VnCoreNLP: A Vietnamese Natural Language Processing Toolkit

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Abstract

We present an easy-to-use and fast toolkit, namely VnCoreNLP—a Java NLP annotation pipeline for Vietnamese. Our VnCoreNLP supports key natural language processing (NLP) tasks including word segmentation, part-of-speech (POS) tagging, named entity recognition (NER) and dependency parsing, and obtains state-of-the-art (SOTA) results for these tasks. We release VnCoreNLP to provide rich linguistic annotations to facilitate research work on Vietnamese NLP. Our VnCoreNLP is open-source under GPL v3, and available at: https://github.com/vncorenlp/VnCoreNLP.

1 Introduction

Research on Vietnamese NLP has been actively explored in the last decade, boosted by the successes of the 4-year KC01.01/2006-2010 national project on Vietnamese language and speech processing (VLSP). Over the last 5 years, benchmark datasets for key Vietnamese NLP tasks are publicly available: datasets for word segmentation and POS tagging were released for the first VLSP evaluation campaign in 2013, a high-quality dependency treebank was published in 2014 (Nguyen et al., 2014), and a NER dataset was published for the VLSP 2016 evaluation campaign. So there is a need of building a NLP pipeline for those key tasks to assist users, and to support researchers and tool developers of downstream tasks.

Nguyen et al. (2010) and Le et al. (2013) built Vietnamese NLP pipelines by wrapping existing word segmenters and POS taggers including: JVnSegmenter (Nguyen et al., 2006), vnTokenizer (Le et al., 2008), JVnTagger (Nguyen et al., 2010) and vnTagger (Le-Hong et al., 2010). However, these word segmenters and POS taggers are no longer considered SOTA models for Vietnamese (Nguyen and Le, 2016; Nguyen et al., 2016b).

Pham et al. (2017) built the NNVLP toolkit for Vietnamese sequence labeling tasks by applying a BiLSTM-CNN-CRF model (Ma and Hovy, 2016). However, Pham et al. (2017) did not make a comparison to SOTA traditional feature-based models. In addition, NNVLP is slow with a processing speed at about 300 words per second, which is not practical for real-world application such as dealing with large-scale data.

In this paper, we present a Java NLP toolkit for Vietnamese, namely VnCoreNLP, which aims to facilitate Vietnamese NLP research by providing rich linguistic annotations through key NLP components of word segmentation, POS tagging, NER and dependency parsing. Figure 1 describes the overall system architecture. The following items highlight typical characteristics of VnCoreNLP:

- **Easy-to-use** – All VnCoreNLP components are wrapped into a single .jar file, so users do not have to install external dependencies. Users can run processing pipelines from either the command-line or the Java API.
- **Fast** – VnCoreNLP is fast, so it can be used for dealing with large-scale data. Also it benefits users suffering from limited computation resources (e.g. users from Vietnam).
- **Accurate** – VnCoreNLP components obtain higher results than all previous published results on the same benchmark datasets.
2 Basic usages

Our design goal is to make VnCoreNLP simple to setup and run from either the command-line or the Java API. Performing linguistic annotations for a given file can be done by using a simple command as in Figure 2.

```bash
$ java -Xmx2g -jar VnCoreNLP.jar -fin input.txt -fout output.txt
```

Figure 2: Minimal command to run VnCoreNLP.

Suppose that the file input.txt in Figure 2 contains a sentence “Ông Nguyễn Khắc Chúc đang làm việc tại Đại học Quốc gia Hà Nội.” (Mr. Nguyễn Khắc Chúc is working at Vietnam National University, Hanoi. Mrs. Lan, Mr. Chúc’s wife, is also working at this university.

String str = “Ông Nguyễn Khắc Chúc đang làm việc tại Đại học Quốc gia Hà Nội. Bà Lan, vợ ông Chúc, cũng làm việc tại đây.”;

Table 1: The output in file output.txt for the sentence ‘Ông Nguyễn Khắc Chúc đang làm việc tại Đại học Quốc gia Hà Nội.” from file input.txt in Figure 2.

|   |   |   |   |   |
|---|---|---|---|---|
| 1 | Ông | O | 4 | sub |
| 2 | Nguyễn_Khắc_Chúc | Np | B-PER | 1 | nmod |
| 3 | đang | R | O | 4 | adv |
| 4 | làm_viec | V | O | 0 | root |
| 5 | tại | E | O | 4 | loc |
| 6 | Đại_học | N | B-ORG | 5 | pob |
| 7 | Quốc_gia | N | I-ORG | 6 | nmod |
| 8 | Hà_Nội | Np | I-ORG | 6 | nmod |
| 9 | . | CH | O | 4 | punct |

Table 1: The output in file output.txt for the sentence ‘Ông Nguyễn Khắc Chúc đang làm việc tại Đại học Quốc gia Hà Nội.” from file input.txt in Figure 2. The output are in a 6-column format representing word index, word form, POS tag, NER label, head index of the current word, and dependency relation type.

Similarly, we can also get the same output by using the API as easy as in Listing 1.

```java
import vn.pipeline.*;
import java.io.*;
public class VnCoreNLPExample {
    public static void main(String[] args) throws IOException {
        VnCoreNLP pipeline = new VnCoreNLP();
        Annotation annotation = new Annotation(str);
        pipeline.annotate(annotation);
        PrintStream outputPrinter = new PrintStream("output.txt");
        pipeline.printToFile(annotation, outputPrinter);
    }
}
```

Listing 2: A simple and complete example code.

3 Components

This section briefly describes each component of VnCoreNLP. Note that our goal is not to develop new approach or model for each component task. Here we focus on incorporating existing models into a single pipeline. In particular, except a new model we develop for the language-dependent component of word segmentation, we apply traditional feature-based models which obtain SOTA results for English POS tagging, NER and dependency parsing to Vietnamese. The reason is based on a well-established belief in the literature that for a less-resourced language such as Vietnamese, we should use traditional feature-based models to obtain fast and accurate performances rather than using neural network-based models.

- **wseg** – Unlike English where white space is a strong indicator of word boundaries, when written in Vietnamese white space is also used to separate syllables that constitute words. So word segmentation is referred to as the key first step in Vietnamese NLP. We have proposed a novel transformation rule-based learning model for Vietnamese word segmentation, which obtains the highest segmentation accuracy and speed to date. See details in Nguyen et al. (2018).
• **pos** – To label words with their POS tag, we apply MarMoT which is a generic CRF framework and a SOTA POS and morphological tagger (Mueller et al., 2013).

• **ner** – To recognize named entities, we apply a dynamic feature induction model that automatically optimizes feature combinations (Choi, 2016).

• **parse** – To perform dependency parsing, we apply the greedy version of a transition-based model with selectional branching (Choi et al., 2015).

4 **Evaluation**

We detail experimental results of the word segmentation (**wseg**) and POS tagging (**pos**) components of VnCoreNLP in Nguyen et al. (2018) and Nguyen et al. (2017b), respectively. In particular, our word segmentation component gets the highest results to date in terms of both segmentation F1 score at 97.90% and speed at 62k words per second. Our POS tagging component also obtains the highest accuracy to date at 95.88% with a fast tagging speed at 25k words per second, and outperforms BiLSTM-CRF-based models. Following subsections present evaluations for the NER (**ner**)

and dependency parsing (**parse**) components.

4.1 **Named entity recognition**

In this section, we make a comparison between SOTA feature-based and neural network-based models, which, to the best of our knowledge, has not done in any prior work on Vietnamese NER.

**Dataset:** The NER shared task at the 2016 VLSP workshop provides a set of 16,861 manually annotated sentences for training and development, and a set of 2,831 manually annotated sentences for test, with four NER labels PER, LOC, ORG and MISC. In both datasets, words are also supplied with gold POS tags. In addition, each word representing a full personal name are separated into syllables that constitute the word. This scheme results in an unrealistic scenario: (i) gold POS tags are not available in a real-world application, and (ii) in the standard representation in Vietnamese word segmentation (Nguyen et al., 2009), a word segmenter outputs a full name as a word. So for a real-world scenario, we merge those contiguous syllables constituting a full name to form a word, and then we replace the gold POS tags by automatic tags predicted by our POS tagging component. From the set of 16,861 sentences, we sample 2,000 sentences for development and using the remaining 14,861 sentences for training.

**Models:** We make an empirical comparison between the VnCoreNLP’s NER component and the following neural network-based models:

- BiLSTM-CRF (Huang et al., 2015) is a sequence labeling model which extends the BiLSTM model with a CRF layer.
- BiLSTM-CRF + CNN-char, i.e. BiLSTM-CNN-CRF, is an extension of BiLSTM-CRF, using CNN to derive character-based representations (Ma and Hovy, 2016).
- BiLSTM-CRF + LSTM-char is an extension of BiLSTM-CRF, using BiLSTM to derive the character-based representations (Lample et al., 2016).
- BiLSTM-CRF+POS is another extension to BiLSTM-CRF, incorporating embeddings of automatically predicted POS tags (Reimers and Gurevych, 2017).

We use an implementation which is optimized for performance of all BiLSTM-CRF-based models from Reimers and Gurevych (2017). We then follow Nguyen et al. (2017b, Section 3.4) to perform hyper-parameter tuning.

**Main results:** Table 2 presents F1 scores and speed of each model on the test set, where VnCoreNLP obtains the second highest score at 88.14% with a fast speed at 19k words per second. In particular, VnCoreNLP is just about 0.1% absolute lower than the most accurate model BiLSTM-CRF + CNN-char, but it obtains 10+ times faster speed than BiLSTM-CRF + CNN-char.

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1. [http://cistern.cis.lmu.de/marmot/](http://cistern.cis.lmu.de/marmot/)
2. [https://emorynlp.github.io/nlp4j/components/named-entity-recognition.html](https://emorynlp.github.io/nlp4j/components/named-entity-recognition.html)
3. [https://emorynlp.github.io/nlp4j/components/dependency-parsing.html](https://emorynlp.github.io/nlp4j/components/dependency-parsing.html)
4. All speeds reported in this paper are computed on a personal computer of Intel Core i7 2.2 GHz.
5. Based on the gold label PER, contiguous syllables such as “Nguyễn/B-PER”, “Khắc/I-PER” and “Chúc/I-PER” are merged to form a word as “Nguyễn_Khắc_Chúc/B-PER.”
6. Note that on the original VLSP 2016 NER data, using the same experimental setup as in Pham et al. (2017), our NER component obtains a F1 score at 93.2% which is higher than NNVLP’s and all other previous published results.
7. [https://github.com/UKPLab/emnlp2017-bilstm-cnn-crf](https://github.com/UKPLab/emnlp2017-bilstm-cnn-crf)
8. We employ pre-trained word vectors from Vu (2016).
| Model | F1  | Speed |
|-------|-----|-------|
| VnCoreNLP | 88.14 | 19k   |
| BiLSTM-CRF | 86.48 | 2.8k  |
| + CNN-char | **88.28** | 1.8k |
| + LSTM-char | 87.71 | 1.3k  |
| BiLSTM-CRF+POS | 86.12 | –     |
| + CNN-char | 88.06 | –     |
| + LSTM-char | 87.43 | –     |

Table 2: F1 scores (in %) on the test set w.r.t. gold word-segmentation. “Speed” denotes the processing speed of the number of words per second (for VnCoreNLP, automatically POS tagging time is also taken into account).

It is surprising that for such an isolated language as Vietnamese where all words are not inflected, using character-based representations helps producing 1+% improvements to the BiLSTM-CRF model. We find that the improvements to BiLSTM-CRF are mostly accounted for the PER label. The reason turns out to be simple: about 50% of named entities are labeled with tag PER, so character-based representations are in fact able to capture common family and middle names in ‘unknown’ full-name words in the test set. In addition, we also find that BiLSTM-CRF-based models do not benefit from additional predicted POS tags. It is probably because BiLSTM can take word order into account, while without word inflection, all grammatical information in Vietnamese is conveyed through its fixed word order, thus explicit predicted POS tags with noise grammatical information are not helpful.

4.2 Dependency parsing

**Experimental setup:** We use the Vietnamese dependency treebank VnDT (Nguyen et al., 2014) consisting of 10,200 sentences in our experiments. Following Nguyen et al. (2016a), we use the last 1020 sentences of VnDT for test while the remaining sentences are used for training. Evaluation metrics are the labeled attachment score (LAS) and unlabeled attachment score (UAS).

**Main results:** Table 3 compares the dependency parsing results of VnCoreNLP with results reported in prior work, using the same experimental setup. The first six rows present the scores with gold POS tags. The next two rows show scores of VnCoreNLP with automatic POS tags,\(^9\) while the last row presents scores of the joint POS tagging and dependency parsing model jPTDP (Nguyen et al., 2017a). Table 3 shows that compared to previously published results, VnCoreNLP produces the highest LAS score. Note that previous results are reported without using additional information of automatically predicted NER labels. In this case, the LAS score accounted for VnCoreNLP without automatic NER features (i.e. VnCoreNLP\(_{-\text{NER}}\) in Table 3) is still higher than previous ones. Notably, we also obtain a fast parsing speed.

| Model | LAS  | UAS  | Speed |
|-------|------|------|-------|
| VnCoreNLP | **73.39** | 79.02 | –     |
| VnCoreNLP\(_{-\text{NER}}\) | 73.21 | 78.91 | –     |
| BIST-bmstparser | 73.17 | **79.39** | –     |
| BIST-barchybrid | 72.53 | 79.33 | –     |
| MSTParser | 70.29 | 76.47 | –     |
| MaltParser | 69.10 | 74.91 | –     |
| Auto POS | VnCoreNLP | 70.23 | 76.93 | 8k    |
| VnCoreNLP\(_{-\text{NER}}\) | 70.10 | 76.85 | 9k    |
| jPTDP | 69.49 | **77.68** | 700   |

Table 3: LAS and UAS scores (in %) computed on all tokens (i.e. including punctuation) on the test set w.r.t. gold word-segmentation. “Speed” is defined as in Table 2. The subscript “–NER” denotes the model without using automatically predicted NER labels as features. The results of the MSTParser (McDonald et al., 2005), MaltParser (Nivre et al., 2007), and BiLSTM-based parsing models BIST-bmstparser and BIST-barchybrid (Kiperwasser and Goldberg, 2016) are reported in Nguyen et al. (2016a). The result of the jPTDP model (Nguyen et al., 2017a) for Vietnamese is mentioned in Nguyen et al. (2017b) and detailed at https://drive.google.com/drive/folders/0B5eBgc8jrKtpUmhhSmtFLWdrTzQ.

5 Conclusion

In this paper, we have presented the VnCoreNLP toolkit—a simple, fast and accurate NLP processing pipeline—providing core Vietnamese NLP steps: word segmentation, POS tagging, NER and dependency parsing. Current version of VnCoreNLP has been trained without any linguistic optimization, i.e. we only employ existing predefined features in the traditional feature-based models for POS tagging, NER and dependency parsing. So future work will focus on incorporating Vietnamese linguistic features into these feature-based models.

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\(^9\)We replace the gold POS tags by the automatic POS tags predicted by our POS tagging component in both training and test sets.
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