AlbNER: A Corpus for Named Entity Recognition in Albanian

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Abstract

Scarcity of resources such as annotated text corpora for under-resourced languages like Albanian is a serious impediment in computational linguistics and natural language processing research. This paper presents AlbNER, a corpus of 900 sentences with labeled named entities, collected from Albanian Wikipedia articles. Preliminary results with BERT and RoBERTa variants fine-tuned and tested with AlbNER data indicate that model size has slight impact on NER performance, whereas language transfer has a significant one. AlbNER corpus and these obtained results should serve as baselines for future experiments.

1 Introduction

Data-driven artificial intelligence methods have advanced rapidly during the last decade. Two directions that have especially witnessed stunning progress are the ones related to image and text or natural language processing. Trained artificial neural networks are providing excellent results when solving tasks like image segmentation, object detection, medical image analysis and more from the former, and machine translation, text summarization, sentiment analysis and more from the later. There are even some tasks that put images and text together such as image captioning (Sharma et al., 2018) or meme processing (Kougia et al., 2023) which have driven significant innovation.

Within NLP (Natural Language Processing), machine translation has been the task that has driven the biggest leaps, especially since the introduction of the Transformer architecture (Vaswani et al., 2017) and the PLMs (Pretrained Language Models) such as BERT (Devlin et al., 2019). PLMs got quick adaptation and have become the defacto standard paradigm for solving many other NLP tasks, including NER (Named Entity Recognition) which tries to identify and classify key information words or phrases in texts. The main strategy of preparing and utilizing PLMs is by pretraining Transformer blocks (layers) with large amounts of unlabeled texts (not related to any specific task), and later fine-tuning them with labeled texts which are suitable for solving a specific task. In the case of NER, the labeled texts comprise tokens and labels such as PER (person), LOC (location), ORG (organization) etc., which identify the category of each token (Jain et al., 2020).

One difficulty when working with language models is the need for large amount of pretraining texts and the need for labeled and task-specific corpora which are used during the fine-tuning phase. While not being a problem for languages like English, Spanish, Chinese, etc., the latter is a significant restriction when trying to solve tasks for other "smaller" languages, which are also known as lowresource or underrepresented (Aji et al., 2022). Unavailability of such resources limits the progress and the attainable performance on natural language processing and computational linguistics tasks for those languages.

This paper presents AlbNER, a corpus of sentences in Albanian language, created with the goal to foster research in named entity recognition.¹ They were collected from Wikipedia and cover topics related to Albanian history and geography, as well as Albanian historic figures. There are also generic sentences about common facts. Each sentence was tokenized and the resulting tokens were labeled manually. In total, a set of 900 samples (sentences) was obtained.

A set of experiments were run, assessing the performance of a few PLMs fine-tuned and tested with AlbNER data. The results are overall poor, since the PLMs have not been pretrained with Albanian texts. The best results were actually obtained using a multilingual model which was pretrained on many languages, including Albanian. This indicates that knowledge transfer has a high impact on

¹Download from: http://hdl.handle.net/11234/1-5214

Data	Sentences	Tokens
Train	500	8826
Dev	100	1732
Test	300	5266
Total	900	15824

Table 1: Sentences and tokens in AlbNER.

NER performance in Albanian. Another insight is the fact that model size has low impact, since the score differences between the large and the base versions of the tested PLMs were small. These obtained results should serve as baselines for further research in NER for Albanian.

2 Related Work

NER has been a popular task for several years, since it helps to extract relevant and important information. It usually works as a two-step process, starting with the detection of the named entities (words or phrases) in the text, and then classifying them in predefined categories such as *person*, *location*, *organization*, etc.

Some of the earliest solutions that were proposed came out in the nineties and were based on supervised learning techniques such as Decision Trees (Sekine et al., 1998), Hidden Markov Models (Bikel et al., 1997), Maximum Entropy Models (Borthwick et al., 1998), etc. Here, relatively small amounts of sentences were manually labeled and used for training the popular supervised learning algorithms of that time.

Latter on, several attempts were made by integrating knowledge from lexicons (Alfonseca and Manandhar, 2002; Passos et al., 2014), by trying semi-supervised methods (Althobaiti et al., 2015) or probing unsupervised learning techniques (Bhagavatula et al., 2012; Suzuki et al., 2011). Utilizing knowledge bases with Wikipedia resources was also explored (Richman and Schone, 2008). The most recent works obviously use PLMs such as BERT (SUN, 2021), or combinations of PLMs and other structures (Liu et al., 2021).

With respect to the targe language, the NER methods are monolingual, bilingual or multilingual. Most of the works involve English and other popular natural languages. As for the under-represented languages, there has been some attempts to create corpora in Hungarian (Simon and Vadász, 2021), Upper Sorbian (Howson, 2017), Kashubian (Nomachi, 2019), Czech (Straka et al., 2021; Çano and

Data	PER	LOC	ORG	MISC	all
Train	452	486	321	445	1704
Dev	92	73	68	78	311
Test	246	264	141	300	951
Total	790	823	530	823	2966

Table 2: Counts of named entity labels in AlbNER.

Data	PER	LOC	ORG	MISC	all
Train	0.051	0.055	0.036	0.05	0.193
Dev	0.053	0042	0.039	0.045	0.179
Test	0.046	0.05	0.026	0.056	0.18
Total	0.05	0.052	0.033	0.052	0.187

Table 3: Densities of named entity labels in AlbNER.

Bojar, 2019) etc. Some works have also created resources in Albanian, but they are limited to other tasks such as sentiment analysis (Çano, 2023).

3 AlbNER Corpus

Wikipedia pages usually contain information about history and historical figures (persons), geography and places (locations), as well as other named entities. They therefore represent good sources for building NER copora. To build AlbNER, pages from Albanian Wikipedia dump were used.² A total of 900 sentences were extracted and manually curated, fixing typos and other issues.

The sentences were later tokenized and a manual process of NER tagging followed. For the latter, CoNLL-2003 shared task annotation scheme was used.³ It mandates the use of O for non-entity tokens, as well as B-PER and I-PER, B-LOC and I-LOC, B-ORG and I-ORG, and finally B-MISC and I-MISC for persons, locations, organizations and other types of named entities. The initial B and I symbols show that the token is either the beggining of a named entity phrase, or appears inside of it.

The obtained 900 samples were divided in three subsets for model training, developmen and testing. Their respective token counts are shown in Table 1. The average sentence length is 17.58 tokens. Furthermore, Table 2 shows the token count distribution per each named entity category, in each of the AlbNER cuts. The respective named entity densities are summarized in Table 3. Finally, Table 4 illustrates four samples of AlbNER corpus.

²https://dumps.wikimedia.org/sqwiki/latest/ ³https://www.cnts.ua.ac.be/conll2003/ner/ annotation.txt

Token	Tag	Token	Tag	Token	Tag	Token	Tag
U	0	Bregdeti	B-LOC	U	0	Më	0
lind	0	i	I-LOC	shqua	0	1451	0
më	0	Adriatikut	I-LOC	si	0	,	0
11	0	shtrihet	0	prijës	0	u	0
prill	0	nga	0	ushtarak	0	martua	0
1872	0	Gryka	B-LOC	me	0	me	0
në	0	e	I-LOC	kontribut	0	Donikën	B-PER
Drenovë	B-LOC	Bunës	I-LOC	në	0	,	0
,	0	deri	0	mbrojtjen	0	të	0
5	0	në	0	e	0	bijën	0
km	0	Kepin	B-LOC	Plavës	B-LOC	e	0
larg	0	e	I-LOC	dhe	0	Gjergj	B-PER
Korçës	B-LOC	Gjuhëzës	I-LOC	Gucisë	B-LOC	Arianitit	I-PER
	0	•	0	•	0	•	0

Table 4: Illustration of four AlbNER sentences with their respective tokens and the NER tags.

Hyperparemeter	Values	
epochs small (E_s)	5	
epochs total (E_t)	10	
top models (T)	3	
batch size	16	
gradient accumulation steps	[4, 8]	
learning rate	[1e-4, 1e-5]	
cfr	[True, False]	
weitht decay	1e-7	
warmup step ratio	0.1	
max gradient norm	10	

Table 5: Searched values for each hyperparameter.

4 Preliminary Experimental Results

This section presents the results of some basic experiments that were run using AlbNER corpus and a few PLMs fine-tuned for named entity recognition. These results are intended as baselines for future studies.

4.1 Experimental Setup

To easily experiment with PLMs on the NER task, T-NER framework was utilized (Ushio and Camacho-Collados, 2021). It provides software utilities to fine-tune and evaluate various models based on popular PLMs using custom data. The tested models were based on BERT and RoBERTa (Liu et al., 2019) which are two very popular PLMs of the recent years. Two versions of the former were used: BERT-base with 110 M parameters and BERT-large with 340 M parameters. RoBERTa differs from BERT in several training specifications

and in the fact that it was pretrained on bigger texts. Its two main versions, RoBERTa-base and RoBERTa-large have 123 M and 354 M parameters respectively. Probing both base and large versions of these PLMs gives us an idea of how much does the NER task benefit from model size.

It is also important to note that all these four PLMs were pretrained on English texts and finetuned on AlbNER texts which are in Albanian. To have an idea about the knowledge transfer between the two languages and the possible benefits from multilingual pretraining, another version of BERT (denoted BERT-base-ML) was used. This last PLM has been pretrained on Wiki texts of 104 languages, one of which is Albanian.

Each of the five PLMs was fine-tunned on AlbNER following a parameter-search procedure which consists of two steps: (1) fine-tunning with every possible configuration C (obtained from the combination of the searched hyperparameters) for a small number of epochs E_s and computing micro F_1 metric on the development set, and (ii) picking the top T models to continue fine-tunning till E_t epochs. The best model in the second stage will continue fine-tunning as long as it improves on the development set. The list of fine-tunning hyperparameters are shown in Table 5. Searching more values for each hyperparameter could lead to better results, but it would take significantly more time.

4.2 Discussion of Results

Each of the five models described above was tested on the 300 samples of the test cut of AlbNER. The

Model	Pretrain	Fine-tune	micro \mathbf{F}_1	macro \mathbf{F}_1	weighted F ₁
BERT-base	English	Albanian	0.45	0.42	0.44
BERT-large	English	Albanian	0.49	0.46	0.48
RoBERTa-base	English	Albanian	0.52	0.41	0.48
RoBERTa-large	English	Albanian	0.57	0.53	0.57
BERT-base-ML	Multiple	Albanian	0.62	0.59	0.61

Table 6: NER results of various pretrained language models tuned and tested with AlbNER.

micro F_1 , macro F_1 and the weighted F_1 scores obtained for each of them are shown in Table 6.

As can be seen, the results are overall poor, given that F_1 levels of 0.9 or higher can be achived if we fine-tune and test on English corpora (Luoma and Pyysalo, 2020). Knowledge transfer between English and Albanian is obviously limited. We see that BERT-base which is the smallest performs worse than the other models, with a weighted F_1 of 0.44. BERT-large slightly improves over it. RoBERTa-base is smaller than BERT-large in terms of parameters, but has been pretrained in larger text corpora. It slightly outruns BERT-large.

RoBERTa-large improves fairly over RoBERTabase, reaching a weighted F_1 of 0.57. The best model is BERT-base-ML with weighted F_1 of 0.61. Despite being small in number of parameters, it has been pretrained in many languages, including Albanian. This clearly shows that knowledge transfer has a significant impact on NER performance. For this reason, better NER results could be achived by utilizing PLMs which are completely pretrained with Albanian texts, which represents possible future extension of this work.

5 Conclusions

Because of the recent data-driven trends for solving natural language processing tasks, resources such as curated and annotated text corpora have become indispensible. To foster research on named entity recognition in Albanian language, this work creates and presents AlbNER, a corpus of 900 sentences collected from Wikipedia articles which were labeled following CoNLL-2003 annotation scheme. A set of experiments were conducted, utilizing BERT and RoBERTa variants. The preliminary results indicate that NER performance is overall poor if PLMs pretrained with English texts are used. They also indicate that the task benefits little from PLM size, but significantly from language transfer during pretraining and fine-tuning.

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