Toward Human-Friendly ASR Systems: Recovering Capitalization and Punctuation for Vietnamese Text

SUMMARY  Speech recognition is a technique that recognizes words and sentences in audio form and converts them into text sentences. Currently, with the advancement of deep learning technologies, speech recognition has achieved very satisfactory results close to human abilities. However, there are still limitations in identification results such as lack of punctuation, capitalization, and standardized numerical data. Vietnamese also contains local words, homonyms, etc, which make it difficult to read and understand the identification results for users as well as to perform the next tasks in Natural Language Processing (NLP). In this paper, we propose to combine the transformer decoder with conditional random field (CRF) to restore punctuation and capitalization for the Vietnamese automatic speech recognition (ASR) output. By chunking input sentences and merging output sequences, it is possible to handle longer strings with greater accuracy. Experiments show that the method proposed in the Vietnamese post-speech recognition dataset delivers the best results.

key words: capitalization, punctuation, automatic speech recognition

1. Introduction

Research in Vietnamese speech synthesis and speech recognition was first introduced more than twenty years ago. Since 2018, there has been a competition in Vietnamese Language and Speech Processing (VLSP) for researchers on Vietnamese speech processing. The results from the competition show that the accuracy of systems has improved.

In standard automatic speech recognition (ASR) systems, outputs typically consist of lower-case word sequences where the important linguistic and punctuation information are not available. In particular, there is a difference in the display of numbers, year, currency, proper nouns denoting foreign people, places, organization names. Therefore, improving the output of ASR is necessary. It is simpler for people to read and comprehend a text with correct punctuation and capitalization.

In fact, where ASR results are used in natural language processing models, punctuation and capitalization become important information to enhance further the accuracy or identification of machine translation (MT), name entity recognition (NER), etc. To the best of our knowledge, this task for Automated Speech Recognition in Vietnamese has not been explored before. An example enriching ASR with recovering punctuation and capitalization is shown below:

For example, in addition to the regulation of proper nouns (Viet Nam) capitalizes at the starting of a paragraph, and after punctuation (Tu y), there are regulations in Vietnam about the name of agencies, organizations, programs, and projects (STEM).

Studies often follow several directions, such as restoring punctuation, capitalizing separately, or combining parallel processing of punctuation and capitalization tasks. Regarding the only task of restoring capitalization, Lita et al. [1] insisted that capitalization consists of restoring the first word of a sentence and proper noun (names of persons, organizations, locations, etc.), and also called (RuEcaSIng). The proposed method focused on n-gram LMs, which was derived from a corpus with case information. Chelb et al. [2] provided a general technique for modifying maximum entropy probability models. Another approach also was introduced as Conditional Random Fields (CRFs) for capital-

For example, in addition to the regulation of proper nouns (Viet Nam), capitalizes at the starting of a paragraph, and after punctuation (Underlined words). There are regulations in Vietnam about the name of agencies, organizations, programs, and projects (STEM).
In this model, the authors suggested a probabilistic bilingual capitalization model for the capitalization of machine translation outputs and demonstrated better capitalization than the LM model. In the last few years, another proposed method named Recurrent Neural Networks (RNNs) at character level [4], which showed a competitive comparison to CRFs. This method solved effectively the out-of-vocabulary (OOV) words, however, it illustrated the difficulty when handling the long sentences.

Recently, many studies of automatic punctuation restore in transcripts of ASR have been introduced. Punctuation is essential not only for subsequent application performance but also for text readability in ASR transcripts. There are also many approaches to the Punctuation task such as Maximum Entropy [5], Long Short Term Memory [6], Dynamic Conditional Random Fields [7], [8], DNN-CRF (Deep Neural Network - Conditional Random Fields) [9], Bidirectional Recurrent Neural Network [10], Recurrent Neural Networks [11], [12]. Especially, Tundik et al. [13] has proved the outstanding performance of RNN compared to the MaxEnt method [13]. Recently, Tündik et al. [14] also has proposed improving the word sequence-based system using a Convolutional Neural Network (CNN) and described the substantial improvement in the accuracy of punctuations.

It is difficult to perform individually the tasks for optimizing document recovery, therefore, the approaches now try to integrate the handling of punctuation and capitalization recovery in ASR models such as the statistical model [15], n-gram language model [16], [17], Maximum Entropy [18]. The deep learning models have proved a powerful method for punctuation and restore capitalization. Varavs et al. [19] used the Transformer model in Latvian and English to perform these tasks simultaneously. In recent years, transformer models have demonstrated the effect of all types of natural language processing [20]–[23]. Binh Nguyen et al. have experimented with the Transformer model to recover the punctuation and capitalization for English [24] and Vietnamese ASR transcripts as well [25]. The results described the difficulty in tasks solved order, i.e. the punctuation or capitalization should be considered firstly.

In this paper, we propose a method for Vietnamese Automatic Speech Recognition to restore simultaneously the punctuation and capitalization tasks. In particular, we focus on restoring three essential punctuation marks: period (.), comma (,), and question mark (?). In the first section, We will describe an algorithm for Overlapped-Chunk Split and Merging. The proposed model using a combination of Decoder Transformer and CRF for recovering Capitalization and Punctuation will be introduced in the second section. Results and discussion will be introduced statistically in the third section and followed by the conclusion part.

2. Proposed Method

2.1 Capitalization and Punctuation Model

In the previous study, in [25], when recovering the Capitalization task, we used the Transformer model that is type of sequence to sequence model. In this article, we propose a model for recovering ASR Vietnamese’s capitalization and punctuation by one using Transformer Decoder combined with CRF. The structure of the model proposed is indicated in Fig. 1. The model has 3 layers: Embedding, Transformer Decoder and CRF, introduce in the following sections.

2.1.1 Embedding Layer

An embedding is a sufficiently low-dimensional space that transforms from high-dimensional vectors. Machine learning models can work easier on large inputs such as words representation with sparse vectors. An embedding preferably absorbs such input semantics by placing semantically connected inputs closely together in the embedding. An embedding can be learned and reusable using templates. We use word level to feed into the embedding layer in our work.

2.1.2 Transformer Decoder

The Transformer was focused primarily on self-attention, which allows the Transformer to interpret each role in the chain differently while maintaining the same parameters over all positions. This helps Transformer to use a constant number of parameters to process arbitrary-length sequences. The model’s architecture consists of the encoder-decoder layers, where the encoder and decoder both consist of...
of multiple Transformer-specific self-attention and position-wise feed-forward layers [26].

The study in the previous work [25] uses Transformer to do the Capitalization and Punctuation task, it works totally fine, but one problem here is it very time consuming. The reason is the Transformer model uses the sequence to sequence architecture, in the decoder step, it has to generate the output one by one and for each word output, it must calculate the feature for all words generated. The drawback not only is time-consuming, it contains a very sensitive problem is we cannot control what will be generated in the decoder process. It means the Transformer model can generate a new word that not exists in the input (for the plain text model) or it can be more encode word than the number of words input (for the encoding model). Because the Capitalization and Punctuation task is all about tagging the format for a word input (uppercase and punctuation belong to the word), so it better to use the tagging model than generating model to do it. In out work, we use only a part of Transformer model, it is Decoder Transformer to do that tagging task. The Fig. 2 is the view of the propose model.

2.1.3 CRF Layer

For the output layer, the model will yield the tag including ‘U’, ‘L’ to indicate uppercase or remain the input word and the tag ‘$’, ‘.’, ‘,’ ‘?’ to add the punctuation for the input word that it belongs to (‘$’ mean a word don’t have punctuation). Totally, we will have 8 tag for each word: \{US; LS; U; L; U.; L.; U?; L?\}

After the Decoder Transformer block, we can use softmax to determine whether which tag is should be used for the word input. One thing to consider here is the softmax does not care about the order of tag, that means the softmax can output two tag \(U\) and \(L\) stand side by side (almost meaningless in all cases). To take care about the order of output tag, in this work we use CRF layer.

The Conditional Random Field (CRF) was used in our model. Given a sequence \(s = [s_1; s_2; \ldots; s_T]\), the corresponding golden label sequence is \(y = [y_1; y_2; \ldots; y_T]\), and \(Y(s)\) represents all valid label sequences. The probability \(y\) is calculated as:

\[
P(y|s) = \frac{\sum_{t=1}^{T} e^{f(y_{t-1}, y_t, s)}}{\sum_{y' \in Y(s)} \sum_{t=1}^{T} e^{f(y'_{t-1}, y'_t, s)}}
\]

where \(f(y_{t-1}; y_t; s)\) computes the transition score from \(y_{t-1}\) to \(y_t\). The optimization target is to maximize \(P(y|s)\).

The encoded text model results in an encoded format which contains seven classes as presented in Table 1. We prepared encoded text format for training data, example in Fig. 3. The format encoded can support the model train and can infer faster than the plain text as it has fixed and very limited vocabulary. However, it does not have much information about the words and the contextual around the word.

2.2 Algorithm for Overlapped-Chunk Split and Merging

We are aware that ASR’s results are endless. Therefore, before feeding to the model, long input sentences are generally divided into fixed-length. While helping to improve inference by independently and parallel processing of chunks, this approach is prone to the lousy prediction of words around the boundary of the split because there is not enough information about both the left and right context in this field. Instead of using a basic chunk splitting method, we introduce the concurrent techniques of overlap chunk-splitting and merging. Our idea aims to ensure every step of the decoding to have enough neighboring words to achieve a better predict model. We proposed System Architecture for
Recovering Capitalization and Punctuation which consists of three components: overlap chunk split, capitalization and punctuation model, and overlap chunk merging as shown in Fig. 4.

- Firstly, the ASR module’s output will be sent to the Overlapped-Chunk Split module to overlap segments.
- Secondly, the Recovery Capitalization model will take the split segments, parallelly process, and produce an output list.
- Ultimately, by using the overlapped Chunk Merging module, the outputs will be merged in the last sentence.

We need to determine the size of the chunk and overlapping which will be split. From the preliminary experiments, we suggested splintering long input sentences into segments with a $k$ word chunk size and overlapping $k/2$ words into two consecutive chunks.

After consideration, we found that the merge was much more difficult than splitting the overlapped results. Therefore, the question was raised: “How to decide which words will be dropped and which one will be held in a full sentence?” So, we define the min_words_cut parameter to specify the number of words at the end of the first chunk and the number of words held in the second chunk. The range is set from 0 to the overlapping scale. If the min_words_cut is 0 or equal to the overlapped number, then all overlapping words will be held in the first chunk, and they will be deleted in the second chunk.

As shown in Fig. 5, all removed min_words_cut
and kept $\min\_\text{words\_cut}$ are highlighted by the red and blue light, respectively. We found that the middle $\min\_\text{words\_cut}$ part in the overlap chunk has enough context around them to make the model have a better prediction.

3. Experiments and Results

In this paper, we (1) compare the result of Seq2seq, Transformer, Transformer Decoder CRF models on different chunk size with and without chunk-merging (2) affect of the $\min\_\text{words\_cut}$ parameter and (3) evaluation of speed on the Encode and Plain text output with each model. This shows what the proposed model (Transformer Decoder CRF) will improve compared to the previous models.

3.1 Data Preparation

All data is created automatically by crawling through Vietnamese Internet tools including vietnamnet.vn, dantri.com.vn, vnexpress.net. There was a systematic document on terminology and grammar. Then we just kept the alphabet characters to simulate the ASR output. The standard format for all numbers, info, currencies was retained. From the training data, the input format will be lowercase and without punctuation. Table 1 indicates the number of labels for each punctuation and capitalization class available in the test and training data set.

| Class | Training | Testing |
|-------|----------|---------|
| U     | 15.4M    | 74K     |
| L     | 69.3M    | 507K    |
| $     | 76.6M    | 525K    |
| .     | 2.7M     | 24K     |
| ,     | 5.3M     | 30K     |
| ?     | 53K      | 2.6K    |

Table 2 Compare the number of models parameters

| Model                | Encode | Plain |
|----------------------|--------|-------|
| LSTM                 | 6.5M   | 11.3M |
| Transformer          | 37M    | 42M   |
| Transformer Decoder-CRF | 7.4M  | -     |

We train on an NVIDIA 2080ti GPU. The corpus consists of 85 million words. Each example contain 8 to 44 words. Randomized size was between 4 and 22 words for the chunk.

3.2 Evaluation of Chunk-Merging

Figure 6 displays the chart compared to the result of Seq2seq, Transformer, Transformer Decoder CRF models on different chunk size (4-22) with and without chunk-merging.

Clearly, models using chunk-merging always gives better results. Especially, at the propose model is Transformer Decoder CRF with chunk-merging has the highest achievement is 0.88. The results confirm our hypothesis that the model is not enough context for an efficient forecast at the start and end of each sample. This shortcoming can be overcome by adding more context in a way that overlapping and chunk-merging.

It can be seen clearly that, chunk-merging model always provides much better results. Especially, the proposed Transformer Decoder CRF model using chunk-merging illustrates the highest achievement (0.88). The results again confirm our hypothesis that the model is not enough context.
How does chunk size affect the results? In the seq2seq model, chunk size is quite sensitive to the accuracy of the output, possibly due to the nature of the encode, decode loss of information despite the attention architecture applied. In the proposed model, the Transformer Decoder CRF, the information is transmitted directly without going through the encode process, chunk size does not affect the output.

We provide a table of results for the proposed model - the Transformer Decoder CRF with and without chunk-merging. Inside, we only make statistics in classes (‘U’, ‘L’, ‘?’), ignore classes (‘I’, ‘$’), because the exact number is much, not necessary to compare the effectiveness.

As we can see, in Table 3, chunk-merging method is better performance than non-chunk-merging. F1-score on all classes are improved from 1% to 5%. The results show that the overlapped words provide the model with more prediction information, and our chunk-merging process can select a proper portion of the overlapping area.

### Table 3  Comparison of transformer decoder CRF result with and without using chunk merging

| Model               | Class | Precision | Recall | F1-score |
|---------------------|-------|-----------|--------|----------|
| Chunk Merging       | U     | 0.90      | 0.86   | 0.88     |
| Transformer Decoder |       | 0.71      | 0.57   | 0.63     |
| CRF                 |       | 0.66      | 0.53   | 0.59     |
| ?                   |       | 0.75      | 0.52   | 0.62     |
| Non-Chunk Merging   | U     | 0.89      | 0.85   | 0.87     |
| Transformer Decoder |       | 0.69      | 0.54   | 0.61     |
| CRF                 |       | 0.65      | 0.50   | 0.57     |
|                     | ?     | 0.74      | 0.47   | 0.58     |

3.3 Evaluation Using Output of Encoded-Text and Plain-Text

The result for the models using encoded-text and plain text is compared in Fig. 7. We see that, Seq2seq and Transformer with plain text have better result than using encoded text output.

Nonetheless, the model that uses encoded text is reduced in size and quicker for inference. Besides, if using plain text output, the vocab for the CRF output will become too large. Theoretically would be 8 times the vocab of the input. It should not be reasonable. So, in this article, we only evaluate a new model, the Transformer Decoder CRF using encoded text. The chart shows that the new model gives much better results.

To study the min_words_cut effect on the resulting quality, since we chose chunk-size to be 10, so we experimented with min_words_cut in the range of 0 to 10 in the proposed model - the Transformer Decoder CRF. The results from Fig. 7 demonstrate that the result is the maximum f1-scores in the middle of the chunk size. It shows that the upper and lower predictions of min_words_cut are stable and independent.

Figure 8 displays the confusion matrix of the Transformer Decoder CRF model with Encode output. The matrix shows that “?” is the most difficult class to predict. Besides, the matrix also indicates that the model always predicts efficiently when the input is a word, and lowercase prediction is better than uppercase prediction.

3.4 Evaluation of Speed

The result compares the execution time of 3 models with encoded and plain text output show in Table 4 with 2080ti (GPU), batch_size: 128. The encode text output even shows...
superior performance when it is used with proposed model - the Transformer Decoder CRF.

4. Conclusion

In this article, we propose a method to recover capitalization and punctuation for Vietnamese ASR output which utilizes the new Transformer Decoder – CRF model combined with a sentence augmentation named Overlapped-Chunk Split and Merging. This combination method aims to improve the ability to extract the longer-range context information so that improves performance while working with the long paragraph. After evaluation, our proposed method presents the superior performance compared to the most re-

**Fig. 7** F1-score models with encode and plain text output on different min_word_cut

**Fig. 8** Confusion matrix of transformer decoder CRF with encode output

**Table 4** Evaluation of speed (tokens/second)

| Output     | Transformer    | Seq2seq        | Transformer Decoder CRF |
|------------|----------------|----------------|-------------------------|
| Encode     | 263s → 2209t/s| 217s → 2678t/s| 90s → 6457t/s           |
| Plain text | 355s → 1637t/s| 230s → 2526t/s| —                       |
cient baseline models in both speed and accuracy. Under the same condition as the original Transformer model, the Transformer Decoder – CRF provides a significantly smaller number of parameters, therefore increases the speed. The chunk-merging method indicates a better performance than the original one at about 1% to 5% of F1-score. Furthermore, using encoded text input also improves the performance of the overall system. In the future work, we will integrate this solution with an ASR model to build an end-to-end model that can transform speech into a useful normalization text document. In addition, as the result of the ASR can be standarized, we can also perform named entity recognition with much better accuracy than raw the ASR output. Finally, we will conduct further experiments on other languages to verify the generalization of the method.

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