A Fast and Accurate Vietnamese Word Segmenter

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Abstract

We propose a novel approach to Vietnamese word segmentation. Our approach is based on the Single Classification Ripple Down Rules methodology (Compton and Jansen, 1990), where rules are stored in an exception structure and new rules are only added to correct segmentation errors given by existing rules. Experimental results on the benchmark Vietnamese treebank show that our approach outperforms previous state-of-the-art approaches JVnSegmenter, vnTokenizer, DongDu and UETsegmenter in terms of both accuracy and performance speed. Our code is open-source and available at: `https://github.com/datquocnguyen/RDRsegmenter`.

Keywords: Vietnamese, Word segmentation, Single classification ripple down rules

1. Introduction

Word segmentation is referred to as an important first step for Vietnamese NLP tasks (Dien et al., 2001; Ha, 2003; Duc Cong et al., 2016). Unlike English, white space is a weak indicator of word boundaries in Vietnamese because when written, it is also used to separate syllables that constitute words. For example, a written text "thuế thu nhập cá nhân" (individual$_{\text{cá\_nhân}}$ income$_{\text{thu\_nhập}}$ tax$_{\text{thuế}}$) consisting of 5 syllables forms a two-word phrase "thuế_thu_nhập cá_nhân."[1] More specifically, about 85% of Vietnamese word types are composed of at least two syllables and 80%+ of syllable types are words by themselves (Thang et al., 2008; Le et al., 2008), thus creating challenges in Vietnamese word segmentation (Nguyen et al., 2012).

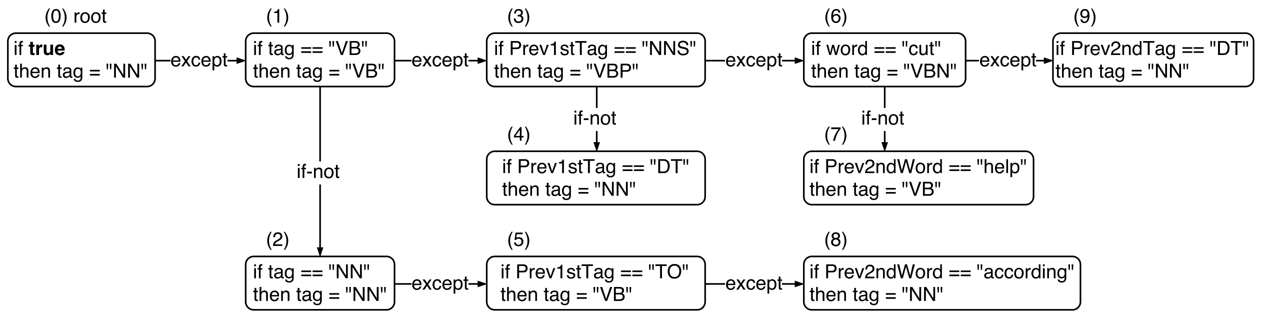
Many approaches are proposed for the Vietnamese word segmentation task. Le et al. (2008), Pham et al. (2009) and Tran et al. (2012) applied the maximum matching strategy (NanYuan and YanBin, 1991) to generate all possible segmentations for each input sentence; then to select the best segmentation, Le et al. (2008) and Tran et al. (2012) used n-gram language models while Pham et al. (2009) employed part-of-speech (POS) information from an external POS tagger. In addition, Nguyen et al. (2006), Dinh and Vu (2006) and Tran et al. (2010) considered this segmentation task as a sequence labeling task, using either a linear-chain CRF, SVM or MaxEnt model to assign each syllable a segmentation tag such as B (Begin of a word) or I (Inside of a word). Another promising approach is joint word segmentation and POS tagging (Takahashi and Yamamoto, 2016; Nguyen et al., 2017b), which assigns a combined segmentation and POS tag to each syllable. Furthermore, Luu and Kazuhide (2012), Liu and Lin (2014) and Nguyen and Le (2016) proposed methods based on pointwise prediction (Neubig and Mori, 2010), where a binary classifier is trained to identify whether or not there is a word boundary between two syllables.

In this paper, we propose a novel method to Vietnamese word segmentation. Our method automatically constructs a Single Classification Ripple Down Rules (*SCRDR*) tree (Compton and Jansen, 1990) to correct wrong segmentations given by a longest matching-based word segmenter. On the benchmark Vietnamese treebank (Nguyen et al., 2009), experimental results show that our method obtains better accuracy and performance speed than the previous state-of-the-art methods JVnSegmenter (Nguyen et al., 2006), vnTokenizer (Le et al., 2008), DongDu (Luu and Kazuhide, 2012) and UETsegmenter (Nguyen and Le, 2016).

2. SCRDR methodology

This section gives a brief introduction of the SCRDR methodology (Compton and Jansen, 1988; Compton and Jansen, 1990; Richards, 2009). A SCRDR tree is a binary tree with only two unique types of edges "except" and "if-not", where every node is associated with a *rule* in a form of "*if* **condition** *then* **conclusion**." To ensure that the tree always produces a conclusion, the rule at its root (default) node has a trivial condition which is always satisfied.

[1]In the traditional underscore-based representation in the Vietnamese word segmentation task (Nguyen et al., 2009), white space is only used to separate words while underscore is used to separate syllables inside a word.



(0) root
if true then tag = "NN"
except
(1)
if tag == "VB" then tag = "VB"
except
(3)
if Prev1stTag == "NNS" then tag = "VBP"
except
(6)
if word == "cut" then tag = "VBN"
except
(9)
if Prev2ndTag == "DT" then tag = "NN"
if-not
(4)
if Prev1stTag == "DT" then tag = "NN"
if-not
(7)
if Prev2ndWord == "help" then tag = "VB"
if-not
(2)
if tag == "NN" then tag = "NN"
except
(5)
if Prev1stTag == "TO" then tag = "VB"
except
(8)
if Prev2ndWord == "according" then tag = "NN"

Figure 1: An illustration of a SCRDR tree for POS tagging. This figure is adapted from Nguyen et al. (2016).

Each case to be evaluated starts at the root node and ripples down as follows: (i) If the case satisfies the condition of a current node's rule, the case is then passed on to the current node's "except" child if this "except" child exists. (ii) Otherwise, if the case does not satisfy the condition, it is then passed on to the current node's "if-not" child. So, the conclusion returned by the tree is the conclusion of the last satisfied rule in the evaluation path to a leaf node.

For example, Figure 1 illustrates a SCRDR tree for POS tagging. Let us consider a concrete case "*as/IN investors/NNS anticipate/VB a/DT recovery/NN*" where "*anticipate*" and "*VB*" is the current considered pair of word and its initial POS tag. Because this case satisfies the conditions of the rules at nodes (0), (1) and (3), it is passed on to node (6) using the "except" edge. The case does not satisfy the condition of the rule at node (6), thus it is passed on to node (7) using the "if-not" edge. Finally, the case does not satisfy the condition of the rule at the leaf node (7). So, the rule at node (3)—the last satisfied rule in the the evaluation path (0)-(1)-(3)-(6)-(7)—concludes "*VBP*" should be the POS tag of the word "*anticipate*" instead of the initial POS tag "*VB*."

To correct a wrong conclusion returned for a given case, a new node containing a new *exception* rule may be attached to the last node in the evaluation path. If the last node's rule is the last satisfied rule given the case, the new node is added as its child with the "except" edge; otherwise, the new node is attached with the "if-not" edge.

SCRDR has been successfully applied in NLP tasks for temporal relation extraction (Pham and Hoffmann, 2006), word lemmatization (Plisson et al., 2008), POS tagging (Xu and Hoffmann, 2010; Nguyen et al., 2011b; Nguyen et al., 2014; Nguyen et al., 2016), named entity recognition (Nguyen and Pham, 2012) and question answering (Nguyen et al., 2011a; Nguyen et al., 2013; Nguyen et al., 2017a). The works by Plisson et al. (2008), Nguyen et al. (2011b), Nguyen et al. (2014) and Nguyen et al. (2016) build the tree automatically, while others manually construct the tree.

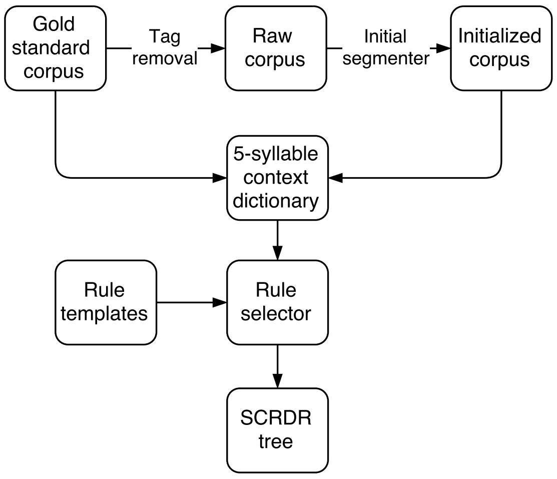


Figure 2: Diagram of our approach.

3. Our approach

This section describes our new error-driven approach to automatically construct a SCRDR tree to correct wrong segmentations produced by an initial word segmenter.

Following Nguyen et al. (2006) and Tran et al. (2010), we also formalize the word segmentation problem as a sequence labeling task. In particular, each syllable is labeled by either segmentation tag B (Begin of a word) or I (Inside of a word). As a result, our approach can be viewed as an extension to word segmentation of the automatic SCRDR approach for POS tagging (Nguyen et al., 2014; Nguyen et al., 2016). Our learning diagram is described in Figure 2.

We start with an underscore-based *gold standard training corpus* consisting of manually word-segmented sentences, e.g. "thuế_thu_nhập cá_nhân" (individual$_{\text{cá\_nhân}}$ income$_{\text{thu\_nhập}}$ tax$_{\text{thuế}}$) and transform this corpus into a BI-formed representation (e.g. "thuế/B thu/I nhập/I cá/B nhân/I"). We then extract syllables to construct the *raw corpus* (which does not have B and I segmentation tags, and would look like "thuế thu nhập cá nhân").

Tuple as key	Value	
(“”, “”, “”, “”, **thuế**, **B**, thu, B, nhập, I)	B	√
(“”, “”, thuế, B, **thu**, **B**, nhập, I, cá, B)	I	X
(thuế, B, thu, B, **nhập**, **I**, cá, B, nhân, I)	I	√
(thu, B, nhập, I, **cá**, **B**, nhân, I, “”, “”)	B	√
(nhập, I, cá, B, **nhân**, **I**, “”, “”, “”, “”)	I	√

Table 1: Examples of key-value pairs in the 5-syllable context dictionary $\mathcal{D}$ when comparing the BI-formed gold standard corpus “thuế/B thu/I nhập/I cá/B nhân/I” and the BI-formed initialized corpus “thuế/B thu/B nhập/I cá/B nhân/I.” Here, “” denotes an empty element in tuples. √ and X represent the correct and incorrect initial segmentations, respectively.

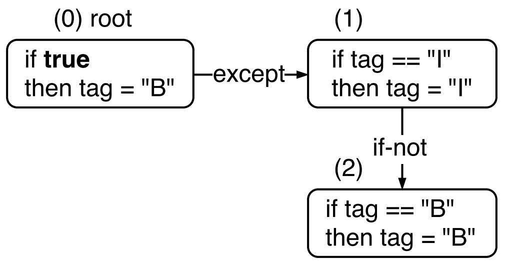


Figure 3: SCRDR tree initialization.

We apply an *initial segmenter* on the input raw corpus to get the output BI-formed *initialized corpus*. For example, given the input raw text “thuế thu nhập cá nhân”, the initial segmenter returns the output BI-formed initialized text “thuế/B thu/B nhập/I cá/B nhân/I.” The initial segmenter in our approach is based on the longest matching strategy (Poowarawan, 1986), using a Vietnamese lexicon from Le et al. (2008).

We then compare the BI-formed gold standard corpus and the BI-formed initialized corpus to generate a *5-syllable context dictionary* $\mathcal{D}$ where each key-value pair consists of a 5-syllable window tuple as key and a gold standard tag as value. Here, each tuple captures a 5-syllable window context of a current syllable and its initial segmentation tag B/I in a format of (Previous-2nd-syllable, Previous-2nd-tag, Previous-1st-syllable, Previous-1st-tag, syllable, tag, Next-1st-syllable, Next-1st-tag, Next-2nd-syllable, Next-2nd-tag) from the initialized corpus,[2] while the gold standard tag is the corresponding segmentation tag of the current syllable in the gold standard corpus. So, a wrong segmentation is when the initial segmentation tag is different from the gold standard tag, as shown in the second row in Table 1.

Based on the 5-syllable context dictionary $\mathcal{D}$, the *rule*

syllable	s_{-2}, s_{-1}, s_0, s_{+1}, s_{+2}
	(s_{-2}, s_0), (s_{-1}, s_0), (s_{-1}, s_{+1}), (s_0, s_{+1}) (s_0, s_{+2})
	(s_{-2}, s_{-1}, s_0), (s_{-1}, s_0, s_{+1}), (s_0, s_{+1}, s_{+2})
tag	t_{-2}, t_{-1}, t_0, t_{+1}, t_{+2}
	(t_{-2}, t_{-1}), (t_{-1}, t_{+1}), (t_{+1}, t_{+2})
syllable & tag	(t_{-1}, s_0), (s_0, t_{+1}), (t_{-1}, s_0, t_{+1}), (t_{-2}, t_{-1}, s_0) (s_0, t_{+1}, t_{+2})

Table 2: Short descriptions of our rule templates. “s” refers to syllable and “t” refers to B/I segmentation label while subscripts -2, -1, 0, 1, 2 denote indices. For example, (s_{-1}, s_{+1}) represents the rule template “IF Previous-1st-syllable == **tuple.Previous-1st-syllable** && Next-1st-syllable == **tuple.Next-1st-syllable** THEN tag = **gold-standard-tag**”, where elements in **bold** are replaced by concrete values from tuple and gold tag pairs in the 5-syllable context dictionary $\mathcal{D}$. Given (s_{-1}, s_{+1}) and the second row in Table 1, we have a concrete rule “IF Previous-1st-syllable == **thuế** && Next-1st-syllable == **nhập** THEN tag = **I**.”

selector selects the most suitable rules to construct the *SCRDR tree*. Concrete rules are generated based on *rule templates*. Table 2 presents short descriptions of the rule templates. The SCRDR tree is initialized with a default rule—the rule at the root node—and its two exception rules, as shown in Figure 3. Our learning process to automatically add new exception rules to the SCRDR tree is as follows:

- Let us consider a node N in the tree. We define a subset $\mathcal{T}_{\mathsf{N}}$ of the context dictionary $\mathcal{D}$ such that the rule at N is the last satisfied rule in the evaluation path for every tuple in $\mathcal{T}_{\mathsf{N}}$ but N returns a wrong segmentation tag. For example, given node (2) in Figure 3 and $\mathcal{D}$ in Table 1, $\mathcal{T}_{(2)}$ would contain a pair of the tuple (“”, “”, thuế, B, **thu**, **B**, nhập, I cá, B) and gold segmentation tag **I** from the second row in Table 1. A new node containing a new exception rule must be added to the current tree to correct the errors given by N.[3]

- The new exception rule is selected from all concrete rules, in which these concrete rules are generated by applying the rule templates to all tuples in $\mathcal{T}_{\mathsf{N}}$. The selected rule must satisfy following constraints: (1) If N is not one of the first three nodes in Figure 3, then the selected rule's condition must not be satisfied by every tuple for which N already returns a correct segmentation tag. (2) The selected rule is associated with the highest

[2]Syllables in each tuple are all converted into a lowercase form.

[3]See the second last paragraph in Section 2. for how to attach a new node to an existing SCRDR tree.

value of the subtraction $a - b$. Here a is the number of tuples in $\mathcal{T}_N$ in which each tuple not only satisfies the rule's condition but also gets a correct segmentation tag given by the rule's conclusion, while b is the number of tuples in $\mathcal{T}_N$ in which each tuple also satisfies the rule's condition but gets a wrong segmentation tag given by the rule's conclusion. (3) The value $a - b$ must be not smaller than a given threshold.

- This process is repeated until at any node it cannot select a new exception rule satisfying constraints above.

With the learned SCRDR tree, we perform word segmentation on unsegmented text as follows: The initial segmenter takes the input unsegmented text to generate a BI-formed initialized text. Next, by sliding a 5-syllable window from left to right, a tuple is generated for each syllable in the initialized text; then the learned SCRDR tree takes the input tuple to return a final segmentation tag to the corresponding syllable. Finally, the output of this labeling process is converted to the traditional underscore-based representation.

4. Experiments

4.1. Experimental setup

Following Nguyen and Le (2016), we conduct experiments and compare the performance of our approach—which we call RDRsegmenter—with published results of other state-of-the-art approaches on the benchmark Vietnamese treebank (Nguyen et al., 2009). The training set consists of 75k manually word-segmented sentences (about 23 words per sentence in average).[4] The test set consists of 2120 sentences (about 31 words per sentence) in 10 files from *800001.seg* to *800010.seg*.[5] We use F_1 score as the main evaluation metric to measure the performance of word segmentation.

Note that to determine the threshold in our RDRsegmenter, we sampled a development set of 5k sentences from the full training set and used the remaining 70k sentences for training. We found an optimal threshold value at 2 producing the highest F_1 score on the development set. Then we learned a SCRDR tree from the full training set with the optimal threshold, resulting in 1447 rules in total.

[4]The data, officially released in 2013, is provided for research or educational purpose by the national project VLSP on Vietnamese language and speech processing.

[5]The test set was originally released for evaluation in the POS tagging shared task at the VLSP 2013 workshop.

Approach	Precision	Recall	F_1
vnTokenizer	96.98	97.69	97.33
JVnSegmenter-Maxent	96.60	97.40	97.00
JVnSegmenter-CRFs	96.63	97.49	97.06
DongDu	96.35	97.46	96.90
UETsegmenter	**97.51**	98.23	97.87
Our **RDRsegmenter**	97.46	**98.35**	**97.90**

Table 3: Vietnamese word segmentation results (in %). The results of vnTokenizer, JVnSegmenter and DongDu are reported in Nguyen and Le (2016).

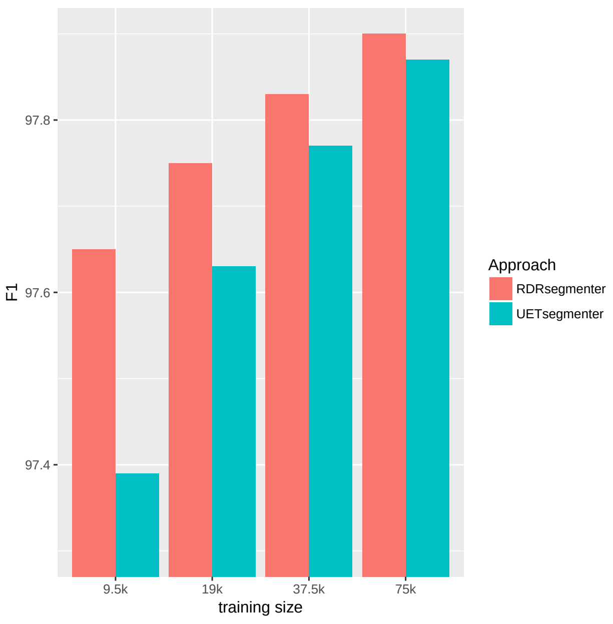


Figure 4: F_1 scores (in %) when varying the training size at 9.5k, 19k, 37.5k and full 75k sentences.

4.2. Main results

Table 3 compares the Vietnamese word segmentation results of our RDRsegmenter with results reported in prior work, using the same experimental setup.

Table 3 shows that RDRsegmenter obtains the highest F_1 score. In particular, RDRSegmenter obtains 0.5+% higher F_1 than vnTokenizer (Le et al., 2008) though both approaches use the same lexicon for initial segmentation. In terms of a sequence labeling task, RDRSegmenter outperforms JVnSegmenter (Nguyen et al., 2006) with 0.8+% improvement. Compared with the pointwise prediction approaches DongDu (Luu and Kazuhide, 2012) and UETsegmenter (Nguyen and Le, 2016), RDRsegmenter does significantly better than DongDu and somewhat better than UETsegmenter. In Figure 4, we show F_1 scores of RDRsegmenter and UETsegmenter at different training sizes, showing that RDRsegmenter clearly improves performance in a smaller dataset scenario.

It is worth noting that on a personal computer of Intel Core i7 2.2 GHz, our RDRsegmenter processes at a speed of 62k words per second in a single threaded implementation, which is 1.3 times faster than UETsegmenter.[6] In addition, Nguyen and Le (2016) showed that UETsegmenter is faster than vnTokenizer, JVnSegmenter and DongDu.[7] So RDRsegmenter is also faster than vnTokenizer, JVnSegmenter and DongDu.

5. Conclusion

In this paper, we have proposed a new error-driven method to automatically construct a Single Classification Ripple Down Rules tree for Vietnamese word segmentation. Experiments on the benchmark Vietnamese treebank show that our method obtains better accuracy and speed than previous approaches. Our code is available at: `https://github.com/datquocnguyen/RDRsegmenter`.
Note that excluding the language-specific initial segmenter, our method generally can be viewed as a language independent approach. Here, a Vietnamese syllable is analogous to a character in other languages such as Chinese and Japanese. So we will adapt our method to those languages in future work.

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[6]We repeated the segmentation process on the test set 100 times, and then computed the averaged speed. Note that model loading time was not taken into account, in which RDRsegmenter took 50 miniseconds while UETsegmenter took 10 seconds.

[7]Evaluated on a computer of Intel Core i5-3337U 1.80GHz, Nguyen and Le (2016) showed that JVnSegmenter, vnTokenizer, DongDu and UETsegmenter obtained performance speeds at 1k, 5k, 17k and 33k words per second, respectively. All of them are implemented in Java except DongDu which is in C++. Our RDRsegmenter is also implemented in Java.

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