

# Homeworks: Natural Language Processing



SAPIENZA  
UNIVERSITÀ DI ROMA

Simone Antonelli

Master degree in Computer Science  
Sapienza, University of Rome

A. Y. 2019 - 2020



# Homework 1: Named Entity Recognition

---

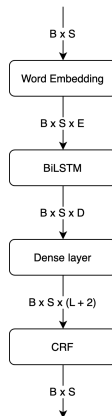
Named Entity Recognition (NER) task is a sequence labeling task that consists in identifying the categories to which words of a sentence belong:

- Organization (ORG);
- Location (LOC);
- Person (PER);
- Other (O).

# Homework 1: Architecture

The adopted architecture to solve NER task is composed by:

- Word embedding layer;
- Bidirectional LSTM;
- Conditional Random Field.



B: Batch size  
S: Sequence length  
E: Embedding dimension  
D: LSTM Dimension  
L: number of Labels

# Homework 1: Word Embedding

---

A word embedding is a learned representation for sentences where words that have similar meaning should have a similar representation.

The best performances of the model are obtained using fastText pretrained word embedding<sup>1</sup>.

---

<sup>1</sup>Edouard Grave, Piotr Bojanowski, Prakhar Gupta, Armand Joulin, and Tomas Mikolov. 2018. Learning word vectors for 157 languages.

# Homework 1: BiLSTM

---

- Long short-term memories (LSTM) are a variant of the Recurrent Neural Networks (RNN)
- The Bidirectional LSTM is used to create the context of each token in the sentence leveraging two different LSTM to capture the left-context and the right-context
- Useful for the conditional random field layer

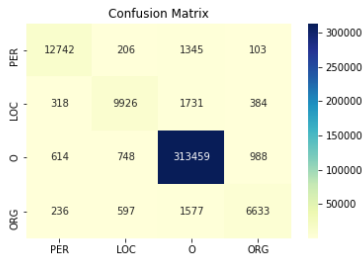
## Homework 1: CRF

---

- Conditional probabilistic model used when there are dependencies across output labels
- In NER task to predict the label of each token is needed to make use of neighbor tag information
- It uses a score function to predict the best sequence of labels

# Homework 1: Results

Due to the high imbalance of the dataset the metric used to evaluate the model is the macro f1-score.



Model	F1-score
BiLSTM + W + CRF	88%

## Homework 2: Semantic Role Labeling

---

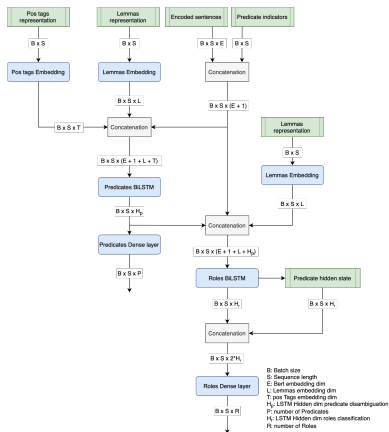
Semantic Role Labeling is the task that extracts the predicate-argument structure of a sentence. It is divided in 4 steps:

1. Predicate identification
2. Predicate disambiguation
3. Argument identification
4. Argument classification



## Homework 2: Architecture

Since the faced tasks seems like sequence labeling tasks, the main component of the model is the bidirectional LSTM.



## Homework 2: Data preprocessing

---

To represent the sentences is used BERT, a transformer-based model which gives as output the contextualized embeddings of each word of a given sentence.

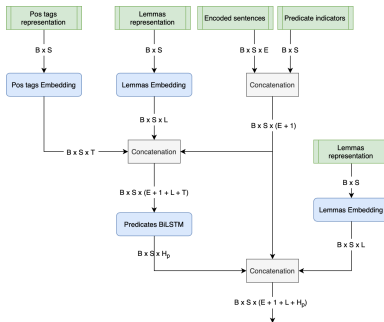
The representation given by BERT is used to feed the model<sup>2</sup>. The pretrained model used in this homework is the simplest ('bert-base-cased') which has 12 layers and a hidden size equals to 768.

---

<sup>2</sup>Peng Shi and Jimmy Lin. 2019. Simple bert models for relation extraction and semantic role labeling.

## Homework 2: Encoding input

Further information about the sentences are provided by the given dataset, so those are leveraged to give to the model much information as possible on the sentences' tokens<sup>3</sup>.



<sup>3</sup>Diego Marcheggiani, Anton Frolov, and Ivan Titov. 2017. A simple and accurate syntax-agnostic neural model for dependency-based semantic role

## Homework 2: How the model works

---

- The model is fed with a sentence-predicate pair, so the sentences with many predicates are splitted online;
- The representation is given as input to the BiLSTM which deals with predicate disambiguation;
- The output is concatenated to the embeddings and then is given as input to the BiLSTM that faces role classification;
- Before doing role classification, to the hidden state of each token is concatenated with the hidden representation of the predicate in the sentence.

## Homework 2: Results

Architecture model	Predicate disambiguation	Argument identification	Argument classification
BiLSTM ( $W + P_i$ )	-	84.48 %	76.45 %
BiLSTM ( $B + P_i$ )	-	91.30 %	82.50 %
BiLSTM ( $B + P_i + T + L + P$ )	-	<b>93.91 %</b>	<b>90.09 %</b>
Stacked BiLSTM ( $B + P_i + O + L$ )	<b>95.17 %</b>	<b>93.50 %</b>	<b>87.83 %</b>

