An Empirical Study of Using Pre-trained BERT Models for Vietnamese Relation Extraction Task at VLSP 2020

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Abstract
In this paper, we present an empirical study of using pre-trained BERT models for relation extraction task at VLSP 2020 Evaluation Campaign. We applied two state-of-the-art BERT-based models: R-BERT and BERT model with entity starts. For each model, we compared two pre-trained BERT models: FPTAI/vibert and NlpHUST/vibert4news. We found that NlpHUST/vibert4news model significantly outperforms FPTAI/vibert for Vietnamese relation extraction task. Finally, we proposed a simple ensemble model which combines R-BERT and BERT with entity starts. Our proposed ensemble model slightly improved against two single models on the development data provided by the task organizers.

1 Introduction
Relation extraction task is to extract entity mention pairs from a sentence and determine relation types between them. Relation extraction systems can be applied in question answering (Xu et al., 2016), detecting contradiction (Pham et al., 2013), and in extracting gene-disease relationships (Chun et al., 2006), protein-protein interaction (Huang et al., 2004) from biomedical texts.

In VLSP 2020, relation extraction task is organized in order to assess and advance relation extraction work for Vietnamese language. In this paper we present an empirical study of BERT-based models for relation extraction task in VLSP 2020. We applied two state of the art BERT-based models for relation extraction: R-BERT (Wu and He, 2019) and BERT with entity starts (Soares et al., 2019). Two models use entity markers to capture location information of entity mentions. For each model, we investigated the effect of choosing pre-train BERT models in the task by comparing two Vietnamese pre-trained BERT models: NlpHUST/vibert4news and FPTAI/vibert (Bui et al., 2020). In our understanding, our paper is the first work that provides the comparison of pre-trained BERT models for Vietnamese relation extraction.

2 BERT-based Models for Relation Classification
In following sections, we describe two BERT-based models for relation classification, which we investigated in this paper.

2.1 Pre-trained BERT Models
The pre-trained BERT model (Devlin et al., 2019) is a masked language model which is built from multiple layers of bidirectional Transformer encoders (Vaswani et al., 2017). We can fine-tune pre-trained BERT models to obtain state of the art results on many NLP tasks such as text classification, question answering, natural language inference.

Currently, pre-trained BERT models are available for many languages. For Vietnamese, in our understanding, there are three available pre-trained BERT models: PhoBERT (Nguyen and Nguyen, 2020), FPTAI/vibert (Bui et al., 2020) and NlpHUST/vibert4news\(^1\). Three models are different in pre-training data, selected tokenization, and training settings. In this paper, we investigated two pre-trained BERT models: FPTAI/vibert and NlpHUST/vibert4news for the relation extraction task.

2.2 Problem Formalization
In this paper, we focus on relation classification task in the supervised setting. Training data is a sequence of relation examples. Each relation sample is a tuple \( r = (x, s_1, s_2, y) \). We define \( x = \text{vibert4news} \) is available on https://huggingface.co/NlpHUST/vibert4news-base-cased

\(^1\)vibert4news
2.3 R-BERT

In R-BERT (Wu and He, 2019), for a sequence \( x \) and two target entities \( e_1 \) and \( e_2 \) which specified by indexes of \( s_1 \) and \( s_2 \), to make BERT module capture the location information of the two entities, a special token ‘$’ is added at the beginning and end of the first entity, and a special token ‘#’ is added at both the beginning and end of the second entity. [CLS] token is also added to the beginning of the sequence.

For example, after inserting special tokens, a sequence with two target entities “Phi Sơn” and “SLNA” becomes to:

“[CLS] Cầu thủ $ Phi Sơn $ đã ghi bàn cho # SLNA # vào phút thứ 80 của trận đấu .”

The sequence \( x \) with entity markers is put to a BERT model to get hidden states of tokens in the sequence. Then, we calculate averages of hidden states of tokens within the two target entities and put through a tanh activation function and a fully connected layer to make vector representations of the two entities. Let \( H_0', H_1', H_2' \) be hidden states at [CLS] and vector representations of \( e_1 \) and \( e_2 \). We concatenate three hidden states and add a softmax layer for relation classification.

2.4 BERT with Entity Starts (BERT-ES)

We applied the BERT model with entity starts (BERT-ES) (Soares et al., 2019) for Vietnamese relation classification. In the model, similar as R-BERT, special tokens are added at the beginning and end of two target entities. Different from (Soares et al., 2019), we used entity markers ‘$’ and ‘#’ instead of markers ‘[E1]’, ‘[E1]’, ‘[E1]’, and ‘[/E2]’. We did not added [SEP] at the end of a sequence. In BERT-ES, hidden states at starts of two target entities are concatenated and put through a softmax layer for final classification.

3 Proposed Methods

In this work, we applied R-BERT and BERT-ES as we presented in Section 2, and proposed an ensemble model of R-BERT and BERT-ES. In following sections, we present how we prepared data for training BERT-based models and how we combined two single models: R-BERT and BERT-ES.

3.1 Data Preprocessing

Relation extraction data provided by VLSP 2020 organizers in WebAnno TSV 3.2 format (Eckart de Castillo et al., 2016). In the data, sentences are not segmented and tokens are tokenized by white spaces. Punctuations are still attached in tokens. According to the task guideline, we consider only intra-sentential relations, so sentence segmentation is required in data preprocessing. We used VnCoreNLP toolkit (Vu et al., 2018) for both sentence segmentation and tokenization. For the sake of simplicity, we just used syllables as tokens of sentences. VnCoreNLP sometimes made mistakes in sentence segmentation, and as the result, we missed some relations for those cases.

3.2 Relation Sample Generation

From each sentence, for training and evaluation, we made relation samples which are tuples \( r = (x, s_1, s_2, y) \) as described in Section 2. Since in the data, named entities with their labels are provided, a simple way of making relation samples is generating all possible entity mention pairs from entity mentions of a sentence. We used OTHER label for entity mention pairs that lack relation between them. All entity mentions pairs that are not included in gold-standard data are used as OTHER samples.

In the annotation guideline provided by VLSP 2020 organizers, there are constraints about types of two target entities of relation types as shown in Table 1. Thus, we consider only entity mention pairs whose types satisfy those constraints. In training data, sometimes types of two target entities do not follow the annotation guideline. We accepted those entity pairs in making relation samples from provided train and development datasets. However, in processing test data for making submitted results, we consider only entity pairs whose types follow the annotation guideline.

Since the relation PERSONAL-SOCIAL is undirected, for this type, if we consider both pairs \((e_1, e_2)\) and \((e_2, e_1)\) in which \(e_1\) and \(e_2\) are PER-
Table 1: Relation types permitted arguments and directionality.

| No. | Relation           | Arguments                      | Directionality |
|-----|--------------------|--------------------------------|----------------|
| 1   | LOCATED            | PER - LOC, ORG – LOC           | Directed       |
| 2   | PART–WHOLE         | LOC – LOC, ORG – ORG, ORG-LOC  | Directed       |
| 3   | PERSONAL–SOCIAL    | PER – PER                      | Undirected     |
| 4   | AFFILIATION        | PER – ORG, PER-LOC, ORG – ORG, LOC-ORG | Directed |

Table 2: Label distribution of relation samples generated from train and dev data.

| Relation       | Train | Dev   |
|----------------|-------|-------|
| LOCATED        | 507   | 304   |
| PART-WHOLE     | 1,016 | 402   |
| PERSONAL-SOCIAL| 101   | 95    |
| AFFILIATION    | 756   | 489   |
| OTHER          | 23,904| 13,239|
| Total          | 26,284| 14,529|

Table 3: Hyper-parameters used in training models.

| Hyper-Parameters | Value |
|------------------|-------|
| Max sequence length | 384   |
| Training epochs   | 10    |
| Train batch size  | 16    |
| Learning rate     | 2e-5  |

SON entities, it may introduce redundancy. Thus, we added an extra constraint for PER-PER pairs that \( e_1 \) must come before \( e_2 \) in a sentence.

In the training data, we found a very long sentence with more than 200 relations. We omitted that sentence from the training data, because that sentence will lead to too many OTHER relation samples.

3.3 Proposed Ensemble Model

In our work, we tried to combine R-BERT and BERT-ES to make an ensemble model. We did that by calculating weighted averages of probabilities returned by R-BERT and BERT-ES. Since in our experiments, BERT-ES performed slightly better than R-BERT on the development set, we used weights 0.4 and 0.6 for R-BERT and BERT-ES, respectively.

4 Experiments and Results

We conducted experiments to compare three BERT-based models on Vietnamese relation extraction data: R-BERT, BERT-ES, and the proposed ensemble model. We also investigated the effects of two Vietnamese pre-trained BERT models on the performance of models.

4.1 Data

The proved training data contains 506 documents, and the development dataset contains 250 documents. After data preprocessing and relation sample generation, we obtained relations with label distributions shown in Table 2.

4.2 Experimental Settings

In development, we trained models on the training data and evaluated models on the development data. However, in making results for submission, we combined provided training and development data for training models which were used to generate submitted results.

Table 3 shows hyper-parameters we used for training models. For sequences which are longer than max sequence length, we used a segment whose length is equal to max sequence length and include two entity mentions.

We used micro-F1 and macro-F1 of four relation labels without label OTHER as evaluation measures.

4.3 Results

Table 4 shows the evaluation results on the development dataset. We can see that using NlpHUST/vibert4news significantly outperformed FPTAI/vibert in both Micro-F1 and Macro-F1 scores. BERT-ES performed slightly better than R-BERT. The proposed ensemble model is slightly improved against R-BERT and BERT-ES in term of Micro-F1 score.

4.4 Result Analysis

We looked details of precision, recall, and F1 scores for each relation type. Table 5 shows results of the ensemble model with vibert4news pre-trained model. PERSONAL-SOCIAL turned out to be a difficult label. The proposed ensemble obtained low Recall, and F1 score for that label. The
| Model            | Pre-trained BERT Model       | Macro-F1 | Micro-F1 |
|------------------|------------------------------|----------|----------|
| R-BERT           | NlpHUST/vibert4news          | 0.6392   | 0.7092   |
| R-BERT           | FPTAI/vibert                 | 0.596    | 0.6736   |
| BERT-ES          | NlpHUST/vibert4news          | **0.6439** | 0.7101   |
| BERT-ES          | FPTAI/vibert                 | 0.5976   | 0.6822   |
| Ensemble Model   | NlpHUST/vibert4news          | 0.6412   | 0.7108   |
| Ensemble Model   | FPTAI/vibert                 | 0.6029   | 0.6851   |

Table 4: Evaluation results on dev dataset.

| AFFILIATION   | 0.7615 | 0.744 | 0.7528 |
| LOCATED       | 0.7053 | 0.7007 | 0.7030 |
| PART – WHOLE  | 0.65   | 0.8085 | 0.7206 |
| PERSONAL - SOCIAL | 0.6136 | 0.2842 | 0.3885 |

Table 5: Precision, Recall, F1 for each relation type.

| Data size | 10GB | 20GB |
|------------|------|------|
| Data domain | News | News |
| Tokenization | Subword | Syllable |
| Vocab size | 38168 | 62000 |

Table 6: Comparison of NlpHUST/vibert4news and FPTAI/vibert.

reason might be that the relations of PERSONAL-SOCIAL is few in the training data while the patterns of PERSONAL-SOCIAL relations are wider than other relation types.

5 Discussion

In experiments, we compared effects of two pre-trained BERT models: NlpHUST/vibert4news and FPTAI/vibert on relation extraction. The two pre-trained models have the same BERT architecture (BERT base model) but are different in chosen tokenizers, vocabulary size, pre-training data, and training procedure. Table 6 shows a comparison of the two models.

FPTAI/vibert was trained on 10GB of texts collected from online newspapers while NlpHUST/vibert4news was trained on 20GB of texts in news domain. FPTAI/vibert used subword tokenization, and vocabulary of FPTAI/vibert was modified from mBERT while tokenization of vibert4news is based on syllables.

We come up with some reasons why using NlpHUST/vibert4news significantly outperformed FPTAI/vibert for Vietnamese relation extraction.

- Pre-training data used to trained vibert4news is much larger than FPTAI/vibert.
- Tokenization used in NlpHUST/vibert4news is based on syllables while FPTAI/vibert used subwords and modified the original vocabulary of mBERT. We hypothesize that syllables which are basic units in Vietnamese are more appropriate than subwords for Vietnamese NLP tasks.

Due to time limit, we did not investigate PhoBERT (Nguyen and Nguyen, 2020) which used word-level corpus to train the model. As future work, we plan to compare vibert4news that uses syllable-based tokenization with PhoBERT that uses word-level/subword tokenization for Vietnamese relation extraction.

6 Conclusion

We have presented an empirical study of BERT-based models for relation extraction task at VLSP 2020 Evaluation Campaign. Experimental results shows that BERT-ES model which uses entity markers and entity starts obtained better results than R-BERT model, and choosing an appropriate pre-trained BERT model is important for the task. We showed that pre-trained model NlpHUST/vibert4news outperformed FPTAI/vibert for Vietnamese relation extraction task. In future work, we plan to investigate PhoBERT (Nguyen and Nguyen, 2020) for Vietnamese relation extraction in order to understand the effect of using word segmentation to the task.
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