Learning How to Translate North Korean through South Korean

Hwichan Kim†, Sangwhan Moon‡,†, Naoaki Okazaki‡, Mamoru Komachi†
†Tokyo Metropolitan University, 6-6 Asahigaoka, Hino, Tokyo 191-0065, Japan
‡Tokyo Institute of Technology, 2-12-1 Ookayama, Meguro, Tokyo 152-8550, Japan
†Google LLC, 1600 Amphitheatre Parkway Mountain View, CA 94043, USA

kim-hwichan@ed.tmu.ac.jp, sangwhan@iki.fi, okazaki@c.titech.ac.jp, komachi@tmu.ac.jp

Abstract
South and North Korea both use the Korean language. However, Korean NLP research has focused on South Korean only, and existing NLP systems of the Korean language, such as neural machine translation (NMT) models, cannot properly handle North Korean inputs. Training a model using North Korean data is the most straightforward approach to solving this problem, but there is insufficient data to train NMT models. In this study, we create data for North Korean NMT models using a comparable corpus. First, we manually create evaluation data for automatic alignment and machine translation. Then, we investigate automatic alignment methods suitable for North Korean. Finally, we verify that a model trained by North Korean bilingual data without human annotation can significantly boost North Korean translation accuracy compared to existing South Korean models in zero-shot settings.

Keywords: Parallel corpus construction, Machine translation, Korean

1. Introduction
South and North Koreans use the same Korean language, with the same grammar. However, there are some differences between South and North Korean vocabularies and spelling rules (Lee, 1990; Yun and Kang, 2019).

Several NLP researchers have recently been working on the Korean language. For example, the Workshop of Asian Translation (Nakazawa et al., 2021) has been conducting a series of shared tasks annually, including on Korean language variants. However, these studies are focused exclusively on the South Korean language; none of the developed NLP systems support the North Korean language. For example, public neural machine translation (NMT) systems cannot translate North Korean-specific words (Table 1). Although training models on North Korean data is a simple and effective way to improve the quality of North Korean translation, parallel data for training are unavailable.

In this study, we tackle North Korean to English and Japanese bilingual data creation from comparable corpora to train a North Korean NMT model. Our contribution in this paper is threefold: (1) We manually create North Korean evaluation data for the development of MT systems. (2) We investigate automatic article and sentence alignment methods suitable for North Korean, and create a small amount of North Korean parallel training data using a method that achieved the highest alignment quality. (3) We compare North Korean to English and Japanese NMT models and show that our North Korean data can significantly enhance the translation quality when used in conjunction with South Korean datasets.

2. Related Work
2.1. Automatic Parallel Corpus Alignment
Building NMT systems requires parallel data consisting of parallel sentences. However, the manual creation of parallel sentences is costly and time-consuming. Consequently, research on the automatic alignment of parallel sentences from parallel documents is actively underway. The typical methods proposed to date are based on using a bilingual dictionary for sentence alignment (Chen, 1993; Etchegoyhen and Azpeitia, 2016; Azpeitia et al., 2017). These methods translate source words to target words using a bilingual dictionary, and then align the sentences based on the similarity between the translated sentences. Sennrich and Volk (2010), Gomes and Lopes (2016), and Karimi et al. (2018) used an existing machine translation (MT) system instead of a bilingual dictionary. If we adopt this approach to North Korean alignment, using a South Korean MT system is a possible approach because there are no publicly available North Korean MT systems or models.

The alignment methods based on cross-lingual representations are useful methods that map sentences to the cross-lingual semantic space and align them according to their closeness (Schwenk and Douze, 2017; Schwenk, 2018; Artetxe and Schwenk, 2019). Sun et al. (2021) used an existing machine translation (MT) system instead of a bilingual dictionary. If we adopt this approach to North Korean alignment, using a South Korean MT system is a possible approach because there are no publicly available North Korean MT systems or models.

Kim et al. (2020) proposed a North Korean and English evaluation dataset for machine translation by manually rewriting sentences of a South Korean dataset to conform with North Korean spelling rules. However, as they are written from a South Korean dataset, the sentences in the data are not considered of North Korean provenance.
ble corpora (BUCC) task (Zweigenbaum et al., 2017). This approach used representations of a multilingual NMT model encoder as the cross-lingual representations. In this study, we compare these two approaches of using an MT system and LASER, and create North Korean training parallel data through an approach that achieved the highest alignment quality.

### 2.2. Machine Translation for Dialects

In addition to South and North Korean, several languages have dialects such as Brazilian and European Portuguese, Canadian and European French. Lakew et al. (2018) demonstrated that the translation accuracy is dropped when using the different dialect’s training data with target one.

One of the reasons for this problem is the spelling, lexical, and grammar divergence between dialects. Therefore, to mitigate the reduction in translation accuracy, the differences between the dialects must be absorbed. Rule-based transformation between dialects is one of the approaches for achieving this (Marujo et al., 2011; Tan et al., 2012). Additionally, several studies have attempted to construct an MT system between the dialects (Durrani et al., 2010; Popović et al., 2016; Harrat et al., 2019). However, rule-based transformation cannot address the differences between the vocabularies, and to construct a machine translation system, a parallel corpus is necessary between the dialects.

Transfer learning is also a useful approach if there are parallel data between the dialect and target language. Transfer learning, which is an approach to fine-tune the NMT model trained by the parallel corpus of another language pair (transfer source) with the one of low-resource-language pair (transfer destination), is an effective approach for improving the accuracy in a low-resource-language scenario. Previous studies have demonstrated that transfer learning works efficiently when the transfer source and destination languages are linguistically similar (Zoph et al., 2016; Dabre et al., 2017). Dialects typically have almost the same grammar and many vocabularies in common. In fact, Lakew et al. (2018) showed that the transfer learning is effective for the dialects of Portuguese and French.

Since the differences between South and North Korean languages are not only in the grammar but also vocabulary, it is difficult to absorb the differences with only the rule-based transformation. Furthermore, there is no available bilingual dictionary and parallel data between the South and North Korean. However, we can construct parallel data between North Korean and a target language using North Korean news articles. Consequently, in this study, we adopt the transfer learning approach, using South Korean and the target language NMT model as the transfer source.

### 3. North Korean Parallel Corpus Construction

In this study, we create North Korean parallel corpus from North Korean news articles. We use a news portal, Uriminzokkiri that publishes news articles from various North Korean (NK) news sources. These articles are translated into English (EN), Chinese, Russian and Japanese (JA). In this study, we use North Korean, English, and Japanese articles.

Table 2 lists the total numbers of articles and their sentences. One of the problems with the data sourced from this site is that articles and sentences are not aligned between North Korean and each of the other languages. Therefore, we manually and automatically align them to create North Korean parallel corpus.

---

**Table 1:** Translation example. SK denotes the South Korean model, and SK→NK denotes the model fine-tuned by our North Korean data. The squiggles indicate mistranslated words.

| NK source | Reference | SK | SK→NK | Google | NAVER |
|-----------|-----------|----|-------|--------|-------|
| 4월 24일 로씨아연방 올라지보스토크시에 도착하시였다. | He arrived at Vladivostok, the Russian Federation on Wednesday. | He arrived at the city of Ulazibosto on April 24th. | He arrived in Vladivostok, the Russian Federation on April 24. | On April 24th, you arrived in the city of Ulagivostok in the Russian Federation. | On April 24th, he arrived at Ulazibos Tok City, a training room for RoC. |

**Table 2:** Number of articles and sentences. The number of articles differs because unique articles exist in each language.

| Language | Articles | Sentences |
|----------|----------|-----------|
| North Korean | 408 | 6,622 |
| English | 414 | 6,770 |
| Japanese | 415 | 6,220 |

---

2 A shared task on parallel sentence extraction from parallel documents.

---

3 In this study, we used articles from September 2017 to June 2021, when we started our experiment. The URLs of articles prior to September 2017 are available, but we are unable to access them. We obtained permission to re-distribute the article data.
Table 3: Manually created sentence and article alignment evaluation data. These figures indicate the numbers of monolingual sentences and articles (Mono) in each language and annotated alignments of parallel sentences and articles (Para).

|            | Mono | Para |
|------------|------|------|
| NK–EN      |      |      |
| NK–JA      |      |      |
| Sentences  | 290  | 285  |
| Articles   | 408  | 359  |

Table 4: Sentence and article alignment F1 scores. † indicates the statistical significance (p < 0.05) between the bidi-SK and LASER.

|            | NK–EN | NK–JA |
|------------|-------|-------|
| Naive      | 0.1   | 0.5   |
| LASER      | 96.7  | 96.9  |
| to-SK      | 94.3  | 97.4  |
| from-SK    | 96.1  | 95.3  |
| bidi-SK    | 96.9  | 97.5  |

Table 5: Number of sentences in the manually aligned dev and test data, and the automatically aligned training data. We randomly split 1,000 parallel sentences in half and use them as dev and test data. The numbers in parentheses are those of sentences in the setting that use the bidi-SK for article alignment.

|            | dev | test | train |
|------------|-----|------|-------|
| NK–EN      | 500 | 500  | 4,109 (4,343) |
| NK–JA      | 500 | 500  | 3,739 (3,913) |

3.1. Manual Evaluation Data Alignment

We manually align the NK–EN and NK–JA articles and sentences to create evaluation data for MT. At first, we align all articles (Table 2). Then, we randomly sample the sentences from the English and Japanese articles and manually select the parallel sentences from the North Korean articles. The alignments between these languages require an annotator that can read and understand Korean, English, and Japanese. Therefore, we assign a trilingual annotator—a Korean living in Japan who is enrolled in a computer science master’s program. To measure inter-annotator agreement, we additionally ask two bilingual Koreans to perform annotation.

Furthermore, we create evaluation data for North Korean article and sentence alignments to investigate automatic alignment methods suitable for North Korean. For the article alignment evaluation, we use the aligned articles. For the sentence alignment evaluation, we select one article and manually align sentences it contained. We ask this alignment to the trilingual annotator.

3.2. Automatic Training Data Alignment through South Korean NMT

Previous studies have proposed several alignment approaches, such as using a bilingual dictionary [Chen, 1993; Azpeitia et al., 2017]. Furthermore, approaches have been proposed that use the representations from the cross-lingual models, which are trained with a supervised method [Schwenk, 2018] [Artetxe and Schwenk, 2019b] or an unsupervised method [Keung et al., 2020; Sun et al., 2021]. However, these approaches cannot be used for North Korean alignment as there are no resources immediately available, including, but not limited to, bilingual dictionaries, parallel sentences, and monolingual data.

Although there are some differences between South and North Korean, both forms of Korean have the same basic grammar, and share many vocabularies in common. Therefore, a South Korean NMT model can translate North Korean sentences to some extent. In this study, inspired by this aspect and a previous approach that used an existing MT model [Karimi et al., 2018], we design an automatic North Korean alignment method using the South Korean NMT model instead of a North Korean one.

**Sentence alignment.** In sentence alignment, we assume that parallel North Korean and target language documents are available, defined as \( N = \{n_1, ..., n_i\} \) and \( T = \{t_1, ..., t_k\} \). Here, \( n_i \) corresponds to a sentence in \( N \) and \( t_k \) for \( T \), and \( i, k \) are the number of sentences in a given document.

A sentence alignment method based on South Korean NMT consists of two steps. In the first step, we translate \( N \) and \( T \) into both target language and South Korean using South Korean NMT models. We define the translated documents \( \tilde{N} \) and \( \tilde{T} \) as \( \tilde{N} = \{\tilde{n}_1, ..., \tilde{n}_i\} \) and \( \tilde{T} = \{\tilde{t}_1, ..., \tilde{t}_k\} \) and the translated sentences \( \tilde{n}_i \) and \( \tilde{t}_k \) as \( \tilde{n}_i \) and \( \tilde{t}_k \).

In the second step, we measure similarity score between the original and translated sentences, and greedily select sentence pairs with the highest similarity score as bilingual sentences. An index of bilingual sentence corresponding to \( \tilde{t}_k \) is as follows:

\[
j = \arg \max_{j \in \{1, ..., i\}} [\text{sim}(n_j, \tilde{t}_k) + \text{sim}(\tilde{n}_j, t_k)]
\]

where sim is a function to measure the similarities between sentence vectors. We use tf-idf to vectorize a sentence and a margin-based function [Artetxe and Schwenk, 2019a] as the sim following LASER [Artetxe and Schwenk, 2019b].
In this study, we use bi-directional South Korean NMT models, but this framework can also works in a unidirectional model. We refer to these methods as follows: to-SK denotes the South Korean model, from-SK denotes the South Korean model, and bidi-SK denotes bi-directional South Korean models.

**Article alignment.** In this study, we also extend this method for aligning articles, which uses the similarity between the sentences translated by South Korean NMT models. In the article alignment, we use the concatenated sentences of title and document to vectorize each article.

4. North Korean Alignment Experiments

4.1. Experimental Settings

**Manual evaluation data alignment.** To create the MT evaluation data, we align the articles (Table 2) and 1,000 sentences randomly extracted from the English and Japanese articles. We ask the trilingual annotator to align these articles and sentences. We also ask the bilingual annotators to align 100 articles and sentences randomly sampled from them. Then, we measure the inter-annotator agreement using these 100 articles and sentences.

To create the sentence alignment evaluation data, we chose the article with the most English and Japanese sentences per NK–EN and NK–JA pair. The numbers of each language’s sentences were 290, 300 and 143, 100 in NK–EN and NK–JA pairs, respectively. We ask the trilingual annotator to align these sentences.

**Automatic training data alignment.** We use the news domain translation dataset from AI Hub to train South Korean NMT models. The datasets have 720k and 920k sentences, in SK–EN and SK–JA pairs, respectively. We pre-tokenize Japanese sentences using MeCab with an IPA dictionary and then split each language’s sentences into subwords using SentencePiece (7) model with 32k vocabulary size per language. We use a transformer-base (Vaswani et al., 2017) for the NMT model using fairseq (8). When tokenizing the sentences for the to-SK, from-SK, and bidi-SK, we train another SentencePiece model using the original sentences and their translations using the South Korean model (Table 2).

Additionally, we set the vocabulary size to 2k, as there are only a handful of sentences in each article (Table 2). We compare the method based on South Korean NMT model to two baselines. (1) A naïve method aligning the sentences per index in the document. (2) LASER (Artetxe and Schwenk, 2019b), which is a cross-lingual model trained by bilingual data between several languages. Notably, North Korean sentences were not included in the training data of LASER. When aligning articles using LASER, we mean-pool each sentence’s vectors as LASER to vectorize articles.

As evaluation metric, we use F1 scores that is an official metric in the BUCC shared task (Zweigenbaum et al., 2017). Specifically, precision and recall are calculated as percentages of correct pairs among selected and gold pairs. We compare each method based on the F1 scores and select the best performing method to align the training data.

4.2. Experimental Results

**Manual evaluation data alignment.** We discuss the results of the article and sentence alignments for the MT evaluation data. The match rates of the article and sentence alignments between the trilingual and bilingual annotators are 99%, 95% and 99%, 100% for the NK–EN and NK–JA pairs, respectively. Based on this, we confirm that the aligned articles and sentences are in agreement between the annotators. As the results of manual alignments, we obtain 359 and 356 parallel articles and 1,000 parallel sentences for the NK–EN and NK–JA pairs, respectively. We also obtain evaluation data for automatic sentence alignment that consisted of 285 and 100 parallel sentences through the alignments of the sentences of a parallel article chosen per NK–EN

---

https://aihub.or.kr/
https://taku910.github.io/mecab/
Table 6: BLEU scores of each model. These BLEU scores are the averages of three models. The rows for Human and bidi-SK are the settings of using human annotation and the bidi-SK for article alignment, respectively.

| article | model | SK–EN | NK–EN | SK–JA | NK-JA |
|---------|-------|-------|-------|-------|-------|
|         |       | dev   | test  | dev   | test  | dev   | test  | dev   | test  |
| SK      |       | 37.6±.22 | 37.7±.20 | 11.4±.17 | 11.9±.21 | 71.0±.04 | 70.9±.05 | 36.8±.19 | 37.8±.09 |
| NK      |       | 0.5±.06 | 0.5±.03 | 21.4±.15 | 20.4±.20 | 1.5±.03 | 1.5±.07 | 36.8±.20 | 34.0±.21 |
| Human   | SK→NK | 11.0±.04 | 11.1±.05 | 36.7±.12 | 35.6±.12 | 69.3±.11 | 61.3±.07 | 69.7±.11 | 69.7±.14 |
|         | SK+NK | 37.4±.08 | 37.3±.06 | 34.2±.07 | 33.6±.23 | 70.4±.17 | 70.4±.16 | 67.9±.14 | 67.5±.05 |
| NK      |       | 0.5±.09 | 0.5±.09 | 21.5±.14 | 20.5±.23 | 1.2±.06 | 1.2±.06 | 33.3±.09 | 30.1±.19 |
| bidi-SK | SK→NK | 24.2±.05 | 24.3±.11 | 36.2±.28 | 35.2±.34 | 47.2±.09 | 47.2±.09 | 70.5±.14 | 69.4±.26 |
|         | SK+NK | 37.3±.11 | 37.2±.12 | 34.6±.22 | 33.8±.02 | 70.6±.14 | 70.6±.11 | 67.8±.13 | 67.1±.11 |

Table 7: BLEU scores without long substring duplication with the training data.

| article | model | NK–EN | NK–JA |
|---------|-------|-------|-------|
|         |       | dev   | test  | dev   | test  |
| SK      |       | 9.3±.29 | 9.3±.29 | 39.9±.23 | 39.5±.20 |
| NK      |       | 9.6±.23 | 10.0±.20 | 24.4±.24 | 24.3±.32 |
| Human   | SK→NK | 26.0±.15 | 25.3±.10 | 66.7±.12 | 65.7±.11 |
|         | SK+NK | 23.5±.16 | 22.5±.34 | 63.4±.15 | 65.8±.25 |
| NK      |       | 8.7±.23 | 7.8±.25 | 22.2±.19 | 22.5±.25 |
| bidi-SK | SK→NK | 25.9±.20 | 24.0±.25 | 66.9±.12 | 66.0±.19 |
|         | SK+NK | 22.7±.16 | 21.9±.24 | 63.0±.22 | 62.6±.18 |

and NK–JA pairs. We summarize the evaluation data for sentence and article alignments in Table 3.

**Automatic training data alignment.** We show the alignment quality of each method using the manually created evaluation data (Table 3). Table 4 shows the F1 scores of each sentence alignment method. LASER, a strong baseline, achieves 96.8 and 96.9 in each language pair, respectively, and significantly outperforms the naive method. The to-SK and from-SK also align the sentences with high scores. The bidi-SK further improves the F1 scores and slightly outperforms the LASER. Table 4 also shows the article alignment F1 scores of each method. The bidi-SK achieves the highest scores of 97.6 and 98.4 for the NK–EN and NK–JA pairs. These results show that bidi-SK is suitable for North Korean sentence and article alignment. Therefore, we adopt the bidi-SK for aligning North Korean training data. We exclude the sentences included in the manually created evaluation data from the documents, and then, apply the bidi-SK to align parallel sentences. A summary of our North Korean parallel corpus constructed through manual and automatic alignment is presented in Table 5.

**Characteristic of North Korean parallel corpus.** We discuss the characteristics of the North Korean parallel corpus. Owing to the nature of North Korean articles, our corpus contains a significant amount of duplicated substrings. Following Lee et al. (Lee et al., 2021), we measure the duplication probability of word substrings in South and North Korean training data of English and Japanese sides. The duplication probabilities for each substring length are in Figure 1a. This figure indicates that the probabilities of substrings with more than ten consecutive duplicate words are higher in North Korean than those of South Korean data. We also calculate the duplication probabilities between the dev and train sentences as shown Figure 1b. It indicates that North Korean evaluation data contains many duplicates of long substrings with training data.

Thus, our North Korean parallel corpus has some limitations regarding the size and diversity of sentences. However, our corpus is useful for developing a North Korean translation system because there is no other corpus with such data available. Additionally, the results of the automatic alignment experiments will serve as a useful reference when creating more parallel corpora in the future.

**5. North Korean NMT Experiments**

**5.1. Experimental Settings**

We use the same South Korean datasets and implementation of the NMT model as presented in Section 4.1. We use merged sentences of South and North Korean bilingual data for training the SentencePiece model, and set the vocabulary size as 32k per language. We compare the models trained by only South or North...
Vladivostok word mantly diverged in South Korea. For example, the
translate words that are spelled differently or have se-
tage of using the North Korean data is the ability to
The most significant advan-
Qualitative evaluation.
show the same trend.
the relations between the BLEU scores of each model
10 points compared to the scores in Table 6. However,
elements are almost the same, whereas those of the NK,
string duplication. The BLEU scores of the SK mod-
ing the North Korean evaluation data without long sub-
train data. Table 7 shows the BLEU scores obtained us-
ate that duplicate more than ten substrings with the
evaluate the models by deleting the sentences of dev and
test that use our proposed method.
5.2. Experimental Results
Quantitative evaluation. Table [6] shows the BLEU
scores of each model. The SK→NK model achieves
the highest BLEU scores in the evaluations of NK→EN
and NK→JA pairs. This result indicates that the models
trained by only SK or NK data cannot translate North
Korean sentences well, but fine-tuning the SK model
using a small amount of North Korean data can signifi-
cantly boost the translation quality. The SK+NK model
also improves the BLEU scores and mitigates degrada-
tion in the SK→EN and SK→JA evaluations compared
to the SK→NK model. Therefore, we consider that im-
proving the SK+NK model is a good way to develop
a universal Korean NMT model. In addition, surpris-
ingly, the models that use our method for aligning the
articles achieve similar scores as the models that use
human annotation.
As discussed in Subsection 4.2, the North Korean eval-
uation data contains many duplicates of long substrings
with training data. Because duplicates of long sub-
strings between the train and evaluation data leads to an
overestimation of the North Korean models, we eval-
uate the models by deleting the sentences of dev and
test that duplicate more than ten substrings with the
train data. Table [7] shows the BLEU scores obtained us-
using the North Korean evaluation data without long sub-
string duplication. The BLEU scores of the SK mod-
els are almost the same, whereas those of the NK,
SK→NK, and SK+NK models have decreased by 4–
10 points compared to the scores in Table [6]. However,
the relations between the BLEU scores of each model
show the same trend.
Qualitative evaluation. The most significant advan-
tage of using the North Korean data is the ability to
translate words that are spelled differently or have se-
mantically diverged in South Korea. For example, the
word Vladivostok is written as “블라디보스토크” in
South Korea but “올라지보스토크” in North Korea.
Therefore, whereas publicly available South Korean
models such as those of Google[8] and NAVER[9] are
unable to translate “올라지보스토크,” which means
Vladivostok, the models trained with North Korean data
are able to produce correct translations (Table [1]). On
the other hand, the compound word plenary meeting
is written as “전원회의” in North Korean. Both the
words “전원” and “회의” are also used in South Ko-
rean, but these words are not used in conjunction as
plenary meeting. The South Korean models translate
“전원회의” to full session, which is similar, but not
perfect. In contrast, the models using North Korean data
translate it correctly (Table [3]). Notably, the NK model,
which uses a small amount of North Korean data, trans-
lates “전원회의” appropriately, but it cannot translate
fluently. Specifically, the NK model translates “제7기”
and “제6기” to 4th and 8th, respectively, and repeats
the words decided on the issue of convening (Table [5]).

6. Conclusion
In this study, we manually created evaluation data for
automatic alignment and MT systems. Moreover, we
showed that bidi-SK is suitable for the alignment of
North Korean parallel sentences, and constructed North
Korean training data using bidi-SK. Finally, we demon-
strated that our training data can enhance North Ko-
rean translation quality. Although our North Korean
MT datasets have some limitations with regards to size
and diversity of sentences, the findings of our study are
useful for the development of a North Korean transla-
tion system. To support further research, we also pro-
vide the data and code used in our experiments.
Our translation experiments also indicated a trade-off
between the accuracy of South and North Korean trans-
lations. Therefore, a universal Korean NMT system
that can handle both Korean language variants is still
an open problem to be solved.

7. Bibliographical References
Artetxe, M. and Schwenk, H. (2019a). Margin-based
parallel corpus mining with multilingual sentence
embeddings. In Proceedings of the 57th Annual

https://translate.google.com
https://papago.naver.com
Meeting of the Association for Computational Linguistics.

Artetxe, M. and Schwenk, H. (2019b). Massively multilingual sentence embeddings for zero-shot cross-lingual transfer and beyond. Transactions of the Association for Computational Linguistics, 7:597–610.

Azpeitia, A., Etchegoyhen, T., and Martínez Garcia, E. (2017). Weighted set-theoretic alignment of comparable sentences. In Proceedings of the 10th Workshop on Building and Using Comparable Corpora.

Chen, S. F. (1993). Aligning sentences in bilingual corpora using lexical information. In Proceedings of 31st Annual Meeting of the Association for Computational Linguistics.

Chen, S. F. (1993). Aligning sentences in bilingual corpora using lexical information. In Proceedings of 31st Annual Meeting of the Association for Computational Linguistics.

Dabre, R., Nakagawa, T., and Kazawa, H. (2017). An empirical study of language relatedness for transfer learning in neural machine translation. In Proceedings of the 31st Pacific Asia Conference on Language, Information and Computation.

Durrani, N., Sajjad, H., Fraser, A., and Schmid, H. (2010). Hindi-to-Urdu machine translation through transliteration. In Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics.

Etchegoyhen, T. and Azpeitia, A. (2016). Set-theoretic alignment for comparable corpora. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers).

Gomes, L. and Lopes, G. P. (2016). First steps towards coverage-based sentence alignment. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16).

Harrat, S., Meftouh, K., and Smalii, K. (2019). Machine translation for arabic dialects (survey). Information Processing & Management, 56(2):262–273.

Karimi, A., Ansari, E., and Sadeghi Bigham, B. (2018). Extracting an English-Persian parallel corpus from comparable corpora. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018).

Keung, P., Salazar, J., Lu, Y., and Smith, N. A. (2020). Unsupervised bitext mining and translation via self-trained contextual embeddings. Transactions of the Association for Computational Linguistics, 8:828–841.

Kim, H., Hirasawa, T., and Komachi, M. (2020). Zero-shot North Korean to English neural machine translation by character tokenization and phoneme decomposition. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop.

Lakew, S. M., Erofeeva, A., and Federico, M. (2018). Neural machine translation into language varieties. In Proceedings of the Third Conference on Machine Translation: Research Papers.

Lee, K., Ippolito, D., Nystrom, A., Zhang, C., Eck, D., Callison-Burch, C., and Carlini, N. (2021). Deducing training data makes language models better. arXiv preprint arXiv:2107.06499.

Lee, H. B. (1990). Differences in language use between North and South Korea. International Journal of the Sociology of Language, 1990(82):71–86.

Maruo, L., Grazina, N., Luis, T., Ling, W., Coheur, L., and Trancoso, I. (2011). BP2EP - adaptation of Brazilian Portuguese texts to European Portuguese. In Proceedings of the 15th Annual conference of the European Association for Machine Translation.

Nakazawa, T., Nakayama, H., Ding, C., Dabre, R., Higashiyama, S., Mino, H., Goto, L. Pa, W. P., Kunchukuttan, A., Parida, S., Bojar, O., Chu, C., Eriguchi, A., Abe, K., and Oda, Yusuke Kurohashi, S. (2021). Overview of the 8th workshop on Asian translation. In Proceedings of the 8th Workshop on Asian Translation.

Popovic, M., Arcan, M., and Klubička, F. (2016). Language related issues for machine translation between closely related Slavic languages. In Proceedings of the Third Workshop on NLP for Similar Languages, Varieties and Dialects (VarDial3).

Schwenk, H. and Douze, M. (2017). Learning joint multilingual sentence representations with neural machine translation. In Proceedings of the 2nd Workshop on Representation Learning for NLP.

Schwenk, H. (2018). Filtering and mining parallel data in a joint multilingual space. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers).

Sennrich, R. and Volk, M. (2010). MT-based sentence alignment for OCR-generated parallel texts. In Proceedings of the 9th Conference of the Association for Machine Translation in the Americas: Research Papers.

Sun, Y., Zhu, S., Yifan, F., and Mi, C. (2021). Parallel sentences mining with transfer learning in an unsupervised setting. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Student Research Workshop.

Tan, T.-P., Goh, S.-S., and Khaw, Y.-M. (2012). A Malay dialect translation and synthesis system: Proposal and preliminary system. In 2012 International Conference on Asian Language Processing.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L. U., and Polosukhin, I. (2017). Attention is all you need. In Advances in Neural Information Processing Systems.

Yun, S. and Kang, Y. (2019). Variation of the word-initial liquid in North and South Korean dialects under contact. Journal of Phonetics, 77:100918.

Zoph, B., Yuret, D., May, J., and Knight, K. (2016). Transfer learning for low-resource neural machine translation. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing.

Zweigenbaum, P., Sharoff, S., and Rapp, R. (2017).
Overview of the second BUCC shared task: Spotting parallel sentences in comparable corpora. In Proceedings of the 10th Workshop on Building and Using Comparable Corpora.

8. Language Resource References