Abstract

We take a practical approach to solving sequence labeling problem assuming unavailability of domain expertise and scarcity of informational and computational resources. To this end, we utilize a universal end-to-end Bi-LSTM-based neural sequence labeling model applicable to a wide range of NLP tasks and languages. The model combines morphological, semantic, and structural cues extracted from data to arrive at informed predictions. The model’s performance is evaluated on eight benchmark datasets (covering three tasks: POS-tagging, NER, and Chunking, and four languages: English, German, Dutch, and Spanish). We observe state-of-the-art results on four of them: CoNLL-2012 (English NER), CoNLL-2002 (Dutch NER), GermEval 2014 (German NER), Tiger Corpus (German POS-tag.), and competitive performance on the rest. Our source code and detailed experimental results are publicly available.

1 Introduction

A variety of NLP tasks can be formulated as general sequence labeling problem: given a sequence of tokens and a fixed set of labels, assign one of the labels to each token in a sequence. We consider three concrete sequence labeling tasks: Part-of-speech (POS) tagging, Named Entity Recognition (NER), and Chunking (also known as shallow parsing). POS-tagging reduces to assigning a part-of-speech label to each word in a sentence; NER requires detecting (potentially multi-word) named entities, like person or organization names; chunking aims at identifying syntactic constituents within a sentence, like noun- or verb-phrases.

Traditionally, sequence labeling tasks were tackled using linear statistical models, for instance: Hidden Markov Models (Kupiec, 1992), Maximum Entropy Markov Models (McCallum et al., 2000), and Conditional Random Fields (Laferty et al., 2001). In their seminal paper, Collobert et al. (2011) have introduced a deep neural network-based solution to the problem, which has spawned immense research in this direction. Multiple works have introduced different neural architectures for universal sequence labeling afterwards (Huang et al., 2015; Lample et al., 2016; Ma and Hovy, 2016; Chiu and Nichols, 2016; Yang et al., 2016). However, aiming for better results on a particular dataset, these and numerous other works typically employ some form of feature engineering (Ando and Zhang, 2005; Shen and Sarkar, 2005; Collobert et al., 2011; Huang et al., 2015), external data for training (Ling et al., 2015; Lample et al., 2016) or in a form of lexicons and gazetteers (Ratinov and Roth, 2009; Passos et al., 2014; Chiu and Nichols, 2016), extensive hyper-parameter search (Chiu and Nichols, 2016; Ma and Hovy, 2016), or multi-task learning (Durrett and Klein, 2014; Yang et al., 2016).

In this paper, we take an alternative stance by looking at the problem of sequence labeling from a practical perspective. The performance enhancements enumerated above typically require availability of expertise, time, or external resources. Some (or even all) of these may be unavailable to users in a practical situation. Therefore, we deliberately eschew any form of feature engineering, pre-training, external data (with the exception of publicly available word embeddings), and time-consuming hyper-parameter optimization. To this end, we formulate a single general-purpose sequence labeling model and apply it to eight different benchmark datasets to estimate the effectiveness of our approach.

Our model utilizes a bi-directional LSTM (Graves and Schmidhuber, 2005) to extract morphological information from the bytes of words in
a sentence. These, combined with word embeddings bearing semantic cues, are fed to another Bi-LSTM to obtain word-level scores. Ultimately, the word-level scores are passed through a CRF layer (Lafferty et al., 2001) to facilitate structured prediction of the labels.

The rest of the paper is organized as follows. Section 2 specifies the proposed model in detail. Sections 3 and 4 describe the datasets and the training procedure used in experiments. The results are presented in Section 5. We review related work in Section 6 and conclude in Section 7.

2 Model

Recurrent Neural Networks (Elman, 1990) are commonly used for modeling sequences in NLP (Mikolov et al., 2010; Cho et al., 2014; Graves et al., 2013). However, because of well-known challenges of capturing long-term dependencies with plain RNNs (Pascanu et al., 2013), we instead turn to Long Short-Term Memory (LSTM) networks (Hochreiter and Schmidhuber, 1997) capable of alleviating the vanishing/exploding gradient problem by design. The specific LSTM formulation we are using (Zaremba et al., 2014) can be described by the following equations:

\[
i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i) \\
f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f) \\
o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o) \\
c_t = tanh(W_c h_{t-1} + U_c x_t + b_c) \\
c_t = f_t \odot c_{t-1} + i_t \odot c_t \\
h_t = o_t \odot tanh(c_t)
\]

where \( \sigma \) denotes the sigmoid activation function; \( \odot \) - element-wise (Hadamard) product; \( W, U, b \) - learned network parameters; \( i_t, f_t, o_t \) - input, forget, and output gates; \( x_t, c_t, h_t \) - network input, cell state, and network output at time step \( t \) respectively.

One issue with ordinary LSTMs is that they capture dependencies between sequence elements only in one direction, whereas it might be beneficial to learn also backward dependencies (e.g., for informed first label prediction). To overcome this limitation, we use bidirectional LSTM (Bi-LSTM) networks (Graves and Schmidhuber, 2005) comprising two independent LSTM instances (with separate sets of parameters): one processing an input sequence in forward direction and the other in backward direction. The output of Bi-LSTM is formed by concatenating the outputs of the two LSTMs corresponding to each sequence element.

The diagram of the proposed model is shown in Figure 1. The model can be decomposed into three logical components: (1) computing byte embeddings of each word in a sentence by means of the Byte Bi-LSTM; (2) combining byte embeddings with word embeddings and feeding resulting joint word representations to the Word Bi-LSTM to obtain word-level scores; (3) passing word-level scores through the CRF Layer to arrive at joint prediction of labels. We describe each of these components in detail in the following subsections.

2.1 Byte Embeddings

Assuming that input is available in tokenized form, we enable the model to extract morphological information from tokens by analyzing their
character-level representations. Following Ling et al. (2015), we apply a Bi-LSTM network for solving this task. However, to be truly neutral with respect to languages and character sets thereof, we consider a sequence of bytes underlying a UTF-8 encoding of each word instead of its characters.

Formally, given a sequence of words $w_1, ..., w_n$ in a sentence, we first decompose each word into its characters $c_{i1}, ..., c_{im_i}$ including dummy start- and end-of-word characters (we assume that the $i$-th word consists of $m_i$ characters including two dummy ones). Now we convert a sequence of characters to a sequence of underlying UTF-8 bytes $b_{i1}, ..., b_{im_i}$ (for simplicity, here we assume that all characters are single-byte, but this is obviously not necessary). Dummy characters are encoded by special byte values $\text{0x01}$ (start-of-word) and $\text{0x02}$ (end-of-word). Next, we compute byte projections of bytes in a sequence by multiplying the byte projection matrix $B$ by a one-of-$256$ coded vector representation of each byte. The matrix $B \in \mathbb{R}^{db \times 256}$ is a learned model parameter. Each of the obtained byte projection vectors $p_{i1}, ..., p_{im_i}$ has a fixed dimensionality $db$, which is a hyper-parameter of the model.

Next, the byte projection sequence $p_{i1}, ..., p_{im_i}$ is fed to the Byte Bi-LSTM network. The last outputs of its forward and backward LSTMs are concatenated to obtain "byte embedding" vector of the $i$-th word $\text{be}_i$. These fixed-size vectors are assumed to capture morphological information about corresponding words in a sentence.

### 2.2 Word-level Representation

Morphological information alone is probably not representative enough to reliably predict target labels in a general sequence labeling setting. For this reason, we would also want to supply our prediction framework with semantic information. We fulfill this requirement by mixing in pre-trained word embeddings of words in a sentence. Then, following Huang et al. (2015), we infer word-level representation using a Bi-LSTM network.

Formally, given a vocabulary of size $V$ and fixed (not learned) word embedding matrix $E \in \mathbb{R}^{d_e \times V}$, the word embedding vector of the $i$-th word $\text{we}_i$ is obtained by multiplying $E$ by a one-of-$V$ coded vector representation of the word’s position in the vocabulary ($d_e$ is the dimensionality of embedding vectors and depends on the choice of word embeddings). For all out-of-vocabulary words we use the same additional "unknown" word embedding vector.

Next, computed byte embedding of $i$-th word $\text{be}_i$ is concatenated with its word embedding $\text{we}_i$ to produce a joint embedding $\text{je}_i$. This way we obtain a sequence of joint embeddings $\text{je}_1, ..., \text{je}_n$ corresponding to the words $w_1, ..., w_n$ in a sentence. The joint embeddings are assumed to capture both morphological and semantic information about the words. They are fed as inputs to the Word Bi-LSTM network. The outputs of the network at each time step are passed through a linear layer (with no activation function) to yield $L$-dimensional word-level score vectors $s_1, ..., s_n$, where $L$ denotes the number of distinct labels. In essence, word-level score vectors may be interpreted as unnormalized log-probabilities (logits) over the labels at each time step.

Theoretically, we could stop here by applying softmax to each word-level score vector to infer a distribution over possible labels at each time step. However, this approach (albeit bearing a certain degree of context-awareness due to the presence of the upstream Word Bi-LSTM) would treat each word more or less locally, lacking a global view over predicted labels. This is why we turn to a CRF layer as the last step of label inference.

### 2.3 CRF Layer

Oftentimes, labels predicted at different time steps follow certain structural patterns. As an example, the IOB labeling scheme has specific rules constraining label transitions: for example, an I-ORG label can follow only a B-ORG or another I-ORG but no other label. To learn patterns like this one, following Lample et al. (2016), we utilize Conditional Random Fields (CRFs) (Lafferty et al., 2001) in the final component of our model. CRFs can capture dependencies between labels predicted at different time steps by modeling probabilities of transitions from one step to the other. Linear chain CRFs model transitions between neighboring pairs of labels in a sequence and allow solving a structured prediction problem in a computationally feasible way.

We recall that a sequence of word-level score vectors $s_1, ..., s_n$ is inferred by the Word Bi-LSTM. The $j$-th component of the $i$-th score vector $s_{ij}$ represents unnormalized log-probability of assigning $j$-th label to the word at the $i$-th position. Joint prediction is modeled by introducing a
The probability of observing a particular sequence of labels \( y = y_1, \ldots, y_n \) given a sequence of words \( w = w_1, \ldots, w_n \):

\[
f(y|w) = \sum_{i=1}^{n} s_{y_{i+1}y_{i}} + \sum_{i=1}^{n-1} A_{y_{i}y_{i+1}}
\]

where \( A \in \mathbb{R}^{L \times L} \) is a matrix of label transition scores (\( A_{ij} \) is a score of transition from label \( i \) to label \( j \); \( L \) represents the number of distinct labels) and word-level scores \( s_{ij} \), obviously depend on \( w \). The matrix \( A \) is another learned model parameter.

The probability of observing a particular sequence of labels \( y = y_1, \ldots, y_n \) given a sequence of words \( w = w_1, \ldots, w_n \) can be computed by applying softmax over total scores of all possible label assignments \( \tilde{y} \) to a sequence of words \( w \) (\( \theta \) denotes the set of all learned model parameters):

\[
p(y|w; \theta) = \frac{e^{f(y|w)}}{\sum_{\tilde{y}} e^{f(\tilde{y}|w)}} \tag{1}
\]

And the corresponding log-probability is:

\[
\log p(y|w; \theta) = f(y|w) - \log \sum_{\tilde{y}} e^{f(\tilde{y}|w)} \tag{2}
\]

We learn the model parameters by maximizing log-likelihood (2) of \( \theta \) given the ground truth labels \( y \) corresponding to the input sequence \( w \). Computing the normalizing factor from equation (1), as well as deriving the most likely sequence of labels during test time is performed using dynamic programming (Rabiner, 1989).

### 3 Datasets

We evaluate the performance of our approach on eight benchmark datasets covering four languages and three sequence labeling tasks. Certain statistics of those are shown in Table 1. The labels of all NER and Chunking datasets are converted to IOBES tagging scheme, as it is reported to increase predictive performance (Ratinov and Roth, 2009). We briefly discuss each of the datasets in the subsections below.

#### 3.1 CoNLL 2000

The CoNLL 2000 dataset (Tjong Kim Sang and Buchholz, 2000) was introduced as a part of a shared task on Chunking. Sections 15-18 of the Wall Street Journal part of the Penn Treebank corpus (Marcus et al., 1993) are used for training, section 20 for testing. Due to the lack of specifically demarcated development set, we use randomly sampled 10% of the training set for this purpose (see Section 4 for the details of training).

#### 3.2 CoNLL 2002

The CoNLL 2002 dataset (Tjong Kim Sang, 2002) was used for shared task on language-independent Named Entity Recognition. The data represents news wire covering two languages: Spanish and Dutch. In our experiments we treat Spanish and Dutch data separately, as two different datasets. The dataset is annotated by four entity types: persons (PER), organizations (ORG), locations (LOC), and miscellaneous names (MISC).

#### 3.3 CoNLL 2003

CoNLL 2003 (Tjong Kim Sang and De Meulder, 2003) is a NER dataset structurally similar to CoNLL 2002 (including entity types), but in English and German. English data is based on news stories from Reuters Corpus (Rose et al., 2002). We use the English portion of the dataset in the experiments.

#### 3.4 CoNLL 2012

The CoNLL 2012 dataset (Pradhan et al., 2012) was created for a shared task on multilingual unrestricted coreference resolution. The dataset is

| Dataset               | training set | development set | testing set | labels (classes) |
|-----------------------|--------------|-----------------|-------------|-----------------|
|                       | sentences | tokens | sentences | tokens | sentences | tokens |             |             |
| CoNLL 2000 (English, Chunking) | 8,936 | 211,727 | -       | -       | 2,012 | 47,377 | 45 (11)    |
| CoNLL 2002 (Spanish, NER)     | 8,323 | 264,715 | 1,915  | 52,923  | 1,517 | 51,533 | 17 (4)     |
| CoNLL 2002 (Dutch, NER)       | 15,806 | 202,644 | 2,895  | 37,687  | 5,195 | 68,875 | 17 (4)     |
| CoNLL 2003 (German, NER)      | 14,041 | 203,621 | 3,250  | 51,362  | 3,453 | 46,435 | 17 (4)     |
| CoNLL 2012 (English, NER)     | 59,924 | 1,088,503 | 8,528 | 147,724 | 8,262 | 152,728 | 73 (18)    |
| GermEval 2014 (German, NER)   | 24,000 | 452,853 | 2,200  | 41,653  | 5,100 | 96,499 | 40 (12)    |
| WSJ/PTB (English, POS-tag.)   | 38,219 | 912,344 | 5,527  | 131,768 | 5,462 | 129,654 | 45 (45)    |
| Tiger Corpus                 | 40,472 | 719,530 | 5,000  | 76,704  | 5,000 | 92,004 | 54 (54)    |

Table 1: Statistics of eight benchmark datasets used in the experiments.
based on OntoNotes corpus v5.0 (Hovy et al., 2006) and, among others, has named entity annotations. It is substantially larger and more diverse than the previously described NER datasets (see Table 1 for detailed comparison). Although some sources (Durrett and Klein, 2014; Chiu and Nichols, 2016) refer to the dataset as "OntoNotes", we stick to the name "CoNLL 2012" as the train/dev/test split that is used by this and other works is not defined in the OntoNotes corpus. Following Durrett and Klein (2014), we exclude the New Testament part of the data, as it is lacking gold annotations.

3.5 GermEval 2014

GermEval 2014 (Benikova et al., 2014) is a recently organized shared task on German Named Entity Recognition. The corresponding dataset has four main entity types (Location, Person, Organization, and Other) and two sub-types of each type, "-deriv" and "-part", indicating derivation from and inclusion of a named entity respectively. The original dataset has two levels of labeling: outer and inner. However, we use only outer labels in the experiments and compare our results to other works on the "M3: Outer Chunks" metric.

3.6 Wall Street Journal / Penn Treebank

The Wall Street Journal section of the Penn Treebank corpus (Marcus et al., 1993) is commonly used as a benchmark dataset for the English POS-tagging task. We follow this tradition and use a standard split of sections: 0-18 for training, 19-21 for development, and 22-24 for testing (Toutanova et al., 2003).

3.7 Tiger Corpus

Tiger Corpus (Brants et al., 2002) is an extensive collection of German newspaper texts. The dataset has several different types of annotations. We use part-of-speech annotations for setting up a German POS tagging task. Following Fraser et al. (2013), we use the first 40,472 of the originally ordered sentences for training, the next 5,000 for development, and the last 5,000 for testing.

4 Training

The training procedure described in this section is used for every experiment on every dataset mentioned in this paper. The model is trained end-to-end, accepting tokenized sentences as input and predicting per-token labels as output.

The model is trained using an Adam optimizer (Kingma and Ba, 2014). Following Ma and Hovy (2016), we apply staircase learning rate decay:

$$\eta_t = \frac{\eta_0}{1 + \rho(t - 1)}$$

where $\eta_t$ is the learning rate used throughout $t$-th epoch ($t$ starts at 1), $\eta_0$ is the initial learning rate, and $\rho$ is the learning rate decay factor. In our experiments we use $\eta_0 = 10^{-3}$ and $\rho = 0.05$.

Motivated by the initial experiments, the dimension $d_b$ of the byte projections is set to 50, the size of Byte and Word Bi-LSTM to 64 and 128 respectively. Training lasts for 100 epochs with a batch size of 8 sentences. Early stopping (Caruana et al., 2001) is used: at the end of every epoch the model is evaluated against the development set; eventually, the parameter values performing best on the development set are declared the final values.

Due to the high level of expressive power of the proposed model, we use dropout (Srivastava et al., 2014), with the rate of 0.5, to reduce the possibility of overfitting. Dropout is applied to word embeddings and byte projections, as well as the outputs of Byte Bi-LSTM and Word Bi-LSTM. As per Zaremba et al. (2014), we don’t apply dropout to state transitions of the LSTM networks.

Publicly available word embeddings are used for every language in the experiments. For English datasets we use 100-dimensional uncased GloVe embeddings (Pennington et al., 2014) trained on English Wikipedia and Gigaword 5 corpora and comprising 400K unique word forms. For other languages we use 64-dimensional cased Polyglot embeddings (Al-Rfou et al., 2013) trained on a respective Wikipedia corpus and comprising 100K unique (case-sensitive) word forms per language. Maintaining our commitment to the practical approach, we freeze the word embeddings during training not allowing them to train (except for the "unknown" word embedding, which is trained).

To achieve higher efficiency, we compute the joint embedding of every unique word in a batch only once (Ling et al., 2015). Unique joint embeddings are scattered according to the word positions in the input sentences, before being fed to the Word Bi-LSTM. The gradient with respect to each unique byte embedding is accumulated before being back-propagated once through the Byte Bi-LSTM. Albeit marginal during training (in small batches), performance improvement becomes considerable during inference (in larger batches).
5 Results

We present the results of our experiments in two different contexts. Table 2 shows the performance of different model configurations gauged in ablation studies. Tables 3, 4, 5, 6, 7, 8, 9, and 10 juxtapose our results on each dataset with those of other works reporting their results on the same dataset. When citing results of other works, we indicate the best performance reported in the corresponding publication (independent of the methodology used). Each of our scores reported in Tables 2-10 was achieved by a trained model on the dataset’s official test set. The scores were verified using CoNLL 2000 evaluation script\(^2\).

The ablation studies examined different partial configurations of the full model described in Section 2 evaluated on each of the eight datasets. The configurations were obtained by altering the contents of joint embeddings and omitting the CRF layer. Joint embeddings were set to only word, only byte, or both word and byte embeddings. For each of these three settings, the CRF layer was included or excluded, amounting to six configurations in total.

The results of the ablation studies in Table 2 show that, on every dataset, word and byte embeddings used jointly substantially outperformed any one of them used individually. This emphasizes

---

\(^2\)https://www.clips.uantwerpen.be/conll2000/chunking/conlleval

\(^3\)The result is taken from Durrett and Klein (2014).
the importance of using both embedding types, bringing in both semantic and morphological information about the words, for solving the general sequence labeling task. The role of the CRF layer proved to be crucial for all NER and Chunking, but not POS-tagging tasks. Configurations with and without CRF layer, given the same word representation, demonstrated very similar results on both English and German POS-tagging datasets. This supports the conjecture that a CRF layer can provide substantial incremental benefit, when used for solving a structured prediction task (e.g., NER and Chunking). It is also worth mentioning that on five out of eight datasets, using byte embeddings alone yielded better results than using word embeddings alone, both with and without CRF layer. This may be caused by the fact that word embeddings are external (and not necessarily related) to the data, while byte embeddings are always learned from the data itself.

Comparison of our results with those of other works, shown in Tables 3 through 10, manifests that our model has achieved state-of-the-art performance on four out of eight datasets: namely, 85.61 F1 on CoNLL 2002 (Dutch NER), 87.48 F1 on CoNLL 2012 (English NER), 79.21 F1 on GermEval 2014 (German NER), and 98.40% on Tiger Corpus (German POS-tagging). We consider the scores obtained on the remaining four datasets to be competitive.

6 Related Work

Arguably, the modern era of deep neural network-based NLP, in particular that of sequence label-
One of the two models proposed by Lample et al. (2016) is quite similar to ours, except that the authors have assumed a fixed set of characters for each language, whereas we turn to bytes as a universal medium of encoding character-level information. Also, Lample et al. (2016) have pre-trained their own word embeddings, which turned out to have a crucial impact on their results.

An interesting approach of applying cross-lingual multi-task learning to sequence labeling problem was introduced in the work of Yang et al. (2016). The authors have used hierarchical bi-directional GRU (on character and word levels) and optimized a modified version of a CRF objective function. Their model, in conjunction with the applied multi-task learning framework, has allowed the authors to obtain state-of-the-art results on multiple datasets.

7 Conclusion

We evaluate the performance of a single general-purpose neural sequence labeling model, assuming unavailability of domain expertise and scarcity of informational and computational resources. The work explores the frontiers of what may be achieved with a generic and resource-efficient sequence labeling framework applied to a diverse set of NLP tasks and languages.

For this purpose, we’ve applied the model (Section 2) and the end-to-end training methodology (Section 4) to eight benchmark datasets (Section 3), covering four languages and three tasks. The obtained results have convinced us that, with a model of sufficient learning capacity, it is indeed possible to achieve competitive sequence labeling performance without the burden of delving into specificities of each particular task and language, and summoning additional resources.

For the future work, we envision the integration of multi-task learning techniques (e.g., those used by Yang et al. (2016)) into the proposed approach. We suppose that this may improve the current results without compromising our general applicability and practicality assumptions.

References

Rodrigo Agerri and German Rigau. 2016. Robust multilingual named entity recognition with shallow semi-supervised features. *Artificial Intelligence*, 238:63–82.

Rami Al-Rfou, Bryan Perozzi, and Steven Skiena. 2013. Polyglot: Distributed word representations for multilingual nlp. *CoNLL-2013*, page 183.

Rie Kubota Ando and Tong Zhang. 2005. A framework for learning predictive structures from multiple tasks and unlabeled data. *Journal of Machine Learning Research*, 6(Nov):1817–1853.

Darina Benikova, Chris Biemann, Max Kisseleff, and Sebastian Pado. 2014. Germeval 2014 named entity recognition shared task: companion paper. *Organization*, 7:281.

Sabine Brants, Stefanie Dipper, Silvia Hansen, Wolfgang Lezius, and George Smith. 2002. The tiger treebank. In *Proceedings of the workshop on treebanks and linguistic theories*, volume 168.

Xavier Carreras, Lluís Marquez, and Lluís Padró. 2002. Named entity extraction using adaboost. In *proceedings of the 6th conference on Natural language learning-Volume 20*, pages 1–4. Association for Computational Linguistics.

Rich Caruana, Steve Lawrence, and C Lee Giles. 2001. Overfitting in neural nets: Backpropagation, conjugate gradient, and early stopping. In *Advances in neural information processing systems*, pages 402–408.

Jason PC Chiu and Eric Nichols. 2016. Named entity recognition with bidirectional lstm-cnns. *Transactions of the Association for Computational Linguistics*, 4:357–370.

Kyunghyun Cho, Bart van Merriënboer, Dzmitry Bahdanau, and Yoshua Bengio. 2014. On the properties of neural machine translation: Encoder–decoder approaches. *Syntax, Semantics and Structure in Statistical Translation*, page 103.

Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural language processing (almost) from scratch. *Journal of Machine Learning Research*, 12(Aug):2493–2537.

Greg Durrett and Dan Klein. 2014. A joint model for entity analysis: Coreference, typing, and linking. *Transactions of the Association for Computational Linguistics*, 2:477–490.

Jeffrey L Elman. 1990. Finding structure in time. *Cognitive science*, 14(2):179–211.

Alexander Fraser, Helmut Schmid, Richárd Farkas, Renjing Wang, and Hinrich Schütze. 2013. Knowledge sources for constituent parsing of german, a morphologically rich and less-configurational language. *Computational Linguistics*, 39(1):57–85.

Dan Gillick, Cliff Brunk, Oriol Vinyals, and Amarag Subramanya. 2016. Multilingual language processing from bytes. In *Proceedings of NAACL-HLT*, pages 1296–1306.
Alex Graves, Abdel-rahman Mohamed, and Geoffrey Hinton. 2013. Speech recognition with deep recurrent neural networks. In Acoustics, speech and signal processing (icassp), 2013 ieee international conference on, pages 6645–6649. IEE.

Alex Graves and Jürgen Schmidhuber. 2005. Frame-wise phoneme classification with bidirectional lstm and other neural network architectures. Neural Networks, 18(5-6):602–610.

C Hänig, S Bordag, and S Thomas. 2014. Modular classifier ensemble architecture for named entity recognition on low resource systems. In Proceedings of the KONVENS GermEval Shared Task on Named Entity Recognition, Hildesheim, Germany.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735–1780.

Eduard Hovy, Mitchell Marcus, Martha Palmer, Lance Ramshaw, and Ralph Weischedel. 2006. Ontonotes: the 90% solution. In Proceedings of the human language technology conference of the NAACL, Companion Volume: Short Papers, pages 57–60. Association for Computational Linguistics.

Zhiheng Huang, Wei Xu, and Kai Yu. 2015. Bidirectional lstm-crf models for sequence tagging. arXiv preprint arXiv:1508.01991.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Julian Kupiec. 1992. Robust part-of-speech tagging using a hidden markov model. Computer Speech & Language, 6(3):225–242.

Matthieu Labeau, Kevin Löser, and Alexandre Alauzen. 2015. Non-lexical neural architecture for fine-grained pos tagging. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 232–237.

John D Lafferty, Andrew McCallum, and Fernando CN Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In Proceedings of the Eighteenth International Conference on Machine Learning, pages 282–289. Morgan Kaufmann Publishers Inc.

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. 2016. Neural architectures for named entity recognition. In Proceedings of NAACL-HLT, pages 260–270.

Wang Ling, Chris Dyer, Alan W. Black, Isabel Trancoso, Ramon Fernandez, Silvio Amir, Luis Marujo, and Tiago Luís. 2015. Finding function in form: Compositional character models for open vocabulary word representation. In EMNLP.

Gang Luo, Xiaojiang Huang, Chin-Yew Lin, and Zaqing Nie. 2015. Joint entity recognition and disambiguation. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 879–888.

Xuezhe Ma and Eduard Hovy. 2016. End-to-end sequence labeling via bi-directional lstm-cnns-crf. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, pages 1064–1074.

Mitchell P Marcus, Mary Ann Marcinkiewicz, and Beatrice Santorini. 1993. Building a large annotated corpus of english: The penn treebank. Computational linguistics, 19(2):313–330.

Andrew McCallum, Dayne Freitag, and Fernando CN Pereira. 2000. Maximum entropy markov models for information extraction and segmentation. In Icml, volume 17, pages 591–598.

Tomáš Mikolov, Martin Karafiát, Lukáš Burget, Jan Černocký, and Sanjeev Khudanpur. 2010. Recurrent neural network based language model. In Eleventh Annual Conference of the International Speech Communication Association.

Thomas Müller, Helmut Schmid, and Hinrich Schütze. 2013. Efficient higher-order crfs for morphological tagging. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 322–332.

Thomas Müller and Hinrich Schütze. 2015. Robust morphological tagging with word representations. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 526–536.

Dat Quoc Nguyen, Dai Quoc Nguyen, Dang Duc Pham, and Son Bao Pham. 2016. A robust transformation-based learning approach using ripple down rules for part-of-speech tagging. AI Communications, 29(3):409–422.

Joel Nothman, Nicky Ringland, Will Radford, Tara Murphy, and James R Curran. 2013. Learning multilingual named entity recognition from wikipedia. Artificial Intelligence, 194:151–175.

Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. 2013. On the difficulty of training recurrent neural networks. In International Conference on Machine Learning, pages 1310–1318.

Alexandre Passos, Vineet Kumar, and Andrew McCallum. 2014. Lexicon infused phrase embeddings for named entity resolution. CoNLL-2014, page 78.

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pages 1532–1543.
Matthew Peters, Waleed Ammar, Chandra Bhagavatula, and Russell Power. 2017. Semi-supervised sequence tagging with bidirectional language models. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, pages 1756–1765.

Sameer Pradhan, Alessandro Moschitti, Nianwen Xue, Olga Uryupina, and Yuchen Zhang. 2012. Conll-2012 shared task: Modeling multilingual unrestricted coreference in ontonotes. In Joint Conference on EMNLP and CoNLL-Shared Task, pages 1–40. Association for Computational Linguistics.

Lawrence R Rabiner. 1989. A tutorial on hidden markov models and selected applications in speech recognition. Proceedings of the IEEE, 77(2):257–286.

Lev Ratinov and Dan Roth. 2009. Design challenges and misconceptions in named entity recognition. In Proceedings of the Thirteenth Conference on Computational Natural Language Learning, pages 147–155. Association for Computational Linguistics.

Nils Reimers, Judith Eckle-Kohler, Carsten Schnoer, Jungi Kim, and Iryna Gurevych. 2014. GermEval-2014: Nested named entity recognition with neural networks. In Proceedings of the KONVENS GermEval Shared Task on Named Entity Recognition, Hildeshaim, Germany.

Tony Rose, Mark Stevenson, and Miles Whitehead. 2002. The reuters corpus volume 1-from yesterday’s news to tomorrow’s language resources. In LREC, volume 2, pages 827–832. Las Palmas.

Cicero Santos and Victor Guimarães. 2015. Boosting named entity recognition with neural character embeddings. In Proceedings of the Fifth Named Entity Workshop, pages 25–33.

Cicero D Santos and Bianca Zadrozny. 2014. Learning character-level representations for part-of-speech tagging. In Proceedings of the 31st International Conference on Machine Learning (ICML-14), pages 1818–1826.

Peter Schüller. 2014. Mostner: Morphology-aware split-tag german nmr with factory. In Proceedings of the KONVENS GermEval Shared Task on Named Entity Recognition, Hildeshaim, Germany.

Hong Shen and Anoop Sarkar. 2005. Voting between multiple data representations for text chunking. In Conference of the Canadian Society for Computational Studies of Intelligence, pages 389–400. Springer.

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: A simple way to prevent neural networks from overfitting. The Journal of Machine Learning Research, 15(1):1929–1958.

Emma Strubell, Patrick Verga, David Belanger, and Andrew McCallum. 2017. Fast and accurate entity recognition with iterated dilated convolutions. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2670–2680.

Xu Sun. 2014. Structure regularization for structured prediction. In Advances in Neural Information Processing Systems, pages 2402–2410.

Xu Sun, Louis-Philippe Morency, Daisuke Okanohara, and Jun’ichi Tsujii. 2008. Modeling latent-dynamic in shallow parsing: a latent conditional model with improved inference. In Proceedings of the 22nd International Conference on Computational Linguistics-Volume 1, pages 841–848. Association for Computational Linguistics.

Erik F Tjong Kim Sang. 2002. Introduction to the conll-2000 shared task: Language-independent named entity recognition. In Proceedings of CoNLL-2002, pages 155–158. Taipei, Taiwan.

Erik F Tjong Kim Sang and Sabine Buchholz. 2000. Introduction to the conll-2000 shared task: Chunking. In Proceedings of the 2nd workshop on Learning language in logic and the 4th conference on Computational natural language learning-Volume 7, pages 127–132. Association for Computational Linguistics.

Erik F Tjong Kim Sang and Fien De Meulder. 2003. Introduction to the conll-2003 shared task: Language-independent named entity recognition. In Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003-Volume 4, pages 142–147. Association for Computational Linguistics.

Kristina Toutanova, Dan Klein, Christopher D Manning, and Yoram Singer. 2003. Feature-rich part-of-speech tagging with a cyclic dependency network. In Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology-Volume 1, pages 173–180. Association for Computational Linguistics.

Zhilin Yang, Ruslan Salakhutdinov, and William Cohen. 2016. Multi-task cross-lingual sequence tagging from scratch. arXiv preprint arXiv:1603.06270.

Wojciech Zaremba, Ilya Sutskever, and Oriol Vinyals. 2014. Recurrent neural network regularization. arXiv preprint arXiv:1409.2329.

Feifei Zhai, Saloni Potdar, Bing Xiang, and Bowen Zhou. 2017. Neural models for sequence chunking. In AAAI, pages 3365–3371.