End-to-end Recurrent Neural Network Models for Vietnamese Named Entity Recognition: Word-level vs. Character-level

Thai-Hoang Pham¹ and Phuong Le-Hong²

¹ R&D Department, Alt Inc, Hanoi, Vietnam phamthaihoang.hn@gmail.com,
² College of Science
Vietname National University in Hanoi, Vietnam phuonglh@vnu.edu.vn

Abstract. This paper demonstrates end-to-end neural network architectures for Vietnamese named entity recognition. Our best model is a combination of bidirectional Long Short-Term Memory (Bi-LSTM), Convolutional Neural Network (CNN), Conditional Random Field (CRF), using pre-trained word embeddings as input, which achieves an F_1 score of 88.59% on a standard test set. Our system is able to achieve a comparable performance to the first-rank system of the VLSP campaign without using any syntactic or hand-crafted features. We also give an extensive empirical study on using common deep learning models for Vietnamese NER, at both word and character level.

Keywords: Vietnamese, named entity recognition, end-to-end, Long Short-Term Memory, Conditional Random Field, Convolutional Neural Network

1 Introduction

Named entity recognition (NER) is a fundamental task in natural language processing and information extraction. It involves identifying noun phrases and classifying each of them into a predefined class. In 1995, the 6th Message Understanding Conference (MUC)³ started evaluating NER systems for English, and in subsequent shared tasks of CoNLL 2002⁴ and CoNLL 2003⁵ conferences, language independent NER systems were evaluated. In these evaluation tasks, four named entity types were considered, including names of persons, organizations, locations, and names of miscellaneous entities that do not belong to these three types.

More recently, the Vietnamese Language and Speech Processing (VLSP)⁶ community has organized an evaluation campaign to systematically compare

³ http://cs.nyu.edu/faculty/grishman/muc6.html

⁴ http://www.cnts.ua.ac.be/conll2002/ner/

⁵ http://www.cnts.ua.ac.be/conll2003/ner/

⁶ http://vlsp.org.vn/

NER systems for the Vietnamese language. Similar to the CoNLL 2003 share task, four named entity types are evaluated: persons (PER), organizations (ORG), locations (LOC), and miscellaneous entities (MISC). The data are collected from electronic newspapers published on the web.

In this paper, we present a state-of-the-art NER system for the Vietnamese language without using any hand-crafted features. Our system is competitive with the first-rank system of the VLSP campaign that used many syntactic and hand-crafted features. In summary, the overall F_1 score of our system is 88.59% on the standard test set provided by the organizing committee of the evaluation campaign⁷. The contributions of this work include:

- We propose a truly end-to-end deep learning model which gives the state-of-the-art performance on a standard NER data set for Vietnamese. Our best model is a combination of Bi-LSTM, CNN, and CRF models, which achieves an F₁ score of 88.59%.
- We give an extensive empirical study on using common deep learning models for Vietnamese NER, at both word and character level. These models are also comparable to conventional sequence labeling models, including Maximum Entropy Markov Models (MEMMs) and CRFs.
- We make our NER system open source for research purpose, which is believed to be a good contribution to the future development of Vietnamese NER in particular and Vietnamese language processing research in general.

The remainder of this paper is structured as follows. Section 2 summarizes related work on NER. Section 3 describes end-to-end models used in our system. Section 4 gives experimental results and discussions. Finally, Section 5 concludes the paper.

2 Related Work

Within the large body of research on NER which have been published in the last two decades, we identify two main approaches. The first approach is characterized by the use of well-established sequence labeling models such as conditional random field (CRF), hidden markov model, support vector machine, maximum entropy and so on. The performance of these models is heavily dependent on hand-crafted features. In particular, most of the participants at CoNLL-2003 shared task attempted to use information other than the available training data such as gazetteers and unannotated data. The best system at CoNLL-2003 shared task is the work of [5] which achieved an F_1 score of 88.76%. After that, [17] surpassed them by using phrase features extracted from an external database. Moreover, training NER models jointly with related tasks helps improve their performance. For instance, [4] trained a CRF model for joint-learning three tasks, including coreference resolution, entity linking, and NER,

 $^{^7}$ The first-rank system of the VLSP 2016 NER evaluation campaign has F_1 =88.78% on the test set.

and achieved the state-of-the-art result on OntoNotes dataset. With a similar approach, [18] gained the best performance on CoNLL-2003 shared task dataset.

With a recent resurgence of the deep learning approach, several neural architectures have been proposed for NER task. These methods have a long story, but they have been focused only recently by the advance of computational power and high-quality word embeddings. The first neural network model is the work of [23] that used a feed-forward neural network with one hidden layer. This model achieved the state-of-the-art result on the MUC6 dataset. After that, [8] used a long short-term memory network for this problem. Recently, [3] used a convolution neural network over a sequence of word embeddings with a conditional random field on the top. This model achieved near state-of-the-art results on some sequence labeling tasks such as POS tagging, chunking, and NER. From 2015 until now, the long short-term memory model has been the best approach for many sequence labeling tasks. [10] used bidirectional LSTM with CRF layer for joint decoding. Instead of using hand-crafted feature as [10], [2] proposed a hybrid model that combined bidirectional LSTM with convolutional neural networks (CNN) to learn both character-level and word-level representations. Unlike [2], [13] used bidirectional LSTM to model both character and wordlevel information. The work of [19] proposed a truly end-to-end model that used only word embeddings for detecting entities. This model is the combination of CNN, bidirectional LSTM, and CRF models. Approaching this problem at the character-level sequence, the LSTM-CRF model of [11] achieved the nearly state-of-the-art results in seven languages.

3 Methodology

3.1 Long Short-Term Memory Networks

Recurrent Neural Network The recurrent neural network (RNN) is a class of artificial neural network designed for sequence labeling task. It takes input as a sequence of vector and returns another sequence. The simple architecture of RNN has an input layer \mathbf{x} , hidden layer \mathbf{h} and output layer \mathbf{y} . At each time step t, the values of each layer are computed as follows:

$$\mathbf{h}_t = f(\mathbf{U}\mathbf{x}_t + \mathbf{W}\mathbf{h}_{t-1})$$

$$\mathbf{y}_t = g(\mathbf{V}\mathbf{h}_t)$$

where \mathbf{U} , \mathbf{W} , and \mathbf{V} are the connection weight matrices in RNN, and f(z) and g(z) are sigmoid and softmax activation functions.

Long Short-Term Memory Long short-term memory (LSTM) [9] is a variant of RNN which is designed to deal with these gradient vanishing and exploding problems [1,22] when learning with long-range sequences. LSTM networks are the same as RNN, except that the hidden layer updates are replaced by memory cells. Basically, a memory cell unit is composed of three multiplicative gates that

control the proportions of information to forget and to pass on to the next time step. As a result, it is better for exploiting long-range dependency data. The memory cell is computed as follows:

$$\begin{aligned} &\mathbf{i}_t = \sigma(\mathbf{W}_i \mathbf{h}_{t-1} + \mathbf{U}_i \mathbf{x}_t + \mathbf{b}_i) \\ &\mathbf{f}_t = \sigma(\mathbf{W}_f \mathbf{h}_{t-1} + \mathbf{U}_f \mathbf{x}_t + \mathbf{b}_f) \\ &\mathbf{c}_t = \mathbf{f}_t \odot c_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_c \mathbf{h}_{t-1} + \mathbf{U}_c \mathbf{x}_t + \mathbf{b}_c) \\ &\mathbf{o}_t = \sigma(\mathbf{W}_o \mathbf{h}_{t-1} + \mathbf{U}_o \mathbf{x}_t + \mathbf{b}_o) \\ &\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \end{aligned}$$

where σ is the element-wise sigmoid function and \odot is the element-wise product, **i**, **f**, **o** and **c** are the input gate, forget gate, output gate and cell vector respectively. $\mathbf{U}_i, \mathbf{U}_f, \mathbf{U}_c, \mathbf{U}_o$ are connection weight matrices between input **x** and gates, and $\mathbf{U}_i, \mathbf{U}_f, \mathbf{U}_c, \mathbf{U}_o$ are connection weight matrices between gates and hidden state **h**. $\mathbf{b}_i, \mathbf{b}_f, \mathbf{b}_c, \mathbf{b}_o$ are the bias vectors.

Bidirectional Long Short-Term Memory The original LSTM uses only previous contexts for prediction. For many sequence labeling tasks, it is advisable when taking the contexts from two directions. Thus, we utilize the bidirectional LSTM (Bi-LSTM) [7,6] for both word and character-level systems.

3.2 Conditional Random Field

Conditional Random Field (CRF) [12] is a type of graphical model designed for labeling sequence of data. Although the LSTM is likely to handle the sequence of the input data by learning the dependencies between the input at each time step but it predicts the outputs independently. The CRF, therefore, is beneficial to explore the correlations between outputs and jointly decode the best sequence of labels. In NER task, we implement the CRF on the top of Bi-LSTM instead of the softmax layer and take outputs of Bi-LSTM as the inputs of this model. The parameter of the CRF is the transition matrix A where $A_{i,j}$ represents the transition score from tag i to tag j. The score of the input sentence \mathbf{x} along with the sequence of tags \mathbf{y} is computed as follow:

$$S(\mathbf{x}, \mathbf{y}, \theta \cup A_{i,j}) = \sum_{t=1}^{T} (A_{y_{t-1}, y_t} + f_{\theta_{(y_t, t)}})$$

where θ is the parameters of Bi-LSTM, f_{θ} is the score outputed by Bi-LSTM, and T is the number of time steps. Then the tag-sequence likelihood is computed by the softmax equation:

$$p(\mathbf{y}|\mathbf{x}, A) = \frac{\exp(S(\mathbf{x}, \mathbf{y}, \theta \cup A_{i,j}))}{\sum_{\mathbf{y}' \in \mathbf{Y}} \exp(S(\mathbf{x}, \mathbf{y}', \theta \cup A_{i,j}))}$$

where \mathbf{Y} is the set of all possible output sequences. In the training stage, we maximize the log-likelihood function:

$$L = \sum_{i=1}^{N} \log p(\mathbf{y}^{i} | \mathbf{x}^{i}; A)$$

where N is the number of training samples. In the inference stage, the Viterbi algorithm is used to find the output sequence \mathbf{y}^* that maximize the conditional probability:

$$\mathbf{y}^* = \underset{\mathbf{y} \in \mathbf{Y}}{\operatorname{arg\,max}} \quad p(\mathbf{y}|\mathbf{x}, A)$$

3.3 Learning Word Embedings

It has been shown that distributed representations of words (words embeddings) help improve the accuracy of a various natural language models. In this work, we investigate three methods to create word embeddings using a skip-gram model, a CNN model and a Bi-LSTM model.

Pre-Trained Word Vectors Learnt by Skip-gram Model To create word embeddings for Vietnamese, we train a skip-gram model using the word2vec⁸ tool on a dataset consisting of 7.3GB of text from 2 million articles collected through a Vietnamese news portal.⁹ The text is first normalized to lower case and all special characters are removed. The common symbols such as the comma, the semicolon, the colon, the full stop and the percentage sign are replaced with the special token punct, and all numeral sequences are replaced with the special token number. Each word in the Vietnamese language may consist of more than one syllables with spaces in between, which could be regarded as multiple words by the unsupervised models. Hence it is necessary to replace the spaces within each word with underscores to create full word tokens. The tokenization process follows the method described in [16]. For words that appear in VLSP corpus but not appear in word embeddings set, we create random vectors for these words by uniformly sampling from the range $\left[-\sqrt{\frac{3}{dim}}, +\sqrt{\frac{3}{dim}}\right]$ where dim is the dimension of embeddings.

Character-Level Word Vectors Learnt by Convolutional Neural Network Convolutional neural network (CNN) is a type of feed-forward neural networks that that uses many identical copies of the same neuron. This characteristic of CNN permits this network to have lots of neurons and, therefore, express computationally large models while keeping the number of actual parameters relativity small. For NLP tasks, previous works have shown that CNN is likely to extract morphological features such as prefix and suffix effectively [24,2,19].

⁸ https://code.google.com/archive/p/word2vec/

⁹ http://www.baomoi.com

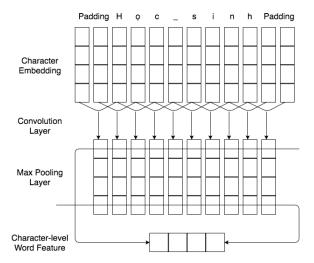


Fig. 1. The CNN for extracting character-level word features of word Hoc_sinh (Student).

For this reason, we incorporate the CNN to the word-level model to get richer information from character-level word vectors. These vectors are learnt during training together with the parameters of the word models. The CNN we use in this paper is described in Figure 1.

Character-Level Word Vectors Learnt by Long Short-Term Memory The second way for generating character-level word vectors is using Bi-LSTM. In particular, we incorporate this model to the word-level model to learn character-level word vectors. Character-level word vectors are concatenations of two last hidden states from forward and backward layers of Bi-LSTM. These vectors are also learnt during training together with the parameters of the word models. The Bi-LSTM model we use for this task is described in Figure 2.

3.4 Our Proposed Models

We propose two different types of models based on the level of input, either using word sequence or character sequence. Concretely, in the first type, each input sentence is fed to the model as a sequence of words, while in the second type, it is fed as a sequence of characters. Both of the two model types share the same pipeline in that it takes as input a sequence of distributed representations of the underlying processing unit (word or character), that sequence is then passed to a Bi-LSTM, and then a CRF layer takes as input the output of the Bi-LSTM to predict the best named entity output sequence.

Word-Levels Models In the first type, we investigate four different word embeddings, including (Word-0) random vectors, (Word-1) skip-gram vectors,

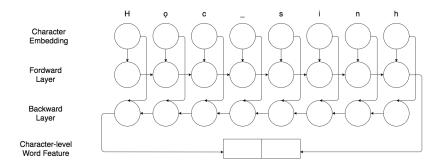


Fig. 2. The Bi-LSTM for extracting character-level word features of word *Hoc_sinh* (Student).

(Word-2) skip-gram vectors concatenated with CNN-generated word features, and (Word-3) skip-gram vectors concatenated with LSTM-generated word features. Figure 3 describes the architecture of the word-level models.

Character-Level Model In the second type, we investigate one model in that its input is a sequence of vectors corresponding to characters of the input sentence. We call this model (Char-0). Because the size of Vietnamese character set is relatively small, our data set is sufficient to learn distributed representations for Vietnamese characters. We therefore initialize random vectors for these characters by uniformly sampling from the range $[-\sqrt{\frac{3}{dim}}, +\sqrt{\frac{3}{dim}}]$ where dim is the dimension of embeddings. These character vectors are then learnt during training together with the parameters of the models.

The training data for NER is in CoNLL-2003 format, where both input and output sequence are annotated at word-level. For this reason, it is necessary to convert the dataset from word-level sequences to character-level sequences. We use a simple method in which all characters of a word are labeled with the same tag. For example, the label of all characters of a person named entity is P. Similarly, all characters of location, organization, and miscellaneous tokens are labelled with letters L, G, and M respectively. The characters of other words and spaces are labelled by O. Figure 4 shows the transformation from word-level to character-level of an example sentence Anh rõi EU hôm qua (UK left EU yesterday) and Figure 5 describes the architecture of the character-level models.

4 Results and Discussions

4.1 VLSP Corpus

We evaluate our system on the VLSP NER shared task 2016 corpus. This corpus consists of electronic newspapers published on the web. There are four named entity types in this corpus, names of person, location, organization and other

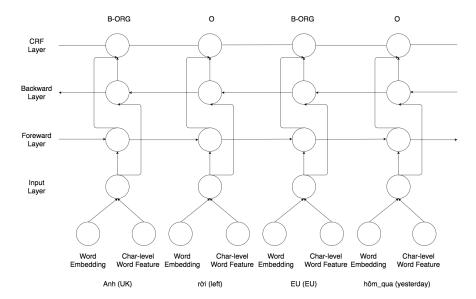


Fig. 3. Word-level model type for input sentence Anh rời EU hôm qua. (UK left EU yesterday.) Word-0 and Word-1 models uses only word embeddings as input, while Word-2 and Word-3 models uses both word embeddings and word features generated either by CNN or Bi-LSTM.

Anh rời EU hôm_qua B-ORG O B-ORG O

Fig. 4. Word and character-level sequence labeling of the sentence Anh $r\partial i$ EU $h\partial m$ qua. (UK left EU yesterday.)

named entities. Four types of NEs are compatible with their descriptions in the CoNLL shared task 2003. The examples of each entity type are described in Table 1

Data have been preprocessed with word segmentation and POS tagging. Because POS tags and chunking tags are determined automatically by public tools, they may contain mistakes. The format of this corpus follows that of the CoNLL 2003 shared task. It consists of five columns. The order of these columns are word, POS tag, chunking tag, named entity label, and nested named entity label. Our system focuses on only named entity without nesting, so we do not use the fifth column. Named entity labels are annotated using the IOB notation as in the CoNLL shared tasks. There are 9 labels: B-PER and I-PER are used for persons, B-ORG and I-ORG are used for organizations, B-LOC and I-LOC are used for locations, B-MISC and I-MISC are used for other named entities and O

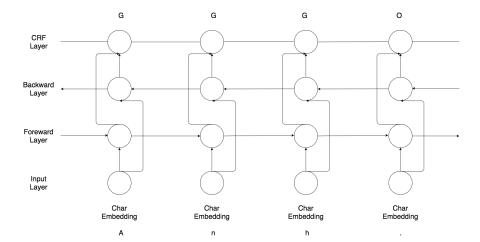


Fig. 5. Character-level model type for input sentence Anh. (UK.)

Table	1.	Examples	ot	Vietnamese	Entity	Types
-------	----	----------	----	------------	--------	-------

Entity Types	Examples
Person	thành phố Hồ Chí Minh (Ho Chi Minh
	city), núi Bà Đen (Ba Den mountain),
	sông Bạch Đằng (Bach Dang river)
Location	công ty Formosa (Formosa company),
	nhà máy thủy điện Hòa Bình (Hoa
	Binh hydroelectric factory)
Organization	ông Lân (Mr. Lan), bà Hà (Mrs. Ha)
Miscellaneous nan	nes tiếng Indonesia (Indonesian), người
	Canada (Canadian)

is used for other elements. Table 2 shows the quantity of named entity annotated in the training set and the test set.

Because our systems are end-to-end architecture, we focus only on the word and named entity label columns. To alleviate the data sparseness, we perform the following preprocessing for our system:

- All tokens containing digit number are replaced by a special token *number*.
- All punctuations are replaced by a special token *punct*.

Moreover, we take one part of training data for validation. The detail of each data set is described in Table 3.

4.2 Evaluation Method

The performance is measured with F_1 score, where $F_1 = \frac{2*P*R}{P+R}$. Precision (P) is the percentage of named entities found by the learning system that are correct. Recall (R) is the percentage of named entities present in the corpus that are

Table 2. Statistics of named entities in VLSP corpus

Entity Types	Training Set	Testing Set
Location	6,247	1,379
Organization	1,213	274
Person	7,480	1,294
Miscellaneous names	282	49
All	15,222	2,996

Table 3. Size of each data set in VLSP corpus

Data sets	Number of sentences
Train	14,861
Dev	2,000
Test	2,831

found by the system. A named entity is correct only if it is an exact match of the corresponding entity in the data file. For character-level model, after predicting label for each character, we convert these outputs back to the word-level sequence to evaluate. The performance of our system is evaluated by the automatic evaluation script of the CoNLL 2003 shared task.¹⁰.

4.3 Results

Word-Level Model vs. Character-Level Model In the first experiment, we compare the effectiveness of word and character-level approaches without using any external corpus. For this reason, in this experiment, we do not use any pretrained word embeddings by comparing two models: Word-0 and Char-0. Both of the two models take embeddings as inputs of Bi-LSTM and predict outputs by the CRF top layer. Table 4 presents the performance of these systems.

Table 4. Performances of word and character-level models

Entity	Word-0			Char-0		
	_	R	F_1	P	R	F_1
	88.37					
MISC	90.48	77.55	83.52	84.21	65.31	73.56
ORG	60.57	38.83	47.32	50.00	33.58	40.17
	89.49					
ALL	86.78	67.90	76.19	80.08	80.37	80.23

We see that the character-level model outperforms the word-level model by about 4%. It is because the size of the character set is much smaller than that of word set. The VLSP corpus, therefore, is enough for learning effectively character

¹⁰ http://www.cnts.ua.ac.be/conll2003/ner/

embeddings. For word embeddings, we need a bigger corpus to learn useful word vectors.

Effect of Word Embeddings It is beneficial to use the external corpus to learn the word embeddings. In the second experiment, we use skip-gram word embeddings and compare Word-1 and Word-0 models. The improvement by using pre-trained word embeddings for the word-level model is shown in Table 5.

Table 5. Performances of random and word2vec embeddings for word-level model

Entity	Word-0			Word-1		
	1 -		F_1	-		F_1
LOC						
MISC	90.48	77.55	83.52	90.00	73.47	80.90
ORG	60.57	38.83	47.32	72.77	50.92	59.91
PER	89.49	66.51	76.31	88.92	71.38	79.19
ALL	86.78	67.90	76.19	87.21	75.35	80.85

By using pre-trained word embeddings, the performance of word-level model increases by about 4%, to 80.85%. This accuracy is comparable to that of the character-level model. It proves the effectiveness of using good embeddings for both words and characters in the Bi-LSTM-CRF model.

Effect of Character-Level Word Features In the third experiment, we evaluate the performance of Word-2 and Word-3 models. Recall that these two models make use of both pre-trained skip-gram word embeddings and character-level word features generated either by CNN or Bi-LSTM. The obtained performances are described in Table 6.

Table 6. Performances of word-level models

Entity	Word-3			Word-2			Word-1		
	1*	10	T 1	-	1-0	F_1	P	R	F_1
LOC									
MISC	94.29	67.35	78.57	97.30	73.47	83.72	90.00	73.47	80.90
ORG	69.23	52.75	59.88	72.77	62.64	67.32	72.77	50.92	59.91
PER	90.12	72.62	80.43	93.60	88.24	90.84	88.92	71.38	79.19
ALL	88.82	77.87	82.98	90.97	85.93	88.38	87.21	75.35	80.85

We observe a significant improvement of performance when character-level word features learnt by CNN are integrated with pre-trained word embeddings.

This model achieves an overall F_1 score of 88.38%. The character-level word features learnt by Bi-LSTM are not as good as those learnt by CNN, achieves only an overall F_1 score of 82.98%, but they also help improve the performance of the model in comparison to the **Word-1** model.

Comparison with Previous Systems In VLSP 2016 workshop, several different systems have been proposed for Vietnamese NER. In this campaign, they have evaluated over three entities types LOC, ORG, PER. In all fairness, we also evaluate our performances over these tags on the same training and test set. The accuracy of our best model over three entity types is 88.59%, which is competitive with the best participating system [15] in that shared task. That system, however, used many hand-crafted features to improve the performance of maximum entropy classifier (ME) while our system is truly end-to-end model that takes only word sequences as inputs. Most approaches in VLSP 2016 used the CRF and ME models, whose performance is heavily dependent on feature engineering. Table 7 shows those models and their performance.

Table 7. Comparison to participating NER systems at VLSP 2016

Team	Model	Performance		
[15]	ME	88.78		
Word-2	Bi-LSTM-CNN-CRF	88.59		
[Anonymous] ¹¹	CRF	86.62		
[20]	ME	84.08		
[21]	Bi-LSTM-CRF	83.80		
[14]	CRF	78.40		

There is one work [21] that applied deep learning approach for this task. They used the implementation provided by [13]. There are two types of LSTM models in this open source software: Bi-LSTM-CRF and Stack-LSTM. The model that is most similar to ours is Bi-LSTM-CRF. The accuracy of this system is 83.25%. Our system outperforms this model due to some possible reasons. First, they used random vectors as word embeddings and update them during the training stage. The VLSP corpus size is relatively small so it is not good enough for learning word representations. Our word embeddings are trained on a collection of Vietnamese newspapers that is much larger and more abundant than the VLSP corpus. Second, they used LSTM to model character-level features, while we used CNN in our model. Previous works have shown that CNN is very useful to extract these features [24,2,19].

¹¹ This team provided a system without the technical report.

5 Conclusion

In this work, we have investigated a variety of end-to-end recurrent neural network architectures at both word and character-level for Vietnamese named entity recognition. Our best end-to-end system is the combination of Bi-LSTM, CNN, and CRF models, and uses pre-trained word embeddings as input, which achieves an F_1 score of 88.59% on the standard test corpus published recently by the Vietnamese Language and Speech community. Our system is competitive with the first-rank system of the related NER shared task without using any hand-crafted features.

Acknowledgement

The second author is partly funded by the Vietnam National University, Hanoi (VNU) under project number QG.15.04. Any opinions, findings and conclusion expressed in this paper are those of the authors and do not necessarily reflect the view of VNU.

References

- 1. Bengio, Y., Simard, P., Frasconi, P.: Learning long-term dependencies with gradient descent is difficult. IEEE transactions on neural networks 5(2), 157–166 (1994)
- 2. Chiu, J.P., Nichols, E.: Named entity recognition with bidirectional lstm-cnns. Transactions of the Association for Computational Linguistics 4, 357–370 (2016)
- Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., Kuksa, P.: Natural language processing (almost) from scratch. Journal of Machine Learning Research 12, 2493–2537 (2011)
- 4. Durrett, G., Klein, D.: A joint model for entity analysis: Coreference, typing, and linking. Transactions of the Association for Computational Linguistics 2, 477–490 (2014)
- Florian, R., Ittycheriah, A., Jing, H., Zhang, T.: Named entity recognition through classifier combination. In: Daelemans, W., Osborne, M. (eds.) Proceedings of CoNLL-2003. pp. 168–171. Edmonton, Canada (2003)
- Graves, A., rahmand Mohamed, A., Hinton, G.: Speech recognition with deep recurrent neural networks. In: Proceedings of 2013 IEEE international conference on acoustics, speech and signal processing. pp. 6645–6649. IEEE, Vancouver, BC, Canada (2013)
- Graves, A., Schmidhuber, J.: Framewise phoneme classification with bidirectional lstm networks. In: Proceedings of 2005 IEEE International Joint Conference on Neural Networks. vol. 4, pp. 2047–2052. IEEE, Montreal, QC, Canada (2005)
- 8. Hammerton, J.: Named entity recognition with long short-term memory. In: Proceedings of the seventh conference on Natural language learning at HLT-NAACL. vol. 4, pp. 172–175. Association for Computational Linguistics (2003)
- 9. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural computation 9(8), 1735–1780 (1997)
- 10. Huang, Z., Xu, W., Yu, K.: Bidirectional lstm-crf models for sequence tagging. arXiv preprint arXiv:1508.01991 (2015)

- Kuru, O., Can, O.A., Yuret, D.: Charner: Character-level named entity recognition. In: Proceedings of The 26th International Conference on Computational Linguistics. pp. 911–921 (2016)
- 12. Lafferty, J., McCallum, A., Pereira, F.: Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In: Proceedings of The Eighteenth International Conference on Machine Learning. vol. 1, pp. 282–289 (2001)
- 13. Lample, G., Ballesteros, M., Subramanian, S., Kawakami, K., Dyer, C.: Neural architectures for named entity recognition. arXiv preprint arXiv:1603.01360 (2016)
- Le, T.H., Nguyen, T.T.T., Do, T.H., Nguyen, X.T.: Named entity recognition in vietnamese text. In: Proceedings of The Fourth International Workshop on Vietnamese Language and Speech Processing. Hanoi, Vietnam (2016)
- 15. Le-Hong, P.: Vietnamese named entity recognition using token regular expressions and bidirectional inference. In: Proceedings of The Fourth International Workshop on Vietnamese Language and Speech Processing. Hanoi, Vietnam (2016)
- Le-Hong, P., Nguyen, T.M.H., Roussanaly, A., Ho, T.V.: A hybrid approach to word segmentation of Vietnamese texts. In: Language and Automata Theory and Applications, Lecture Notes in Computer Science, vol. 5196, pp. 240–249. Springer Berlin Heidelberg (2008)
- 17. Lin, D., Wu, X.: Phrase clustering for discriminative learning. In: Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP. vol. 2, pp. 1030–1038. Association for Computational Linguistics (2009)
- Luo, G., Xiaojiang Huang, Chin-Yew Lin, Z.N.: Joint entity recognition and disambiguation. In: Proceedings of the 2015 Conference on Empirical Methods on Natural Language Processing. pp. 879–888. Association for Computational Linguistics (2015)
- 19. Ma, X., Hovy, E.: End-to-end sequence labeling via bi-directional lstm-cnns-crf. arXiv preprint arXiv:1603.01354 (2016)
- Nguyen, T.C.V., Pham, T.S., Vuong, T.H., Nguyen, N.V., Tran, M.V.: Dsktlabner: Nested named entity recognition in vietnamese text. In: Proceedings of The Fourth International Workshop on Vietnamese Language and Speech Processing. Hanoi, Vietnam (2016)
- Nguyen, T.S., Nguyen, L.M., Tran, X.C.: Vietnamese named entity recognition at vlsp 2016 evaluation campaign. In: Proceedings of The Fourth International Workshop on Vietnamese Language and Speech Processing. Hanoi, Vietnam (2016)
- Pascanu, R., Mikolov, T., Bengio, Y.: On the difficulty of training recurrent neural networks. In: The 30th International Conference on Machine Learning. vol. 28, pp. 1310–1318. Atlanta, USA (2013)
- 23. Petasis, G., Petridis, S., Paliouras, G., Karkaletsis, V., Perantonis, S., Spyropoulos, C.: Symbolic and neural learning for named-entity recognition. In: Symposium on Computational Intelligence and Learning. pp. 58–66. Citeseer, Chios, Greece (2000)
- 24. dos Santos, C., Guimaraes, V., RJ Niterói, a.R.d.J.: Boosting named entity recognition with neural character embeddings. In: Proceedings of NEWS 2015 The Fifth Named Entities Workshop. pp. 25–33 (2015)