A New Recurrent Neural CRF for Learning Non-linear Edge Features

Shuming Ma and Xu Sun

MOE Key Laboratory of Computational Linguistics, Peking University
School of Electronics Engineering and Computer Science, Peking University
{shumingma, xusun}@pku.edu.cn

Abstract

Conditional Random Field (CRF) and recurrent neural models have achieved success in structured prediction. More recently, there is a marriage of CRF and recurrent neural models, so that we can gain from both non-linear dense features and globally normalized CRF objective. These recurrent neural CRF models mainly focus on encode node features in CRF undirected graphs. However, edge features prove important to CRF in structured prediction. In this work, we introduce a new recurrent neural CRF model, which learns non-linear edge features, and thus makes non-linear features encoded completely. We compare our model with different neural models in well-known structured prediction tasks. Experiments show that our model outperforms state-of-the-art methods in NP chunking, shallow parsing, Chinese word segmentation and POS tagging.

Introduction

Conditional Random Field (CRF) is a widely used algorithm for structured prediction. It is an undirected graphical model trained to maximize a conditional probability. The undirected graph can be encoded with a set of features (node features and edge features). Usually, these features are sparse and well manual designed.

For minimizing the effort in feature engineering, neural network models are used to automatically extract features (Chen and Manning 2014; Collobert et al. 2011). These models learn dense features, which have better representation of both syntax and semantic information. Because of the success of CRF and neural networks, many models take advantage of both of them. Collobert et al. (2011) used CRF objective to compute sentence-level probability of convolutional neural networks. Durrett and Klein (2015) introduced a neural CRF model to join sparse features and dense features for parsing. Andor et al. (2016) proposed a transition-based neural model with a globally normalized CRF objective, and they use feedforward neural networks to learn neural features. The marriage of feedforward neural network and CRF is natural because feedforward neural network scores local unstructured decisions while CRF makes global structured decisions. It is harder to combine recurrent neural model with CRF because both of them use structural inference. Huang et al. (2015) provided a solution to combine recurrent structure with CRF structure, and gained good performance in sequence labelling. However, their model only encode node features while both node features and edge features are important to CRF.

In order to completely encode non-linear features for CRF, we propose a new recurrent neural CRF model. Our model uses LSTM to learn edge information of input words, and takes LSTM output as CRF energy function. We do not change the internal structure of both LSTM and CRF, so it easily decodes via standard recurrent propagation and CRF dynamic programming inference, without any extra effort. In our model, we use edge embedding to capture connections inside input structure. LSTM is used to learn hidden edge features from edge embedding. After that, CRF globally normalizes the scores of LSTM output. Andor et al. (2016) proved that globally normalized CRF objective solved label bias problem for neural models.

The contribution of our paper can be listed as follow:

• We propose a neural model which can learn non-linear edge features. We find that learning non-linear edge features is even more important than node features due to the ability of modelling non-linear structure dependence.
• We experiment our model in several well-known sequence labelling tasks, including shallow parsing, NP chunking, POS tagging and Chinese word segmentation. It shows that our model can outperform state-of-the-art methods in these tasks.

Background

In structured prediction, our goal is to predict structure \( y \) given the observations \( x \). The \( i^{th} \) label in structure \( y \) is denoted as \( y_i \), and the \( i^{th} \) observation is \( x_i \). CRF (Lafferty, McCallum, and Pereira 2001) is a popular and effective algorithm for structured prediction. It has a log-linear conditional probability with respect to energy functions over local cliques and transition cliques:

\[
\log(p(y|x)) \propto \sum_i E_{local}(y_i, x, i) + \sum_i E_{trans}(y_{i-1}, y_i, x, i)
\]
where \( E_{\text{local}}(y_i, x, i) \) is energy function over local clique at position \( i \), and \( E_{\text{trans}}(y_{i-1}, y_i, x, i) \) is energy function over transition clique.

Energy functions are used to learn features. Since conventional CRF is log-linear model, both local clique and transition clique have linear energy functions:

\[
E_{\text{local}}(y_i, x, i) = \mu_i g_i(y_i, x, i) \quad (2)
\]

\[
E_{\text{trans}}(y_{i-1}, y_i, x, i) = \lambda_k f_k(y_{i-1}, y_i, x, i) \quad (3)
\]

where \( f_k \) is the indicator function of the \( k^{th} \) feature for the transition clique \( (y_{i-1}, y_i, x) \), \( g_i \) is the indicator function of \( i^{th} \) feature for the local clique \( (y_i, x) \), and \( \lambda_k \) and \( \mu_i \) are parameters of CRF.

Therefore, conventional CRF can only learn linear features. To learn high-order features, LSTM is combined with CRF model (Huang, Xu, and Yu 2015). At each time step, LSTM recurrently inputs a word and outputs scores of each predicted labels. The output function of LSTM can be used as energy function over local cliques:

\[
E_{\text{local}}(y_i, x, i) = \sum_i s_i[y_i] \quad (4)
\]

\[
s_i = W^{(s)} h_i \quad (5)
\]

where \( h_i \) is the hidden state of LSTM at the \( i^{th} \) time step, \( s_i[y_i] \) is the \( y_i^{th} \) element of vector \( s_i \), and \( A[k, l] \) is a transition score for jumping from \( j^{th} \) tag to \( k^{th} \) tag.

As for transition cliques, energy function is a transition matrix of variables \( A_{i,j} \) for jumping from \( i^{th} \) tag to \( j^{th} \) tag:

\[
E_{\text{trans}}(y_{i-1}, y_i, x, i) = A_{i,j} \quad (6)
\]

so energy function over transition cliques is linear as conventional CRF. Therefore, LSTM-CRF learns non-linear node features (over local cliques) and linear edge features (over transition cliques).

For further contain more context information, LSTM layer can be replaced with bidirectional LSTM (BiLSTM) layer. BiLSTM contains both forward information and backward information, so that BiLSTM-CRF performs better than LSTM-CRF.

**Proposal**

Current LSTM-CRF only learns linear edge features in that it has linear energy function over transition cliques. Do and Artieres (2010) show that non-linear energy function performs better in extracting features for structured prediction. For a non-linear energy function, we propose a new recurrent neural CRF, which uses LSTM as energy function over transition cliques. Therefore, our model is able to learn non-linear edge features.

**Edge Embedding**

For learning non-linear edge features, we use edge embedding to provide raw edge information. In natural language processing, input structure is usually a sequence of words, so edges of input structure is connections of neighboring words. We have three methods to produce edge embedding from input structure.

**Bigram**: Bigram embedding is an intuition way to contain neighboring words features. We can build a bigram dictionary and assign a vector to each key. It proves to be efficient in several model (Pei, Ge, and Chang 2014; Chen et al. 2015), but it may suffer from sparsity and low training speed.

**Concatenation**: Concatenation is a useful way to join two words' information. It is simple and widely used in previous work (Collobert et al. 2011; Huang, Xu, and Yu 2015).

**Feedforward layer**: Feedforward layer is another method to learn information from input words. It inputs two word embedding and outputs edge embedding after a single neural network layer.

**Layers**

Figure 1 shows our proposed Recurrent Neural CRF model. Our model contains three layers: input layer, LSTM layer and CRF layer.

**Input Layer**: Input layer is used to input words and provide edge embedding for LSTM layer. Edge embedding is from the concatenation of neighboring word vectors, and it provides raw primary edge features.

![Diagram](image-url)
**Non-linear edge features**

**LSTM-CRF**

This work

For learning non-linear features, we replace the linear function, allowing computing gradients via dynamic programming. In our model, objective function is similar to CRF objective function (Lafferty, McCallum, and Pereira 2001). The regularized objective function of recurrent neural CRF can be described as:

$$L(\theta) = \sum_{j=1}^{m} R_j(\theta) + \frac{\lambda}{2} \| \theta \|^2$$  

(13)

where $m$ is the number of samples in the corpus. We denote the unnormalized score of a sample for Edge-Node Recurrent Neural CRF as:

$$F(x_j, y_j, \theta) = \sum_{i} t_i[y_{i-1}, y_i] + \sum_{i} s_i[y_i]$$  

(14)

And this score for Edge-based model is:

$$F(x_j, y_j, \theta) = \sum_{i} t_i[y_{i-1}, y_i] + \sum_{i} q[y_i]$$  

(15)

Then $R_j(\theta)$ in Equation 13 can be written as:

$$R_j(\theta) = \log \sum_{y'} \exp(F(x_j, y', \theta)) - F(x_j, y_j, \theta)$$  

(16)
Large Margin Criteria: Large margin criteria is first introduced by Taskar et al. (2005). In large margin criteria, the margin between the scores of correct tag sequence and incorrect sequence will be larger than a given large margin:

$$F(x_j, y_j, \theta) \geq F(x_j, y'_j, \theta) + \Delta(y_j, y')$$ (17)

where $\Delta(y_j, y'_j)$ is the number of incorrect tags in $y'_j$.

So the $R_j(\theta)$ in objective function is:

$$R_j(\theta) = \max_{y'_j} F(x_j, y'_j, \theta) - F(x_j, y_j, \theta) + \Delta(y_j, y'_j)$$ (18)

Optimization

To minimize the objective function, we use AdaGrad (Duchi, Hazan, and Singer 2011), which is a widely used algorithm recently. The parameter $\theta$ for the $t^{th}$ update can be calculated as:

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\sum_{t=1}^{T} g_{t,i}^2}} g_{t,i}$$ (19)

where $\alpha$ is the initial learning rate, and $g_{t,i}$ is the gradient of parameter $\theta$ for the $t^{th}$ update.

Related Work

Recently, neural networks models have been widely used in natural language processing (Bengio et al. 2003; Mikolov et al. 2010; Socher et al. 2013; Chen et al. 2015; Sun 2016). Among various neural models, recurrent neural networks (Elman 1990) proves to perform well in sequence labelling tasks. LSTM (Hochreiter and Schmidhuber 1997; Graves and Schmidhuber 2005) improves the performance of RNN by solving the vanishing and exploding gradient problem. Later, bidirectional recurrent model (Graves, Mohamed, and Hinton 2013) is proposed to capture the backward information.

CRF model (Lafferty, McCallum, and Pereira 2001) has achieved much success in natural language processing. Many models try to combine CRF with neural networks for more structure dependence. Peng et al. (2009) introduces a conditional neural fields model. Collobert et al. (2011) first implements convolutional neural networks with the CRF objective. Zheng et al. (2015) integrates CRF with RNN. Durrett and Klein (2015) uses feed forward neural networks with CRF for parsing. Huang et al. (2015) use recurrent neural networks to learn non-linear node features. They show that BiLSTM-CRF is more robust than neural models without CRF. Do and Artieres (2010) suggest feedforward neural networks to learn neural features. Zhou et al. (2015) proposes a transition based neural model with CRF for parsing. Finally, Andor et al. (2016) proves that a globally normalized CRF objective helps deal with label bias problem in neural models.

Compared with these neural CRF models, our recurrent neural CRF has a recurrent structure with the ability to learn non-linear edge features. Recurrent structure helps capture long distant information, and non-linear edge features provide more non-linear structure dependence. Table 2 shows the correlation between our proposed recurrent neural CRF model and other existing neural CRF models.

Experiments

We perform some experiments to analyze our proposed models. We choose well-known sequence labelling tasks, including NP chunking, shallow parsing, POS tagging and Chinese word segmentation as our benchmark so that our experiment results are comparable. We compare our model with other popular neural models, and analyze the effect of non-linear edge features.

Tasks

We introduce our benchmark tasks as follows:

NP Chunking: NP Chunking is short for Noun Phrase Chunking, that the non-recursive cores of noun phrases called based NPs are identified. Our datasets are from CoNLL-2000 shallow-parsing shared task, which consists of 8936 sentences in training set and 2012 sentences in test set. We further split the training set and extract 90% sentences as development set. Following previous work, we label the sentences with BIO2 format, including 3 tags (B-NP, I-NP, O). Our evaluation metric is F-score.

Shallow Parsing: Shallow parsing is a task similar to NP Chunking, but it needs to identify all chunk types (VP, PP, DT...). The dataset is also from CoNLL-2000, and it contains 23 tags. We use F-score as the evaluation metric.

POS tagging: POS tagging is short for Part-of-Speech Tagging, that each word is annotated with a particular part-of-speech. We use the standard benchmark dataset from the Penn Treebank. We use Sections 0-18 of the treebank as the training set, Sections 19-21 as the development set, and Sections 22-24 as the test set. We use tag accuracy as evaluation metric.

Chinese word segmentation for social media text: Word segmentation is a fundamental task for Chinese language processing (Sun, Wang, and Li 2012; Xu and Sun 2016). Although current models perform well in formal text, many of them do badly in informal text like social media text. Our corpus is from NLPCC2016 shared task. Since we have no access to test set, we split training set and extract 10% samples as test set. We use F-score as our evaluation metric.

Embeddings

Embeddings are distributed vectors to represent the semantic of words (Bengio et al. 2003; Mikolov et al. 2013). It proves that embeddings can influence the performance of neural models. In our models, we use random initialized word embeddings as well as Senna embeddings (Collobert et al. 2011). Our experiments show that Senna Embeddings can slightly improve the performance of our models. We also incorporate the feature embeddings as suggested by previous work (Collobert et al. 2011). The features include a window of last 2 words and next 2 words, as well as the word suffixes up to 2 characters. Besides, we make use of part-of-speech tags in NP chunking and shallow parsing. To alleviate heavy feature engineering, we do not use other features like bigram or trigram, though they may increase the accuracy as shown in (Pei, Ge, and Chang 2014) and (Chen et al. 2015). All these feature embeddings are random initialized.
Figure 2: Performance of our Edge-based-2 model and existing recurrent neural models in test sets. It shows that our model outperforms the baseline neural models in these tasks.

We also try three methods to learn edge embedding, including concatenate current words embeddings with feature embeddings as our edge embedding in our model.

**Settings**

We tune our hyper-parameters on the development sets. Our model is not sensitive to the dimension of hidden states when it is large enough. For the balance of accuracy and time cost, we set this number to 300 for NP chunking and shallow parsing, and the number is 200 for POS tagging and Chinese word segmentation. The dimension of input embeddings is set to be 100. The initial learning rate of AdaGrad algorithm is 0.1, and the regularization parameter is $10^{-6}$. The dropout method proves to avoid overfitting in neural models (Srivastava et al. 2014), but we find it has limited impact in our models. Besides, we select probabilistic criteria to train our model for its steady convergence and robust performance.

**Baselines**

We choose current popular neural models as our baselines, including RNN, LSTM, BiLSTM and BiLSTM-CRF. RNN and LSTM are basic recurrent neural models. For further learn bidirectional context information, we also implement Bi-LSTM for our tasks. We compare our model with these model to show the gain from combining neural model with CRF objective. Finally, BiLSTM-CRF is our strong baseline. We compare our model with BiLSTM-CRF to show that learning non-linear edge features is more important than single non-linear node features.

**Results**

We analyze the performance of our models in the above benchmark tasks. Our baselines include popular neural models. We train each model for 40 passes through the training sets. The performance curves of these models in test sets are provided as showed in Figure 2. It shows that our Edge-based model outperforms the baseline neural models, including RNN, LSTM, BiLSTM and BiLSTM-CRF.

According to Table 3, our models significantly outperform recurrent models without edge information in three tasks. It concludes that globally normalized objective can bring better performance in that it can model more structure dependence. Besides, our models also have higher accuracy than models with linear edge features, which shows that modelling non-linear edge features is very important for neural models. It seems that Edge-based-2 achieves better result than Edge-based-1 in NP chunking and shallow parsing, so combining non-linear edge features with node features is helpful in these two tasks.

We also compare our models with some existing systems as shown in Table 4.

**NP Chunking**: In NP Chunking, a popular algorithm is second-order CRF (Sha and Pereira 2003), which can achieve a score of 94.30%. McDonald et al. (2005) implemented a multilabel learning algorithm, with a score of
We propose a new recurrent neural CRF model for learning non-linear edge features. Our model is capable to completely encoding non-linear features for CRF. Experiments show that our model outperforms state-of-the-art methods in several structured prediction tasks, including NP chunking, shallow parsing, Chinese word segmentation and POS tagging.
Acknowledgements
This work was supported in part by National Natural Science Foundation of China (No. 61300063). Xu Sun is the corresponding author of this paper.

References
Ando, R. K., and Zhang, T. 2005. A high-performance semi-supervised learning method for text chunking. In ACL 2005.
Andor, D.; Alberti, C.; Weiss, D.; Severyn, A.; Presta, A.; Ganchev, K.; Petrov, S.; and Collins, M. 2016. Globally normalized transition-based neural networks. arXiv preprint arXiv:1603.06042.
Bengio, Y.; Ducharme, R.; Vincent, P.; and Janvin, C. 2003. A neural probabilistic language model. Journal of Machine Learning Research 3:1137–1155.
Chen, D., and Manning, C. D. 2014. A fast and accurate dependency parser using neural networks. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), 740–750.
Chen, X.; Qiu, X.; Zhu, C.; Liu, P.; and Huang, X. 2015. Long short-term memory neural networks for chinese word segmentation. In EMNLP 2015, 1197–1206.
Collobert, R.; Weston, J.; Bottou, L.; Karlen, M.; Kavukcuoglu, K.; and Kuksa, P. P. 2011. Natural language processing (almost) from scratch. Journal of Machine Learning Research 12:2493–2537.
Do, T. M. T., and Arti`eres, T. 2010. Neural conditional random fields. In Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics, AISTATS 2010, 177–184.
Duchi, J. C.; Hazan, E.; and Singer, Y. 2011. Adaptive subgradient methods for online learning and stochastic optimization. Journal of Machine Learning Research 12:2121–2159.
Durrett, G., and Klein, D. 2015. Neural CRF parsing. In ACL 2015, 302–312.
Elman, J. L. 1990. Finding structure in time. Cognitive Science 14(2):179–211.
Graves, A., and Schmidhuber, J. 2005. Framewise phoneme classification with bidirectional LSTM and other neural network architectures. Neural Networks 18(5-6):602–610.
Graves, A.; Mohamed, A.; and Hinton, G. E. 2013. Speech recognition with deep recurrent neural networks. In ICASSP 2013, 6645–6649.
Hochreiter, S., and Schmidhuber, J. 1997. Long short-term memory. Neural Computation 9(8):1735–1780.
Huang, Z.; Xu, W.; and Yu, K. 2015. Bidirectional LSTM-CRF models for sequence tagging. arXiv preprint arXiv:1508.01991.
Lafferty, J. D.; McCallum, A.; and Pereira, F. C. N. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In Proceedings of the Eighteenth International Conference on Machine Learning (ICML 2001), 282–289.
McDonald, R. T.; Crammer, K.; and Pereira, F. 2005. Flexible text segmentation with structured multilabel classification. In HLT/EMNLP 2005.
Mikolov, T.; Karafiát, M.; Burget, L.; Černocký, J.; and Khudanpur, S. 2010. Recurrent neural network based language model. In INTERSPEECH 2010, 1045–1048.
Mikolov, T.; Sutskever, I.; Chen, K.; Corrado, G. S.; and Dean, J. 2013. Distributed representations of words and phrases and their compositionality. In Advances in Neural Information Processing Systems 26: 27th Annual Conference on Neural Information Processing Systems 2013, 3111–3119.
Pei, W.; Ge, T.; and Chang, B. 2014. Max-margin tensor neural network for chinese word segmentation. In ACL 2014, 293–303.
Peng, J.; Bo, L.; and Xu, J. 2009. Conditional neural fields. In Advances in Neural Information Processing Systems 22: 23rd Annual Conference on Neural Information Processing Systems 2009, 1419–1427.
Sha, F., and Pereira, F. C. N. 2003. Shallow parsing with conditional random fields. In HLT-NAACL 2003.
Shen, H., and Sarkar, A. 2005. Voting between multiple data representations for text chunking. In Advances in Artificial Intelligence, 18th Conference of the Canadian Society for Computational Studies of Intelligence, 389–400.
Shen, L.; Satta, G.; and Joshi, A. K. 2007. Guided learning for bidirectional sequence classification. In ACL 2007.
Socher, R.; Bauer, J.; Manning, C. D.; and Ng, A. Y. 2013. Parsing with compositional vector grammars. In ACL 2013, 455–465.
Srivastava, N.; Hinton, G. E.; Krizhevsky, A.; Sutskever, I.; and Salakhutdinov, R. 2014. Dropout: a simple way to prevent neural networks from overfitting. Journal of Machine Learning Research 15(1):1929–1958.
Sun, X.; Morency, L.; Okanohara, D.; Tsuruoka, Y.; and Tsujii, J. 2008. Modeling latent-dynamic in shallow parsing: A latent conditional model with improved inference. In COLING 2008, 841–848.
Sun, X.; Wang, H.; and Li, W. 2012. Fast online training with frequency-adaptive learning rates for chinese word segmentation and new word detection. In ACL 2012, 253–262.
Sun, X. 2014. Structure regularization for structured prediction. In Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, 2402–2410.
Sun, X. 2016. Asynchronous parallel learning for neural networks and structured models with dense features. In COLING 2016.
Taskar, B.; Chatalbashev, V.; Koller, D.; and Guestrin, C. 2005. Learning structured prediction models: a large margin approach. In (ICML 2005), 896–903.
Xu, J., and Sun, X. 2016. Dependency-based gated recursive neural network for chinese word segmentation. In ACL 2016.
Zhang, T.; Damerau, F.; and Johnson, D. 2002. Text chunking based on a generalization of winnow. *Journal of Machine Learning Research* 2:615–637.

Zheng, S.; Jayasumana, S.; Romera-Paredes, B.; Vineet, V.; Su, Z.; Du, D.; Huang, C.; and Torr, P. H. S. 2015. Conditional random fields as recurrent neural networks. In *2015 IEEE International Conference on Computer Vision, ICCV 2015*, 1529–1537.

Zhou, H.; Zhang, Y.; Huang, S.; and Chen, J. 2015. A neural probabilistic structured-prediction model for transition-based dependency parsing. In *ACL 2015*, 1213–1222.