Span Labeling Approach for Vietnamese and Chinese Word Segmentation

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Abstract In this paper, we propose a span labeling approach to model n-gram information for Vietnamese word segmentation, namely SPANSEG. We compare the span labeling approach with the conditional random field by using encoders with the same architecture. Since Vietnamese and Chinese have similar linguistic phenomena, we evaluated the proposed method on the Vietnamese treebank benchmark dataset and five Chinese benchmark datasets. Through our experimental results, the proposed approach SPANSEG achieves higher performance than the sequence tagging approach with the state-of-the-art F-score of 98.31\% on the Vietnamese treebank benchmark, when they both apply the contextual pre-trained language model XLM-RoBERTa and the predicted word boundary information. Besides, we do fine-tuning experiments for the span labeling approach on BERT and ZEN pre-trained language model for Chinese with fewer parameters, faster inference time, and competitive or higher F-scores than the previous state-of-the-art approach, word segmentation with word-hood memory networks, on five Chinese benchmarks.

Keywords: Natural Language Processing · Word Segmentation · Vietnamese · Chinese.

1 Introduction

Word segmentation is the first essential task for both Vietnamese and Chinese. The input of Vietnamese word segmentation (VWS) is the sequence of syllables delimited by space. In contrast, the input of Chinese word segmentation (CWS) is the sequence of characters without explicit delimiter. The use of a Vietnamese syllable is similar to a Chinese character. Despite deep learning dealing with natural language processing tasks without the word segmentation phase, the research on word segmentation is still necessary regarding the linguistic aspect. Since Vietnamese and Chinese have similar linguistic phenomena such as overlapping ambiguity in VWS [13] and in CWS [26], therefore the research about VWS and CWS is a challenging problem.

Many previous approaches for VWS have been proposed. For instance, in the early stage of VWS, Dinh et al. [6] supposed VWS as a stochastic transduction problem.
Therefore, they represented the input sentence as an unweighted Finite-State Acceptor. As a consequence, Le et al. [13] proposed the ambiguity resolver using a bi-gram language model as a component in their model for VWS. After that, Nguyen et al. [16] used conditional random fields (CRFs) and support vector machines (SVMs) for VWS. Recently, Nguyen and Le [22] utilized rules based on the predicted word boundary and threshold for the classifier in the post-processing stage to control overlapping ambiguities for VWS. Besides, Nguyen et al. [18] proposes a method for auto-learning rule based on the predicted word boundary for VWS. Furthermore, Nguyen [17] proposed the joint neural network model for Vietnamese word segmentation, part-of-speech tagging, and dependency parsing. Lastly, Nguyen et al. [20] proposed feature extraction to deal with overlapping ambiguity and capturing word containing suffixes.

From our observation, the number of research and approaches for CWS is greater than VWS. The research [1, 10, 15, 24, 28, 32] treated CWS as a character-based sequence labeling task. The contextual feature extractions were proved helpful in CWS [10]. After that, neural networks were powerful for CWS [1, 10, 15]. The measuring word-hood for n-grams was an effective method for non-neural network model [26] and neural network model [27]. Besides, the multi-criteria learning from many different datasets is a strong method [2, 12, 23]. Remarkably, Tian et al. [27] incorporated the word-hood for n-gram into neural network model effectively.

We have an observation that most of the approaches for VWS and CWS treated word segmentation as a token-based sequence tagging problem, where the token is a syllable in VWS and character in CWS. Secondly, the intersection of VWS and CWS approaches leverages the context to model n-gram of token information, such as measuring the word-hood of the n-gram in CWS. All of the previous approaches in CWS incorporate the word-hood information as a module of their models. Therefore, our research hypothesizes whether we can model a simple model that can simulate measuring word-hood operation.

From our observation and hypothesis, we get the inspiration of span representation in constituency parsing [25] to propose our SPANSEG model for VWS and CWS. The main idea of our SPANSEG is to model all n-grams in the input sentence and score them. Modeling an n-gram is equivalent to find the probability of a span being a word. Via experimental results, the proposed approach SPANSEG achieves higher performance than the sequence tagging approach when both utilize contextual pre-trained language model XLM-RoBERTa and predicted word boundary information on the Vietnamese treebank benchmark with the state-of-the-art F-score of 98.31%. Additionally, we do fine-tuning experiments for the span labeling method on BERT and ZEN pre-trained language model for Chinese with fewer parameters, faster inference time, and competitive or higher F-scores than the previous state-of-the-art approach, word segmentation with word-hood memory networks, on five Chinese benchmarks.

2 The Proposed Framework

Differing from previous studies, we regard word segmentation as a span labeling task. The architecture of our proposed model, namely SPANSEG, is illustrated in Figure 1, where the general span labeling paradigm is at the top of the figure. This paper is the first work approach to word segmentation as a span labeling task to the best of our
Figure 1. The architecture of SPANSEG for VWS. The input sentence is “học sinh học sinh học” (student learn biology) including five syllables (“học”, “sinh”, “học”, “sinh”, and “học”). The gold-standard segmentation for the input sentence is “học_sinh học sinh_học” including three words (“học_sinh”, “học”, and “sinh_học”). The initial BIES (Begin, Inside, End, or Singleton) word boundary tags (differing from gold-standard segmentation) were predicted by an off-the-shelf toolkit RDRsegmenter [18].
2: “học”, 3: “sinh”, 4: “học”). With this consideration, the gold-standard segmentation “học_sinh hoc sinh_học” (student learn biology) (including three words (“học_sinh”, “học”, and “sinh_học”)) is presented by three spans (0, 2) (“học_sinh”), (2, 3) (“học”), and (3, 5) (“sinh_học”). By approaching word segmentation as a span labeling task, we have three positive samples (three circles filled with gray color) for the input sentence in Figure 1, whereas other circles filled with white color with solid border are negative samples for the input sentence in Figure 1. Also, in Figure 1, we note that all circles with dashed border (e.g. spans (0, 0), (1, 1), ..., (n, n), where n is the length of the input sentence) are skipped in SPANSEG because they do not represent spans.

After presenting SPANSEG, in the rest of this section, we firstly introduce problem representation of word segmentation as a span labeling task (in subsection 2.1). Secondly, we introduce the proposed span post-processing algorithm for word segmentation (in subsection 2.2). The first and second subsections are two important points of our research. Thirdly, we describe the span scoring module (in subsection 2.3). In the last two subsections, we provide the architecture encoder for VWS and CWS. We describe the model SPANSEG for VWS (in subsection 2.4). Lastly, we describe SPANSEG for CWS (in subsection 2.5).

### 2.1 Word segmentation as span labeling task for Vietnamese and Chinese

The input sentence of word segmentation task is a sequence of tokens \(X = x_1 \ldots x_n\) with the length of \(n\). The token \(x_i\) is a syllable or character toward Vietnamese or Chinese, respectively. Given the input \(X\), the output of word segmentation is a sequence of words \(W = w_1 \ldots w_m\) with the length of \(m\), where \(1 \leq m \leq n\). We have a property that the word \(w_j\) is constituted by one token or consecutive tokens. So, we use the sequence of tokens \(x_i \ldots x_i+k-1\) for denoting the word \(w_j\) be constituted by \(k\) consecutive tokens beginning at token \(x_i\), where \(1 \leq k \leq n\) (concretely, \(k = 1\) representing single words and \(2 \leq k \leq n\) representing compound words for both Vietnamese and Chinese). Inspired by the work of Stern et al. [25] for constituency parsing, we use the span \((i - 1, i - 1 + k)\) to represent the word constituted by \(k\) consecutive tokens \(x_i \ldots x_{i+k-1}\) beginning at token \(x_i\). Therefore, the goal of the span labeling task for both VWS and CWS is to find the list of spans \(\hat{S}\) such that every token \(x_i\) is spanned, and there is no overlapping between every two spans. Formally, the word segmentation model as span labeling task for both VWS and CWS can be formalized as:

\[
\hat{S} = \text{SPANPOSTPROCESSING}(\hat{Y})
\]

where \(\text{SPANPOSTPROCESSING}(\cdot)\) simply is a algorithm for producing the word segmentation boundary satisfying non-overlapping between every two spans. The \(\hat{Y}\) is the set of predicted spans as following:

\[
\hat{Y} = \{(l, r) | 0 \leq l \leq n-1 \text{ and } l < r \leq n \text{ and } \text{SCORER}(X', l, r) > 0.5\}
\]

where \(n\) is the length of the input sentence. The \(\text{SCORER}(\cdot)\) is the scoring module for the span \((l, r)\) of sentence \(X\). The output of \(\text{SCORER}(\cdot)\) has a value in the range of 0 to 1. In our research, we choose the sigmoid function as an activation function at the last
layer of\textsc{Scorer}(\cdot) module. Lastly, the word segmentation as a span labeling task is the binary classification problem. We use the binary cross-entropy loss for the cost function as following:

\[ J(\theta) = -\frac{1}{|D|} \sum_{(\mathcal{X}, \mathcal{S}) \in D} \left( \frac{1}{n(n+1)/2} \sum_{l=0}^{n-1} \sum_{r=l+1}^{n} \left[ (l, r) \in \mathcal{S} \right] \log \left( \text{Scorer}(\mathcal{X}, l, r) \right) 
+ \left[ (l, r) \notin \mathcal{S} \right] \log \left( 1 - \text{Scorer}(\mathcal{X}, l, r) \right) \right) \]  

(3)

where $\mathcal{D}$ is the training set and $|\mathcal{D}|$ is the size of training set. For each pair $(\mathcal{X}, \mathcal{S})$ in training set $\mathcal{D}$, we compute binary cross-entropy loss for all spans $(l, r)$, where $0 \leq l \leq n - 1$ and $l < r \leq n$, and $n$ is the length of sentence $\mathcal{X}$. The term $[(l, r) \in \mathcal{S}]$ has the value of 1 if span $(l, r)$ belongs to the list $\mathcal{S}$ of sentence $\mathcal{X}$ and conversely, of 0. Similarly, the term $[(l, r) \notin \mathcal{S}]$ has the value of 1 if span $(l, r)$ does not belong to the list $\mathcal{S}$ of sentence $\mathcal{X}$ and conversely, of 0. Lastly, we make a note that in our training and prediction progress, we will discard spans with length greater than 7 for both Vietnamese and Chinese (7 is maximum n-gram length following [5] for Chinese, so we decide to choose 7 for Vietnamese according to the statistics in the work of [20]).

2.2 Post-Processing Algorithm For Predicted Spans

In the previous subsection 2.1, we presented word segmentation as a span labeling task for Vietnamese and Chinese. In this subsection, we present our proposed post-processing algorithm for predicted spans from the span labeling problem. However, we found that in the predicted spans set $\hat{\mathcal{Y}}$ there exists overlapping between some two spans. We deal with the overlapping ambiguity by choosing the spans with the highest score and removing the rest. The overlapping ambiguity phenomenon occurs when our \textsc{SpanSeg} predicts compound words. It occurs in our \textsc{SpanSeg} and other word segmenters on Vietnamese [13] and Chinese [26].

Apart from overlapping ambiguity, our \textsc{SpanSeg} faces the missing word boundary problem. That problem can be caused by originally predicted spans or as a result of solving overlapping ambiguity. We choose the missing word boundary based on all predicted spans $(i - 1, i - 1 + k)$ with $k = 1$ for single words to deal with the missing word boundary problem. To sum up, our proposed post-processing algorithm for predicted spans from the span labeling problem, namely \textsc{SpanPostProcessing}, deals with overlapping ambiguity and missing spans from predicted spans. The detail of our \textsc{SpanPostProcessing} is presented in Algorithm 1.

2.3 Span Scoring Module

In two previous subsections 2.1 and 2.2, we presented two critical points of our research. There we mentioned the \textsc{Scorer}(\cdot) module many times. In this section, we present \textsc{Scorer}(\cdot) module. It is based on the familiar module that name Biaffine [7]. While Zhang et al. [33] experimenting with the Biaffine module for constituency parsing, we use the Biaffine module for span labeling word segmentation. The Biaffine module
Algorithm 1 SPANPostProcessing

Require:

- The input sentence $X$ with the length of $n$;
- The scoring module $\text{SCORER}()$ for any span $(l, r)$ in $X$, where $0 \leq l \leq n - 1$ and $l < r \leq n$;
- The set of predicted spans $\hat{Y}$, sorted in ascending order.

Ensure:

- The list of valid predicted spans $\hat{S}$, satisfying non-overlapping between every two spans.

\begin{algorithm}
\begin{algorithmic}
  \Require
  \State $S_{novlp} = [(0, 0)]$ \Comment{The list of predicted spans without overlapping ambiguity.}
  \State $\hat{S} = []$ \Comment{The final list of valid predicted spans.}
  \For{$\hat{y}$ in $\hat{Y}$} \Comment{$\hat{y}[0]$ is the left boundary and $\hat{y}[1]$ is the right boundary of each span $\hat{y}$.}
    \If{$S_{novlp}[1][1] < \hat{y}[0]$} \Comment{Check for missing boundary.}
      \State $S_{novlp}$.append($(S_{novlp}[1][1], \hat{y}[0])$) \Comment{Add the missing span to $S_{novlp}$.}
    \EndIf
    \If{$S_{novlp}[1][0] \leq \hat{y}[0] < S_{novlp}[1][1]$} \Comment{Check for overlapping ambiguity.}
      \If{$\text{SCORER}(X, S_{novlp}[1][0], S_{novlp}[1][1]) < \text{SCORER}(X, \hat{y}[0], \hat{y}[1])$}
        \State $S_{novlp}$.pop() \Comment{Remove the span causing overlapping with the lower score than $\hat{y}$.}
        \State $S_{novlp}$.append($(\hat{y}[0], \hat{y}[1])$) \Comment{Add the span $\hat{y}$ to $S_{novlp}$.}
      \EndIf
    \EndIf
  \EndFor
  \If{$S_{novlp}[1][1] < n$} \Comment{Check for missing boundary.}
    \State $S_{novlp}$.append($(S_{novlp}[1][1], n)$) \Comment{Add the missing span to $S_{novlp}$.}
  \EndIf
  \For{$i, \hat{y}$ in enumerate$(S_{novlp})$} \Comment{$\hat{y}[0]$ is the left boundary and $\hat{y}[1]$ is the right boundary of each span $\hat{y}$, and $i$ is the index of $\hat{y}$ in list $S_{novlp}$.}
    \If{$0 < i$ and $S_{novlp}[i - 1][1] < \hat{y}[0]$} \Comment{Check for missing boundary.}
      \State missed_boundaries = $[S_{novlp}[i - 1][1]]$
      \For{bound in range$(S_{novlp}[i - 1][1], \hat{y}[0])$}
        \If{$\text{SCORER}(X, \text{bound, bound + 1}) > 0.5$} \Comment{Check for single word.}
          \State missed_boundaries.append(bound + 1)
        \EndIf
      \EndFor
      \State $\hat{S}$.append($(\text{missed_boundaries}[j], \text{missed_boundaries}[j + 1])$) \Comment{Add the missing span to $\hat{S}$.}
    \EndIf
  \EndFor
  \State $\hat{S}$.append$(\hat{y}[0], \hat{y}[1])$ \Comment{Add the non-overlapping span to $\hat{S}$.}
\end{algorithmic}
\end{algorithm}

is used in [7] to capture the directed relation between two words in a sentence for dependency parsing. In the constituency parsing problem, Zhang et al. [33] used the
Biaffine module to find the representation of phrases. Our research uses the Biaffine module to model the representation of n-gram for the word segmentation task.

As we can see in Figure 1, each token \( x_i \) in the input sentence has two context-aware word representations including left and right boundary representations except the begin ("<s>") and end ("</s>") tokens. In case we use the BiLSTM (Bidirectional Long Short Term Memory) encoder, the left boundary representation of token \( x_i \) is the concatenation of the hidden state forward vector \( f_{i-1} \) and the hidden state backward vector \( b_i \) and the right boundary representation of token \( x_i \) is the concatenation of the hidden state forward vector \( f_i \) and the hidden state backward vector \( b_{i+1} \), following Stern et al. [25]. In case we use BERT [4] or ZEN [5] encoder, we chunk the last hidden state vector into two vectors with the same size as forward and backward vectors of the BiLSTM encoder. Even though we use the BiLSTM, BERT, or ZEN encoder, we always have the left and right boundary representation for each token \( x_i \) in the input sentence. Therefore, in Figure 1, we see that the right boundary representation \( f_i \oplus b_{i+1} \) of token \( x_i \) is the left boundary representation of token \( x_{i+1} \). As the work of Zhang et al. [33], we use two MLPs to make the difference between the right boundary representation of token \( x_i \) and the left boundary representation of token \( x_{i+1} \). To sum up, we have the left \( r^\text{left}_i \) and right \( r^\text{right}_i \) boundary representations of token \( x_i \) as following:

\[
\begin{align*}
    r^\text{left}_i &= \text{MLP}^{\text{left}}(f_{i-1} \oplus b_i) \\
    r^\text{right}_i &= \text{MLP}^{\text{right}}(f_i \oplus b_{i+1})
\end{align*}
\]

Finally, inspired by Zhang et al. [33], given the input sentence \( \mathcal{X} \), the span scoring module \( \text{SCORER}(\cdot) \) for span (\( l, r \)) in our SPANSEG model is computed by using a biaffine operation over the left boundary representation of token \( x_l \) and the right boundary representation of token \( x_r \) as following:

\[
\text{SCORER}(\mathcal{X}, l, r) = \text{sigmoid} \left( \begin{bmatrix} r^\text{left}_l \\ 1 \end{bmatrix}^T W r^\text{right}_r \right)
\]

where \( W \in \mathbb{R}^{d \times d} \). To sum up, the \( \text{SCORER}(\mathcal{X}, l, r) \) gives us a score to predict whether a span (\( l, r \)) is a word.

### 2.4 Encoder and input representation for VWS

In three previous subsection 2.1, 2.2, and 2.3, we describe three mutual parts of the SPANSEG model for Vietnamese and Chinese. In this subsection, we present the encoder and the input representation for VWS of the SPANSEG model. Firstly, the default configuration of SPANSEG for the input representation of token \( x_i \) is composed as following:

\[
\text{default_embedding}_i = \left( \text{static_syl_embedding}_i + \text{dynamic_syl_embedding}_i \right) \oplus \text{char_embedding}_i
\]

where the symbol \( \oplus \) denotes the concatenation operation. The \text{static_syl_embedding}_i is extracted from the pre-trained Vietnamese syllable embedding with the dimension of 100
provided by Nguyen et al. [19]. So, the dimension of vector $\texttt{dynamic\_syl\_embedding}_i$ also is 100. We initialize randomly and update the value of $\texttt{dynamic\_syl\_embedding}_i$ in the training progress. We do not update the value of $\texttt{static\_syl\_embedding}_i$ during training model. Besides, we also use a character embedding for the input representation by using BiLSTM network for sequence of characters in token $x_i$ to obtain $\texttt{char\_embedding}_i$.

The default configuration does not utilize the Vietnamese predicted word boundary information as many previous works on VWS did. Following the work of Nguyen [17], we additionally use the boundary BIES tag embedding for the input representation of token $x_i$. Therefore, the second configuration of SPANSEG, namely SPANSEG (TAG) is presented as following:

$$\texttt{default\_tag\_embedding}_i = \texttt{default\_embedding}_i \oplus \texttt{bies\_tag\_embedding}_i$$ (8)

where the value of $\texttt{bies\_tag\_embedding}_i$ (with the dimension of 100) is initialized randomly and updated; and the boundary BIES tag is predicted by the off-the-shelf toolkit RDRsegmenter [18].

Recently, many contextual pre-trained language models were proposed inspired by the work of Devlin et al. [4]. However, our research utilizes contextual pre-trained multilingual language model XLM-Roberta (XLM-R) [3] with the base architecture for VWS since there is no contextual pre-trained monolingual language model for Vietnamese at this time. So, the third configuration of SPANSEG, namely SPANSEG (XLM-R), is presented as following:

$$\texttt{default\_xlmr\_embedding}_i = \texttt{default\_embedding}_i \oplus \texttt{xlmr\_embedding}_i$$ (9)

where the $\texttt{xlmr\_embedding}_i$ is the projected vector from the hidden state of the last four layers of the XLM-R model. The dimension of $\texttt{xlmr\_embedding}_i$ is 100. We do not update parameters of the XLM-R model during the training process.

Lastly, we make the fourth configuration for SPANSEG, namely SPANSEG (TAG + XLM-R). This configuration aims to combine all syllables, characters, predicted word boundaries, and contextual information for VWS.

$$\texttt{default\_tag\_xlmr\_embedding}_i = \texttt{default\_embedding}_i \oplus \texttt{bies\_tag\_embedding}_i \oplus \texttt{xlmr\_embedding}_i$$ (10)

After we have the input representation for each token $x_i$ of the input sentence $\mathcal{X}$, we feed them into the BiLSTM network to obtain the forward $f_i$ and backward $b_i$ vectors. The forward $f_i$ and backward $b_i$ vectors is used in the SCORER(·) module in subsection 2.3.

### 2.5 Encoder and input representation for CWS

To make a fair comparison to the state-of-the-art model for CWS, we used the same encoder as the work of Tian et al. [27]. Following the work [27], we choose two BERT [4] and ZEN [5] encoders with the base architecture. The BERT and ZEN are two famous
encoders utilizing contextual information for Chinese language processing, in which the ZEN encoder enhances n-gram of characters information. For each character \( x_i \) in the input sentence \( X \), we chunk the hidden state vector of the last layer of BERT or ZEN into two vectors with the same size as the forward \( f_i \) and backward \( b_i \) vectors in the BiLSTM network. Finally, the forward \( f_i \) and backward \( b_i \) vectors are used in the SCORER(∙) module in subsection 2.3. We update the parameters of BERT and ZEN in training progress following the work of Tian et al. [27].

3 Experimental Settings

3.1 Datasets

The largest VWS benchmark dataset\(^4\) is a part of the Vietnamese treebank (VTB) project [21]. We use the same split as the work of Nguyen et al. [18]. The summary of the VTB dataset for the word segmentation task is provided in Table 1.

Table 1. Statistics of the Vietnamese treebank dataset for word segmentation. We provide the number of sentences, characters, syllables, words, character types, syllable types, word types. We also compute the out-of-vocabulary (OOV) rate as the percentage of unseen words in the development and test set.

|          | VTB         |
|----------|-------------|
|          | Train       | Dev  | Test  |
| # sentences | 74,889  | 500  | 2,120 |
| # characters  | 6,779,116 | 55,476 | 307,932 |
| # syllables    | 2,176,398 | 17,429 | 96,560 |
| # words        | 1,722,271 | 13,165 | 66,346 |
| # character types | 155   | 117  | 121  |
| # syllable types | 17,840 | 1,785 | 2,025 |
| # word types   | 41,355   | 2,227 | 3,730 |
| OOV Rate       | 2.2      | 1.6  |      |

For evaluating our SPANSEG on CWS, we employ five benchmark datasets including MSR, PKU, AS, CityU (from SIGHAN 2005 Bakeoff [8]), and CTB6 [31]. We convert traditional Chinese characters in AS and CityU into simplified ones following previous studies [1, 23, 27]. We follow the official training/test data split of MSR, PKU, AS, and CityU, in which we randomly extract 10% of the training dataset for development as many previous works. For CTB6, we the same split as the work of Tian et al. [27]. For pre-processing phase of all CWS dataset in our research, we inherit the process\(^5\) of Tian

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4 The details of VTB dataset are presented at [https://vlsp.org.vn/vlsp2013/eval/ ws-pos](https://vlsp.org.vn/vlsp2013/eval/ws-pos).
5 [https://github.com/SVAIGBA/WMSeg](https://github.com/SVAIGBA/WMSeg)
et al. [27]. The summary of five Chinese benchmark datasets for the word segmentation task is presented in Table 2.

**Table 2.** Statistics of five Chinese benchmark dataset for word segmentation. We provide the number of sentences, characters, words, character types, word types. We also compute the out-of-vocabulary (OOV) rate as the percentage of unseen words in the test set.

|             | MSR   | PKU   | AS    | CityU | CTB6  |
|-------------|-------|-------|-------|-------|-------|
| # sentences | Train | Test  | Train | Test  | Train | Test  | Train | Test  | Train | Dev   | Test  |
|             | 86,918| 3,985 | 19,054| 1,944 | 708,953| 14,429| 53,019| 1,492 | 23,420| 2,079 | 2,798 |
| # characters| Train | Test  | Train | Test  | Train | Test  | Train | Test  | Train | Dev   | Test  |
|             | 4,050,469| 184,355| 1,826,448| 172,733| 8,368,050| 197,681| 2,403,354| 67,689| 1,055,583| 100,316| 134,149|
| # words    | Train | Test  | Train | Test  | Train | Test  | Train | Test  | Train | Dev   | Test  |
|             | 2,368,391| 106,873| 1,109,947| 104,372| 5,449,581| 122,610| 1,455,630| 40,936| 641,368| 59,955 | 81,378|
| # character types | Train | Test  | Train | Test  | Train | Test  | Train | Test  | Train | Dev   | Test  |
|             | 5,140 | 2,838 | 4,675 | 2,918 | 5,948 | 3,378 | 4,006 | 2,642 | 4,235 | 2,648 | 2,917 |
| # word types| Train | Test  | Train | Test  | Train | Test  | Train | Test  | Train | Dev   | Test  |
|             | 88,104| 12,923| 55,303| 13,148| 140,009| 18,757| 68,928| 8,989 | 42,246| 9,811 | 12,278|
| OOV Rate   | -     | 2.7   | -     | 5.8   | -     | 4.3   | -     | 7.2   | -     | 5.4   | 5.6   |

### 3.2 Model Implementation

**The detail of SPANSEG for Vietnamese** For the encoder mentioned in the subsection 2.4, the number of layers of BiLSTM is 3, and the hidden size of BiLSTM is 400. The size of MLPs mentioned in the subsection 2.3 is 500. The dropout rate for embedding, BiLSTM, and MLPs is 0.33. We inherit hyper-parameters from the work of [7]. We trained all models up to 100 with the early stopping strategy with patience epochs of 20. We used AdamW optimizer [11] with the default configuration and learning rate of $10^{-3}$. The batch size for training and evaluating is up to 5000.

**The detail of SPANSEG for Chinese** For the encoder mentioned in the subsection 2.5, we do fine-tuning experiments based on BERT [4] and ZEN [5] encoders. The size of MLPs mentioned in the subsection 2.3 is 500. The dropout rate for BERT and ZEN is 0.1. We trained all models up to 30 with the early stopping strategy with patience epochs of 5. We used AdamW optimizer [11] with the default configuration and learning rate of $10^{-5}$. The batch size for training and evaluating is 16.

### 4 Results and Analysis

#### 4.1 Main Results

For VWS, we also implement the BiLSTM-CRF model with the same backbone and hyper-parameters as our SPANSEG. The overall results are presented in Table 3. On the default configuration, our SPANSEG gives a higher result than BiLSTM-CRF with the F-score of 97.76%. On the configuration with pre-trained XLM-R, our SPANSEG (XLM-R) gives a higher result than BiLSTM-CRF (XLM-R) with the F-score of 97.95%. On the configuration with predicted boundary BIES tag from off-the-shelf toolkit RDRsegmenter [18], the BiLSTM-CRF (TAG) gives a higher result than our SPANSEG (TAG) with the F-score of 98.10%. Finally, on the configuration with a combination of all features, our SPANSEG (TAG+XLM-R) gives a higher result than BiLSTM-CRF.
(TAG+XLM-R) with the F-score of 98.31%, which is also the state-of-the-art performance on VTB. We can see that the contextual information is essential for SPANSEG since SPANSEG models the left and right boundary of a word rather than the between to consecutive tokens.

Table 3. Performance (F-score) comparison between SPANSEG (with different configurations) and previous state-of-the-art models on the test set of VTB dataset.

| Model                           | P    | R    | F    | R_{OOV} |
|---------------------------------|------|------|------|---------|
| vnTokenizer [13]                | 96.98| 97.69| 97.33| -       |
| JVnSegmenter-Maxent [16]       | 96.60| 97.40| 97.00| -       |
| JVnSegmenter-CRFs [16]         | 96.63| 97.49| 97.06| -       |
| DongDu [14]                    | 96.35| 97.46| 96.90| -       |
| UETsegmenter [22]              | 97.51| 98.23| 97.87| -       |
| RDRsegmenter [18]              | 97.46| 98.35| 97.90| -       |
| UUTsegmenter [20]              | 97.81| 98.57| 98.19| -       |
| BiLSTM-CRF                     | 97.42| 97.84| 97.63| 72.47   |
| SPANSEG (BERT)                 | 97.58| 97.94| 97.76| 74.65   |
| BiLSTM-CRF (XLM-R)             | 97.69| 97.99| 97.84| 72.66   |
| SPANSEG (XLM-R)                | 97.75| 98.16| 97.95| 70.01   |
| BiLSTM-CRF (TAG)               | 97.91| 98.28| 98.10| 69.16   |
| SPANSEG (TAG)                  | 97.67| 98.28| 97.97| 65.94   |
| BiLSTM-CRF (TAG+XLM-R)         | 97.94| 98.44| 98.19| 68.87   |
| SPANSEG (TAG+XLM-R)            | **98.21**| 98.41| **98.31**| 72.28   |

For CWS, we presented the performances of our SPANSEG in Table 4. We do not compare our method with previous studies approaching multi-criteria learning since simply the training data is different. Our research focuses on the comparison between our SPANSEG and sequence tagging approaches. Firstly, we can see that our SPANSEG (BERT) achieves higher results than state-of-the-art methods WMS (BERT-CRF) [27] on four datasets including MSR (98.31%), PKU (96.56%), AS (96.62%), and CTB6 (97.26%) except CityU (97.74%). Our SPANSEG (ZEN) do not achieve the stable performance as SPANSEG (BERT). The potential reason for this problem is that both ZEN [5] encoder and our SPANSEG try to model n-gram of Chinese characters causing inconsistency.

Lastly, we test the WMS and our SPANSEG when dealing with the largest benchmark dataset AS on Chinese to discuss the size of the model and the inference time. The statistics are presented in Table 5, showing that our SPANSEG has the smaller size and faster inference time than WMS. The statistics can be explained by WMS [27] containing word-hood memory networks to encode both n-grams and the word-hood information, while our SPANSEG encodes n-grams information via span representation.
Table 4. Performance (F-score) comparison between SPANSEG (BERT and ZEN) and previous state-of-the-art models on the test set of five Chinese benchmark datasets. The symbol [*] denotes the methods learning from data annotated through different segmentation criteria, which means that the labeled training data are different from the rest.

| Model               | MSR  | PKU  | AS   | CITYU | CTB6 |
|---------------------|------|------|------|-------|------|
| Chen et al. [1]     | 97.40| 96.50| -    | -     | 96.00|
| Xu and Sun [30]     | 96.30| 96.10| -    | -     | 95.80|
| Zhang et al. [32]   | 97.70| 95.70| -    | -     | 95.95|
| Chen et al. [2] [*] | 96.04| 71.60| 94.32| 72.64 | 95.55|
| Wang and Xu [29]    | 98.00| 96.50| -    | -     | -    |
| Zhou et al. [34]    | 97.80| 96.00| -    | -     | 96.20|
| Ma et al. [15]      | 98.10| 80.00| 96.10| 78.80 | 96.20|
| Gong et al. [9]     | 97.78| 64.20| 96.15| 69.88 | 96.22|
| Higashiyama et al. [10] | 97.80| -    | -    | -     | 96.40|
| Qiu et al. [23] [*] | 98.05| 78.92| 96.41| 78.91 | 96.91|
| WMSSEG (BERT-CRF) [27] | 98.28| 86.67| 96.51| 86.76 | 97.80|
| WMSSEG (ZEN-CRF) [27] | 98.40| 84.87| 96.53| 85.36 | 97.93|
| METASEG [12] [*]    | 98.50| 96.92| 97.01| 98.20 | 97.89|
| SPANSEG (BERT)      | 98.31| 85.32| 96.56| 85.53 | 97.36|
| SPANSEG (ZEN)       | 98.35| 85.66| 96.35| 83.66 | 97.96|

Table 5. Statistics of model size (MB) and inference time (minute) of WMSSEG [27] and our SPANSEG dealing with the training set of the AS dataset on Chinese. We use the same batch size as the work of Tian et al. [27]. The inference time is done by using Tesla P100-PCIE GPU with memory size of 16,280 MiB via Google Colaboratory.

| Model               | BERT Encoder | ZEN Encoder |
|---------------------|--------------|-------------|
|                     | WMSSEG      | SPANSEG     | WMSSEG | SPANSEG | WMSSEG | SPANSEG |
| Size (MB)            | 704          | 397         | 1,150  | 872 |
| Inference Time (minute) | 28          | 15          | 46     | 32 |

4.2 Analysis

Table 6. Error statistics of the overlapping ambiguity problem involving three consecutive tokens on VWS dataset. The symbols ✓ and ✗ denote predicting correctly and incorrectly, respectively.

| Configuration | BiLSTM-CRF | SPANSEG | XLM-R | TAG | TAG+XLM-R |
|---------------|-----------|---------|-------|-----|-----------|
| ✗             | ✗         | ✗       | 15    | 19  | 7         |
| ✓             | ✗         | 7       | 0     | 4   | 0         |
| ✗             | ✓         | 7       | 0     | 18  | 1         |

To explore how our SPANSEG learns to predict VWS and CWS, we select the statistics of the overlapping ambiguity problem involving three consecutive tokens. The first case
is that given the gold standard tags “B E S”, the prediction is incorrect if its tags “S B E”, and is correct if its tags “B E S”. The second case is that given the gold standard tags “S B E”, the prediction is incorrect if its tags “B E S”, and is correct if its tags “S B E”. Notably, we do not count the case that is not one in two cases we describe. We present the error statistics for Vietnamese in Table 6. We can see that the contextual information from XLM-R helps both BiLSTM-CRF and our SPANSEG in reducing ambiguity. However, according to Table 3, the predicted word boundary information helps both BiLSTM-CRF and our SPANSEG in increasing overall performance but causes the overlapping ambiguity problem. Our SPANSEG (TAG) solves overlapping ambiguity better than BiLSTM-CRF (TAG) when utilizing predicted word boundary information. Lastly, we also provide error statistics for Chinese in Table 7. We can see that overlapping ambiguity is the crucial problem for both WMSEG [27] and our SPANSEG on MSR, PKU, and AS datasets.

Table 7. Error statistics of the overlapping ambiguity problem involving three consecutive tokens on five Chinese benchmark datasets. The symbols ✓ and ✗ denote predicting correctly and incorrectly, respectively.

| WMSEG [27] | SPANSEG | MSR | PKU | AS | CTYU | CTR6 |
|------------|---------|-----|-----|----|------|------|
| ✗          | ✓       | 14  | 13  | 12 | 2    | 3    |
| ✓          | ✗       | 2   | 2   | 2  | 1    | 2    |
| ✗          | ✓       | 2   | 1   | 5  | 0    | 0    |

5 Conclusion

This paper proposes a span labeling approach, namely SPANSEG, for VWS. Straightforwardly, our approach encodes the n-gram information by using span representations. We evaluate our SPANSEG on the Vietnamese treebank dataset for the word segmentation task with the predicted word boundary information and the contextual pre-trained embedding from the XLM-RoBerta model. The experimental results on VWS show that our SPANSEG is better than BiLSTM-CRF when utilizing the predicted word boundary and contextual information with the state-of-the-art F-score of 98.31%. We also evaluate our SPANSEG on five Chinese benchmark datasets to verify our approach. Our SPANSEG achieves competitive or higher F-scores through experimental results, fewer parameters, and faster inference time than the previous state-of-the-art method, WMSEG. Lastly, we also show that overlapping ambiguity is a complex problem for VWS and CWS. Via the error analysis on the Vietnamese treebank dataset, we found that utilizing the predicted word boundary information causes overlapping ambiguity; however, our SPANSEG is better than BiLSTM-CRF in this case. Finally, our SPANSEG will be made available to the open-source community for further research and development.

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