# LSTM Easy-first Dependency Parsing with Pre-trained Word Embeddings and Character-level Word Embeddings in Vietnamese

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Abstract—In Vietnamese dependency parsing, several methods have been proposed. Dependency parser which uses deep neural network model has been reported that achieved state-of-theart results. In this paper, we proposed a new method which applies LSTM easy-first dependency parsing with pre-trained word embeddings and character-level word embeddings. Our method achieves an accuracy of 80.91% of unlabeled attachment score and 72.98% of labeled attachment score on the Vietnamese Dependency Treebank (VnDT).

#### I. Introduction

Over the last decade, there has been considerable interest in dependency parsing which generates grammatical relations between two words in the sentence. For instance, in the CoNLL 2007 shared task [1], each participating team tested their system in thirteen different languages. In 2014, the SPMRL shared task [2] was held to evaluate dependency parsing on nine morphologically rich languages.

Since CoNLL-X [3], there are two dominant dependency parsing models which are transition-based parsing and graph-based parsing. These names are first mentioned in [4]. Both two models are data-driven parsers which are learned from an annotated corpus and have shorter development time than rule-based system [4].

The last few years has witnessed a rapid development of neural-network methods. Many works showed that neural-network methods can achieve state-of-the-art results on different tasks of Natural Language Processing such as Named Entity Recognition (NER) [5], Machine Translation [6], [8]. In dependency parsing, there are studies using deep neural-networks to encode features without hand-crafted definition [9], [10], [11] and [12].

In Vietnamese, there are several researchers working on dependency parsing. Nguyen et al. [14] and Nguyen et al. [15] automatically convert a constituent treebank to a dependency treebank. Nguyen and Nguyen [16] used supertags features and Vu-Manh et al. [17] used word embeddings on the transition-based parser. Nguyen et al [18] used BiLSTM encoder to generate word representation vectors and obtained a state-of-the-art result on Vietnamese Dependency Treebank (VnDT) [15].

We found that [18] did not incorporate pre-trained word embeddings in the vector representation of words. Although this feature can improve the accuracy of dependency parsing because of its rich context information [11] [12] and [17].

Beside the pre-trained word embeddings, character-level word embeddings has been found useful for NER [5] or dependency parsing [13]. It represents words by combining their character embeddings so it does not depend on the word-based lookup dictionary. However, no previous study has investigated the impact of character-level word embeddings on dependency parsing for Vietnamese.

The parser we used is a variant of transition-based parser called tree LSTM easy-first [11] which is fast speed and similar to human annotation [19]. The tree LSTM easy-first is reported as the state-of-the-art parser for Chinese [11]. Because Chinese syntax structures is very similar to Vietnamese, we believe that this parser can give a good accuracy for Vietnamese dependency parsing.

In this paper, we focused on applying two word representation features on Vietnamese dependency parsing, which are pre-trained word embeddings and character-level word embeddings. Although Vu-Manh et al. [17] have already used pre-trained word embeddings for Vietnamese dependency parsing. Their paper used MaltParser [7] which is incomparison with other neural network parsers like Tree LSTM easy-first parser. Our paper is the first study which applied character-level word embedding to dependency parsing on VnDT as well as the first time easy-first parser was utilized with character-level word embeddings in either Vietnamese or English. Our method makes an improvement in parsing accuracy (0.79% UAS and 1.51% LAS) and achieves state-of-the-art performance on Vietnamese dependency parsing (80.91% UAS and 72.98% LAS).

The remainder of the paper is organized as follows: Section 2 describes easy-first parsing algorithm used in this paper. Word representation features are represented in Section 3. We evaluate the results of the methods in Section 4 and draw the conclusion and future work in Section 5.

#### II. EASY-FIRST PARSING

Easy-first parsing is a type of syntactic parsing algorithm which is a variant of transition-based parsing. This method is first proposed by Goldberg and Elhadad [19]. Several studies were proposed for improving the accuracy of this method such as Ma et al [20] using beam search strategy to effectively explore the search space of parsing process. Another method was proposed by Kiperwasser & Goldberg [11] which uses deep neural network to learn model's parameters, entire dependency

tree was encoded by LSTMs and was applied as deep features for effective learning.

#### A. The parsing process

In the parsing process, there are a list of partial structures called *pending* which is the main data-structure of the parser, the parser will stop if the pending have only one element in it. A partial structure can be a token or a dependency structure which is built from the previous parse steps. At each step of the parsing process, the algorithm generates all possible actions. These actions are ranked by a scoring function. The highest scoring action is chosen to applied to the *pending*. There are two types of actions which are **LEFT** and **RIGHT**. Let  $p_1, p_2, p_3..., p_n$ be the elements of pending. The action LEFT(i,r) adds the dependency edge  $(p_{i+1}, p_i)$  with the relation r and remove  $p_i$  from the *pending*, while the action **RIGHT**(i,r) adds the dependency edge  $(p_i, p_{i+1})$  with the relation r and remove  $p_{i+1}$  from the *pending*. Figure 1 demonstrates how to parse the sentence "Tôi có một con mèo" using easy-first algorithm. Let Arcs be the list of dependency edges in parsing process. At step 1, action **LEFT(4, nmod)** is chosen, edge (mèo, con, nmod) is added to Arcs. At step 2, action LEFT(3,det) is ranked highest so the edge (mèo, một, det) is added to Arcs. At the third step, the chosen action is **RIGHT**(2, dobj) and the edge (có, mèo, dobj) is added to Arcs. At the final step, action **LEFT**(1,nsubj) was chosen and produce the output dependency structure.

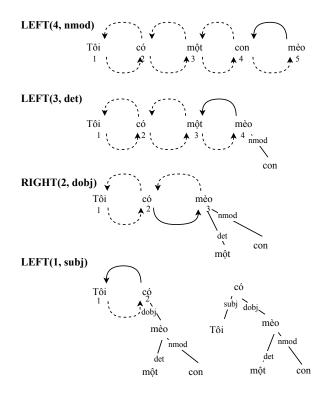


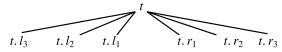
Figure 1. The sentence "Tôi có một con mèo"is parsed using easy-first algorithm.

At one step of the parsing process, for a *pending* with n elements, there are n-1 attachment points where actions can be applied to. For each attachment point, there will be 2\*R

actions where R is the number of total dependency relations. Therefore, there are 2R(n-1) actions can be chosen at each step so there are more than one valid action sequences leads to the dependency structure of the sentence. That gives more examples to the learning algorithm.

#### B. The LSTMs Easy-first algorithm

In this paper, we used an extended version of the easy-first algorithm [11], which employs LSTMs to represent a dependency structure as a vector and used multilayer perceptron (MLP) to score the parse actions. The dependency structure can be described as follows [11]:



- The dependency structure is a tree with root node t and t is associated with the head word  $w_t$ .
- For every child of t, if the head word of this child is on the left of w<sub>t</sub> according to their positions in the sentence, this child will be the left child, otherwise, this child will be the right child. The nearest child of the head node is indexed as 1 while the left most or right most child has the largest index.
- Let enc(t) be the vector representing dependency structure t. All of left children  $t.l_1...t.l_{k_l}$  are fed to an LSTM called  $LSTM_L$ , all of right children  $t.r_1...t.r_{k_r}$  are fed to an LSTM called  $LSTM_R$ . The first input of LSTM is the vector representation of the head word  $v_i(t)$ , the last input is the vector representation of left-most child or right-most child. The output of  $LSTM_L$  and  $LSTM_R$  are concatenated  $e_l(t) \circ e_r(t)$ . The dimension of the concatenated vector is reduced using linear transformation, followed by a non-linear activate function. The result vector represents dependency structure.

$$enc(t) = g(W^e.(e_l(t) \circ e_r(t) \circ l(t)) + b^e) \tag{1}$$

$$e_l(t) = LSTM_L(v_i(t), enc(t.l1)...enc(t.l_{k_l}))$$
 (2)

$$e_r(t) = LSTM_R(v_i(t), enc(t.r1)...enc(t.r_{k_r}))$$
 (3)

• The process runs recursively and stop at leaf nodes where  $v_i(leaf)$  is the vector representation of word i in sentence. Which will be described in the Section 3. Figure 2 shows the network of dependency structure of the sentence "Tôi có một con mèo".

$$enc(leaf) = g(W^e.(e_l(leaf) \circ e_r(leaf)) + b^e)$$
 (4)

$$e_l(leaf) = LSTM_L(v_i(leaf))$$
 (5)

$$e_r(leaf) = LSTM_R(v_i(leaf))$$
 (6)

Pseudocode for Tree LSTM Easy-first parsing is described in Algorithm 1 [11]. The parsing algorithm is similar to the original [19] but with some differences:

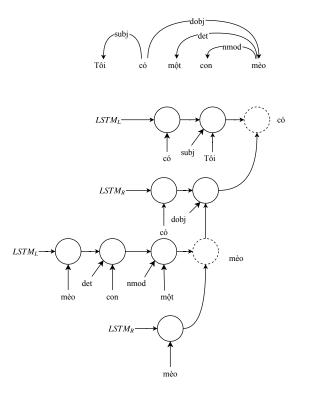


Figure 2. Networks of dependency structure of sentence "Tôi có một con mèo". The solid circle is is a representation of the hidden state of LSTM networks, the dotted circle is a representation of the function of concatenating two LSTM networks. The inputs of LSTM hidden state include previously hidden state, vector representation of the child node and a vector represented for dependency relation between child node and head node.

- When the action was applied to pending, the vector of modifier will be appended to the LSTMs of the head  $(LSTM_L \text{ or } LSTM_R)$ .
- There are two scoring functions which are modeled as multi-layer perceptrons (MLP) Score<sub>U</sub> and Score<sub>R</sub>. Score<sub>U</sub> scores an action based on its head and modifier while Score<sub>R</sub> scores an action based on head, modifier and the relation of this action. Scoring functions are using information of partial structure at the attachment point as well as its neighbors. The score of an action a with relation r in Score<sub>U</sub> or Score<sub>R</sub> is an element of the output layer of MLP. Size of the output layer of MLP<sub>U</sub> is 2 while MLP<sub>R</sub> is 2R where R is the total number of dependency relations:

$$Score_U(i, a) = MLP_U(x_i)[a]$$
 (7)

$$Score_L(i, a, r) = MLP_L(x_i)[r, a]$$
 (8)

$$x_i = p_{i-2} \circ \dots \circ p_{i+3} \tag{9}$$

 The score of an action is the sum of Score<sub>U</sub> result and Score<sub>R</sub> result:

$$Score(i, a, r) = Score_U(i, a) + Score_L(i, a, r)$$
 (10)

**Algorithm 1:** LSTM Easy-first dependency parsing algorithm

```
Input: a sentence= w_1...w_n, parameter w
   Output: sentence's dependency arcs
 1 \ Arcs \leftarrow \{\};
  for i in \{0..len(sentence)-1\} do
       pending[i].w = w_i;
 3
       pending[i].LSTM_L.init().append(w_i);
       pending[i].LSTM_R.init().append(w_i);
5
 6 end
   while len(pending) > 1 do
7
       actions \leftarrow \{\};
8
       for i in 0...len(pending) - 1 do
 9
           for r in Rels do
10
              for a in [LEFT, RIGHT] do
11
12
                 actions.append(i, a, r);
               end
13
          end
14
15
       end
        (i, a, r) = \operatorname{argmax}_{act \in actions} Score(act, w);
16
       if a == LEFT then
17
           Arcs.append(p_{i+1}, p_i, r);
18
           pending[i+1].LSTM_L.append(p_i, r);
19
           pending.remove(p_i);
20
       else if a == RIGHT then
21
           Arcs.append(p_i, p_{i+1}, r);
22
           pending[i].LSTM_R.append(p_{i+1}, r);
23
           pending.remove(p_{i+1});
24
25 end
26 return Arcs
```

#### C. The training process

For parameters update, a hinge loss function with margin 1 is used [11]:

$$\max\{0, 1 - \max_{i, a, r \in G} Score(i, a, r) + \max_{i, a, r \in A \setminus G} Score(i, a, r)\}$$

$$(11)$$

Pseudocode of training phrase is described in Algorithm 2 [11]. Where A is set of valid actions and G is set of all possible actions at the current step. For validation checking, the parser uses Oracle which is a set of defined rules based on gold dependency structure of a sentence. The Oracle used in Tree LSTM Easy-first is  $dynamic\ oracle\ [22]$ . If an invalid action was chosen, in the next step, the parser will treat an action which leads to best acceptable dependency structure as the valid action. The rules used in Tree LSTM Easy-first parser are defined as follows:

- *Head, modifier and relation* of action must be in the gold dependency structure of the sentence.
- *Modifer* of the action must be complete which means that all children of the modifier have been explored at the previous step.

• If the gold head of modifier is removed from pending, the action then is valid if the dependency relation of modifier is the same with the relation in the gold dependency structure despite that the head is different.

**Algorithm 2:** LSTM Easy-first training algorithm for dependency parsing

```
Input: a sentence= w_1...w_n, parameter w
   Output: sentence's dependency arcs
 1 for i in 1...n do
       errors \leftarrow [];
 2
       for sentence in corpus do
 3
           for i in 0..len(sentence)-1 do
 4
                pending[i].w = w_i;
 5
                pending[i].LSTM_L.init().append(w_i);
 7
               pending[i].LSTM_R.init().append(w_i);
            end
 8
            while len(pending) > 1 do
                actions \leftarrow \{\};
10
                for i in \{0...len(pending) - 1\} do
11
                    for r in Rels do
12
                        for a in [LEFT, RIGHT] do
13
                            if is_valid(i, a, r) then
14
                                 G.append(i, a, r);
15
                             else
16
17
                                 A.append(i, a, r);
                        end
18
                    end
19
                end
20
                 i, a, r, s = \operatorname{argmax}_{act \in A} Score(act, w);
21
                i', a', r', s' = \operatorname{argmax}_{act \in G} Score(act, w);
22
                if s > 1 + s' then
23
                    i_{best}, a_{best}, r_{best} = i, a, r;
24
25
                else
                    i_{best}, a_{best}, r_{best} = i', a', r';
26
                    errors.append(1 - s + s');
27
                apply\_action(i_{best}, a_{best}, r_{best});
28
                if len(errors) > 50 then
29
                    update;
30
                    errors \leftarrow [];
31
                end
32
           end
33
       end
34
       if len(errors) > 0 then
35
           update;
36
       end
37
38 end
```

When the loss of parse step is greater than zero, this step is count as one error. If the total errors are greater than 50, all parameters are updated using Adam Optimizer.

#### III. WORDS REPRESENTATION

#### A. Representing words using word form and POS tag

The baseline approach of representing words as vectors is used information of word form and POS tag which are embeddings and jointly trained with the networks. Word-form and POS-tag vectors are concatenated and transformed to  $v_i'$  via a linear transformation followed by a non-linear activation function. Kiperwasser and Goldberg [11] used Bidirectional LSTMs to incorporate the context information of words in a sentence. For the word  $i^{th}$  in sentence, network  $LSTM_F$  runs from the begining of the sentence to word  $i^{th}$  while  $LSTM_B$  runs in reverse order. Outputs of two networks are concatenated to produce vector  $v_i$  representing word i. The figure 3 illustrates how a word is represented using BiLSTMs.

$$v_i' = g(W^v.(w_i \circ p_i) + b^v)$$
 (12)

$$f_i = LSTM_F(v_1', v_2', ...v_i')$$
 (13)

$$b_i = LSTM_B(v'_n, v'_{n-1}, ..., v'_i)$$
(14)

$$v_i = (f_i \circ b_i) \tag{15}$$

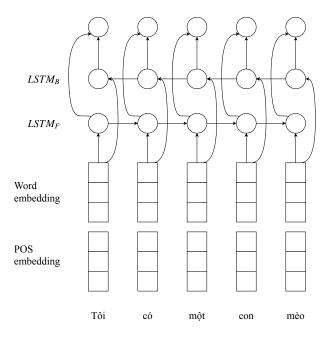


Figure 3. Words's vector representation using BiLSTMs

# B. Pretrained word embeddings

A common way to incorporate context information of words is using word representations learned from unannotated corpora. In pre-trained word embeddings, each word in vocabulary is associated with a high dimensional real-valued vector which is learned from neural network model. Vocabulary can be considered as points in vector space and words which are similar in meaning are closer in vector space. The representation can capture syntactic and semantic

relationships between words. To investigate the effect of pretrained word embedding, we used two existing pre-trained word embedding models on Vietnamese (skip-gram [23] and subwords [24]) and used them as additional information along with word form embedding and POS tag embedding:

$$v_i' = g(W^v.(w_i \circ p_i \circ extn_i) + b^v) \tag{16}$$

#### C. Character-level word embedding

The main contribution of this study is using character-level word embeddings as additional information of word representation in the easy-first algorithm and applied it on VnDT. Unlike pre-trained word embeddings, character-level word embeddings can deal with out-of-vocabulary (OOV) problem because unknown words can be generated using their component characters. As characters are shared across words, character embedding combination still presents semantic information of words like pre-trained words embeddings.

We used the same network structure as in [13]. Character embeddings of words is fed to the bidirectional LSTMs which include two LSTMs called **Forward** and **Backward**. The input of the forward network is the character embeddings of the characters from the beginning to the end of the word while inputs of the backward network is characters of the word in the reverse order. The output of the two networks is concatenated to one vector which represents information of words. Character embeddings are learned jointly with the training process. The figure 4 shows an example of using character embeddings for representing a word.

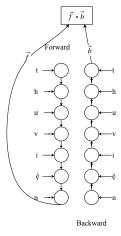


Figure 4. The word "thư viện" is represented by character embedding with  $\operatorname{BiLSTM}$ 

The hyper-parameters of the networks used for training character embeddings are detailed in Table I.

Table I
HYPER-PARAMETERS USED FOR CHARACTER EMBEDDING NETWORKS

Char embedding dimension	100
BI-LSTM Layers	2
BI-LSTM Dimensions	100 + 100

#### IV. RESULTS AND DISCUSSION

In our experiments, we use the VnDT [15] which has 10,200 dependency structures. For comparison purposes, we split the data in the same way as [18], last 1020 sentences for testing (POS and automatic POS tagging) and the rest for training. The POS tagging tool we used is VnTagger <sup>1</sup>, its accuracy is 94.4% on our test set. The performance is measured with unlabeled attachment score (**UAS**) and labeled attachment score (**LAS**).

We used two pre-trained word embeddings datasets which were trained with two different models on Vietnamese: skipgram<sup>2</sup> and subwords<sup>3</sup>. Information on these two datasets is described in table II. Coverage column shows the percentage of words in the VnDT treebank which appears in pre-trained word embeddings.

Because of the difference between word tokenization methods, many words in VnDT do not exist in pre-trained word embeddings, this is the reason for the low percentage of vocabulary coverage of both datasets. If a word cannot be found in pre-trained word embeddings, this word will be treated as an unknown word and represented by the *unknown* vector. This unknown vector do not carry much useful context information of words that leads to poor performance in parsing.

Table II Information of two Pre-trained word embeddings

	Model	Dim	Vocabulary	Coverage	
	Subword	300	200,000	20%	
ĺ	Skip-gram	300	100,000	67%	

For fully exploration of pre-trained word embeddings and character-level word embeddings, we design our experiments as follows:

- Word embeddings + POS tag embeddings.
- Word embeddings + POS tag embeddings + Character embeddings.
- Word embeddings + POS tag embeddings + Pre-trained word embeddings.
- Word embeddings + POS tag embeddings + Character embeddings + Pre-trained word embeddings.

We also compare the result of the easy-first algorithm with the current state-of-the-art parsers proposed by Kiperwasser and Goldberg [12] which uses BiLSTM encoder to represent words in the sentence, the word vector is used as features in transition-based parser (BistT) and graph-based parser (BistG) [11] <sup>4</sup>. The implementation of Tree LSTM easy-first is provided at https://github.com/elikip/htparser. The results are demonstrated in Table III. In the table, the results of BistT and BistG are taken from [19] because this is reported as the state-of-the-art parser on VnDT.

<sup>&</sup>lt;sup>1</sup>https://github.com/scorpion1206/VnTagger

<sup>&</sup>lt;sup>2</sup>https://github.com/pth1993/NNVLP

<sup>&</sup>lt;sup>3</sup>https://github.com/facebookresearch/fastText

<sup>&</sup>lt;sup>4</sup>https://github.com/elikip/bist-parser

Table III Vietnamese dependency parsing results on different parsers

Model	Gold POS Tag		Auto POS Tag	
Woder	UAS%	LAS%	UAS%	LAS%
BistT	79.33	72.53	76.56	68.22
BistG	79.39	73.17	76.28	68.40
Easy-first (Word + POS)	79.29	71.44	77.51	68.27
+ Char	80.58	72.95	78.01	68.82
+ Skip-gram	79.69	72.23	76.91	67.77
+ Char	80.91	72.98	78.26	69.04
+ Sub-word	79.50	71.94	77.16	67.96
+ Char	80.56	72.37	78.13	68.56

Using character-level word embeddings as additional information improve the accuracy of easy-first parser (0.79% UAS and 1.51% LAS). Replacing word embedding with character-level word embedding shows slight increase in the performance of the parser (0.39% UAS and 0.09% LAS). These results show that using character-level word embeddings can improve the accuracy of parsing.

Using both skip-gram and subword pre-trained word embeddings increase the accuracy of the parser. Despite that the difference of vocabulary coverage between skip-gram and subword is high (40%), the accuracy of the parser using skip-gram is only higher than subword 0.16%. We found that in our test data, the different of token coverage (percentage of token in test data which appears in pre-trained word embeddings) between two datasets is only 5% (75.39% for skip-gram and 70.95% for subword).

Among all features we applied to Tree LSTM easy-first parser, the combination of *word embedding* + *POS-tag embedding* + *character-level word embedding* + *pre-trained word embedding* gives the best parse result (80.91% UAS and 72.98% LAS). Our model has outperformed the BistG parser and obtained state-of-the-art performance on the VnDT.

## V. CONCLUSION

We have demonstrated the effectiveness of pre-train word embedding and character-level word embedding as features for Vietnamese easy-first dependency parsing.

In future work, we would like to train character-level word embedding on larger corpora and use it as pre-trained features like pre-trained word embeddings.

### VI. ACKNOWLEDGEMENT

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