HW3 Report

Emanuele Alessi 1486470

Preface

In this homework I have implemented a Semantic Role Labeling model with the aim of identifying and labeling predicates and roles of the arguments given in the CoNLL 2009 dataset.

1. Mandatory task

1.1. Role classifier

The architecture of the neural network is represented in three layers: the first layer contains the concatenation between the Glove embeddings (100 dimesions, not trainable), the part-of-speech tag embeddings (50 dimension, trainable) and the 0/1 value which represents the predicate flag (if the current word of the sentence has not an associated predicate then the value is 0; 1 otherwhise); the second layer and the third layer contains respectively a bidirectional LSTM and a softmax classifier which gives in output the labels (roles represented as integer values) with the maximum score.

The main algorithm is the following:

1. Parse the CoNLL 2009 dataset in order to convert the lemmas, roles and part-of-speech tags of the sentences into unique integer values and save them in a list;
2. Divide the list into batches;
3. Train the LSTM passing the batches (lemmas + part-of-speech tags + flags) and the labels (roles)
4. Save the model to continue training if necessary

I also implemented a technique to reduce the class imbalance and obtain better results: I pass to the LSTM a vector (1 dimension) of coefficients which multiplies the masked losses; the vector contains 1 or 0.2 values (1 for the lemmas that have an associated predicate; 0.2 otherwhise).

1.2. Results

To train the LSTM the BiLSTM I choose the following parameters:

Batch size	BiLSTM hidden size	Optimizer	Learning rate
10	128	Adam	0.001

After the training phase, I have obtained with 10 epochs the following scores on the CoNLL 2009 development set:

F1 (Macro)	Precision	Recall	Accuracy
76,8%	67,7%	88,8%	96,6%

For this task the reference files are *role_classifier.py*, *data_preprocessing.py* and *evaluation.py*.

2 Extension 1.2 (predicate identification and disambiguation)

2.1. HW2 system

For the **Extension 1.2** I decided to use my HW2 system (a.k.a. "WordSenseDisambiguator", located in the "WSD" folder) to implement the word sense disambiguation.

Because of the slightly low scores achieved in the previous delivery, I wanted to modify it in order to make it more performant, so I fixed many bugs and functions and I added many tricks such as class imbalance reducing technique (explained in point 1.1).

The neural architecture (BiLSTM) and the hyper parameters are the same of the last delivery.

2.2. HW2 system results

For the training phase, the chosen hyper parameters are:

Batch size	BiLSTM hidden size	Optimizer	Learning rate
10	100	Adam	0.001

After 15 epoch of train on Semcor dataset I achieved the following scores:

	F1	Accuracy
Senseval2	69,2%	81,4%
Senseval3	70,5%	84,8%
Semeval2007	66,2%	92,8%
Semeval2013	63,0%	89,4%
Semeval2015	64,6%	79,6%

2.3. BabelNet to PropBank alignment creation

After the training phase, I created the association (one-to-one) between the synsets of BabelNet and the predicates of PropBank.

The idea (pseudocode) of how I implemented the alignment is the following:

```
wsd = WordSenseDisambiguator()                          # HW2 system instance
d = {}                                                  # keys are synsets and values are predicates lists
for each sentence in CoNLL 2009 do
        predictions = wsd.predict(lemmas of sentence)   # a list of predictions (BabelNet synsets)
        for i = 1 to predictions length do
                if predictions[i] ≠ 'UNK' and predicate of sentence[i] ≠ '_' then
                        d[predictions[i]].append(predicate of sentence[i])
for each pair (synset, predicates) in d:
        write a line in babelnet2propbank.txt which contains the synset and the most common predicate in predicates
```

For this task the reference files are all the code located in WSD folder, *babelnet2propbank.py* and *pos_map.py* (this one is used to map the part-of-speech tags of Propbank to the part-of-speech tags of Semcor).

2.4. Predicate classifier

Similarly to the neural architecture of the role classifier is represented in three layers: the first layer contains the concatenation between the Glove embeddings (100 dimesions, not trainable) and the part-of-speech tag embeddings (50 dimension, trainable); the second layer contains the bidirectional LSTM and the third layer contains a softmax classifier which gives in output the labels (predicates represented as integer values) with the maximum score.

First of all, In this task I tried two different approaches in order to compare them and choose the most performant one.

In each approach I used the same hyper parameters and training techniques. I have also implemented the class imbalance reducing technique in this task (see point 1.1)

- The first approach is to train the predicate classifier passing as input the batches and the labels which are contained in CoNLL 2009 and Semcor datasets, exploiting *babelnet2propbank.txt* to map the synsets of BabelNet with the predicates of PropBank;

- The second approach is to train the predicate classifier passing as input only the batches and the labels which are contained in CoNLL 2009 dataset

2.5. Results

I noticed that using only CoNLL 2009 dataset as trainset for the predicate classification task is the best choice, so I decided to train the predicate classifier using the second approach.

For the training phase I choose the following parameters:

Batch size	BiLSTM hidden size	Optimizer	Learning rate
10	100	Adam	0.001

After 15 training epochs I achieved the following results:

F1 (Macro)	Precision	Recall	Accuracy
88,6%	85,3%	92,1%	95,7%

For this task the reference file is *predicate_classifier.py*.

The next pages contain the references to the papers that inspired me, the neural architecture picture and the confusion matrix for the mandatory task.

NOTE: due to time constraints, I could not load backups of LSTM models on gitlab, if you are interested in them, please send me an email.

References

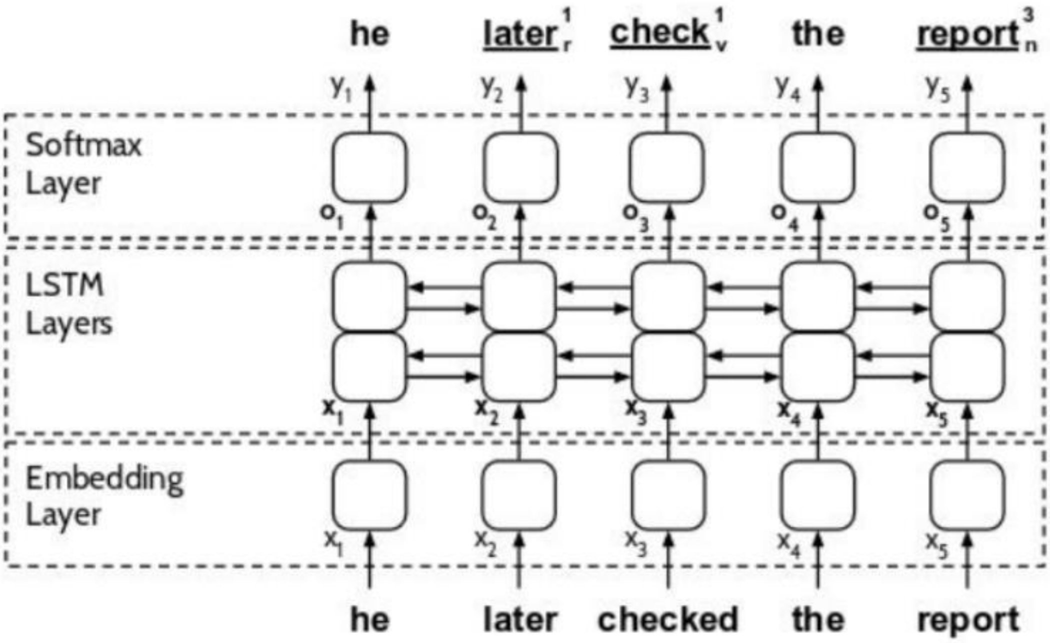
Roth M., Lapata M. - Neural semantic role labeling with dependency path embeddings

Hajic J. et al – The CoNLL 2009 shared task: syntactic and semantic dependencies in multiple languages

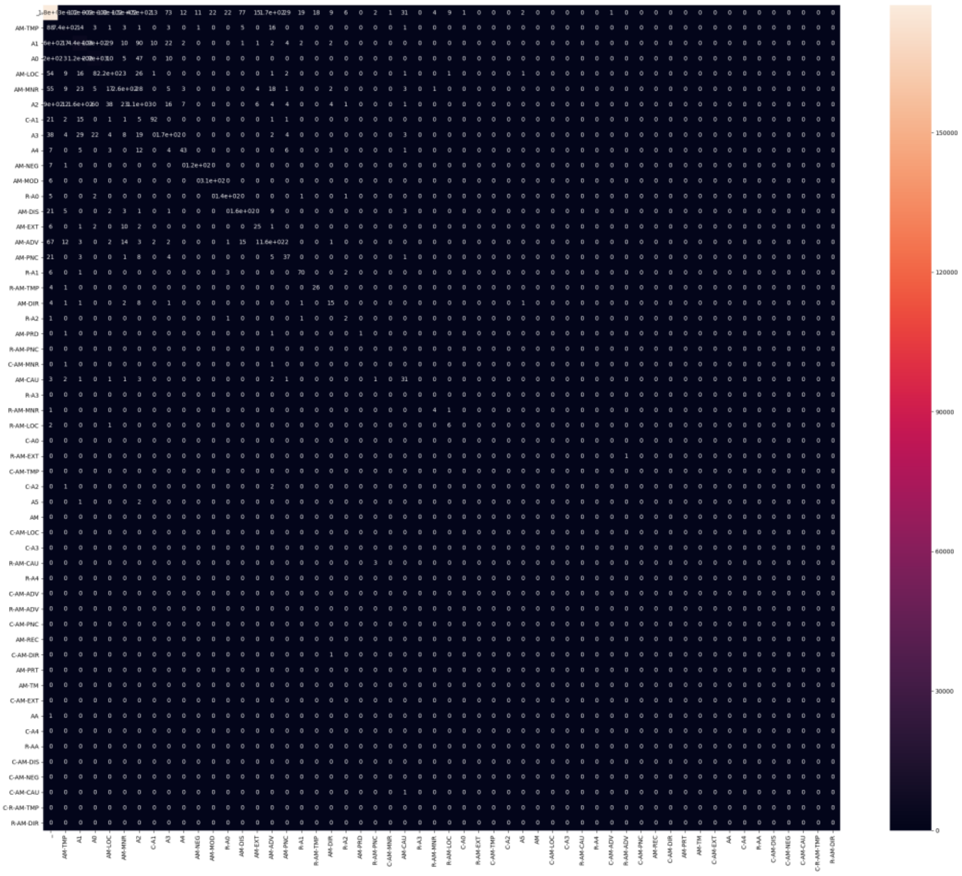
He L., Lee K., Lewis M., Zettlemoyer L. – Deep semantic role labeling: what works and what's next

Marcheggiani D., Frolov A., Titov I. – A simple and accurate syntax-agnostic neural model for dependency-based semantic role labeling

Palmer M., Gildea D., Xue N. – Semantic role labeling



1 - Neural architecture structure that I used



2 - Confusion matrix of the mandatory task