

Exploiting Parallel Corpus for Handling Out-of-vocabulary Words

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Abstract

This paper presents a hybrid model for handling out-of-vocabulary words in Japanese-to-English statistical machine translation output by exploiting parallel corpus. As the Japanese writing system makes use of four different script sets (*kanji*, *hiragana*, *katakana*, and *romaji*), we treat these scripts differently. A machine transliteration model is built to transliterate out-of-vocabulary Japanese *katakana* words into English words. A Japanese dependency structure analyzer is employed to tackle out-of-vocabulary *kanji* and *hiragana* words. The evaluation results demonstrate that it is an effective approach for addressing out-of-vocabulary word problems and decreasing the OOVs rate in the Japanese-to-English machine translation tasks.

1 Introduction

Phrase-based statistical machine translation systems rely on parallel corpora for learning translation rules and phrases, which are stored in “phrase tables”. Words that cannot be found in phrase tables thus result in out-of-vocabulary words (OOVs) for a machine translation system. The large number of loanwords and orthographic variants in Japanese makes the OOVs problem more severe than in other languages. As stated in (Oh et al., 2006), most of out-of-vocabulary words in translations from Japanese are made up of proper nouns and technical terms, which are phonetically transliterated from other languages. In addition, the highly irregular Japanese orthography as is analyzed in (Halpern, 2002) poses a challenge for machine translation tasks.

Japanese is written in four different sets of scripts: *kanji*, *hiragana*, *katakana*, and *romaji* (Halpern, 2002). *Kanji* is a logographic

system consisting of characters borrowed from the Chinese characters. *Hiragana* is a syllabary system used mainly for functional elements. *Katakana* is also a syllabary system. Along with *hiragana*, they are generally referred as *kana*. *Katakana* is used to write new words or loan words, i.e., words that are borrowed and transliterated from foreign languages. *Romaji* is just the Latin alphabet.

In this paper, we present a method of tackling out-of-vocabulary words to improve the performance of machine translation. This method consists of two components. The first component relies on a machine transliteration model for *katakana* words that is based on the phrase-based machine translation framework. Furthermore, by making use of limited resources, i.e., the same parallel corpus used to build the machine translation system, a method of automatically acquiring bilingual word pairs for transliteration training data from this parallel corpus is used. With these enriched bilingual pairs, the transliteration model is further improved. In the second component, a Japanese dependency structure analyzer is used to build a *kanji-hiragana* system for handling orthographic variants.

The structure of the paper is as follows. Section 2 reviews related works. In Section 3, we present a back-transliteration model which is based on the SMT framework for handling *katakana* OOV words. Section 4 describes a method of tackling *kanji* and *hiragana* OOV words. Section 5 and 6 deal with the experiments and error analysis. Conclusion and future directions are drawn in Section 7.

2 Related Work

A number of works have been proposed to tackle the *katakana* out-of-vocabulary words by making

use of machine transliteration. According to (Oh et al., 2006), machine transliteration can be classified into four models: grapheme-based transliteration model, phoneme-based transliteration model, hybrid transliteration model, and correspondence-based transliteration model.

A grapheme-based transliteration model tries to map directly from source graphemes to target graphemes (Li et al., 2004; Sherif and Kondrak, 2007; Garain et al., 2012; Lehal and Saini, 2012b). In the phoneme-based model, phonetic information or pronunciation is used, and thus additional processing step of converting source grapheme to source phoneme is required. It tries to transform the source graphemes to target graphemes via phonemes as a pivot (Knight and Graehl, 1998; Gao et al., 2004; Ravi and Knight, 2009). A hybrid transliteration approach tries to use both the grapheme-based transliteration model and the phoneme-based model (Bilac and Tanaka, 2004; Lehal and Saini, 2012a). As described in (Oh et al., 2006), the correspondence-based transliteration model (Oh and Choi, 2002) is also considered as a hybrid approach. However, it differs from the others in that it takes into consideration of the correspondence between a source grapheme and a source phoneme, while a general hybrid approach simply uses a combination of grapheme-based model and phoneme-based model through linear interpolation.

Machine transliteration, especially those methods that adopt statistical models, rely on training data to learn transliteration rules. Several studies on the automatic acquisition of transliteration pairs for different language pairs (e.g., English - Chinese, English - Japanese, English - Korean) have been proposed in recent years.

Tsuji (2002) proposed a rule-based method of extracting *katakana* and English word pairs from bilingual corpora. A generative model is used to model transliteration rules, which are determined manually. As pointed out by Bilac and Tanaka (2005), there are two limitations of the method. One is the manually determined transliteration rules, which may pose the question of reduplication. The other is the efficiency problem of the generation of transliteration candidates. Brill et al. (2001) exploited non-aligned monolingual web search engine query logs to acquire *katakana* - English transliteration pairs. They firstly converted the *katakana* form to Latin script. A trainable

noisy channel error model was then employed to map and harvest (*katakana*, English) pairs. The method, however, failed to deal with compounds, i.e., a single *katakana* word may match more than one English words. Lee and Chang (2003) proposed using a statistical machine transliteration model to identify English - Chinese word pairs from parallel texts by exploiting phonetic similarities. Oh and Isahara (2006) presented a transliteration lexicon acquisition model to extract transliteration pairs from mining the web by relying on phonetic similarity and joint-validation.

While many techniques have been proposed to handle Japanese *katakana* words and translate these words into English, few works have focused on *kanji* and *hiragana*. As is shown in (Halpern, 2002), the Japanese orthography is highly irregular, which contributes to a substantial number of out-of-vocabulary words in the machine translation output. A number of orthographic variation patterns have been analyzed by Halpern (2002): (1) okurigana variants, which are usually attached to a *kanji* stem; (2) cross-script orthographic variants, in which the same word can be written in a mixture of several scripts; (3) *kanji* variants, which can be written in different forms; (4) *kun* homophones, which means word pronounced the same but written differently.

In this paper, we use a grapheme-based transliteration model to transform Japanese *katakana* out-of-vocabulary words to English, i.e., a model that maps directly from *katakana* characters to English characters without phonetic conversion. Furthermore, this model is used to acquire *katakana* and English transliteration word pairs from parallel corpus for enlarging the training data, which, in turn, improves the performance of the grapheme-based model. For handling *kanji* and *hiragana* out-of-vocabulary words, we propose to use a Japanese dependency structure analyzer and the source (i.e., Japanese) part of a parallel corpus to build a model for normalizing orthographic variants and translate them into English words.

3 Katakana OOV Model

Machine transliteration is the process of automatically converting terms in the source language into those terms that are phonetically equivalent in the target language. For example, the English word “chromatography” is transliterated in Japanese *katakana* word as “クロマトグラフィー”. The

task of transliterating the Japanese words (e.g., クロマトグラフィー) back into English words (e.g., chromatography) is referred in (Knight and Graehl, 1998) as *back-transliteration*.

We view the back-transliteration of unknown Japanese *katakana* words into English words as the task of performing character-level phrase-based statistical machine translation. It is based on the SMT framework as described in (Koehn et al., 2003). The task is defined as translating a Japanese *katakana* word $J_1^n = \{J_1, \dots, J_n\}$ to a English word $E_1^i = \{E_1, \dots, E_i\}$, where each element of J_1^n and E_1^i is Japanese grapheme and English character. For a given Japanese *katakana* J , one tries to find out the most probable English word E . The process is formulated as

$$\arg \max_E P(E|J) = \arg \max_E P(J|E)P(E) \quad (1)$$

where $P(J|E)$ is translation model and $P(E)$ is the language model. Here the translation unit is considered to be graphemes or characters instead of words, and alignment is between graphemes and characters as is shown in Figure 1.

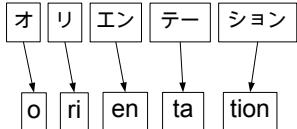


Figure 1: Character alignment

As the statistical model requires bilingual training data, a method of acquiring Japanese *katakana* - English word pairs from parallel corpus will be presented in the following section. The structure of the proposed method is summarized in Figure 2.

3.1 Acquisition of Word Pairs

In this section, we will describe our method of obtaining *katakana* - English word pairs by making use of parallel corpus.

The procedure consists of two stages. In the first stage, bilingual entries from a freely-available dictionary, JMdict (Japanese - Multilingual dictionary) (Breen, 2004), are first employed to construct a *seed* training data. By making use of this *seed* training set, a back-transliteration model that is based on the phrase-based SMT framework is then built. In the second stage, a list

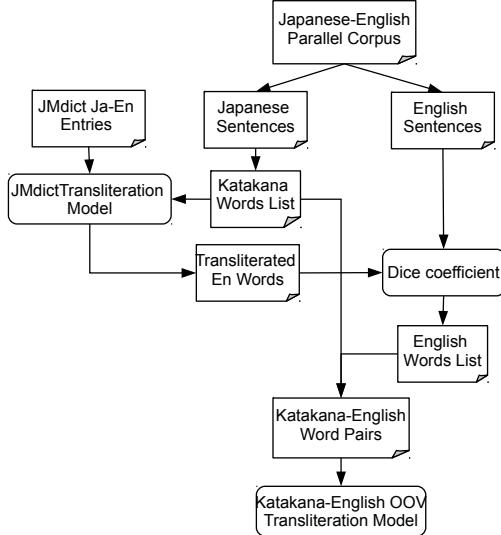


Figure 2: Illustration of katakana OOV model

of *katakana* words is firstly extracted from the Japanese (source) part of the parallel corpus. These *katakana* words are then taken as the input of the back-transliteration model, which generate “transliterated” English words. After computing the Dice coefficient between the “transliterated” word and candidate words from the English (target) part of the parallel corpus, a list of pairs of *katakana* - English words is finally generated.

To measure the similarities between the transliterated word w_x and target candidate word w_y , the Dice coefficient (Dice, 1945) is used. It is defined as

$$Dice(w_x, w_y) = \frac{2n(w_x, w_y)}{n(w_x) + n(w_y)} \quad (2)$$

where $n(w_x)$ and $n(w_y)$ are the number of bigram occurrences in word w_x and w_y respectively, and $n(w_x, w_y)$ represents the number of bigram occurrences found in both words.

3.1.1 One-to-many Correspondence

There is the case where a single *katakana* word may match a sequence of English words. Examples are shown in Table 1. In order to take into consideration of one-to-many match and extract those word pairs from parallel corpus, we pre-processed the English part of the corpus. Given a *katakana* word, for its counterpart, the English sentence, we segment it into n-grams, where $n \leq 3$. The Dice coefficient is then calculated between

the “transliterated” word of this *katakana* and English n-grams (i.e., unigrams, bigrams, and trigrams) to measure the similarities. This method allows to harvest not only one-to-one but also one-to-many (*katakana*, English) word pairs from parallel corpus.

Katakana	English
トナーパターン	toner pattern
フラッシュメモリ	flash memory
アイスクリーム	ice cream
グラフィックユーザインターフェース	graphic user interface
デジタルシグナルプロセッサ	digital signal processor
プロダクトライフサイクル	product life cycle

Table 1: One-to-many correspondence

4 Kanji-hiragana OOV Model

Japanese is written in four scripts (*kanji*, *hiragana*, *katakana*, and *romaji*). Use of these sets of scripts in a mixture causes the highly irregular orthography. As analyzed in (Halpern, 2002), there are a number of orthographic variation patterns: okurigana variants, cross-script orthographic variants, kana variants, kun homophones, and so on. Table 2 shows an example of okurigana variants and kun homophones. These Japanese orthographic variants pose a special challenge for machine translation tasks.

Patterns	English	Reading	Variants
Okurigana variants	‘moving’	/hikkoshi/	引越し 引っ越し 引越
	‘effort’	/torikumi/	取り組み 取組み 取組
Kun homophones	‘bridge’ ‘chopsticks’	/hashi/	橋 箸
	‘account’ ‘course’	/kouza/	口座 講座

Table 2: Orthographic variants

In this section, we will present our approach for tackling and normalizing out-of-vocabulary *kanji* and *hiragana* words. The architecture of the approach is summarized in Figure 3. The method comprises two processes: (a) building a model; (b) normalizing and translating *kanji-hiragana* OOVs. In the first process, firstly, we use the Japanese part of the parallel corpus (the same Japanese-English parallel corpus used for training in the standard

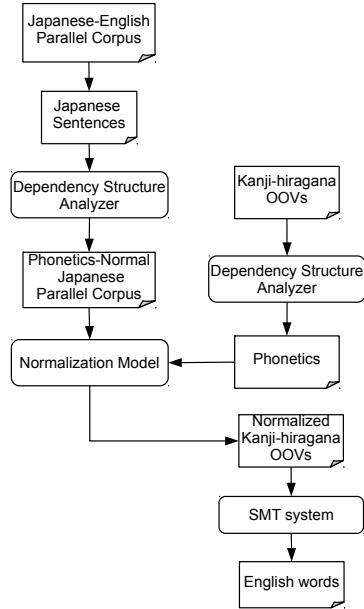


Figure 3: Illustration of kanji-hiragana OOV model

フカ オウトウ セイギョ ヲ アイドル カイテン スウ セイギョ ヲ ティック ワリコミ シヨリ ガ ホウデン デンリュウ ヲ カイシ サレル。 モールド ブデアル。 シュツリョク ベースアドレス ヲ ドウヨウ ナイブ シンゴウ モ ゲンティ サレル キリカエル クミアワセ ニヨル	負荷 応答 制御 を アイドル 回転 数 制御 を ティック 割り込み 处理 が 放電 電流 を 開始 さ れる。 モールド 部 で ある。 出力 ベースアドレス を 同様 内部 信号 も 限 定 さ れる 切り換える 組み合わせ による
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Figure 4: Sample of phonetic-to-standard Japanese parallel corpus

phrase-based SMT) as the input to the Japanese dependency structure analyzer CaboCha (Kudo and Matsumoto, 2002). A phonetic-to-standard Japanese parallel corpus (Figure 4) is then obtained to train a monolingual Japanese model which is also built upon a phrase-based statistical machine translation framework. In the second process, the dependency structure analyzer CaboCha is applied to generate corresponding phonetics from a list of *kanji-hiragana* out-of-vocabulary words. These OOVs in the phonetic forms are then input to the monolingual model to produce a list of normalized *kanji-hiragana* words. Finally, the normalized OOV words will be translated into English.

5 Experiments

In this section, we will present the results of three experiments. In the first setting, we evaluate the performance of back-transliteration model. The data sets used in the back-transliteration system comprise one-to-one or one-to-many *Katakana*-English word pairs, which are segmented at the character level. In the second setting, the performance of the model for normalizing *kanji-hiragana* is assessed. In the third setting, the performance of handling both *Katakana* and *kanji-hiragana* out-of-vocabulary words in a machine translation output will be evaluated.

5.1 Katakana Transliteration Test

To train a back-transliteration model which is built upon a phrase-based statistical machine translation framework, we used the state-of-the-art machine translation toolkit: Moses decoder (Koehn et al., 2007), alignment tool GIZA++ (Och and Ney, 2003), MERT (Minimum Error Rate Training) (Och, 2003) to tune the parameters, and the SRI Language Modeling toolkit (Stolcke, 2002) to build character-level target language model.

The data set for training (499,871 entries) we used in the experiment contains the JMdict entries and word pairs extracted from parallel corpus. The JMdict consists of 166,794 Japanese - English entries. 19,132 *katakana* - English entries are extracted from the dictionary. We also extracted 480,739 *katakana* - English word pairs from NTCIR Japanese - English parallel corpus. The development set is made of 500 word pairs, and 500 entries are used for test set.

The experimental results are shown in Table 3.

For evaluation metric, we used BLEU at the character level (Papineni et al., 2002; Denoual and Lepage, 2005; Li et al., 2011). Word accuracy and character accuracy (Karimi et al., 2011) are also used to assess the performance of the system. Word accuracy (WA) is calculated as:

$$WA = \frac{\text{number of correct transliterations}}{\text{total number of test words}} \quad (3)$$

Character accuracy (CA) is based on the Levenshtein edit distance (Levenshtein, 1966) and it is defined as:

$$CA = \frac{\text{len}(T) - ED(T, L(T_i))}{\text{len}(T)} \quad (4)$$

where $\text{len}(T)$ is the length of reference word T . $L(T_i)$ is the suggested transliteration at rank i , and ED is the Levenshtein edit distance (insertion, deletion, and substitution) between two words. The character accuracy takes an average of all the test entries.

System	BLEU	WA	CA
<i>Katakana</i> transl.	80.56	50.60%	86.33%

Table 3: Evaluation results of transliteration test

An analysis of number of character errors in entry strings is shown in Table 4. 253 out of 500 entries (50.60%) match exactly the same as the reference words. Strings contain one and two character errors are 86 (17.20%) and 56 (11.20%), respectively. In total, strings with less than two character errors represent 79.00% of overall test entries. There are 50 (10.00%) and 55 (11.00%) entries contain three or more character errors.

Examples of *katakana* - English transliteration output are given in Table 5. For some *katakana* words, they are transliterated correctly as references. For other *katakana* words, it shows that the output of transliteration contain spelling errors. For example, the grapheme “アン” can be transliterated into “an”, “en”, or “un”. For the *katakana* word “アンハッピー” (unhappy), it is erroneously transliterated into “anhappy” .

5.2 Kanji-hiragana Normalization Test

In the second setting, we will assess the performance of *kanji-hiragana* normalization model as it is described in Section 4. As the monolingual Japanese normalization model is also built upon

Character errors	Entries	Percentage
0 character error	253	50.60%
1 character error	86	17.20%
2 character error	56	11.20%
3 character error	50	10.00%
Others	55	11.00%

Table 4: Analysis of number of character errors

	Katakana	Reference	Output
0	インベンション	invention	invention
0	インプット	input	input
0	アンカー	anchor	anchor
1	アンカーマン	anchorman	ancherman
1	アンハッピー	unhappy	anhappy
1	アントレ	entree	entre
2	インテルクチュアル	intellectual	intelctual
2	インビジブル	invisible	inbsible
2	インテリア	interior	interia
n	インターフェアランス	interference	interfealnce
n	アンフェア	unfair	anfare
n	アンタッチャブル	untouchable	antatchable

Table 5: Examples of character errors

the statistical machine translation framework, we used the same toolkit as those in Section 5.1. For the training set, we applied the Japanese dependency structure analyzer CaboCha on the Japanese part of the parallel corpus (300,000 lines) and obtained a phonetic-to-standard Japanese parallel corpus (see Figure 4). The development set and test set consist of 1,000 lines and 5,000 words, respectively. Since this experiment is not a task of measuring the accuracy of the output of the model (i.e., it is a test of how the monolingual model can normalize the Japanese *kanji-hiragana* words), we did not use any evaluation metrics, such as BLEU, WA, and CA.

Table 6 shows an analysis of number of character differences between *kanji-hiragana* words and their normalized forms. The number of entries matches exactly the same as the original Japanese words is 3908, which represents 78.16% of all test entries. There are 21.84% of the entries which are normalized to different forms. Examples of number of character differences is shown in Table 7. The normalized output forms can generally be categorized into three types: *kun homophones*, *okurigana variants*, and others. *Kun homophones* would cause orthographic ambiguity. Words in the category *okurigana variants* are normalized into

different forms but they have the same meaning. It shows that the monolingual normalization model is useful for solving out-of-vocabulary *okurigana variants* and helps reducing the out-of-vocabulary words rate. There are other words that are not normalized for which the phonetic representations is output directly.

Character diff.	Entries	Percentage
0 character diff.	3,908	78.16%
1 character diff.	424	8.48%
2 character diff.	509	10.18%
3 character diff.	44	0.88%
Others	115	2.30%

Table 6: Analysis of number of character differences

Japanese	Phonetics	Norm. output
0 駐車 (parking)	チュウシャ	駐車 (parking)
0 飲み物 (beverage)	ノミモノ	飲み物 (beverage)
0 電極 (electrode)	デンキヨク	電極 (electrode)

kun homophones

1 視点 (perspective)	シテン	支点 (fulcrum)
1 通貨 (currency)	ツウカ	通過 (pass)
1 講座 (course)	コウザ	口座 (account)
2 注視 (gaze)	チュウシ	中止 (stop)
2 意思 (intention)	イシ	医師 (doctor)
2 近郊 (suburbs)	キンコウ	均衡 (balance)
n 当たり (per)	アタリ	辺 (side)

okurigana variants

1 読みとり (read)	ヨミトリ	読み取り
1 繰返し (repeat)	クリカエシ	繰り返し
1 呼出し (call)	ヨビダシ	呼び出し
2 繰め (collect)	マトメ	まとめ
2 鈎合 (balance)	ツリアイ	釣り合い
2 振替 (transfer)	フリカエ	振り替え
n うま味 (umami)	ウマミ	旨み

others

n 切替 (switch)	キリカエ	切り換え
n 雪崩 (avalanche)	ナダレ	ナダレ
n 藤木 (personal name)	フジキ	フジキ

Table 7: Examples of character differences can be seen by comparing the Japanese column with the Normalized output column

5.3 Out-of-vocabulary Words Test

In the third setting, we evaluate the performance of handling out-of-vocabulary words for machine translation by making use of *katakana* OOV model and *kanji-hiragana* OOV model. The system architecture is summarized in Figure 5. From the output of a machine translation system, out-of-vocabulary words are firstly extracted. OOV *katakana* words are then transliterated into En-

glish by using the back-transliteration model and OOV *kanji-hiragana* words are normalized and translated into English words by using the normalization model. A standard phrase-based statistical machine translation system is built by making use of the same toolkit as described in Section 5.1. KyTea (Neubig et al., 2011) is used to perform segmentation on *katakana* OOV words.

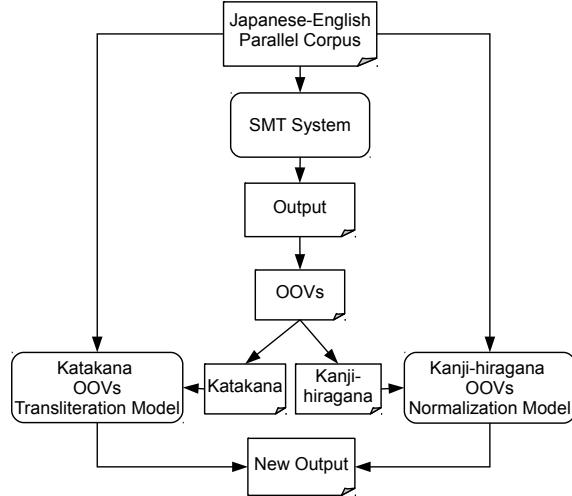


Figure 5: Illustration of system architecture

For data sets in the baseline SMT system, we used a sample of NTCIR Japanese - English parallel corpus. The training set is made of 300,000 lines. The development set contains 1,000 lines, and 10,000 lines are used for test set.

As for the evaluation, while the quality of a machine translation system is usually measured in BLEU scores, it may not be fair to examine the results in BLEU scores for measuring the improvement and contribution of out-of-vocabulary *katakana* transliteration and *kanji-hiragana* normalization to a machine translation system. Here we provide the BLEU scores as a reference. Table 8 shows the evaluation results of OOV words test. By comparing with the baseline system, it shows that there is a slight gain in BLEU for transliterating out-of-vocabulary *katakana* words and normalizing and translating *kanji-hiragana* words. We also extracted sentences that contain out-of-vocabulary words (813 lines) from the test set. In comparison with the baseline, sentences with translated out-of-vocabulary words give better result.

An analysis of out-of-vocabulary words in the machine translation output is presented in Table 9.

System	BLEU
Japanese - English MT baseline	24.72
MT with translated OOV word	24.77
Sentence with OOV (MT baseline)	16.04
Sentence with OOV (translated OOV word)	16.57

Table 8: Evaluation results of OOV words test

In the output of a test set of 10,000 sentences, there are 1,105 out-of-vocabulary Japanese words. Among these OOV words, 447 out of 1,105 are *katakana* words, which is 40.45%. The number of OOV *kanji-hiragana* words are 658 (59.55%).

	Data
Test sentences	10,000
Out-of-vocabulary words	1,105
OOV <i>katakana</i>	447
OOV <i>kanji-hiragana</i>	658

Table 9: Analysis of out-of-vocabulary words

6 Error Analysis

The main points observed from a scrutinous analysis of the results of *katakana* OOV model and *kanji-hiragana* OOV model and countermeasures against them are as follows:

Katakana OOV model: some compound *katakana* words are not segmented appropriately, which result in erroneous English transliteration. Further improvement on back-transliteration model would be expected when the accuracy of segmentation of *katakana* words is improved.

- the word: インストルメンタルパネル
segment: インストル | メンタル | パネル
transliterate: instrumental panel
- the word: レイティングディスクリプタ
segment: レイティング | デイス | クリプタ
transliterate: rating dis criptor
- the word: カムセンサ
segment: カムセンサ
transliterate: camsensor

Kanji-hiragana OOV model: handling *kanji-hiragana* words is very difficult due to the orthographic variants and the complexity of the Japanese writing system. The model is useful for handling *okurigana* variants. For example, the

word “閉込め” is normalized into “閉じ込め” and translated correctly into “confinement”. However, 68% (447) of the normalized *kanji-hiragana* words cannot be translated into English. Some words are normalized and transformed into different written forms as they are pronounced the same (*kun homophones*), which leads to ambiguity. Further classification and treatment of *kanji-hiragana* words is needed as it is observed from the machine translation output that 145 out of 658 out-of-vocabulary words (22.04%) are personal names, place names, and organization names, i.e., named entities. Building a mapping table between the phonetics of words and their romanization representations might be effective for tackling names, which may further improve the performance of *kanji-hiragana* model.

- *kun homophones*: 変事
phonetics: ヘンジ
normalize: 变事
translate: reply
- name: 宗二
phonetics: ソウジ
normalize: 相似
translate: analogous
- name: 富士通
phonetics: フジツウ
normalize: 富士通
translate: 富士通

7 Conclusion and Future Work

We have described a method of handling both *katakana* and *kanji-hiragana* out-of-vocabulary words by exploiting parallel corpus. A grapheme-based back-transliteration model is built upon the phrase-based statistical machine translation framework for transliterating *katakana* into English words. This model is also used to enriching training set by extracting Japanese *katakana* and English word pairs from parallel corpus. A normalization model is built to tackle and translate *kanji-hiragana* words. While there are limitations of the model, it can be an aid to normalize and translate *okurigana variants*.

It is summarized in (Karimi et al., 2011) that grapheme-based models tend to provide better performance than phoneme-based models. This is because that the transliteration process consists of fewer steps and that there is less reliance on external pronunciation dictionaries. They also

pointed out that transliteration models can usually be used in combination to improve the performance. In the future, we would like to try to use the transliteration models in a complimentary manner. The experimental results reveal that segmentation of Japanese *katakana* words should be improved, which will be our future work. We also plan to investigate the effects of handling of names in reduction of out-of-vocabulary words.

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