
DESIGN AND IMPLEMENTATION OF AN OPEN SOURCE GREEK POS TAGGER AND ENTITY RECOGNIZER USING SPACY

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ABSTRACT

This paper proposes a machine learning approach to part-of-speech tagging and named entity recognition for Greek, focusing on the extraction of morphological features and classification of tokens into a small set of classes for named entities. The architecture model that was used is introduced. The greek version of the spaCy platform was added into the source code, a feature that did not exist before our contribution, and was used for building the models. Additionally, a part of speech tagger was trained that can detect the morphology of the tokens and performs higher than the state-of-the-art results when classifying only the part of speech. For named entity recognition using spaCy, a model that extends the standard ENAMEX type (organization, location, person) was built. Certain experiments that were conducted indicate the need for flexibility in out-of-vocabulary words and there is an effort for resolving this issue. Finally, the evaluation results are discussed.

Keywords Part-of-Speech Tagging, Named Entity Recognition, spaCy, Greek text.

1. Introduction

In the research field of Natural Language Processing (NLP) there are several tasks that contribute to understanding natural text. These tasks can manipulate natural language, such as tokenization process, and consequently can be used in other implementations, in order to extract syntactic or semantic information. One such task for syntactic components is Part of Speech Tagging (POS Tagging). Part of Speech Tagging in corpus linguistics is a process where a word is assigned with a label of the grammatical term, given the context it appears in. In many languages, POS Tagging models achieve an accuracy of 96 to 97 percent [1].

Part of Speech Tagging for highly inflective languages, such as Greek is quite a difficult task. In the Greek Language, words can have different morphological forms, depending on the part of speech (verbs have up to ten different forms). For that purpose, there is a need for a tagset that can support morphological features for improvement of Greek POS Tagging [2].

Another main task for extracting semantic information is Named Entity Recognition (NER). Named Entity Recognition is a process where a word or a set of words reference to a world object. Most Natural Language Processing models classify named entities that describe people, locations, organizations, following the ENAMEX type or can be more complex by detecting numerical types, like percentages (NUMEX) or dates (TIMEX) [3].

The greek Part of Speech Tagging and Named Entity Recognition models presented in this paper were developed using the spaCy library [4]. SpaCy is an open source, Natural Language Processing library that supports a variety of tasks, including POS Tagging, Named Entity Recognition, Dependency Parsing, etc. SpaCy uses sophisticated neural

network-based models for the implementation of Natural Language Processing components that achieve state-of-the-art results in many of these tasks.

In the following chapters the process for implementing Part of Speech Tagging and Named Entity Recognition for the Greek Language is explained. A dataset with extended POS Tags was found and matched to a set of morphological rules, according to a treebank. The dataset was then processed, fed to the spaCy model and used for training. Similarly, for Named Entity Recognition, datasets from different sources were compared to a custom set of rules for named entities. Finally, different experiments were conducted for evaluating the accuracy of the models.

2. SpaCy's deep learning model for POS tagging and Named Entity Recognition

SpaCy uses a deep learning formula for implementing NLP models, summarised as “embed, encode, attend, predict”. In spaCy's approach text is inserted in the model in the form of unique numerical values (ID) for every input that can represent a token of a corpus or a class of the NLP task (part of speech tag, named entity class). At the embedding stage, features such as the prefix, the suffix, the shape and the lowercase form of a word are used for the extraction of hashed values that reflect word similarities.

At this stage a vocabulary with hashed values and their vectors exist in the model. For the exploitation of adjacent vectors in the state of encoding, values pass through the Convolutional Neural Network (CNN) and get merged with their context. The result of the encoding process is a matrix of vectors that represents information. Before the prediction of an ID, the matrix has to be passed through the Attention Layer of the CNN, using a query vector to summarize the input.

At prediction, a Softmax function is used for the prediction of a super tag with part of speech and morphology information. Similarly for named entities, the available class is predicted. After the training process of the model, the CNN is able to be used for NLP tasks.

In the latest release of spaCy the deep learning models are reported to be “10 times smaller, 20% more accurate and cheaper to run than the previous generation” [4]. The models are implemented using Thinc, spaCy's machine learning library.

3. Creating a Greek POS Tagger using spaCy

The Institute for Language and Speech Processing was the first to implement a Part of Speech Tagger with morphological features and has evaluated the experiments in terms of the error rate of the predicted classes [5]. These models can be accessed from web services offered by the Institute ¹. However, the creation of a compound Greek POS tagger using spaCy, a fast and accurate NLP python framework is new.

For the creation of a Part of Speech Tagger in the Greek Language a number of steps was followed. The tags from the “Makedonia” dataset, which is described below, were extracted and matched to a set of morphological rules. The tokens in the dataset were adjusted to annotation rules that the model will use. Different parameters in the configuration of spaCy's model were tested while training and their results are presented in 3.4.

3.1. Dataset evaluation and selection

The dataset comes from texts of the Greek newspaper “Makedonia”. The articles in the newspaper are categorized in different subjects, such as sports, health, economy and political news. Data retrieval was done from the website ² of the clarin project [6] and consist of a set of xml files with information at paragraph, sentence and word level. It must be underlined that this annotation was performed by the Institute for Language and Speech Processing and data is licenced under the CC - BY - NC - SA licence.

Information about the dataset includes the tokens of a set of articles and their position in a sentence, the lemma and the part of speech of every token. The various values of POS tags were retrieved and incorporated into a tag map. The labels and morphology they describe are explained below.

¹<http://nlp.ilsp.gr/soaplab2-axis/>

²<https://inventory.clarin.gr/>

3.2. Creation of the Tag Map with reference to Universal Dependencies

Different labels were found at the dataset and were matched to a label map, where for each label the part of the speech and their morphology are analyzed. In more detail, the first two characters refer to the part of speech and accordingly extend to more information about it. The label map supports 16 standard part of speech tags: Adjective, Adposition, Adverb, Coordinating Conjunction, Determiner, Interjection, Noun, Numeral, Particle, Pronoun, Proper Noun, Punctuation, Subordinating Conjunction, Symbol, Verb and Other. Each tag describes morphological features of the word, depending on the part of the speech to which it refers like the gender, the number, and the case [7]. It must be mentioned that the extraction of morphological rules and the matching with the tags was done using the Greek version of the Universal Dependencies [8].

3.3. POS Tagger training

The articles from the newspaper were fed in spaCy library into the proper format for training. Different parameters were tested, in order to get the optimal result. The dataset was shuffled, using the same seed for all the experiments and was split into a train set (70%), a test set (20%) and a validation set (10%). Information was passed through the training algorithm in batches with an increasing batch size from 4 to 32 and a step of 1.001. Additionally, a dropout rate was configured in every batch, initialized to 0.6 which dropped during the training process to 0.4. Most of the experiments were trained using 30 epochs.

The main area of study for the experiments focuses on three important components. At first, we investigate the difference in results between part of speech taggers that classify morphological features and taggers that detect only the part of speech. Moreover, we explore the significance of pretrained vectors used from a model and their effect on the extraction of better results. Most importantly, the usage of subwords of tokens from a tagger as embeddings is issued. For the experiments, precision, recall and f1 score are used as evaluation metrics.

3.4. Evaluation and comparison of results

In the first experiment the model was trained using pretrained vectors extracted from two different sources, Common Crawl and Wikipedia and can be found at the official FastText web page [9]. Both sources were trained on the same algorithm called FastText [10], an extension of Word2Vec that treats tokens as an average sum of sub-words and finds similarities of words based on their n-grams. The configuration of the FastText model for Wikipedia vectors is according to [11], whilst the model for CC vectors is a position-weight CBOW 5 length n-grams with a window size of 5 tokens and 10 negative words. The file with the Common Crawl vectors consists of 2.000.000 tokens with 300 dimension, whereas the file with the Wikipedia vectors consists of 300.000 tokens with 300 dimension. The results can be viewed in the following table, with the first part describing the Common Crawl results and the second one the Wikipedia results.

Classes (Common Crawl)	Precision	Recall	F1 Score
POS and morph classes	96.26	96.28	96.24
Only POS classes	98.75	98.75	98.75
Classes (Wikipedia)	Precision	Recall	F1 Score
POS and morph classes	85.90	84.27	84.46
Only POS classes	90.09	89.40	89.44

TABLE 1. Results based on Common Crawl pretrained vectors and based on Wikipedia pretrained vectors

At the results, POS and morph classes refer to the tag labels explained in 3.2, whilst only POS classes relate to annotated labels that describe only the part of speech. It is evident that even though the CC vectors are noisy, coming from a web source, they lead to better results than Wikipedia, possibly because they have a larger variety of tokens.

In the next experiment, the dataset was used for the composition of embeddings for the part of speech tagger. The dataset was trained on a FastText model with the same parameters that extracted the Common Crawl vectors. As a result, 140.000 vectors with 300 dimension were exported. It must be mentioned that the tagset with the morphological features was used.

The values of the metrics in this case were almost as good and comparable to the CC ones. However, the model trained with a larger vocabulary had higher results. Also, the model with the dataset vectors did not have the flexibility to classify unknown words.

Vectors	Precision	Recall	F1 Score
Common Crawl Vectors	96.26	96.28	96.24
Dataset Vectors	95.74	95.72	95.68

TABLE 2. Usage of pretrained vectors from dataset

As a next step, the test set of the dataset was altered by replacing words with syntactical mistakes to test the tolerance of the model in OOV words. Suffixes of verbs were altered and vowels were replaced with others, affecting 20% of the tokens of the dataset. Using again the more complex tagset for training, the results can be found in Table 3.

Test Set	Precision	Recall	F1 Score
Original Test Set	96.26	96.28	96.24
OOV Test Set	76.40	73.77	72.22

TABLE 3. Performance of spaCy model in OOV words

What can be concluded is that the model did not have a flexibility in OOV words. Of course, this can also be an advantage, meaning that the model recognized the mismatch of a wrong word with its class.

One disadvantage that the previous model had is that for unknown words the model assigned a zero vector, affecting the testing results. In order to minimize this problem, the unknown words were first passed through a FastText model to get a vector from their subwords. The resulting vectors were imported in the vocabulary with the CC vectors before training. The model was also trained using as a vocabulary the unknown words and the tokens from the Common Crawl vectors, both buffered in the same FastText model. Results are listed in Table 4.

Vectors	Precision	Recall	F1 Score
Common Crawl Vectors	96.26	96.28	96.24
Common Crawl + FastText(OOV Vectors)	96.56	96.54	96.51
Common Crawl Vectors	96.26	96.28	96.24
FastText(Common Crawl + OOV Vectors)	96.16	96.15	96.11

TABLE 4. Common Crawl pretrained + vectors annotated from out of vocabulary words and all vectors annotated from FastText (Common Crawl pretrained and from out of vocabulary words)

It was noticed that the model performed better when using the vectors from different FastText models. It was expected that the second experiment would have performed better, as the tokens were inserted into the same FastText model and the vectors exported from both sources should match.

4. Creating a state of the art Named Entity Recognizer using spaCy

In [12] the development of an entity recognizer with named entities that follow a proper set of rules is described with evaluation metrics that reach 86% for precision and 81% for recall. Our implementation follows these rules as well. Also, a pretrained model is offered from a library called polyglot for recognition [13], which has evaluated NER in Greek with statistical machine translation.

For the creation of a Named Entity Recognizer in the Greek Language a number of steps was followed. The entities from the “Makedonia” dataset were extracted and annotated, forming a set of keywords that matched a specific set of rules the entities had to follow. These keywords were used to reform the dataset and also to find entities from a larger dataset, like Wikipedia. The spaCy model was trained using both datasets and their results are compared to a test set. Additionally, the spaCy model was trained using as a feature the POS tags of the tokens. All results are presented in 4.3.

4.1. Dataset evaluation and selection

In the “Makedonia” dataset information about named entities is organized with the index of the character the named entity starts, the index of the character the named entity ends and the class of the named entity. The dataset was parsed and the named entities were added into the keyword list, with every record representing the token (or the set of tokens) and its class. Noise was removed from the list and the records were sorted by the length of the entity. The keyword list had an average of 72.000 records.

4.2. Usage of Wikipedia dataset for training

In order to gain more information about the context of the Greek entities, a percentage of Greek Wikipedia was used. After applying sentence and token segmentation on Wikipedia text and using a pretrained model from polyglot, the keyword list increased. The keyword list had at this point about 350,000 records and consisted of 4 classes: location (LOC), organization (ORG), person (PERSON) and facility (FAC). A percentage of Greek Wikipedia was parsed and used for training in spaCy. The results from the training are presented in 4.3.

4.3. Evaluation and comparison of results

Both datasets were fed into the library in proper format for training. In training process, the entity recognizer had the same configuration with the POS tagger, using the same percentages for train, validation and test sets. It must be noted that all the models used the Common Crawl pretrained vectors for a vocabulary. The results are compared using the macro F1 score.

At first the datasets from both sources (Makedonia, Wikipedia) were used for training with 10 iterations and testing from the model. The results can be viewed in the following table:

Corpus	Average F1 Score
Makedonia Corpus	91.18
Wikipedia Corpus	80.75

TABLE 5. Comparison of Macro Average F1 score with different train sets

It seemed that the average F1 score was higher for the Makedonia corpus, as it was the basis of the configuration for the keyword list. In order to have an objective evaluation, the results of each corpus per entity class were observed.

Class	Average F1 Score	
	Makedonia	Wikipedia
Non Entity	0.99	0.99
FAC	0.84	0.39
LOC	0.94	0.88
ORG	0.93	0.88
PERSON	0.91	0.89

TABLE 6. Results of the different train sets per class

Both sources had good results in non entity tokens, which affected the F1 score. Moreover, the model did not perform well for facilities, as polyglot’s Greek recognizer does not support that class and FAC entities cover a small amount of the list.

In the second experiment, the datasets were compared to a common test set that followed the desired set of rules.

Corpus	Average F1 Score
Makedonia Corpus	73.27
Wikipedia Corpus	46.47

TABLE 7. Comparison of results with common test set

Again, the Makedonia corpus performed better, because of the proper annotation on the keyword list.

In an experiment worth mentioning the correlation of the part of speech with the performance of the recognizer was explored. In this experiment, both pipelines (part of speech, entity recognition) were used for training with 30 iterations and the model was trained twice: with and without the usage of the part of speech information for recognition.

POS feature	Tag F1 Score	Entity F1 Score
No usage of POS feature	96.51	93.15
Usage of POS feature	96.45	93.14

TABLE 8. Results of Makedonia training with discrimination the POS tag as feature of the model

It is evident that the recognizer did not gain knowledge from the part of speech tags of the tokens.

5. Conclusions

Natural Language Processing meets numerous problems in its applications, especially in uncommon languages such as Greek. This paper proposes a machine learning approach to part-of-speech tagging and named entity recognition for Greek, a highly inflected language using spaCy, a very robust and popular framework. Although significant work has been done, there are several more things that can be accomplished. The need of more datasets for the Greek language is evident, but the results are quite satisfying, comparable to other languages.

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