Vietnamese Word Segmentation with SVM: Ambiguity Reduction and Suffix Capture

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Abstract. In this paper, we approach Vietnamese word segmentation as a binary classification by using the Support Vector Machine classifier. We inherit features from prior works such as n-gram of syllables, n-gram of syllable types, and checking conjunction of adjacent syllables in the dictionary. We propose two novel ways to feature extraction, one to reduce the overlap ambiguity and the other to increase the ability to predict unknown words containing suffixes. Different from UETsegmenter and RDRsegmenter, two state-of-the-art Vietnamese word segmentation methods, we do not employ the longest matching algorithm as an initial processing step or any post-processing technique. According to experimental results on benchmark Vietnamese datasets, our proposed method obtained a better F_1 -score than the prior state-of-the-art methods UET-segmenter, and RDRsegmenter.

Keywords: Vietnamese Natural Language Processing \cdot Word Segmentation \cdot POS Tagging.

1 Introduction

Word segmentation is an essential task in Vietnamese natural language processing, which has a significant impact on higher processing levels [1,3,8]. Unlike English, white spaces in Vietnamese written text can function as a syllable separator or a word separator. For example, the Vietnamese string "hiện đại hóa đất nước" (modernize_{hiện_dại_hoá} country_{dất_nước}), which consists of five syllables, is segmented into "hiện_đại_hoá đất_nước". Underscores denote the white spaces which function as syllable separator, and white spaces are used for word separation. Vietnamese word segmentation can be considered as a binary classification problem with two classes: underscore and white-space [12].

Vietnamese is an isolated language and every Vietnamese word has exactly one form [4]. Vietnamese words are constituted by one or more syllables. According to the statistics reported in [4], and [14], about 16% of Vietnamese words are

single-syllable words and 71% are two-syllable words. Single-syllable words account for about 81% of Vietnamese syllables, which means 19% syllables are not meaningful when standing alone. The string "loại hình phạt" (3 syllables) can be segmented as "loại_hình phạt" (type $_{loai}$ _hình penalize $_{phat}$) or "loại hình_phạt" (type $_{loai}$ penalty $_{hinh}$ _phạt). This phenomenon is called "overlap ambiguity involving three consecutive syllables" by the authors in [4]. All of the above have created challenges in Vietnamese word segmentation [13].

We have an observation that solving overlap ambiguity is essential for the Vietnamese word segmentation task. The authors in [4] proposed the ambiguity resolver, which uses a bi-gram language model. Their proposal has slightly improved the Vietnamese word segmentation result. Additionally, the binary classifier for the Vietnamese word segmentation trained by the authors in [14] still causes overlap ambiguity cases. They used rules based on the dictionary and threshold for the classifier in the post-processing phase to handle overlap ambiguities. Experimental results on the benchmark Vietnamese treebank show that the approach of the authors in [14] outperforms the previous state-of-the-art method of the authors in [4]. Therefore, we decided to inspire the idea from the authors in [14] in handling overlap ambiguities. However, we have assumed how the performance of our method changes when using feature templates to reduce overlap ambiguity cases without post-processing.

From a different point of view, the authors in [7] proposed affixes features as a part of the rich feature set in their Vietnamese POS tagging method. Additionally, the authors in [5] utilized potential affixes to improve the performance of unknown words (accuracy of 80.69% on Vietnamese POS tagging task of Vietnamese treebank [12]). In practice, we can not perform part-of-speech (POS) tagging for unknown words if these unknown words can not be constituted by machine annotated word segmentation. Therefore, we decide to study the impact of affixes on the performance of word segmentation. We approach Vietnamese word segmentation with a uni-directional model in which labels are predicted from left to right of a sentence based on a syllable window. Because those labels from the left hand have been predicted, we can utilize information of suffixes to improve Vietnamese word segmentation.

In this paper, we propose a feature-based method using SVM classifier to solve the Vietnamese word segmentation task. Our method considers Vietnamese word segmentation as a binary classification with two classes: underscore and white-space [14], in which a majority of feature templates are inherited from the research of the authors in [8,14]. Two novel feature templates in our method are to reduce ambiguity cases and capture unknown words containing suffixes. Our proposed method obtained better F₁-score than the previous state-of-the-art methods JVnSegmenter [8], vnTokenizer [4], DongDu [6], UETsegmenter [14], and RDRsegmenter [9] measured on the Vietnamese treebank [12] for Vietnamese word segmentation task. Additionally, we used VnMarMoT [10] on the result of our word segmentation method. On the benchmark Vietnamese treebank [12], we achieved result better F₁-score than previous state-of-the-art result [10] on

Vietnamese POS Tagging task when using predicted segmentation instead of gold segmentation.

2 Our Approach

In this section, we first model the word segmentation task. Next, we concentrate on the most critical part of our paper, which is the features extraction phase for the SVM classifier.

2.1 Problem Representation

In the early days of the research on Vietnamese word segmentation, the authors in [1] considered Vietnamese word segmentation as a stochastic transduction problem. They represented the input sentence as an unweighted Finite-State Acceptor (FSA). Recently, the syllable-based and white-space-based representation have been two typical ways of modeling the Vietnamese word segmentation task. The authors in [8] presented the syllable-based representation. In syllable-based representation, three labels B_W, I_W, and O_W are used to indicate syllables that begin a word, syllables inside a word, and syllables outside a word, respectively. Syllables outside a word are punctuation marks such as full stops, commas, question marks, semicolons, and brackets. The authors in [12] presented the white-space-based representation. In this representation, computers are expected to differentiate two types of white space: one appears in between two syllables of the same word, denoted by an underscore; the other separates two different words, denoted by a white space.



Fig. 1: Example of five-syllable window. In this diagram, the string "hiện đại hóa đất nước" (modernize_{hiện đại hoá} country_{đất nước}) consisting of five syllables.

We decided to use white-space-based representation for our Vietnamese word segmentation method because of its clarity. In our approach, we assign underscore or white space labels for each syllable from left to right of the input sentence by utilizing features in the window of five syllables from the current syllable. An example is given in Fig. 1, in which the current syllable is syllable; ("hoá"), and it needs to be classified. The gold label of syllable; is y_i (white space). The five-syllable window of the current syllable contains syllable; ("hiện"), syllable; ("dại"), syllable; ("dát"), and syllable; ("nước"). Additionally, we can utilize previous labels y_{i-1} , y_{i-2} and so on, for feature extraction of the current syllable.

2.2 Feature Extraction

To represent information of each syllable of the input sentence, we use the count vectorization technique. We divide the extracted features into four groups (four-vectors), which are baseline, more-than-four-syllable word, ambiguity reduction, and suffix feature. To obtain only one vector for the current syllable, we concatenated these four vectors.

We would like to introduce some utility operators and functions that we use to present feature templates for Vietnamese word segmentation. Firstly, the f_i symbol represents a function that returns the lowercase-simplified form of syllable_i. Secondly, $f_{i:i+k+1}$ returns the concatenation of lowercase-simplified forms of adjacent syllables from syllable_i to syllable_{i+k} with white-space characters between them. For example given five-syllable window in Fig. 1, the value of f_i symbol is "hoá" and value of $f_{i-1:i+2}$ symbol is "đại hoá đất". Besides, we should take syllable types into account for feature extraction. In our research, we inherit from [14] four syllable types: "lower", "upper", "all upper", and "other", which correspond to the following cases: the syllable has all lowercase letters; the syllable has an upper-case initial letter; the syllable has all upper-case letters; and the syllable is a number or other things. In a similar manner as f_i and $f_{i:i+k+1}$, we use f_i and $f_{i:i+k+1}$ symbols for types of syllables. Lastly, range(f_i , f_i ,

2.2.1 Baseline Features

Table 1: Baseline feature templates for word segmentation.

No.	Templates
1	$\{f_j \text{ for } j \text{ in range}(i-2, i+3)\}$
2	$\{f_{j:j+2} \text{ for } j \text{ in range}(i-2, i+2)\}$
3	$\{(i\text{-}j) \ \textbf{for} \ j \ \textbf{in} \ \textbf{range}(i\text{-}2, i\text{+}2) \ \textbf{if} \ \textbf{inVNDict}(f_{j:j+2})\}$
	$\{(i\text{-}j) \textbf{ for } j \textbf{ in } \textbf{range}(i\text{-}2, i\text{+}1) \textbf{ if } \textbf{inVNDict}(f_{j:j+3})\}$
5	$\{(i\text{-}j) \ \textbf{for} \ j \ \textbf{in} \ \textbf{range}(i\text{-}3, \ i\text{+}1) \ \textbf{if} \ \textbf{inVNDict}(f_{j:j+4})\}$
	$\{t_{j:j+2} \text{ for } j \text{ in } \mathbf{range}(i\text{-}2,i+2) \text{ if } (t_j \neq \text{`LOWER' and } \neg \mathbf{inVNDict}(f_{j:j+2}))\}$
7	$\{t_{j:j+3} \text{ for } j \text{ in } \mathbf{range}(i\text{-}2,i+1) \text{ if } (t_j \neq \text{`LOWER'} \text{ and } \neg \mathbf{inVNDict}(f_{j:j+3}))\}$
8	$(t_i = t_{i+1} = \text{`LOWER'} \text{ and } f_i = f_{i+1})$?
9	$(t_i = t_{i+1} = \text{`UPPER'} \text{ and } \text{isVNFamilyName}(f_i))$?
10	$(t_i = t_{i+1} = \text{`UPPER'} \text{ and isVNMiddleName}(f_i))$?

Table 1 shows all feature templates of the baseline feature group. We have introduced f_i , $f_{i:i+k+1}$, t_i , $t_{i:i+k+1}$ symbols, and range(i, i+k+1) function in the last paragraph of subsection 2.2, for convenience. In Table 1, inVNDict($f_{i:i+k+1}$) returns true if and only if $f_{i:i+k+1}$ is in Vietnamese word dictionary; isVNFamilyName(f_i) returns true if and only if f_i is a Vietnamese family name; isVNMiddleName(f_i) returns true if and only if f_i is a Vietnamese middle

name. Notably, we used the Vietnamese words dictionary⁴, list of Vietnamese family and middle names from research of the authors in [9].

In this baseline feature group, we inherit two ways of extracting feature with five-syllable window for current syllable from [14], which are the lowercase form of syllables (the first and second templates in Table 1) and syllable types (the sixth and seventh templates in Table 1). We also inherit from [14] the following features: full-reduplicative word (the eighth template), Vietnamese family name (the ninth template), Vietnamese middle name (the tenth template). Additionally, we check if a conjunction of two up to four adjacent syllables in a window of seven syllables exists in the dictionary (the third, fourth, and fifth templates). These feature templates are inherited from the research of the authors in [8] except the fifth template.

2.2.2 More-than-four-syllable Word Features

We proposed this feature template based on the research of the authors in [8] to capture the signal of whether the center syllable is a unit of a more-than-four-syllable word. We expect the classifier can predict more-than-four-syllable words although they are rare in Vietnamese.

	oras
No. Templates	

No.	Templates
	$\label{eq:constraint} \boxed{\{(i\text{-}j) \ \textbf{for} \ j \ \textbf{in} \ \mathbf{range}(i\text{-}4, \ i\text{+}1) \ \textbf{if} \ \mathbf{inVNDict}(f_{j:j+5})\}}$
	$\{(i-j) \text{ for } j \text{ in range}(i-5, i+1) \text{ if } inVNDict}(f_{j:j+6})\}$
3	$\{(i-j) \text{ for } j \text{ in } range(i-6, i+1) \text{ if } inVNDict(f_{j:j+7})\}$
	$\{(i-j) \text{ for } j \text{ in } range(i-7, i+1) \text{ if } inVNDict(f_{j:j+8})\}$
5	$\label{eq:constraint} \boxed{ \{(i\text{-}j) \ \textbf{for} \ j \ \textbf{in} \ \textbf{range}(i\text{-}8, \ i\text{+}1) \ \textbf{if} \ \textbf{inVNDict}(f_{j:j+9}) \} }$

We recognize that words are containing up to five to nine syllables (we have shown the distribution of unique words according to lengths in Table 4 of subsection 3.1). Thus, we only take into account the concatenation of adjacent syllables with length ranging from five to nine. Lastly, we check all concatenations in the dictionary (the first, second, third, fourth, and fifth templates in Table 2).

2.2.3 Ambiguity Reduction Features

We assume that some syllables tend not to combine with other syllables in constituting a two-syllable word. For the convenience of presentation, we call the syllable with such a tendency "a separable syllable". We define a separable syllable as a syllable where the number of occurrences a_i of one-syllable words constituted by that syllable is higher than the number of occurrences b_i of more-than-one-syllable words beginning with that syllable.

⁴ https://github.com/datquocnguyen/RDRsegmenter/blob/master/VnVocab

a) syllable i is a separable syllable:	syllable _i	?	syllable _{i+1}	?	syllable _{i+2}	?	syllable _{i+3}	?	syllable _{i+4}
_	current		first_next		second_next		third_next		fourth_next
b) syllable _{i-1:i+2} can be a word:	syllable _{i-1}	_	syllablei	?	syllable _{i+1}	?	syllable _{i+2}	?	syllable _{i+3}
	first_previous	5	current		first_next		second_next		third_next
c) syllable _{i-2:i+2} can be a word:	syllable _{i-2}		syllable _{i-1}		syllable;	9	syllable _{i+1}	9	syllable _{i+2}
c) synable _{1-2:1+2} can be a word.									second next
	second_previou	us j	first_previous	S'	current		first_next		second_next
d) syllable _{i-3:i+2} can be a word:	syllable _{i-3}	_	syllable _{i-2}	_	syllable _{i-1}	_	syllable;	?	syllable _{i+1}
_	third_previous	sec	ond_previous	s fi	rst_previous		current		first_next

Fig. 2: Four situations were used in designing ambiguity reduction feature templates.

However, we do not consider a syllable as a separable syllable if $a_i + b_i$ is not higher than the average of $a_j + b_j$ of all possible separable syllables because of we want to get rid of an uncertain separable syllable. In Vietnamese, there are some conspicuous separable syllables such as "những" (these), "nhưng" (but), "cũng" (also), "đây" (here), and "với" (with). The syllable "văn" (literature) is a non-separable syllable. For example, syllable "văn" usually is the first syllable of many two-syllable words such as "văn_bản" (document), "văn_hoá" (culture), "văn sĩ" (writer), and "văn kiện" (documentation).

Table 3: Feature templates in case of a current syllable is a separable syllable, and the first previous label is SPACE.

No.	Templates
1	$\{\mathbf{inVNDict}(f_{j:j+2}) \ \mathbf{for} \ j \ \mathbf{in} \ \mathbf{range}(i, \ i+4)\}$
2	$\{inVNDict(f_{j:j+3}) \text{ for } j \text{ in } range(i, i+3)\}$
3	$\{\mathbf{inVNDict}(f_{j:j+4}) \ \mathbf{for} \ j \ \mathbf{in} \ \mathbf{range}(i, \ i+2)\}$
4	$\{inVNDict(f_{j:j+5}) \text{ for } j \text{ in range}(i, i+1)\}$

The noticeable difference between our method from research of [14] is that we do not use post-processing for dealing with overlap ambiguities. We proposed a novel way of feature extraction, in which we used boolean variables to record signals of overlap ambiguity cases. In case of the current syllable is a separable syllable and the first-previous label is SPACE (as we can see in Fig. 2), we check the concatenations of lowercase-simplified forms of adjacent syllables in Vietnamese dictionary: $\{f_{i:i+2}, f_{i+1:i+3}, f_{i+2:i+4}, f_{i+3:i+5}\}$ (the first template in Table 3); $\{f_{i:i+3}, f_{i+1:i+4}, f_{i+2:i+5}\}$ (the second template in Table 3), $\{f_{i:i+4}, f_{i+1:i+5}\}$ (the third template in Table 3); $\{f_{i:i+5}\}$ (the fourth template in Table 3. In other words, we check all combinations of every two, three, four, and five adjacent syllables in a five-syllable window (as we can see in Fig. 2) in Vietnamese dictionary. This manipulation records all signals of overlap ambiguity cases, which are considered as features. We perform the same manipulation in case of syllable_{i-1:i+2}, syllable_{i-2:i+2}, and syllable_{i-3:i+2} can be a word (described in Fig. 2).

2.2.4 Suffix Features

In Vietnamese, suffixes are tail-affixes (syllables or one-syllable words) that are placed after a word to create larger words [11]. In our research, we obtain potential suffixes by statistics instead of linguistic knowledge. To obtain potential suffixes, we counted the number of occurrences of the last lower syllables in an out-of-vocabulary three-syllable or four-syllable words. However, we do not consider a syllable as a suffix if its number of occurrences is not higher than the average number of occurrences of all possible suffixes because we want to get rid of uncertain suffixes.

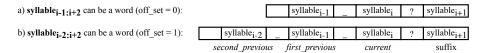


Fig. 3: Diagram of suffix case describes whether we choose "underscore" or "space" for current syllable.

We design suffix features with the expectation that the classifier can predict three-syllable or four-syllable words more accurate in case of next syllable is a suffix (as we can see in Fig. 3). In other words, we want the classifier to pay special attention to the case where the next syllable is a suffix. In case the next syllable is a suffix, we derive current lowercase-simplified forms of conjunction of adjacent syllables f_{i-1-off} set:i+1 (the value of "off_set" follows Fig. 3) as a feature for classifier. The next syllable f_{i+1} is also treated as a feature. Finally, we derive left and right contexts of the current suffix which are f_{i-2-off} set, f_{i-3-off} set, f_{i+2}, and f_{i+3} as features. For example, we assume that in the training set we have the string "xây dựng cơ sở vật chất theo hướng hiện đại hoá, hoàn thành việc xoá lớp học tạm bợ" (build facilities towards modernization, finish eradicating unsettled classrooms) and in the test set there is the string "xây dung nhà dân theo hướng **kiên cố hoá** để phòng chống lụt bão" (build residential houses following solidified methods to protect against storms and floods). We also assume that in this example "kiên cố hoá" (solidified) is out-of-vocabulary. The syllable "hoá" is a suffix in Vietnamese. In this case, the classifier can not predict the word "kiên cổ hoá" in the test set because it is out-of-vocabulary. However, if we leverage the context of this suffix when training, we may predict the word "kiên cổ hoá". Because it has the same the left context, uni-gram "hướng" and bi-gram "theo hướng", as the word "hiện đại hoá" (modernized).

3 Experiment And Result

3.1 Corpora

In our research, we compared the performance of our Vietnamese word segmentation method with published results of other well-known state-of-the-art ap-

Table 4: Distribution of unique words according to number of syllables in a word (%).

Corpus	Number of syllables in a word								
Corpus	1	2	3	4	5-9	>9			
VNWordSeg	38.21	53.59	07.57	00.52	00.11	00.00			
Training dataset									
of VLSP 2013	31.66	58.51	07.33	02.03	00.45	00.02			
POSTag									
Training dataset									
of VLSP 2013	36.49	48.92	11.54	02.63	00.41	00.01			
WordSeg									

proaches. Additionally, we studied the impact of our word segmentation method on the performance of the POS tagging task. For these purposes, we evaluated our methods on the VLSP 2013 WordSeg and VLSP 2013 POSTag corpus⁵, which was released for competition. Both of the two corpora are provided for research or educational purpose by the national project on Vietnamese language and speech processing VLSP⁶. The training dataset of VLSP 2013 WordSeg consists of 75,389 manually word-segmented sentences (approximately 23 words per sentence on average), which is part of Vietnamese treebank corpora [12]. The test dataset of VLSP 2013 WordSeg consists of 2,120 sentences (approximately 31 words per sentence). The training dataset of VLSP 2013 POSTag consists of 26,999 manually word-segmented sentences (about 22.5 words per sentence on average), which was collected from two sources of the national VLSP project [12] and the Vietnam Lexicography Center⁷. The test dataset of VLSP 2013 POSTag consists of 2,120 sentences. Specially, we also experimented with the Vietnamese word segmentation corpus, which was provided by the authors in [8]. In this paper, we temporarily call this corpus "VNWordSeg". VNWordSeg consists of 7,807 manually word-segmented sentences (about 19 words per sentence on average), which was divided into 5 folds for later research [8].

Table 4 shows the distribution of unique words according to the number of syllables in a word in VNWordSeg, Training dataset of VLSP 2013 POSTag, and Training dataset of VLSP 2013 WordSeg. The majority of the three datasets are one- and two- syllables words. More-than-four-syllable words are rare in the three datasets. However, words containing from five to nine syllables account for the notable small ratios (0.11%, 0.45%, and 0.41% in VNWordSeg, Training dataset of VLSP 2013 POSTag, and Training dataset of VLSP 2013 WordSeg, respectively). For more detail, there are 136, 305, and 321 separable syllables (described in subsection 2.2.3) in VNWordSeg, Training dataset of VLSP 2013 POSTag, and Training dataset of VLSP 2013 WordSeg, respectively.

 $^{^{5}}$ http://vlsp.org.vn/vlsp2013/eval/ws-pos

⁶ http://vlsp.org.vn

⁷ https://www.vietlex.com

⁸ https://www.jaist.ac.jp/~hieuxuan/vnwordseg/data

3.2 Experimental Setup

Vietnamese word segmentation has to solve the large-scale classification problem [8]. Therefore, we decided to use the Linear Support Vector Classification (LinearSVC) [15] as a tool for SVM classifier implementation. The LinearSVC on Python 3 programming language was based on LIBLINEAR written on C programming language [2]. By using LinearSVC, we tuned only one parameter, which is the penalty parameter C of the error term in the SVM classifier. We chose the best value of C based on the main evaluation metric F_1 score by using gird search experiments, in which value of C can be 0.001, 0.01, 0.1, 1, 10, or 100.

3.3 Feature Selection Results

Table 5: Our word segmentation results using 5-fold cross-validation with all combinations of features (%). We also re-trained UETsegmenter [14] and RDRsegmenter [9] methods with the same training datasets and testing datasets with the aim of reference.

	Corpus							
				aining Set	Training Set			
Prior Methods/Features	VN	${f WordSeg}$	of	VLSP 2013	of	VLSP 2013		
				POSTag	WordSeg			
	C	F_1 -score	C	$\mathbf{F_{1}\text{-}score}$	C	$\mathbf{F_{1}\text{-}score}$		
UETsegmenter [14]	-	92.0986	-	97.9820	-	98.7954		
RDRsegmenter [9]	-	93.7811	-	98.3069	-	99.0726		
base	1.0	94.4866	0.1	98.5080	0.1	99.2630		
base + long	1.0	94.4858	0.1	98.5371	0.1	99.2762		
base + sep	1.0	94.5686	0.1	98.5647	0.1	99.2963		
base + sfx	1.0	94.4881	0.1	98.5104	0.1	99.2669		
base + long + sep	1.0	94.5686	0.1	98.5848	0.1	99.3024		
base + long + sfx	1.0	94.4910	0.1	98.5434	0.1	99.2811		
base + sep + sfx	1.0	94.5752	0.1	98.5666	0.1	99.2979		
base + long + sep + sfx	1.0	94.5743	0.1	98.5870	0.1	99.3032		

To explore the impacts of feature groups on the performance, we conducted feature selection experiments with all combinations of features on three datasets VNWordSeg, Training dataset of VLSP 2013 POSTag, and Training dataset of VLSP 2013 WordSeg. We denoted "base", "long", "sep", and "sfx" for baseline, more-than-four-syllable word, ambiguity reduction, and suffixes feature groups, respectively.

Table 5 presents feature selection results with all combinations of feature groups. More-than-four-syllable word features have impacts on the Training dataset of VLSP 2013 POSTag (0.02+%) slightly, and Training dataset of VLSP 2013 WordSeg (0.03+%) in comparison with the baseline groups. The ambiguity

reduction features have the most substantial impacts on VNWordSeg (0.08+%). We can also observe that the suffixes features, which have minimal impacts on three corpora (according to our experiments, there are 2, 4, and 3 suffixes on VNWordSeg, Training dataset of VLSP 2013 POSTag, and Training dataset of VLSP 2013 WordSeg, respectively).

3.4 Main Results

Table 6 compares the Vietnamese word segmentation results of our method with results published in previous research works, using the same training and test datasets. Table 6 shows that our method achieved the highest precision, recall, and F_1 -score. Our method obtains 0.29+% higher F_1 -score than RDRsegmenter [9], which is the recent state-of-the-art approach. It should be noted that the results of vnTokenizer [4], JVnSegmenter [8] and DongDu [6] were reported by the authors in [14].

Table 6: Word segmentation results on test dataset of	f VLSP	2013 W	ordSeg	(%)).
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Method	Precision	Recall	$\mathbf{F_{1}\text{-}score}$
vnTokenizer [4]	96.98	97.69	97.33
JVnSegmenter-Maxent [8]	96.60	97.40	97.00
JVnSegmenter-CRFs [8]	96.63	97.49	97.06
DongDu [6]	96.35	97.46	96.90
UETsegmenter [14]	97.51	98.23	97.87
RDRsegmenter [9]	97.46	98.35	97.90
Our WordSeg {all features}	97.81	98.57	98.19

Table 7 shows the Vietnamese word segmentation 5-fold cross-validation results of our method with results published in previous research on the VNWord-Seg corpus. Method of the authors in [17] had been holding the highest F_1 -score on VNWordSeg. However, our method obtains the highest recall score on the VNWordSeg corpus.

Table 7: Word segmentation results using 5-fold cross-validation on VNWordSeg corpus (%).

Method	Precision	Recall	$\overline{\mathbf{F_{1}\text{-}score}}$
Method of the authors in [8]	94.00	94.45	94.23
Method of the authors in [17]	96.71	93.89	95.30
Our WordSeg $\{base + sep + sfx\}$	94.24	94.92	94.58

3.5 Analyses

In order to analyze the word segmentation results in more detail, we computed F_1 score according to number of syllables in a word and three and four syllables words containing suffixes. Additionally, we also re-trained UETsegmenter

[14] with the Vietnamese words dictionary of RDRsegmenter [9] and vice versa. As we can see in Table 8, our method obtains higher F_1 scores than UET-Segmener [14], and RDRsegmenter [9] on one and two syllables words (1 & 2). On three-syllable words (3^a), RDRsegmenter [9] achieves the highest F_1 score. On four-syllable words (4^a), UETsegmenter [14] achieves the highest F_1 score. Notably, UETsegmenter [14] used another Vietnamese words dictionary which contains all 7 three-and-four-syllable unknown words that they predict correctly. Besides, UETSegmener [14] can not predict three syllables words containing suffixes (3^b) when training with the Vietnamese words dictionary of RDRsegmenter [9]. Therefore, we can conclude that RDRsegmenter [9] and our word segmentation method have not solved unknown words containing suffixes badly (3^b). Lastly, different from the result of UETsegmenter [14] on three-syllable words (3^a) and RDRsegmenter [9] on four-syllable words (4^a), our result on three-syllable and words four-syllable words are not left far away by the highest result.

Table 8: Word segmentation results (F_1 score) on **test dataset of VLSP 2013** WordSeg according to number of syllables in a word (%). For convenience, we denote three and four syllables unknown words containing suffixes by 3^b and 4^b (unknown words are detected by checking in the Vietnamese words dictionary of RDRsegmenter [9]). And conversely, we use 3^a and 4^a , indicating three and four syllables words which are not 3^b or 4^b . Notably, we temporarily use **UETws**, **RDRws**, and **UITws** as abbreviations for **UETsegmenter** [14], **RDRsegmenter** [9], and **our word segmentation method using all features**. We also provide proportions of words (%) in parentheses.

Vietnamese	Number of syllables in a word								
Dictionary	Method	1	2	3 ^a	3^{b}	4^{a}	4^{b}	5-9	Total
Resource		(57.75)	(40.42)	(00.74)	(00.13)	(00.68)	(00.05)	(00.22)	
UETws	UETws [14]	98.46	97.97	79.96	89.74	78.62	100.00	21.30	97.87
[14]	RDRws [9]	98.37	97.68	85.41	89.03	74.23	100.00	23.60	97.74
[14]	UITws	98.59	97.96	85.77	89.74	77.26	100.00	34.02	98.01
RDRws	UETws [14]	98.47	97.90	80.40	0.00	79.51	26.32	34.97	97.79
[9]	RDRws [9]	98.57	97.85	86.30	79.19	75.74	0.00	23.60	97.90
[9]	UITws	98.82	98.14	85.23	80.20	78.60	0.00	46.83	98.19

Lastly, Table 9 shows POS tagging performance on the test dataset of VLSP 2013 POSTag with the predicted word segmentation. We re-trained the UETsegmenter tool on VLSP 2013 POSTag. Our Vietnamese word segmentation method has helped VnMarMot [10] of increase in performance on VLSP 2013 POSTag with 0.3+% improvement of F_1 score by comparing with (VnMarMoT [10] using RDRsegmenter [9]) approach.

⁹ https://github.com/phongnt570/UETsegmenter/blob/master/dictionary

Table 9: POS Tagging performance with predicted word segmentation on test dataset of VLSP 2013 POSTag (%).

Method	F_1 -score			
Method	$\mathbf{WordSeg}$	POSTag		
RDRPOSTagger with RDRsegmenter [10]	97.75	93.39		
[(BiLSTM-CRF + CNN-char) with RDRsegmenter [10]]	97.75	93.55		
VnMarMoT with RDRsegmenter [10]	97.75	93.96		
VnMarMoT [10] with Our WordSeg {all features}	98.06	94.27		

4 Conclusion and Future Work

In this paper, we propose a novel feature-based method using the SVM classifier for Vietnamese word segmentation. Overlap ambiguity and unknown words containing suffixes phenomena are real challenges in Vietnamese word segmentation. We prove that our proposed features, ambiguity reduction and suffix-capturing features, help to improve the performance of word segmentation. Experiments on the benchmark Vietnamese datasets show that our method obtains a higher F_1 -score score than state-of-the-art approaches. Finally, according to the experimental results, our Vietnamese word segmentation method has a positive impact on Vietnamese POS tagging. However, the greatest weakness of our ambiguity reduction and suffix features is that we do not care about parts-of-speech information. Therefore, we are planning to refer to the ambiguity solving method of the authors in [16] for our further research. Our code is open-source and available at https://github.com/ngannlt/UITws-v1.

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