國立成功大學
人工智慧科技碩士學位學程
碩士論文

以聯合語義語音詞嵌入強化中日文
神經機器翻譯

Improving Chinese-Japanese Neural Machine Translation with Joint Semantic-Phonetic Word Embedding

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Thesis for Master of Science Degree
July, 2021

中華民國一百一十年七月

以聯合語義語音詞嵌入強化中日文神經機器翻譯

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摘要

中文版簡介。手動換行會自動變成下一段文字區塊。

關鍵字： 關鍵字1、關鍵字2、關鍵字3

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Abstract

Add your abstract here.

Keywords: Keyword1, Keyword2, Keyword3

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Acknowledgements

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<div align="right">Shih-Chieh Wang</div>

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Chapter 1

Introduction

Over the past few years, the field of neural machine translation (NMT) between Chinese and Japanese is still an unresolved problem. Recent studies in Chinese-Japanese NMT have used specific methods such as sub-character level features to improve the translation quality. This is due to the lack of parallel corpus and the difference between logogram (a character or symbol that represents a word) and alphabet (a set of letters used when writing in a language) writing systems. This research explores phonetic information as an additional feature for improving the quality of Chinese-Japanese NMT systems.

1.1 Background

NMT is a popular area of natural language processing (NLP), has been proposed by using an end-to-end model which transforms a source sentence into a latent space and decodes it directly into a target sentence [Sutskever et al., 2014,Cho et al., 2014]. The model is called the encoder-decoder model or sequence-to-sequence model, and they are widely used by large technology companies such as Google, Facebook, Microsoft, and DeepL.

1.1.1 Progress of Neural Machine Translation

The progress of NMT and NLP are inseparable. The development of models, tokenization methods, embeddings, and the solutions to less or no parallel data, all involved in the progress of NMT.

In the development of models, recurrent neural network (RNN) was first applied in NMT research [Sutskever et al., 2014,Cho et al., 2014]. After that, [Bahdanau et al., 2014] designed a mechanism called attention and addressed the problem of insufficient information in the latent space between encoder and decoder based on RNN. The structure of the Transformer was later proposed by [Vaswani et al., 2017], which replace the RNN structure with a full attention mechanism (i.e., self-attention) to achieve better results and was widely used in NMT tasks. This paper will use the attention-based RNN model and Transformer [Bahdanau et al., 2014,Vaswani et al., 2017] as the baseline system for the experiment.

Tokenization is one of the most important parts of any NLP task. It determines how a sentence will be

tokenized, and it will generate different meanings to a sentence with different algorithms. Besides word-level and character-level tokenization, several subword-level tokenization algorithms had become the mainstream. For example: Byte-Pair Encoding (BPE) [Sennrich et al., 2016b], Unigram Language Model [Kudo, 2018], WordPiece [Schuster and Nakajima, 2012], and SentencePiece [Kudo and Richardson, 2018]. This paper will utilize BPE, SentencePiece [Sennrich et al., 2016b,Kudo and Richardson, 2018] and two word-level tokenizer (*Jieba*[1] and *Janome*[2]) as tokenization methods.

The concept of embeddings, also known as distributed representations, was first proposed by [Hinton et al., 1986,Bengio et al., 2003], but was difficult to implement due to hardware limitations. With the development of parallel computing and GPU, many embedding implementations have been proposed, such as Word2Vec [Mikolov et al., 2013], GloVe [Pennington et al., 2014], and fastText [Bojanowski et al., 2017]. The contextualized word embedding is another concept that obtains context-dependent word embedding from the whole sentence, meaning that the same word with different position can obtain different embedding through the model. The representative ones are ELMo [Peters et al., 2018] and BERT [Devlin et al., 2019]. This paper will select Word2Vec [Mikolov et al., 2013] as the tool for creating word embeddings because of its simplicity, rapidity, and convenience of analysis.

Several fields have been studied to solve the problems like low-resources and noisy parallel data in NMT tasks. Back-translation [Sennrich et al., 2016a] is a data augmentation method that uses monolingual data of the target language to generate source data and offset the imbalance between encoder and decoder. Parallel corpus filtering was examined for a large number of NMT tasks [Koehn et al., 2018], using pre-filtering rules and scoring functions to retain good sentence pairs can effectively reduce the corpus size and obtained better translation results. This paper will practice corpus filtering to retain quality training data and reduce corpus size to increase experimental efficiency.

1.1.2   Chinese-Japanese Neural Machine Translation

NMT system has gained a lot of improvement in translating between English and other languages by utilizing the techniques described in section 1.1.1. However, the improvement in translating between Chinese and Japanese is limited. The main reasons are the inadequacy of the corpus and the differences in the writing systems of Chinese, Japanese, and Western languages.

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[1]https://github.com/fxsjy/jieba
[2]https://mocobeta.github.io/janome

Many studies have focused on improving the Chinese-Japanese (zh-ja) NMT system. In addition to using the methods [Imamura et al., 2018,Chu et al., 2017,Zhang et al., 2020] described in section 1.1.1, many feature engineering techniques have been proposed to utilize the features in Chinese Characters (*Hanzi*) and Japanese *Kanji*. For example, a character-level zh-ja NMT system had been improved by using radicals as character feature information [Zhang and Matsumoto, 2017]. Furthermore, the use of decomposed sub-character level information such as ideographs and strokes of Chinese characters, also improved the results [Zhang and Komachi, 2018].

1.1.3 Phonetic Information

Phonetic information is another feature that had been applied to NMT systems. [Khan and Xu, 2019] had suggested that a phonetic representation usually corresponds to semantically distinct characters or words. [Liu et al., 2019] had pointed out that phonetic information can effectively resist the homophone noises generated by typographical mistakes in Chinese sentences. Both papers had improved the performance of the NMT system between Chinese and other Western languages.

This paper attempts to use *Bopomofo* and *Hiragana* as Chinese and Japanese phonetic information to improve the performance of the zh-ja NMT system. Bopomofo also named *Zhuyin* (注音), is located in the Unicode block in the range U+3100–U+312F. It consists of 37 characters and 4 tone marks to transcribe all possible Chinese characters. Although it is the main component of Mandarin Chinese, it usually does not appear in Chinese sentences. That is, the machine loses some of the phonetic information when reading Chinese sentences. Hiragana (平仮名, ひらがな) is a component of Japanese, along with *Katakana* and Kanji. It consists of 46 base characters and is located in the Unicode block in the range U+3040–U+309F. Compared to Bopomofo, Hiragana is often found in Japanese sentences with Katakana and Kanji, forming mixed writing of Kanji and Kana (仮名交じり文). However, Hiragana disappears after forming Kanji, just like Bopomofo forms Hanzi. Therefore, the machine cannot obtain the phonetic information directly from Japanese sentences.

1.2 Objective

This paper aims to determine whether the use of phonetic information can help improve the performance of the zh-ja NMT system. We will use embedding, which is commonly used to represent semantics, to represent the

features of phonetic information. The *gensim* library [3] will be utilized to implement Word2Vec [Mikolov et al., 2013] to extract both semantic and phonetic embedding. The embeddings will be trained on a small corpus (less than 1 million lines of sentences) to see if they are useful for the subsequent NMT task.

Combining the findings from other studies [Liu et al., 2019,Khan and Xu, 2019] described in section 1.1.3, we hypothesize that embeddings with the combination of semantics and phonetics (joint embedding) can improve the performance of the zh-ja NMT system more effectively than embeddings with only semantics or phonetics.

We will perform a series of experiments to test the hypothesis. First, we examine whether the joint embedding can improve the results of the zh-ja NMT system with different tokenization methods. Second, we conduct NMT tasks under four conditions: without any pre-trained embedding, with pre-trained semantic embedding, with pre-trained phonetic embedding, and with joint semantic-phonetic embedding. Third, we analyze the changes that occur when phonetic information is added to the general semantic embedding. The analyses include analogy reasoning, outlier detection, word similarity, and the influence on both homonyms and heteronyms.

1.3 Related Work

The core technique in this paper is to enhance the ability of word embeddings by utilizing feature engineering on phonetic information. Therefore, we are going to review some studies that use additional features to improve word embeddings. The review will be carried out from two perspectives, one is to improve embedding with the features of Chinese characters such as radicals and strokes, and the other is to improve embedding with the features of phonetics. The concept of Word2Vec [Mikolov et al., 2013] is commonly used in reviews, and we will mention it in section 2.3.1 of Chapter 2.

1.3.1 Chinese Word Embedding

We will review some studies which suggested that the rich, decomposed information of Chinese characters can be exploited to train the word embeddings with words or characters jointly. Some of the most popular studies in this field are: *CWE* [Chen et al., 2015], *MGE* [Yin et al., 2016], *JWE* [Yu et al., 2017], and *cw2vec* [Cao et al., 2018]. The following sections review the approaches from JWE and cw2vec because their concepts are

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[3]https://radimrehurek.com/gensim/index.html

relatively new and their performance is better.

Joint Learning Word Embedding Model (JWE)

The authors of JWE [Yu et al., 2017] proposed a model that combines word, character, and sub-character components to learn embeddings. They implemented the model (Figure 1.1) based on the Continuous Bag of Words (CBOW) proposed in Word2Vec [Mikolov et al., 2013], and changed the default input words in CBOW by further adding the characters and sub-character components of input words.
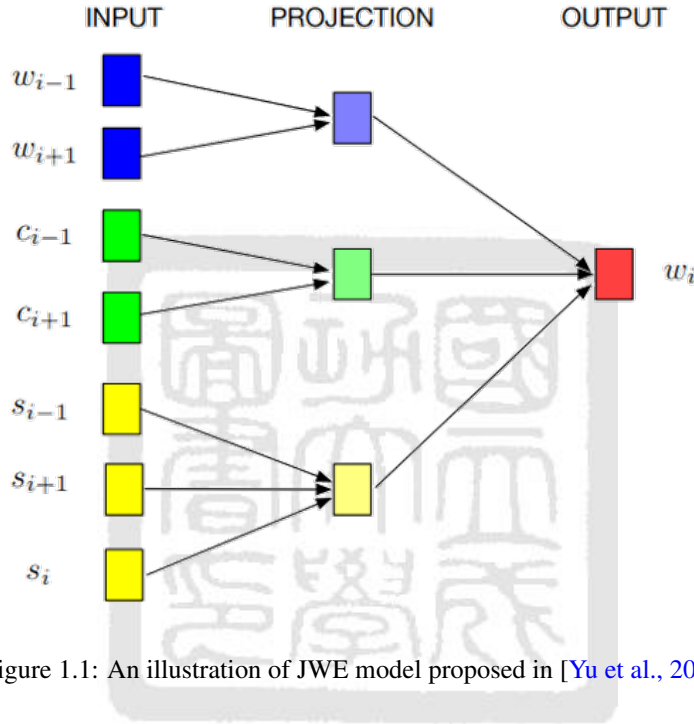

Figure 1.1: An illustration of JWE model proposed in [Yu et al., 2017]

As shown in the Figure 1.1 above, The JWE model is trained to predicts the present word from the context words in the same way as CBOW. The symbol w represents words, w_i is the current word, w_{i-1} and w_{i+1} are the context words. The symbol c represents the characters of context words, c_{i-1} is the characters of $wi - 1$, and c_{i+1} is the characters of c_{i+1}. The symbol s represents the sub-characters of context words. s_i is the sub-character components of w_i, and s_{i-1}, s_{i+1} are the components of w_{i-1} and w_{i+1}. For example, a word 智能 (intelligence) has two characters 智 (wisdom) and 能 (able), and each has sub-character components: 知, 日 and 厶, 月, 匕, 匕. The JWE model aims to maximize the sum of log-likelihoods of 3 conditional probabilities that come from the context words (h_{i1}), characters (h_{i2}), and sub-characters (h_{i3}).

$$L(w_i) = \sum_{k=1}^{3} \log P(w_i \mid h_{ik}) \tag{1.1}$$

cw2vec Model

Inspired by fastText [Bojanowski et al., 2017], The authors of cw2vec [Cao et al., 2018] proposed an n-gram feature based on the strokes of Chinese characters. They first split and transformed the text into stroke information, and mapped the strokes into 5 corresponding stroke ids, then merge the ids and generate n-gram features from these stroke ids. The diagram in the paper (Figure 1.2) shows the complete process.
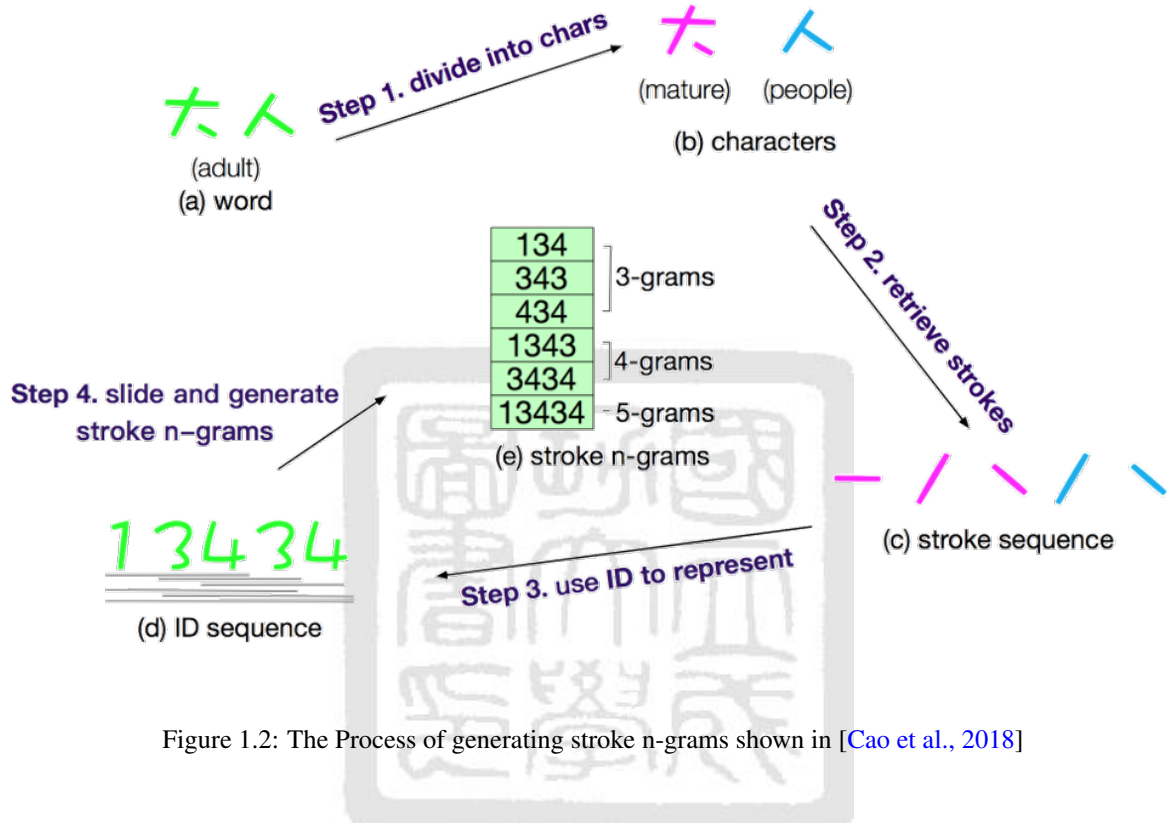
Figure 1.2: The Process of generating stroke n-grams shown in [Cao et al., 2018]

The authors used Skip-Gram, a second method other than CBOW proposed by Word2Vec [Mikolov et al., 2013], as the base model, and replaced word inputs with stroke n-grams (Figure 1.3). It is mentioned in the paper that the final embeddings come from the contextual word vectors.
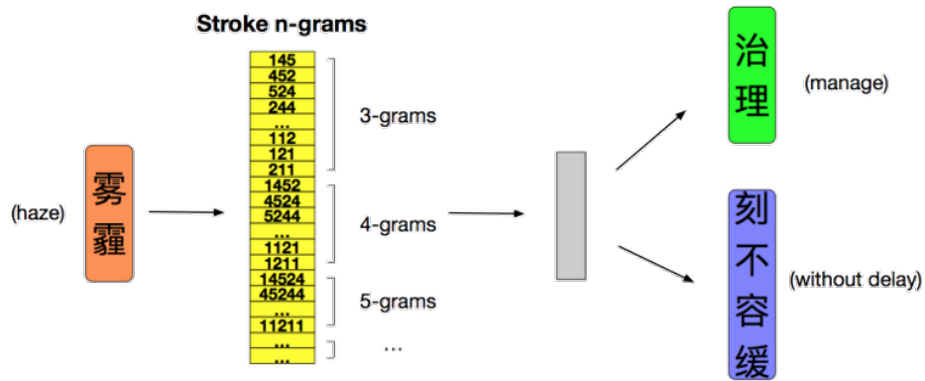

Figure 1.3: An illustration of cw2vec model proposed in [Cao et al., 2018]

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These word embeddings designed for Chinese all utilized the radicals or strokes in Chinese characters. No research has so far used phonetic information extracted from Chinese or Japanese as features.

1.3.2 Phonetic Word Embedding

We will review studies that use phonetic information to construct word embeddings. These studies are closely related to our research, and we will learn from their practical differences and use them as the cornerstone for our experiments.

Phonetic Encoding

The study [Khan and Xu, 2019] extracted sentences from Chinese or Western languages into phonetic encodings [4], which used *Soundex*, *NYSIIS*, *Metaphone*, and *Hanyu Pinyin* as the extraction algorithm. After that, they applied BPE [Sennrich et al., 2016b] to tokenize the sentences and encodings, and trained seperate embeddings from the sentences and each encodings (empty boxes in Figure 1.4). Lastly, they concatenated the embeddings and fed into NMT system.
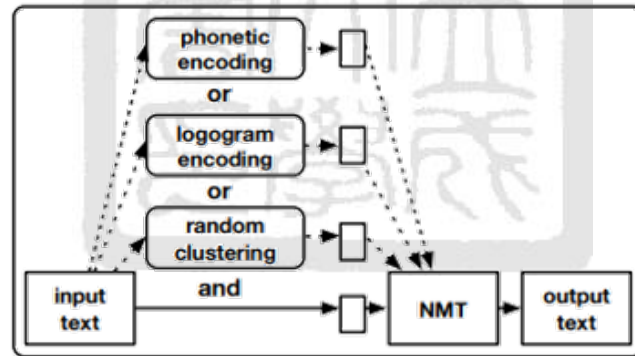
Figure 1.4: Implementation of phonetic encoding proposed in [Khan and Xu, 2019]

This paper did not explain in detail how to implement phonetic information in embedding, but they had presented a hypothesis and verified it. That is, phonetics is a function that groups semantically distinct words. The words with the same pronunciation and spelling are usually distinguished by the different contexts.

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[4]The logogram encoding is also used as a feature but is not explained here. Random clustering is used for comparison purposes.

Joint Textual and Phonetic Embedding

This paper [Liu et al., 2019] focused on using phonetic embedding to adjust the homophone noise problem, which is a frequent problem in a parallel corpus. For instance, when a single word in the source sentence is misplanted as a corresponding homophone (e.g., 有 (yǒu, to have) is wrongly replaced with 友 (yǒu, friend)), the model will read the wrong embedding and training in a wrong direction. The phonetic embedding can be seen as a feature to offset the errors that occur in semantic embeddings with homophone noise.

The paper showed that they trained the text (denoted by a) as semantic embedding (denoted by $\pi(a)$) and phonetic embedding (denoted by $\psi(a)$) respectively, and then combined two embeddings with a configurable parameter (denoted by β) as follows:

$$\pi([a, \psi(a)]) = (1 - \beta) \times \pi(a) + \beta \times \pi(\psi(a)) \tag{1.2}$$

This study did not give the details of constructing embeddings, but they had mentioned that the best result occurs when the β is 0.95. That is, when they used 5% of semantic embedding and 95% of phonetic embedding, they obtained the best performance in their NMT system.

To summarize the findings in these related works. The phonetic encodings can emphasize the difference between semantically diverse sentences. The joint semantic-phonetic embedding also shows the robustness to noise in parallel corpora. All of these features can help improve the performance of the NMT system. However, the methods of using phonetic information as embeddings had been explored mainly in Chinese and Western languages. They also used *Pinyin* instead of Bopomofo as the component to decompose Chinese characters. According to our study, no research has proposed to apply and analyze phonetic information as an additional feature in Chinese and Japanese NMT systems.

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method.

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experiment and result.

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conclusion.

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