise the function returns the sense with maximum score on all possible predicted senses.

REFERENCES

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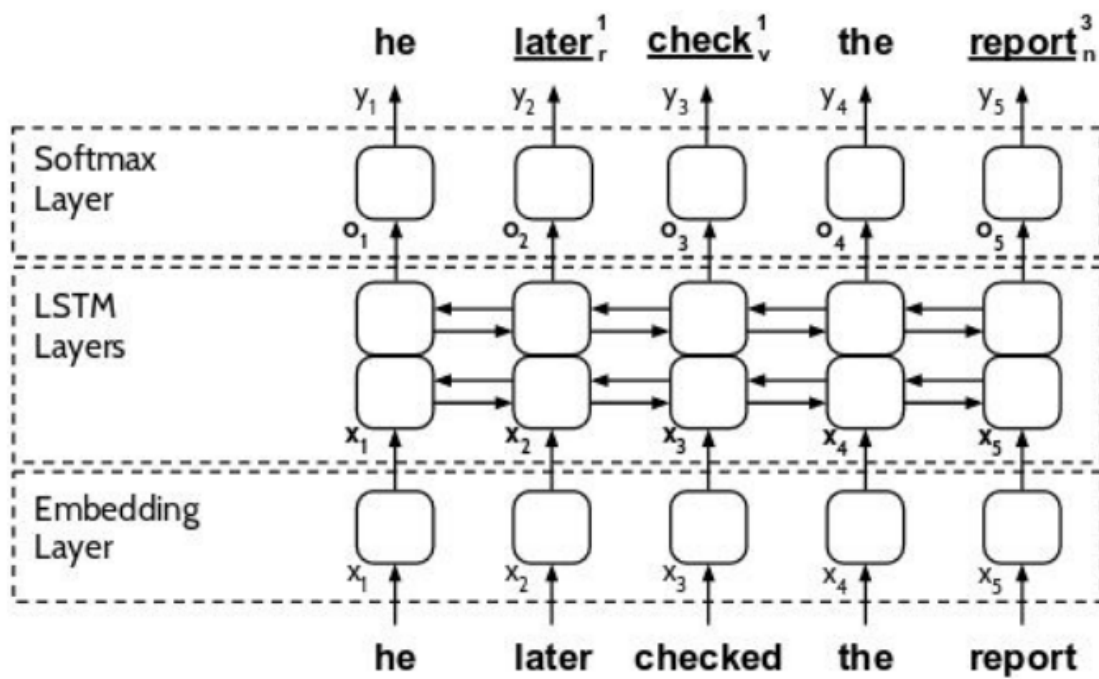
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1 - Neural network structure that it was implemented