Exploring Cross-sentence Contexts for Named Entity Recognition with BERT

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Abstract

Named entity recognition (NER) is frequently addressed as a sequence classification task where each input consists of one sentence of text. It is nevertheless clear that useful information for the task can often be found outside of the scope of a single-sentence context. Recently proposed self-attention models such as BERT can both efficiently capture long-distance relationships in input as well as represent inputs consisting of several sentences, creating new opportunities for approaches that incorporate cross-sentence information in natural language processing tasks. In this paper, we present a systematic study exploring the use of cross-sentence information for NER using BERT models in five languages. We find that adding context in the form of additional sentences to BERT input systematically increases NER performance on all of the tested languages and models. Including multiple sentences in each input also allows us to study the predictions of the same sentences in different contexts. We propose a straightforward method, Contextual Majority Voting (CMV), to combine different predictions for sentences and demonstrate this to further increase NER performance with BERT. Our approach does not require any changes to the underlying BERT architecture, rather relying on restructuring examples for training and prediction. Evaluation on established datasets, including the CoNLL’02 and CoNLL’03 NER benchmarks, demonstrates that our proposed approach can improve on the state-of-the-art NER results on English, Dutch, and Finnish, achieves the best reported BERT-based results on German, and is on par with performance reported with other BERT-based approaches in Spanish. We release all methods implemented in this work under open licenses.

1 Introduction

Named entity recognition (NER) approaches have evolved through various methodological phases, broadly including rule/knowledge-based, unsupervised, feature engineering and supervised learning, and feature inferring approaches [Yadav and Bethard, 2019] [Li et al., 2020]. The use of cross-sentence information in some form has been a normal part of many NER methods in the former categories, but its role has diminished with the current deep learning based approaches. Rule/knowledge-based approaches such as that of Mikheev et al. (1998) typically match strings to lexicons and similar domain knowledge sources, possibly going through text multiple times with refinement based on entities found on earlier passes. Later, manually engineered features were used to incorporate information from the surrounding text, whole documents, data sets and also from external sources. The number of different features and classifiers grew during the years and it was normal that the features also contained cross-sentence information in some form [Passos et al., 2014] [Krishnan and Manning, 2006]. Dense representations of text such as word, character, string and subword embeddings first started to appear in NER methods as additional features fed to classifiers [Collobert et al., 2011]. Step by step, feature engineering has been demoted to a lesser role, as the most recent deep learning approaches learn to create meaningful and context-sensitive representations of text by pretraining with vast amounts of unlabeled data. These contextual representations are often used directly as features for existing NER architectures or, in transfer learning, fine-tuned with labeled data to match a certain task.

In recent years, the development of NLP in general and NER in particular has been greatly influenced by deep transfer learning methods capable of creating contextual representations of words, to the extent
that many of the state-of-the-art NER systems mainly differ from one another on the basis of how these contextual representations are created (Peters et al., 2018; Devlin et al., 2018; Akbik et al., 2018; Baevski et al., 2019). Using such models, sequence tagging tasks are often approached one sentence at a time, essentially discarding any information available in the broader surrounding context, and there is only little recent study on the use of cross-sentence context – sentences around the sentence of interest – to improve sequence tagging performance. In this paper, we present a comprehensive exploration of the use of cross-sentence context for named entity recognition, focusing on the recent BERT deep transfer learning models (Devlin et al., 2018) based on self-attention and the transformer architecture (Vaswani et al., 2017). BERT uses a fixed-size window that limits the amount of text that can be input to the model at one time. The model maximum window size, or maximum sequence length, is fixed during pre-training, with 512 wordpieces a common choice. This window fits dozens of typical sentences of input at a time, allowing us to include extensive sentence context. Here, we first study the effect of predicting tags for individual sentences when they are moved around the window, surrounded by their original document context from the source data. Second, we utilize different predictions for the same sentences to potentially further improve performance, combining predictions using majority voting, adapting an approach that has been used already in early NER implementations (Tjong Kim Sang et al., 2000; Van Halteren et al., 2001; Florian et al., 2003). We evaluate these approaches on five languages, contrasting NER results using BERT without cross-sentence information, sentences in context, and CMV on well-established benchmark datasets. We show that using sentences in context consistently improves NER results on all of the tested languages and CMV further improves the results in most cases. Comparing performance to the current state-of-the-art NER results in the 5 languages, we find that our approach establishes new state-of-the-art results for English, Dutch, and Finnish, the best BERT-based results on German, and effectively matches the performance of a BERT-based method in Spanish.

2 Related work

The state-of-the-art in NER has recently moved from approaches using word/character representations and manually engineered features (Passos et al., 2014; Chiu and Nichols, 2016) toward approaches directly utilizing deep learning-based contextual representations (Akbik et al., 2018; Peters et al., 2018; Devlin et al., 2018; Baevski et al., 2019) while adding few explicit features, if any. While successful in terms of NER performance, these approaches have tended to predict tags for one sentence at a time, discarding information from surrounding sentences. One recent method taking sentence context into account is that of Akbik et al. (2019), which addresses a weakness of an earlier contextual string embedding method (Akbik et al., 2018), specifically the issue of rare word representations occurring in underspecified contexts. Akbik et al. (2019) make the intuitive assumption that such occurrences happen when a named entity is expected to be known to reader, i.e. the name is either introduced earlier in text or is of general in-domain knowledge. Their approach is to maintain a memory of contextual representations of each unique word/string in text and pool together contextual embeddings of a string occurring in text with the contextual embeddings of the same string earlier in text. This pooled contextual embedding is then concatenated with the current contextual embedding to get the final embedding to use in classification.

Another recent approach taking broader context into account for NER was proposed by Luo et al. (2019), where in addition to token representations, also sentence and document level representations are calculated and used for classification using a CRF model. Baevski et al. (2019) state that they use longer paragraphs in pre-training their model, but it is not mentioned in the paper if such longer paragraphs are used also in finetuning the model or predicting tags for NER. Some other approaches such as that of Liu et al. (2019a) include explicit global information in form of e.g. gazetteers. Also, some approaches formulate NER as a span finding task instead of sequence labeling (Banerjee et al., 2019; Li et al., 2019). These approaches would likely allow the use of longer sequences, but the incorporation of cross-sentence information is not explicitly proposed by the authors. In the paper introducing BERT, Devlin et al. (2018) write in the description of their NER evaluation “we include the maximal document context provided by the data.” However, no detailed description of how this inclusion was implemented is provided, and some
NER implementations using BERT have struggled to reproduce the results of the paper. The addition of document context to NER using BERT is discussed also by Virtanen et al. (2019), who add following sentences to each input sample, using the first sentence in each sample for predictions and thus only introducing context appearing after the sentence of interest in the source text.

Of the related work discussed above, our approach most closely resembles that of Virtanen et al. (2019), which in turn directly follows Devlin et al. (2018). By contrast to other studies discussed above, we do not introduce extra features or embeddings representing cross-sentence information, or incorporate extra information in addition to that captured by the BERT model. Instead, we directly utilize the BERT architecture and rely on self-attention and voting to combine predictions for sentences in different contexts.

3 Data

The data used in this study consists of pretrained BERT models and NER datasets for five different languages. We aimed to use monolingual BERT models as numerous recent studies have suggested that well-constructed language-specific models outperform highly multilingual ones (Virtanen et al., 2019; de Vries et al., 2019; Le et al., 2019). We selected the following language-specific pre-trained BERT models for our study, focusing on languages that also have established benchmark data for NER:

- BERTje (de Vries et al., 2019) base cased for Dutch,
- BERT large WWM cased (Devlin et al., 2018) for English,
- FinBERT (Virtanen et al., 2019) for Finnish,
- German-bert from deepset.ai for German, and
- BETO (Caete et al., 2020) for Spanish.

For comparison purposes we also tested multilingual BERT with the Spanish language. We also aimed to apply sufficiently large, widely-used benchmark datasets for evaluating NER results, assessing our methods primarily on the CoNLL’02 and CoNLL’03 Shared task Named entity recognition datasets (Tjong Kim Sang, 2002; Tjong Kim Sang and De Meulder, 2003), which cover four of our five target languages. For the fifth language, Finnish, we use two recently published named entity recognition corpora (Ruokolainen et al., 2019; Luoma et al., 2020). These two Finnish datasets are annotated in a compatible way, and for this study they are combined into a single corpus by simple concatenation, following Luoma et al. (2020).

All of the NER datasets define separate training, development and test sets, and we follow the given subdivision for each. The training sets for each language are used for fine-tuning the corresponding BERT model for NER, development sets are used for evaluation for hyperparameter selection, and the test sets are only used in final experiments for evaluating models trained with the selected hyperparameters. As previous studies vary in whether to combine development to training data for training a final model, we report also results where models are trained with a combined training and development set for final test experiments. The datasets for CoNLL shared task languages contain four different classes of named entities: Person (PER), Organization (ORG), Location (LOC) and Miscellaneous (MISC). The Finnish
| Tokens | English | German | Spanish | Dutch | Finnish |
|---------|---------|--------|---------|-------|---------|
| Train   | 203,621 | 206,931| 264,715 | 202,644| 342,924 |
| Development | 51,362 | 51,444 | 52,923 | 37,687 | 31,872 |
| Test    | 46,435  | 51,943 | 51,533 | 68,875 | 67,425 |
| Entities | English | German | Spanish | Dutch | Finnish |
| Train   | 23,499  | 11,851 | 18,798 | 13,344| 27,026 |
| Development | 5,942  | 4,833 | 4,352 | 2,616 | 2,286 |
| Test    | 5,648   | 3,673  | 3,559  | 3,941 | 5,129  |

Table 1: Key statistics of the NER data sets

NER datasets also use the PER, ORG, and LOC types along with three others, Product (PROD), Event (EVENT), and Date (DATE). For implementation purposes we converted all the datasets to the same format prior to experiments: The character encoding of each file was converted to UTF-8, and the NER labeling scheme was converted to IOB2 (Ratnaparkhi, 1998) also for corpora that were originally in the IOB scheme (Ramshaw and Marcus, 1995). By contrast to the older IOB scheme, in the IOB2 scheme the label for the first token of a named entity is always marked with a B-prefix (e.g. B-PER), even if the previous token is not part of a named entity. The key statistics for the NER datasets are presented in Table 1. Finally, we note that all the datasets except CoNLL’02 Spanish provide information on document boundaries using special –DOCSTART– tokens at the start of each new document.

4 Methods

As the starting point for our exploration including cross-sentence information for NER using BERT, we use an NER pipeline implementation introduced by Virtanen et al. (2019) that closely follows the straightforward approach presented by Devlin et al. (2018). Here, the last layer of the pre-trained BERT model is followed by a single time-distributed dense layer which is fine-tuned together with the pre-trained BERT model weights to produce the softmax probabilities of NER tags for input tokens. No modeling of tag transition probabilities nor any heuristics to validate tag sequences are used.

In the basic implementation, exactly one example is constructed for each sentence of the corpus so that the sentence is placed at the beginning of the BERT window and following sentences from the corpus are used to fill the window (up to the maximum sequence length), with special separator ([SEP]) tokens separating the sentences (Figure 1b). As a special case, the sentences used for filling the window for the last sentences in input data are picked by wrapping back to the beginning of the corpus. Only full sentences are added to each input sample, and padding tokens ([PAD]) are used to fill empty space if the next sentence in the input data does not fit into the window. This approach creates situations where some input samples contain sentences from different original documents, where the documents were next to one another in the corpus. For this reason we also implemented documentwise wrapping of sentences if the input data had document boundaries marked with –DOCSTART– tokens. We used this information to build input samples by filling the sentences at the end of one document with the sentences from beginning of that same document instead of the next sentences in the original data.

Constructing inputs in this way implies that the same sentences from the original data occur in different positions and with varying (sizes of) left and right contexts in different samples. We wanted to examine the predictions in different contexts more closely to see if there are consistent effects on tag prediction quality depending on the starting position of a sentence inside a context. One challenge here was that we were not able to consistently measure performance on different contexts: sentences are of different length, and as they are added to input samples, the beginning of the window was only place where the starting locations of sentences would align. Also, the number of sentences that fit into the window vary substantially. For this reason, it is not possible e.g. to always pick the Nth sentence to study as there are no guarantees one will exist in all examples. This lead us to build input samples for testing predictions at different locations in the following manner: we placed the sentence of interest to start at a specified...
location inside the window, and filled the window in both directions with sentences before / after the sentence of interest in the original data. We tested the starting positions of the sentence of interest from 1 (0 being the [CLS] token) up to the maximum sequence length (512 wordpieces) with intervals of 32 wordpieces. If the sentence of interest was longer than the space between a starting position and the maximum sequence length, the starting position for that particular sentence was moved backwards to fit the sentence in the window.

Ensembles of classifiers are commonly used to improve classification performance at various tasks, and it seems reasonable to assume that predictions for the same input sentences in different positions and contexts create an ensemble-like construct. (This is not an ensemble in the traditional sense, as the number of predictions we get for each sentence varies.) We evaluate two different variations combining the results from multiple predictions in different contexts. The first approach is to assign labels to sentences in each location first, and then take a majority vote of the assigned labels. The other approach was to add together the softmax probabilities of predictions in different contexts, and then take the argmax of the sum. For simplicity, we here term both of these Contextual Majority Voting (CMV) as they are variations of the same underlying idea. The results as well as the best-performing hyperparameters with the two variations are similar in most cases, and thoroughly testing their differences was out of the scope of this study. Testing data for the two were constructed in the same way as the corresponding training data.

For fine-tuning the pre-trained BERT models we largely follow the process introduced in (Devlin et al., 2018). We use the maximum sequence length of 512 in all experiments to include maximal cross-sentence context, the Adam optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 1e^{-6}$) with warmup of 10% of samples, linear training rate decay, a weight decay rate of 0.01, and norm clipping on 1.0. Sample weights are used for inputs so that the special tokens [CLS], [SEP] and [PAD] are given zero weight and everything else 1 when calculating the loss (sparse categorical cross-entropy). We select hyperparameters with an exhaustive search of the grid proposed by Devlin et al., modified to skip batch size 32 and add batch sizes 2 and 4 instead as our initial experiments indicated better performance with smaller batch sizes. That is, the grid search is done over the following parameter ranges:

- Learning rate: 2e-5, 3e-5, 5e-5
- Batch Size: 2, 4, 8, 16
- Epochs: 1, 2, 3, 4

We repeated each experiment 5 times with every hyperparameter combination. The best hyperparameters were selected based on the mean of mention-level F1 scores, as evaluated against the development set.
using a Python implementation of the standard conlleval evaluation script.

As a reference we use a BERT model which is fine-tuned using only single sentences from the input data. For this baseline, predictions are also made on the basis of single sentences (see Figure 1a).

## 5 Results

Based on initial development set results, we decided to focus only on CMV using examples constructed document-wise of the variations of this method (see Section 4). As the differences between variations were not large, we decided to only consider the variant that first assigns labels and then votes between the labels. Similarly, document-wise wrapping appeared to work marginally better in comparison to a variant that did not use document information. The exception here is the Spanish CoNLL dataset, for which document boundary information was not available.

The effect of starting location of sentence of interest and effect of CMV method on development data is illustrated in Figure 2. Our initial expectation was that placing the sentence of interest in the middle of the sequence would generally yield the best performance. However, while something like this effect can be observed e.g. for English (Figure 2a), the pattern does not hold in all cases, and frequently performance can improve when moving the starting position away from either end of the context window. The problem was that the performance in the middle of context did not seem stable enough to pick a reliable starting position to look at prediction time. This can be seen in the figure where the results for different starting locations tend to vary without a clear central optimum.

![Figure 2](image)

**Figure 2:** NER performance on development set measured with CMV and in different sentence starting locations. Lowest curve corresponds to the mean performance over whole hyperparameter range. Middle curve is the results with best hyperparameters (mean of 5 iterations) for each location. The flat line corresponds to best CMV result.

The final test set results for models trained with the best hyperparameters found in parameter selection on the development sets are summarized in Table 2. We report precision, recall and F1-score for models trained only on the training dataset, and additionally F1-scores for models trained with combined training and development sets. For each language/BERT model pair, we report performance for the baseline using only a single sentence per window (Single), the approach where sentences from the following context are included but only predictions for the first sentence in each window are used (First), and, finally, performance with CMV (see also Figure 1). The results for "First" in Spanish with multilingual BERT
| Model               | Precision | Recall | F1     | F1 train+dev  |
|---------------------|-----------|--------|--------|---------------|
|                     |           |        |        |               |
| English, CMV        | 93.06     | 93.78  | 93.42  | 93.57 (0.33)  |
| English, First      | 93.15     | 93.73  | 93.44  | 93.74 (0.25)  |
| English, Single     | 91.12     | 92.28  | 91.70  | 91.94 (0.15)  |
| Dutch, CMV          | 93.12     | 93.26  | 93.19  | 93.49 (0.23)  |
| Dutch, First        | 93.03     | 93.38  | 93.21  | 93.39 (0.26)  |
| Dutch, Single       | 91.57     | 91.49  | 91.53  | 91.92 (0.30)  |
| Finnish, CMV        | 92.91     | 94.42  | 93.66  | 93.78 (0.26)  |
| Finnish, First      | 92.56     | 94.24  | 93.39  | 93.65 (0.26)  |
| Finnish, Single     | 90.74     | 92.11  | 91.42  | 91.97 (0.21)  |
| German, CMV         | 86.91     | 84.38  | 85.63  | 87.31 (0.27)  |
| German, First       | 86.37     | 84.07  | 85.21  | 86.91 (0.11)  |
| German, Single      | 85.55     | 81.81  | 83.64  | 85.67 (0.25)  |
| Spanish, CMV        | 87.80     | 87.98  | 87.89  | 87.97 (0.21)  |
| Spanish, First      | 86.71     | 87.41  | 87.06  | 87.27 (0.25)  |
| Spanish, Single     | 87.43     | 87.90  | 87.66  | 87.52 (0.41)  |
| S-mBERT, CMV        | 87.25     | 88.67  | 87.95  | 88.32 (0.26)  |
| S-mBERT, First      | 87.19     | 87.81  | 87.50  | 87.57 (0.29)  |

Table 2: NER results for different methods and languages.

| Model               | Our F1 | Our F1 (t+d) | BERT best | Current SOTA |
|---------------------|--------|--------------|-----------|--------------|
| English             | 93.44  | 93.54        | 93.37     | 93.5 (Baevski et al., 2019) |
| Dutch               | 93.21  | 93.49        | 90.94     | 92.69 (Straková et al., 2019) |
| Finnish             | 93.66  | 93.78        | 93.11     | 93.11 (Luoma et al., 2020)   |
| German              | 84.89  | 86.97        | 82.82     | 88.32 (Akib et al., 2018)    |
| Spanish             | 87.89  | 87.97        | 88.43     | 88.81 (Straková et al., 2019) |
| Spanish, mBERT      | 87.95  | 88.32        | 88.43     | 88.81 (Straková et al., 2019) |

Table 3: NER results comparison

were not ready by the time of submission. From these results it can be seen that BERT NER predictions systematically benefit from access to cross-sentence context. For all tested languages, models that are fine-tuned and tested with samples containing context information outperform models which do not use any context, relying instead only on single sentences. It is not directly seen from Table 2 that the results using Contextual Majority Vote outperform the results with only right side context information. Both English and Dutch seem to perform well with the First sentence in context. One thing we learned from English and Dutch results is that the CMV outperforms the First sentence in context method with the hyperparams that produced the best result for the First approach. The final results for CMV just were not that good with the hyperparams giving the best performance for CMV in development set.

In Table 3 we compare the results using cross-sentence context with current the state-of-the-art in NER for the languages studied here. We are able to establish a new state-of-the-art result for three languages, English, Dutch and Finnish, as well as improve the best BERT-based score on German. On Spanish we are a bit behind the reported state-of-the-art. Perhaps a bit surprising was that multilingual BERT outperformed the dedicated Spanish language BERT model, failing to replicate the results of Caete et al. (2020), who reported that the Spanish model outperformed that of Wu and Dredze (2019), who had previously reached the best Spanish BERT performance with multilingual BERT. Despite this minor discrepancy, we find that both the simple approach of including following sentences as context as well as CMV are very effective, allowing a straightforward BERT NER model to achieve state-of-the-art performance with only a few modifications of the representation.
6 Discussion

The results presented here, as far as we know it, are the first systematic study on how the cross-sentence information can be utilized with BERT and the methods presented form a good starting point for discussion and further research into the subject. Contextual Majority Voting should be easy to implement for existing BERT-based systems as the actual BERT model and associated infrastructure is not modified. The computational overhead for the needed pre- and postprocessing of the samples is very modest, and the number of training examples is not increased; instead, the samples are simply used more efficiently. It is quite probable that similar ways of including cross-sentence information or majority voting structures may be successfully implemented with other attention-based models as well.

One thing deserving more study is how prediction performance is affected if sentences are not repeated, or repeated fewer times, in examples during prediction. Reducing or entirely avoiding repetition would allow for more efficient use of the model while still providing context for sentences, which might be a reasonable compromise between performance and computational efficiency for large-scale practical applications. A further possibility for future research would be to explore weighted majority voting. Our results lend some support to the idea that predictions made for tokens around in the center of the window are broadly speaking more reliable than predictions for tokens near its edges, where context is limited on one side of the token. Providing higher weight to predictions in the middle of the sequence could potentially help further improve the performance of the aggregation approach.

7 Conclusions

We have presented a simple and easy-to-implement approach for including cross-sentence context for named entity recognition with BERT. The proposed method established new state-of-the-art results in Named Entity Recognition for three languages and is near the state-of-the-art for two other languages, showing how simple ideas may boost the performance of even very strong models. We release all methods implemented in this work under open licenses.

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