Empower Sequence Labeling with Task-Aware Neural Language Model

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Abstract

Linguistic sequence labeling is a general modeling approach that encompasses a variety of problems, such as part-of-speech tagging and named entity recognition. Recent advances in neural networks (NNs) make it possible to build reliable models without handcrafted features. However, in many cases, it is hard to obtain sufficient annotations to train these models. In this study, we develop a novel neural framework to extract abundant knowledge hidden in raw texts to empower the sequence labeling task. Besides word-level knowledge contained in pre-trained word embeddings, character-aware neural language models are incorporated to extract character-level knowledge. Transfer learning techniques are further adopted to mediate different components and guide the language model towards the key knowledge. Compared to previous methods, these task-specific knowledge allows us to adopt a more concise model and conduct more efficient training. Different from most transfer learning methods, the proposed framework does not rely on any additional supervision. It extracts knowledge from self-contained order information of training sequences. Extensive experiments on benchmark datasets demonstrate the effectiveness of leveraging character-level knowledge and the efficiency of co-training. For example, on the CoNLL03 NER task, model training completes in about 6 hours on a single GPU, reaching F1 score of 91.71±0.10 without using any extra annotation.

Introduction

Linguistic sequence labeling is a general modeling approach, being applied to a variety of tasks including part-of-speech tagging, noun phrase chunking, and named entity recognition (NER) (Ma and Hovy 2016; Sha and Pereira 2003). These tasks play a vital role in natural language understanding and fulfill lots of downstream applications, such as relation extraction, syntactic parsing, and entity linking (Liu et al. 2017; Luo et al. 2015).

Label dependency is important to sequence labeling tasks. Hence, traditional methods employed machine learning models like Hidden Markov Models (HMMs) and Conditional Random Fields (CRFs), and have achieved relatively high performance. However, these methods have a heavy reliance on handcrafted features (e.g., whether a word is capitalized) and language-specific resources (e.g., gazetteers). Therefore, it could be difficult to apply them to new tasks or shift to new domains. To overcome this drawback, neural networks (NNs) have been proposed to automatically extract features during model learning. Nevertheless, considering the overwhelming number of parameters in NNs and the relatively small size of most sequence labeling corpus, annotations alone may not be sufficient to train complicated models. Therefore, guiding the learning process with extra information or knowledge becomes a wise choice. So, guiding the learning process with extra information or knowledge becomes a wise choice.

Accordingly, transfer learning and multi-task learning have been proposed. They have been shown to be effective in sharing knowledge across related tasks. Similarly, efforts have been paid to improve the sequence labeling task by co-training related tasks. For example, NER can be improved by leveraging entity linking or chunking (Luo et al. 2015; Peng and Dredze 2016). After all, the required additional supervision might be hard to get, or even nonexistent in low-resource languages or special domains.

Alternatively, knowledge can be extracted from abundant information contained in raw texts to enhance a variety of tasks. Word embedding techniques represent words in a continuous space (Mikolov et al. 2013; Pennington, Socher, and Manning 2014) and retain the semantic relations among words. Consequently, integrating these word embeddings with co-training or pre-training strategies could be beneficial to many tasks (Liu et al. 2017; Lample et al. 2016). Nonetheless, most embedding methods take a word as a basic unit, thus only obtaining word-level knowledge, while character awareness is also crucial and highly valued in most state-of-the-art NN models.

Only recently, character-level knowledge has been leveraged, but still in an embedding manner. Directly adopting pre-trained language models, character-level knowledge has been integrated as context embeddings. Such knowledge has been empirically verified to be helpful in numerous sequence labeling tasks (Peters et al. 2017). However, the knowledge extracted from pre-training is not task-specific. A large portion of it could be irrelevant to the target sequence labeling task, thus requiring a bigger model, external corpus, and longer training. For example, one of such language models was trained on 32 GPUs for more than half a month, which is unrealistic in many situations.

In this paper, we propose an effective sequence label-
ing framework, called LM-LSTM-CRF, which leverages both word-level and character-level knowledge in an efficient way. For character-level knowledge, we incorporate a neural language model with the sequence labeling task and conduct multi-task learning to guide the language model towards task-specific key knowledge. Besides the potential of training a better model, this strategy also poses a new challenge. Based on our experiments, when the tasks are discrepant, language models could be harmful to sequence labeling in a naïve co-training setting. For this reason, we employ highway networks (Srivastava, Greff, and Schmidhuber 2015) to transform the output of character-level layers into different semantic spaces, thus mediating and unifying these two tasks. For word-level knowledge, we choose to fine-tune pre-trained word embeddings instead of co-training or pre-training the whole word-level layers, because the majority of parameters in word-level layers come from the embedding layer and such co-training or pre-training cost lots of time and resources.

We conduct experiments on the CoNLL 2003 NER task, the CoNLL 2000 chunking task, as well as the WSJ portion of the Penn Treebank POS tagging task. LM-LSTM-CRF achieves a significant improvement over the state-of-the-art. Also, our co-training strategy allows us to capture more useful knowledge with a smaller network, thus yielding much better efficiency without loss of effectiveness.

**LM-LSTM-CRF Framework**

The neural architecture of our proposed framework, LM-LSTM-CRF, is visualized in Fig. 1. For a sentence with annotations $y = (y_1, \ldots, y_n)$, its word-level input is marked as $x = (x_1, x_2, \ldots, x_n)$, where $x_i$ is the $i$-th word; its character-level input is recorded as $c = (c_{0,x}, c_{1,1}, c_{1,2}, \ldots, c_{1,b}, c_{2,1}, \ldots, c_{n})$, where $c_{i,j}$ is the j-th character for word $w_i$ and $c_{i,-}$ is the space character after $w_i$. These notations are also summarized in Table 1.

![Figure 1: LM-LSTM-CRF Neural Architecture](image)

| $x$ | word-level input | $x_i$ | $i$-th word |
| $c$ | character-level input | $c_{i,j}$ | $j$-th char in $x_i$ |
| $c_{i,-}$ | space after $x_i$ | $c_{0,-}$ | space before $x_1$ |
| $y$ | label sequence | $y_i$ | label of $x_i$ |
| $f^r_i$ | output of forward character-level LSTM at $c_{i,-}$ |
| $f^f_i$ | output of forward to-LM highway unit |
| $r^f_i$ | output of backward character-level LSTM at $c_{i,-}$ |
| $r^r_i$ | output of backward to-LM highway unit |
| $r^v_i$ | output of backward to-SL highway unit |
| $v_i$ | input of word-level bi-LSTM at $x_i$ |
| $z_i$ | output of word-level bi-LSTM at $x_i$ |

Table 1: Notation Table.

Now, we first discuss the multi-task learning strategy and then introduce the architecture in a bottom-up fashion.

**Multi-task Learning Strategy**

As shown in Fig. 1, our language model and sequence labeling model share the same character-level layer, which fits the setting of multi-task learning and transfer learning. However, different from typical models of this setting, our two tasks are not strongly related. This discordance makes our problem more challenging. E.g., although a naïve co-training setting could be effective to directly use the output from character-level layers in several scenarios (Yang, Salakhutdinov, and Cohen 2017), for our two tasks, it would hurt the performance. This phenomenon would be further discussed in the experiment section.

To mediate these two tasks, we transform the output of the character-level layer into different semantic spaces and use them for different objectives. This strategy allows the character-level layer to focus on general feature extraction and lets the transform layers select task-specific features. Hence, our language model can provide related knowledge
to sequence labeling tasks, without forcing them to share the whole feature space.

Character-level Layer
Character-level neural language models are trained purely on unannotated sequence data but can capture the underlying style and structure. For example, it can mimic Shakespeare’s writing and generate sentences of similar styles, or even master the grammar of programming languages (e.g., XML, JavaScript, and C) and generate syntactically correct codes (Karpathy 2015). Accordingly, we adopted the character-level Long Short Term Memory (LSTM) networks to process character-level input. Aiming to capture lexical features instead of remembering words’ spelling, we adjust the prediction from the next character to the next word. As in Fig. 1, the character-level LSTM would only make predictions for the next word at word boundaries (i.e., space characters or $c_{i,j}$).

Furthermore, we coupled two LSTM units to capture information in both forward and backward directions. Although it seems similar to the bi-LSTM unit, the outputs of these two units are processed and aligned differently. Specifically, we record the output of forward LSTM at $c_{i,j}$, as $f_{i}$, and the output of backward LSTM at $c_{i,j}$ as $r_{j}$.

Highway Layer
In computer vision, Convolutional Neural Networks (CNN) has been proved to be an effective feature extractor, but its output needs to be further transformed by fully-connected layers to achieve the state-of-the-art (LeCun et al. 1998). Bearing this in mind, it becomes natural to stack additional layers upon the flat character-level LSTMs. More specifically, we employ highway units (Srivastava, Greff, and Schmidhuber 2015), which allow unimpeded information flowing across several layers. Typically, highway layers conduct nonlinear transformation as below.

$$m = H(n) = t \otimes g(W_H n + b_H) + (1 - t) \otimes n$$

Here, $\otimes$ is element-wise product, $g(\cdot)$ is a nonlinear transformation such as ReLU in our experiments, $t = \sigma(W_T n + b_T)$ is called transform gate and $(1 - t)$ is called carry gate.

In our final architecture, there are four highway units, named forward-to-LOM, forward-to-SL, backward-to-LM, and backward-to-SL. The first two transfer $f_{i}$ into $f^{L}_{i}$ and $f^{N}_{i}$, while the last two transfer $r_{j}$ into $r^{L}_{j}$ and $r^{N}_{j}$ respectively. $f^{L}_{i}$ and $r^{L}_{i}$ are used in the language model, while $f^{N}_{i}$ and $r^{N}_{j}$ are used in sequence labeling tasks.

Word-level Layer
Bi-LSTM is adopted as the word-level structure to capture information in both directions. As shown in Fig. 1, we concatenate $f^{N}_{i}$ and $r^{N}_{i-1}$ with word embeddings and then feed them into the bi-LSTM. Note that, in the backward character-level LSTM, $c_{i-1,j}$ is the space character before word $x_{j}$, therefore, $f^{N}_{i}$ would be aligned and concatenated with $r^{N}_{i-1}$ instead of $r^{N}_{i}$. For example, in Fig. 1, the word embeddings of ‘Pierre’ will be concatenated with the output of the forward-to-SL over ‘...Pierre_’ and the output of the backward-to-SL over ‘...erreiP_’.

As to word-level knowledge, we chose to fine-tune pre-trained word embeddings, instead of co-training the whole word-level layer. This is because most parameters of our word-level model come from word embeddings, and fine-tuning pre-trained word embeddings have been verified to be effective in leveraging word-level knowledge (Ma and Hovy 2016). Besides, current word embedding methods can easily scale to the large corpus, and pre-trained word embeddings are available in many languages and domains (Fernandez, Yu, and Downey 2017). However, this strategy cannot be applied to the character-level layer, since the embedding layer of character-level layer contains very few parameters. Based on these considerations, we employed different strategies to leverage word-level knowledge from character-level.

CRF for Sequence Labeling
The label dependencies are crucial in sequence labeling tasks. For example, in NER task with BIOES annotation, it is meaningless and illegal to annotate I-PER after B-ORG (i.e., mixing the person and the organization). Therefore, jointly decoding a chain of labels can ensure the resulting label sequence to be meaningful. Conditional random field (CRF) has been included in most state-of-the-art models to capture such information and further avoid generating illegal annotations. Consequently, we build a CRF layer upon the word-level LSTM.

For training instance $\langle x_{i}, c_{i}, y_{i} \rangle$, we suppose the output of word-level LSTM is $Z_{j} = \langle z_{1,i}, z_{2,i}, \ldots, z_{N,i} \rangle$. CRF models describe the probability of generating the whole label sequence with regard to $(x_{i}, c_{i})$ or $Z$. That is, $p(y|x_{i}, c_{i})$ or $p(y|Z)$, where $Y = \langle y_{1}, \ldots, y_{n} \rangle$ is a generic label sequence. Similar to (Ma and Hovy 2016), we define this probability as follows.

$$p(y|x_{i}, c_{i}) = \frac{\prod_{j=1}^{n} \phi(y_{j-1}, y_{j}, z_{j})}{\sum_{\gamma \in Y(Z)} \prod_{j=1}^{n} \phi(y_{j-1}, y_{j}, z_{j})}$$

(1)

Here, $Y(Z)$ is the set of all generic label sequences, $\phi(y_{j-1}, y_{j}, z_{j}) = \exp(W_{y_{j-1}, y_{j}} z_{i} + b_{y_{j-1}, y_{j}})$, where $W_{y_{j-1}, y_{j}}$ and $b_{y_{j-1}, y_{j}}$ are the weight and bias parameters corresponding to the label pair $(y_{j-1}, y_{j})$.

For training, we minimize the following negative log-likelihood.

$$J_{CRF} = -\sum_{i} \log p(y_{i}|Z_{i})$$

(2)

And for testing or decoding, we want to find the optimal sequence $y^{*}$ that maximizes the likelihood.

$$y^{*} = \arg \max_{y \in Y(Z)} p(y|Z)$$

(3)

Although the denominator of Eq. 1 is complicated, we can calculate Eqs. 2 and 3 efficiently by the Viterbi algorithm.

Neural Language Model
The language model is a family of models describing the generation of sequences. In a neural language model, the
generation probability of the sequence \( x = (x_1, ..., x_n) \) in the forward direction (i.e., from left to right) is defined as

\[
p_f(x_1, ..., x_n) = \prod_{i=1}^{N} p_f(x_i | x_1, ..., x_{i-1})
\]

where \( p_f(x_i | x_1, ..., x_{i-1}) \) is computed by NN.

In this paper, our neural language model makes predictions for words but takes the char sequence as input. Specifically, we would calculate \( p_f(x_i | c_{0}, ..., c_{i-1,1}, ..., c_{i-1}) \) instead of \( p_f(x_i | x_1, ..., x_{i-1}) \). This probability is

\[
p_f(x_i | c_{0}, ..., c_{i-1}) = \frac{\exp(w_{x_i}^T f_{N-1})}{\sum_{\bar{x}_j} \exp(w_{\bar{x}_j}^T f_{N-1})}
\]

where \( w_{x_i} \) is the weight vector for predicting word \( x_i \). In order to extract knowledge in both directions, we also adopted a reversed-order language model, which calculates the generation probability from right to left as

\[
p_r(x_1, ..., x_n) = \prod_{i=1}^{N} p_r(x_i | c_{i+1,}, ..., c_{n})
\]

where \( p_r(x_i | c_{i+1}, ..., c_{n}) = \frac{\exp(w_{x_i}^T r_{N})}{\sum_{\bar{x}_j} \exp(w_{\bar{x}_j}^T r_{N})} \)

The following negative log likelihood is applied as the objective function of our language model.

\[
J_{LM} = - \sum_i \log p_f(x_i) - \sum_i \log p_r(x_i) \tag{4}
\]

**Joint Model Learning**

By combining Eqs. 2 and 4, we can write the joint objective function.

\[
J = - \sum_i \left( p(y_i | Z_i) + \lambda \left( \log p_f(x_i) + \log p_r(x_i) \right) \right) \tag{5}
\]

where \( \lambda \) is a weight parameter. In our experiments, \( \lambda \) is always set to 1 without any tuning.

In order to train the neural network efficiently, stochastic optimization has been adopted. And at each iteration, we sample a batch of training instances and perform an update according to the summand function of Eq. 5: \( p(y_i | Z_i) + \lambda \left( \log p_f(x_i) + \log p_r(x_i) \right) \)

**Experiments**

Here, we evaluate LM-LSTM-CRF on three benchmark datasets: the CoNLL 2003 NER dataset (Tjong Kim Sang and De Meulder 2003), the CoNLL 2000 chunking dataset (Tjong Kim Sang and Buchholz 2000), and the Wall Street Journal portion of Penn Treebank dataset (WSJ) (Marcus, Marcinkiewicz, and Santorini 1993).

- **CoNLL03 NER** contains annotations for four entity types: PER, LOC, LOC, and MISC. It has been separated into training, development and test sets.
- **CoNLL00 chunking** defines eleven syntactic chunk types (e.g., NP, VP) in addition to Other. It only includes training and test sets. Following previous works (Peters et al. 2017), we sampled 1000 sentences from training set as a held-out development set.
- **WSJ** contains 25 sections and categorizes each word into 45 POS tags. We adopt the standard split and use sections 0-18 as training data, sections 19-21 as development data, and sections 22-24 as test data (Ma and Hovy 2016; Manning 2011).

The corpus statistics are summarized in Table 2. In the first two datasets, we adopt the official evaluation metric (micro-averaged F1), and use the BIOES scheme instead of IOB2 since meaningful improvement has been reported with this scheme (Ratinov and Roth 2009). For the WSJ dataset, we report the accuracy score. In all three datasets, rare words (i.e., frequency less than 5) are replaced by a special token (<UNK>).

**Network Training**

For a fair comparison, we didn’t spend much time on tuning parameters but borrow the parameter initialization, optimization method, and all related hyper-parameter values (except the state size of LSTM) from the previous work (Ma and Hovy 2016). For the hidden state size of LSTM, we expand it from 200 to 300, because introducing additional knowledge allows us to train a larger network. We will further discuss this change later. Table 3 summarizes some important hyper-parameters. Since the CoNLL00 is similar to the CoNLL03 NER dataset, we conduct experiments with the same parameters on both tasks.

**Initialization.** We use GloVe 100-dimension pre-trained word embeddings released by Stanford\(^1\) and randomly initialize the other parameters (Glorot and Bengio 2010; Joze-fowicz, Zaremba, and Sutskever 2015).

**Optimization.** We employ mini-batch stochastic gradient descent with momentum. The batch size is set to 10, the momentum is set to 0.9, and the learning rate is set to \( \eta_t = 0.1 \rho^{t/10} \), where \( \eta_0 \) is the initial learning rate and \( \rho = 0.5 \) is the decay ratio. Dropout is applied in our model, and its

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\(^1\)http://nlp.stanford.edu/projects/glove/
Network Structure. The hyper-parameters of character-level LSTM are set to the same value of word-level bi-LSTM. We fix the depth of highway layers as 1 to avoid an over-complicated model.

Note that some baseline methods (e.g., (Chiu and Nichols 2016; Peters et al. 2017)) incorporate the development set as a part of training. However, because we are using early stopping based on the evaluation on the development set, our model is trained purely on the training set.

Compared Methods We consider three classes of baseline sequence labeling methods in our experiments.

- **Sequence Labeling Only.** Without any additional supervision or extra resources, LSTM-CRF (Lample et al. 2016) and LSTM-CNN-CRF (Ma and Hovy 2016) are the state-of-art methods. For comparison, we apply these two models on three tasks, carefully tune the parameters, and report the statics of the best working parameter setting. We also list some top reported performance on each dataset from (Collobert et al. 2011; Luo et al. 2015; Chiu and Nichols 2016; Yang, Salakhutdinov, and Cohen 2017; Peters et al. 2017; Manning 2011; Søgaard and Goldberg 2016; Sun 2014) for reference.

- **Joint Model with Other Supervised Tasks.** There are several attempts (Luo et al. 2015; Yang, Salakhutdinov, and Cohen 2017) to enhance sequence labeling tasks by introducing additional annotations from other related tasks (e.g., enhance NER with entity linking labels).

- **Joint Model with Language Model:** Language models have been employed by some recent works to extract knowledge from raw text and thus enhancing sequence labeling task. TagLM (Peters et al. 2017) leverages pre-trained language models and shows the effectiveness with the large external corpus, but the large model scale and long training time make it hard to re-run this model. Another work (Rei 2017) also incorporates the sequence labeling task with the language model, but it’s not worth re-running it considering the low reported performance. For the ease of representation, we also index these models by number, as shown in Tables 4, 5 and 6.

Performance Comparison

In this section, we focus on the comparisons between LM-LSTM-CRF and previous state-of-the-arts, including both effectiveness and efficiency. As demonstrated in Tables 4, 5 and 6, LM-LSTM-CRF significantly outperforms all baselines without additional resources. Moreover, even for those baselines with extra resources, LM-LSTM-CRF beats most of them and is only slightly worse than TagLM (index 4) (Peters et al. 2017).

TagLM (index 4) is equipped with both a extra corpus (about 4000X larger than the CoNLL03 NER dataset) and a tremendous pre-trained forward language model \(4096-8192-1024^2\) (Jozefowicz et al. 2016).

\[4096-8192-1024\] is composed of character-level CNN with 4096 filters, 2 layers of stacked LSTMs with 8192 hidden units each and a 1024-dimension projection unit.

Due to the expensive resources and time required by \(4096-8192-1024\), even the authors of TagLM failed to train a backward language model of the same size, instead, chose a much smaller one \((LSTM-2048-512)\). It is worth noting that, when either extra corpus or \(4096-8192-1024\) is absent, LM-LSTM-CRF always outperforms all baselines without additional resources. Moreover, even the authors of TagLM failed to train a backward language model of the same size, instead, chose a much smaller one \((LSTM-2048-512)\). The performance gap is due to the difference between CPU and GPU implementations. Therefore, we conduct all of our experiments on GPU. Now let’s dive into more details in these tasks.

NER First of all, we have to point out that the results of index 1, 4, 8, 10 and 11 are not directly comparable with others since their final models are trained on both training and development set. As mentioned before, LM-LSTM-CRF outperforms all baselines except TagLM (index 4). For a thorough comparison, we also compare to its variants, TagLM (index 5), TagLM (index 10) and TagLM (index 11). Both index 10 and 11 are trained on the CoNLL03 dataset alone, while index 11 utilizes language model and index 10 doesn’t. Comparing \(F_1\) scores of these two settings, we can find that TagLM (index 11) even performs worse than TagLM (index 10), which reveals that directly applying co-training might hurt the se-

\[LSTM-2048-512\] is composed of a single-layer LSTM with 2048 hidden units and a 512-dimension projection unit.

| Extra Resource | Index & Model | \(F_1\) score |
|---------------|--------------|--------------|
| None          | 0) Collobert et al. 2011 | reported 89.59 |
|              | 1) Chiu et al. 2016⁺ | reported 91.62±0.33 |
|              | 2) Luo et al. 2015 | reported 91.20 |
|               | 3) Yang et al. 2017‡ | reported 91.26 |
| Gazettees     | 4) Peters et al. 2017† | reported 91.93±0.19 |
|              | 5) Peters et al. 2017† | reported 91.62±0.23 |
| AIDA dataset  | 6) Collobert et al. 2011 | reported 88.67 |
|              | 7) Luo et al. 2015 | reported 89.90 |
|              | 8) Chiu et al. 2016⁺ | reported 90.91±0.20 |
|              | 9) Yang et al. 2017‡ | reported 91.20 |
|              | 10) Peters et al. 2017† | reported 90.87±0.13 |
|              | 11) Peters et al. 2017† | reported 90.79±0.15 |
|              | 12) Rei 2017‡ | reported 86.26 |
|              | 13) Lample et al. 2016⁺ | mean 90.76±0.08 |
|              |              | max 91.14 |
|              |              | reported 90.94 |
|              | 14) Ma et al. 2016⁺ | mean 91.13±0.17 |
|              |              | max 91.67 |
|              |              | reported 91.21 |
|              | 15) LM-LSTM-CRF† | mean 91.71±0.10 |
|              |              | max 91.85 |

Table 4: \(F_1\) score on the CoNLL03 NER dataset. We mark models adopting pre-trained word embedding as †, and record models which leverage language models as ‡.
Table 5: Accuracy on the WSJ dataset. We mark models adopting pre-trained word embedding as †, and record models which leverage language models as ‡.

Table 6: F\textsubscript{1} score on the CoNLL00 chunking dataset. We mark models adopting pre-trained word embedding as †, and record models which leverage language models as ‡.

Table 7: Training time and performance of LSTM-CRF, LSTM-CNN-CRF and LM-LSTM-CRF on three datasets with a NVIDIA GeForce GTX 1080 GPU, and record their training time. For the purpose of comparison, we also record the training time of LSTM-CNN-CRF\textsuperscript{*} and LSTM-CRF\textsuperscript{‡} on the same machine.

In terms of efficiency, the language model component in LM-LSTM-CRF only introduces a small number of parameters in two highway units and a soft-max layer, which is negligible compared to the other parameters for the sequence label task. Empirically, based on the results summarized in Table 7, LM-LSTM-CRF costs the lowest training time but achieves the best performance on all three datasets. Considering the difference among the implementations of these models, we think they have roughly the same efficiency. In conclusion, the language model component here does not require lots of additional computation, but does help the sequence labeling perform better.

Besides, we list the required training time and resources of pre-training of model index 4 and 5 on the NER task in Table 8 (Jozefowicz et al. 2016). Comparing to these pre-trained language models on external corpus, our model has no such reliance on extensive corpus, and can achieve similar performance with much more concise model and efficient training. It verifies that our LM-LSTM-CRF model can effectively leverage the language model to extract task-specific knowledge to empower sequence labeling without loss of efficiency.

Analysis
To analyze the performance of LM-LSTM-CRF, we conduct additional experiments on the CoNLL03 NER dataset.

\textsuperscript{4}Code is available at https://github.com/glample/tagger
\textsuperscript{5}https://github.com/LiyuanLucasLiu/LM-LSTM-CRF
\textsuperscript{6}https://github.com/XuezheMax/LasagneNLP
\textsuperscript{7}https://github.com/pytorch/pytorch
NL. The first does not leverage language model without employing those knowledge, LM-LSTM-CRF mediates these two components, and the second directly adopts character-level pre-trained language model. However, as shown in Table 9, one can easily observe that the F1 score of LM-LSTM-CRF keeps increasing when the hidden state size grows, while LSTM-CNN-CRF has a peak at state size 200 and LSTM-CRF has a drop at state size 200. This is because that the language model in LM-LSTM-CRF brings the more knowledge that can consistently support a better parameter fit for larger neural networks.

Highway Layers & Co-training
To elucidate the effect of language model and highway units, we compare LM-LSTM-CRF with its two variants, LM-LSTM-CRF_NL and LM-LSTM-CRF_NH. The first does not leverage language model but keeps the character-layer, and optimizes \( J_{CRF} \) alone to conduct sequence labeling; the second directly leverages language model without employing those highway units. Although there is no highway layer in LM-LSTM-CRF_NH, one may expect it to outperform LM-LSTM-CRF_NL since it leverages the additional knowledge from the language model. However, as shown in Table 10, when hidden state size is 100 or 200, LM-LSTM-CRF_NH is even worse than LM-LSTM-CRF_NL. This observation also accords with previous comparison between TagLM (index 10) and TagLM (index 11) on the CoNLL03 NER dataset. We conjecture that it is because the NER task and the language model is not strongly related to each other. By adding highway layers for the knowledge transformation, LM-LSTM-CRF mediates these two components, and pushes the state-of-the-art to a new stage. In summary, our proposed co-training strategy is effective and introducing the highway layers is necessary.

### Related Work
There exist two threads of related work regarding the topics in this paper, which are sequence labeling and how to improve it with additional information.

#### Sequence Labeling
As one of the fundamental tasks in NLP, linguistic sequence labeling, including POS tagging, chunking, and NER, has been studied for years. Handcrafted features were widely used in traditional methods like CRFs, HMMs, and maximum-entropy classifiers (Lafferty, McCallum, and Pereira 2001; McCallum and Li 2003; Florian et al. 2003; Chieu and Ng 2002), but also make it hard to apply them to new tasks or domains. Recently, getting rid of handcrafted features, there are attempts to build end-to-end systems for sequence labeling tasks, such as BiLSTM-CNN (Chiu and Nichols 2016), LSTM-CRF (Lample et al. 2016), and the current state-of-the-art method in NER and POS tagging tasks, LSTM-CNN-CRF (Ma and Hovy 2016). These models all incorporate character-level structure, and report meaningful improvement over pure word-level model. Also, CRF layer has also been demonstrated to be effective in capturing the dependency among labels. Our model is based on the success of LSTM-CRF model and is further modified to better capture the char-level information in a language model manner.

#### Leveraging Additional Information
Integrating word-level and character-level knowledge has been proved to be helpful to sequence labeling tasks. For example, word embeddings (Mikolov et al. 2013; Pennington, Socher, and Manning 2014) can be utilized by co-training or pre-training strategies (Liu et al. 2017; Lample et al. 2016). However, none of these models utilizes the character-level knowledge. Although directly adopting character-level pre-trained language models could be helpful (Peters et al. 2017). Such pre-trained knowledge is not task-specific and requires a larger neural network, external corpus, and longer training. Our model leverages both word-level and character-level knowledge through a co-training strategy, which leads to a concise, effective, and efficient neural network. Besides, unlike other multi-task learning methods, our model has no reliance on any extra annotation (Peters et al. 2017) or any knowledge base (Shang et al. 2017). Instead, it extracts knowledge from the self-contained order information.

### Conclusion
As a conclusion, our proposed sequence labeling framework, LM-LSTM-CRF, effectively leverages the language model to extract character-level knowledge from the self-contained order information. Highway layers are incorporated to overcome the discordance issue in the naive co-training and allow the extracted knowledge to be helpful. The resulting architecture achieves the state-of-the-art on three benchmark datasets. Besides, benefited from the effectively captured task-specific knowledge, we can build a much more concise model, thus yielding much better efficiency without loss of effectiveness. In the future, we plan to...
further extract and incorporate knowledge from other “unsupervised” learning principles and empower more sequence labeling tasks.

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