Neural Morphological Tagging from Characters for Morphologically Rich Languages

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Abstract
This paper investigates neural character-based morphological tagging for languages with complex morphology and large tag sets. We systematically explore a variety of neural architectures (DNN, CNN, CNNHighway, LSTM, BLSTM) to obtain character-based word vectors combined with bidirectional LSTMs to model across-word context in an end-to-end setting. We explore supplementary use of word-based vectors trained on large amounts of unlabeled data. Our experiments for morphological tagging suggest that for "simple" model configurations, the choice of the network architecture (CNN vs. CNNHighway vs. LSTM vs. BLSTM) or the augmentation with pre-trained word embeddings can be important and clearly impact the accuracy. Increasing the model capacity by adding depth, for example, and carefully optimizing the neural networks can lead to substantial improvements, and the differences in accuracy (but not training time) become much smaller or even negligible. Overall, our best morphological taggers for German and Czech outperform the best results reported in the literature by a large margin.

1 Introduction

Morphological part-of-speech tagging is the process of marking up a word in a text with its morphological information and part of speech (POS), see Fig. [1]. In morphologically rich languages (e.g., Turkish and Finnish), individual words encode substantial amounts of grammatical information (such as number, person, case, gender, tense, aspect, etc.) in the word form, whereas morphologically poor languages (e.g., English) rely more on word order and context to express this information. Most languages (such as German and Czech) lie between these two extremes, and some (e.g. German) exhibit syncretism, that is one-to-many mappings between form and function. For example (Fig. [1]), the isolated word form "meine" can be any combination of "case=[nominative|accusative], number=[singular|plural], gender=feminine" (among others) of the possessive pronoun "my" or a verb ("to mean"). This suggests that both within and across word modeling is needed in general.

Morphologically rich languages exhibit large vocabulary sizes and relatively high out-of-vocabulary (OOV) rates on the word level. Table 1 illustrates this for German (TIGER, de.wikidump) and Czech (PDT). Word-level representations generalize poorly to rarely seen or unseen words and thus, can significantly impair the performance for high OOV rates. To improve generalization, sub-word representations have been proposed. Compared to morphemes as the sub-word unit (Luong et al., 2013), characters have the advantage of being directly available from the text and do not require additional resources and complex pre-processing steps. Character-based approaches may also be useful for informal language (e.g., Tweets) or low-resource languages.

This paper investigates character-based mor-
Figure 1: Example for morphological tagging: The first line in the gray boxes with the part of speech maps to the POS tag, the second line with the morphological information maps to the MORPH tag, the combination of POS tag and MORPH tag gives a single tag POSMORPH used for full morphological tagging.

phological tagging. More specifically, we (i) provide a systematic evaluation of different neural architectures (DNN, CNN, CNNHighway, LSTM, BLSTM) to obtain character-based word vectors (Table 4), (ii) explore the supplementary use of word (rather than character-based) embeddings pre-trained on large amounts of unlabeled data (Table 5), and (iii) show that carefully optimized character-based systems can outperform existing systems by a large margin for German (Table 3) and Czech (Table 6).

The focus of the paper is to gain a better understanding of the relative importance of different basic neural architectures and building blocks. Data from morphologically rich languages are well suited to amplify these differences as a large amount of relevant information is encoded at the word level along with relatively high OOV rates. This helps us to better distinguish between systematic trends and noise when comparing different neural architectures. Similarly, we focus on morphological tagging, which typically has an order of magnitude more tags including also (where tags consist of sequences of a simple POS tag followed by many morphological feature=value pairs, see Fig. 1) than simple POS tagging and correspondingly higher error rates.

The remainder of the paper is organized as follows. Section 2 gives a survey on related work. Section 3 describes the neural network-based approach as explored in this paper. The empirical evaluation is presented in Section 4. Section 5 concludes the paper.

2 Related Work

This work is in the spirit of the ”natural language processing (almost) from scratch” approach (Collobert et al., 2011b), which was tested for word-level processing and various English natural language processing tasks. Several character-based approaches have been proposed for tagging. Existing work for POS tagging includes feature learning using CNNs in combination with a first-order Markov model for classification (Collobert et al., 2011b; dos Santos and Zadrozny, 2014) and recurrent neural network based approaches used in (Ling et al., 2015; Gillick et al., 2015; Plank et al., 2016). The work by (Labeau et al., 2015) uses a CNN/Markov model hybrid for morphological tagging of German. Comprehensive work on morphological tagging based on conditional random fields along with state-of-the-art results can be found in (Müller et al., 2013; Müller and Schütze, 2015). Our work is inspired by previous work (Collobert et al., 2011b; dos Santos and Zadrozny, 2014; Labeau et al., 2015; Ling et al., 2015) but uses a deeper hierarchy of layers in combination with a simple prediction model and provides comprehensive comparative results for alternative neural architectures for morphological tagging.

Several extensions of the neural approach used in this paper have been proposed, including multilingual training (Gillick et al., 2015), auxiliary tasks (Plank et al., 2016), and more structured prediction models (Collobert et al., 2011b; dos Santos and Zadrozny, 2014; Labeau et al., 2015; Ma and Hovy, 2016). It is conceivable that these refinements would lead to further improvements. In
this paper, we focus on optimizing and comparing a number of architectures for obtaining character vectors and try to keep the rest as simple as possible.

Character-based approaches have also been applied to other tasks in natural language processing, such as named entity recognition (Gillick et al., 2015), parsing (Ballesteros et al., 2015) (BLSTM), language modeling (Ling et al., 2015) (BLSTM) and (Kim et al., 2016) (CNNs) or neural machine translation (Costa-Jussà and Fonollosa, 2016).

3 From Characters to Tags

We assume an input sentence \( w_1, \ldots, w_N \) with (possibly complex morphological) output tags \( t_1, \ldots, t_N \). We use a zeroth-order Markov model

\[
p(t_1, \ldots, t_N | w_1, \ldots, w_N) = \prod_{n=1}^{N} p(t_n | w_1, \ldots, w_N) \quad (1)
\]

whose factors are modeled by a neural network. When mapping characters to tags, we use the character representation of the word, \( w = c_1, \ldots, c_M \). This assumes that the segmentation of the sentence into words is known, which is straightforward for the languages under consideration.

Each input word maps to one complex output tag. Hence, we can model the position-wise probabilities \( p(t | w_1, \ldots, w_N) \) with recurrent neural networks, such as long short-term memory recurrent neural networks (LSTMs) (Graves, 2012). Fig. 2 shows such a network architecture where the inputs are the word vectors \( v_1, \ldots, v_N \). On top of the BLSTM, we use position-wise softmax classifiers.

Fig. 2 shows the ”upper” part of our network. This part is used in all experiments reported below. We now turn to the ”lower” parts of our networks, where we experiment with different architectures to obtain character vectors that make up the \( v_i \)s. In fact, in our work, we use both word-based and character-based word vectors. Word-based word vectors are attractive because they can be efficiently pre-trained on supplementary, large amounts of unsupervised data (Mikolov et al., 2013). As shown by (Soricut and Och, 2015), these word vectors also encode morphological information and may provide additional information to the character-based word vectors directly learned from the comparably small amounts of supervised data. We use word-based word vectors in two modes: they are pre-trained and kept fixed during training or jointly optimized with the rest of the network. Word-based vectors are efficient as they can be implemented by a lookup table (LUT) (Fig. 3 (a)) but are bad at generalization because they do not exploit information encoded at the sub-word level.

The character-based word vectors are the output vectors of a sub-network that maps variable-length character strings to fixed-length vectors. In this paper, we compare the following mostly well established network architectures, see also Fig. 3:

- Fully-connected deep neural networks (DNNs): DNNs expect fixed-length input vectors. To satisfy this constraint, we assume a maximum number of characters per word. Fixed-length character strings from words are obtained by padding with a special character. The fixed-length sequence of character vectors can then be converted into a fixed-length vector by concatenation, which is fed to the DNN. DNNs are generic, unstructured networks which tend to be inefficient to learn in general.

- Convolutional neural networks (CNNs) (Collobert et al., 2011b; dos Santos and Zadrozny, 2014; Labeau et al., 2015): Compared to DNNs, CNNs use weight tying and local connections. This makes CNNs more efficient to learn in many settings. CNNs can deal with variable-length input across different batches and produce a variable number of output vectors, which are merged into a single fixed-length vector by max pooling. The context
length is controlled by the pre-defined filter width. For a filter width of $m$, a convolutional layer computes (“hierarchical” in case of multiple layers) character m-gram vectors. CNNs scale well to long sequences and are efficient due to highly optimized libraries.

- **CNNHighway** (Kim et al., 2016; Costa-jussà and Fonollosa, 2016): This CNN variant is similar to vanilla CNNs but maintains a set of one-layer CNNs with different filter widths. This alleviates problems with having a single filter width and selecting an appropriate filter width. The outputs of the different CNNs are concatenated and max pooled, followed by a fully-connected deep neural network with highway connections for additional mixing. CNNHighway includes many layers but is basically a shallow architecture, which tends to make learning easier.

- **LSTMs** (Ling et al., 2015): LSTMs are sequential models and thus a natural choice for character strings. Vanilla LSTMs map each input to one output. To obtain a fixed-length vector, only the last output vector, ideally encoding the whole sequence, is used as the word vector; all other outputs are suppressed. Unlike CNNs, recurrent neural networks can learn context of variable length and do not use a pre-defined context length. In general, multiple layers are required to perform the complex transformations. A disadvantage of deep LSTMs is that they can be difficult to train.

- **Bidirectional LSTMs (BLSTMs)** (Ling et al., 2015; Ballesteros et al., 2015; Plank et al., 2016): BLSTMs are similar to LSTMs but encode the input from left to right and from right to left. The word vector is the concatenation of the output vector of the (topmost) forward LSTM at position $M$ and the output vector of the (topmost) backward LSTM at position 1. For a “perfect” sequence model, it might not be obvious why the word needs to be encoded in both directions.

Where applicable, word-level and character-level word vectors are combined by concatenation. The weights of the network, $\theta$, are jointly estimated using the conditional log-likelihood

$$F(\theta) = -\sum_{n=1}^{N} \log p_{\theta}(t_n|w_1, \ldots, w_N).$$

Learning in recurrent or very deep neural networks is non-trivial and skip/shortcut connections have been proposed to improve the learning of such networks (Pascanu et al., 2014; He et al., 2016). Here, we use such connections (dashed arrows in Fig. 2) in some of the experiments to alleviate potential learning issues.

At test time, the predicted tag sequence is the tag sequence that maximizes the conditional prob-
ability $p(t_1, \ldots, t_N|w_1, \ldots, w_N)$. For the factorization in Eq. 1, the search can be done position-wise. This significantly reduces the computational and implementation complexity compared to first-order Markov models as used in (Collobert et al., 2011b; dos Santos and Zadrozny, 2014; Labeau et al., 2015).

4 Experimental Results

We first test variants of the architecture for German (Section 4.3) and then verify our empirical findings for Czech (Section 4.4).

4.1 Data

We conduct the experiments on the German TIGER corpus¹ and the Czech PDT corpus². For the time being, we have decided against using the recent Universal Dependencies³ because of the lack of comparative results for morphological tagging in the literature. Table 1 (at the beginning of the paper) presents OOV rates and Table 2 some corpus statistics. Part of the experiments is supervised learning on small labeled data sets (TIGER, PDT) and part is also including large unlabeled data (de.wikidump, cs.wikidump)⁴. The tag set sizes observed in the labeled training data depend on the language and the type of tags: 54 (POS, German), 255 (MORPH, German), 681 (POSMORPH, German), and 1,811 (POSMORPH, Czech), where POS stands for the part-of-speech tags, MORPH for the morphological tags (feature=value pairs), and POSMORPH for the combined tag sets POS and MORPH. All words are lowercased. As a result of doing this, we ignore a useful hint for nouns in German (which makes a difference in error rate for the simple but not for the best models) but makes the conclusions less dependent on this German-specific feature.

4.2 Setup

We empirically tuned the hyperparameters on the TIGER development data and used the same setups also for Czech. The best setups for the character-based word vector neural networks are as follows:

- **DNN**: character vector size = 128, one fully-connected layer with 256 hidden nodes
- **CNN**: character vector size = 128, two convolutional layers with 256 filters and a filter width of five each
- **CNNHighway**: the large setup from (Kim et al., 2016), i.e., character vector size = 15, filter widths ranging from one to seven, number of filters as a function of the filter width $\min\{200, 50 \cdot \text{filter width}\}$, two highway layers
- **LSTM**: character vector size = 128, two layers with 1024 and 256 nodes
- **BLSTM**: character vector size = 128, two layers with 256 nodes each

The BLSTM modeling the context of words in a sentence (Fig. 2) consists of two hidden layers, each with 256 hidden nodes.

The training criterion in Eq. 2 is optimized using standard backpropagation and RMSProp (Tieleman and Hinton, 2012) with a learning rate decay of two every tenth epoch. The batch size is 16. We use dropout on all parts of the networks except on the lookup tables to reduce overfitting. In particular and in contrast to (Zaremba et al., 2015), we also use dropout on the recurrent parts of the network because it gives significantly better results. Training is stopped when the error rate on the development set has converged, which typically is after about 50 epochs. We observe hardly any overfitting with the described configurations.

We used Torch (Collobert et al., 2011a) to configure the computation graphs implementing the network architectures.

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¹ http://www.ims.uni-stuttgart.de/forschung/ressourcen/korpora/tiger.html
² https://ufal.mff.cuni.cz/pdt3.0
³ http://universaldependencies.org/
⁴ http://cistern.cis.lmu.de/marmot/
4.3 German

We first establish a baseline for German and compare it with the state of the art. Our baseline model (CNN-BLSTM) consists of the BLSTM in Fig. 2 and the CNN in Fig. 2(e) with a single convolutional layer, which is a simplified version of the best model in (Labeau et al., 2015). The results are summarized in Table 3. We show results for different tag sets (see Section 4.1) to facilitate the comparison with state-of-the-art results.

Our CNN-BLSTM baseline achieves comparable or better results for all tag sets. In particular, our CNN-BLSTM clearly (under consistent conditions) outperforms the related models in (Labeau et al., 2015) and (Ling et al., 2015)\footnote{We downloaded the software from https://github.com/wlin12/JNN to produce consistent results as the results in (Ling et al., 2015) are for the last 100 training sentences only and not for the standard test set. We use the default settings given in the paper for all experiments.}. As expected, word-level word vectors on their own (Fig. 2(a)) perform significantly worse than character-level word vectors, with error rates of 5.76% vs. 2.43% for POS tagging. Combining character-level and word-level word vectors computed on the TIGER training data only did not help.

Word embeddings (Mikolov et al., 2013) or word clusters (Muller and Schütze, 2015) allow us to exploit large amounts of unlabeled data. Using pre-trained word embeddings alone is better than the state of the art (9.27% vs. 10.97% for POSMORPH) but does not improve on our results (9.27% vs. 8.72% for POSMORPH). When combining them with the character-level word vectors, however, large additional gains are observed: 2.43% vs. 1.75% for POS and 8.72% vs. 6.67% for POSMORPH (Table 3).

Next, we compare different architectures to compute character-based word vectors for POSMORPH, see Table 4. Note that here and in contrast to Table 3 we use multiple hidden layers in general, which gives some additional gains. We also tested whether skip connections as shown in Fig. 2 helps learning. A small gain is observed only for LSTM, in all other cases it does not make a difference. Given sufficient capacity (e.g., the number of hidden layers), the different architectures achieve comparable error rates, except for the DNN which performs worse. CNNHighway may perform slightly better than CNN. CNN and CNNHighway are more memory efficient than LSTM and BLSTM but considerably slower in our Torch-based configuration, for example, 0.5 sec/batch (BLSTM) vs. 2 sec/batch (CNNHighway). The only optimization we do here is to compute the word vectors of a batch in parallel.

Finally, we investigate the effect of augmenting the character-based word vectors with pre-trained word embeddings (“word2vec”). The gains for simpler models are promising: 8.72% vs. 6.67% for the one-layer CNN. For more complex models, however, the observed gains are much smaller (6.77% vs. 6.15% for the best LSTM, for example). Overall, the error rates without word2vec vary between 7% and 9% while the error rates with word2vec are all around 7%. In particular, we cannot significantly improve over the best result in Table 4 (6.67% vs. 6.40%). In this example, the convolutional networks seem to better combine with word2vec than the recurrent neural network. The convergence curve for LSTM-BLSTM augmented with word2vec on a subset of the development set is shown in Fig. 4. The initial convergence is faster with word2vec (ignoring the time to generate word2vec) but the two curves eventually converge to the same error rate.

![Convergence curve for LSTM-BLSTM, without and with word2vec.](image)

4.4 Czech

We confirm our empirical findings for German on another morphologically rich language (Czech). The results are summarized in Table 6 for the models that performed best on German. Similar to German, CNNHighway-BLSTM and LSTM-BLSTM perform similarly (0.5% absolute difference in error rate) and clearly better than the baselines (25% or more relative error rate reduction). Augmenting the character-based word vectors with pre-trained embeddings gives some
additional small gain. Again, the gain for CNNHighway-BLSTM is larger than for LSTM-BLSTM.

5 Summary

This paper summarizes our empirical evaluation of the character-based neural network approach to morphological tagging. Our empirical findings for German and Czech are as follows. As long as carefully tuned neural networks of sufficient capacity (e.g., number of hidden layers) are used, the effect of the specific network architecture (e.g., convolutional vs. recurrent) is small for the task under consideration. However, the choice of architecture can greatly affect the training time (in our implementation, the convolutional networks are 2-4 times slower than the recurrent networks). Augmenting the character-based word vectors with word embeddings pre-trained on large amounts of unsupervised data, gives large gains for the small configurations but only small gains on top of the best configurations. Moreover, our best character-based morphological taggers outperform the state-of-the-art results for German and Czech by a relative gain of 30% or more. Future work will include the investigation of multilingual training, higher-order Markov models, and low-resource languages.
Table 3: Test error rates (%) for German, CNN for character-based word vectors has only one layer

| Train data | Setup | POS | MORPH | POSMORPH |
|------------|-------|-----|-------|----------|
| TIGER      | CRF (Müller and Schütze, 2015) | 2.68 | 11.59 |
|            | PCRF (Müller et al., 2013)    | 2.56 | 11.42 |
|            | biRNN, Non-Lex/Struct (Labeau et al., 2015) | 3.59 | 12.88 |
|            | biRNN, Both/Struct (Labeau et al., 2015) | 2.86 | 10.97 |
|            | BLSTM, lower-case (Ling et al., 2015) | 3.07 | 10.04 |
|            | BLSTM, mixed case (Ling et al., 2015) | 2.59 | 9.24 |
|            | CNN-BLSTM, word-based word vectors | 5.76 |       |
|            | char-based word vectors        | 2.43 | 7.98  |
|            | + de.wikidump CRF + MarLiN (Müller and Schütze, 2015) | 2.27 | 10.82 |
|            | CNN-BLSTM, word2vec            | 2.61 | 8.55  |
|            | char-based word vectors+word2vec | 1.75 | 6.16  |

Table 4: Test error rates (%) for German and different character-based word vectors

| POSMORPH    | BLSTM | + skip connection |
|-------------|-------|-------------------|
| CNN baseline (Labeau et al., 2015) | 10.97 |
| BLSTM baseline (Ling et al., 2015) | 10.04 |
| DNN (Fig. 3(b)) | 10.00 |
| CNN (Fig. 3(c)) | 8.10 |
| CNNHighway (Fig. 3(d)) | 7.37 |
| BLSTM (Fig. 3(f)) | 7.50 |
| LSTM (Fig. 3(e)) | 7.45 |

Table 5: Test error rates (%) for German and different character-based word vectors annotated with word2vec

| POSMORPH    | Char-based word vector | + word2vec |
|-------------|------------------------|------------|
| CNN, 1 layer (Fig. 3(c)) | 8.72 | 6.67 |
| CNN, 2 layers (Fig. 3(c)) | 8.10 | 6.66 |
| CNNHighway (Fig. 3(d)) | 7.37 | 6.40 |
| LSTM (Fig. 3(e)) | 6.77 | 6.15 |

Table 6: Test error rates (%) for Czech

| Train data | Setup | MORPH | POSMORPH |
|------------|-------|-------|----------|
| PDT        | PCRF (Müller et al., 2013) | 6.07 | 7.01 |
|            | BLSTM (Ling et al., 2015) | 6.30 | |
|            | CNNHighway-BLSTM | 4.48 | 4.87 |
|            | LSTM-BLSTM | 3.92 | 4.36 |
| + cs.wikidump | CRF + MarLiN (Müller and Schütze, 2015) | 5.67 | |
|            | CNNHighway-BLSTM | 3.79 | 4.19 |
|            | LSTM-BLSTM | 3.95 | 4.07 |
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