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Cross-lingual Word Embeddings Beyond Zero-shot Machine Translation

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Abstract

This thesis explored the possibility of transferring learning from training languages to completely unknown languages in a multilingual neural machine translation system. Using cross-lingual word embeddings as the only knowledge source, we observed little transferability between highly-related languages from our experiment. We also discussed the shortcomings of multilingual neural machine translation architecture that could contribute to the low transferability and provided suggestions that could better share embedding layers from the training language to unknown languages.

Contents

Preface

This thesis was finished under the supervision of Ali Basirat. I would like to thank him first for his guidance, inspiration and passion.

The Saga supercomputer [1] owned by UNINETT Sigma2 hosted all of the experiment in this thesis. Without it this thesis would not be possible.

Thank you Mr. Anders Wall and everyone in the Anders Wall Scholarship Foundation for sponsoring my Master's study. This opportunity led me to meet everyone in the Master Programme in Language Technology, from whom I have learned a lot during the 2-years journey.

Last but not least, I would like to say a thank you to my parents for their unconditional love and support; to all of my friends for the unique memories we have created; and to my girlfriend, who has always been next to me when the virus made everything unusual.

[1] https://www.sigma2.no/systems#saga

1. Introduction

Multilingual neural machine translation (NMT) aims to train a single translation model for multiple languages (Aharoni et al., 2019; M. Johnson et al., 2016). One of its many appealing points, zero-shot translation, enables translations between unseen language pairs when knowledge from one language is transferred across the model's shared parameters. Even though both source and target languages in such an unseen pair should still be in the set of training languages, a multilingual NMT system with zero-shot learning is still attractive as it lowers the cost of obtaining expensive parallel data, particularly when translating low-resource languages.

The success of zero-shot translation depends on the model's ability to learn language invariant features (Arivazhagan et al., 2019). Kim et al. (2019) believes the embedding layers is one of the critical components responsible for learning such generalized features in a multilingual NMT system. By contrast, Aji et al. (2020) concluded that sharing the embedding layer along is not enough for transfer learning in zero-shot machine translation. No matter embedding layers are essential to zero-shot learning or not, they both showed that it would positively impact the multilingual model's transferability as long as the embeddings layers are aligned between the source language and the target language.

By far, research on zero-shot learning in multilingual NMT has been mostly restricted to the limited scope of unseen language pairs. There is less discussion about the multilingual NMT transferability on completely unknown languages that have never been in the training data. This thesis studies the importance of word representation in the multilingual NMT transfer model based on the pre-trained cross-lingual word embeddings (Ammar et al., 2016; Bojanowski et al., 2016; Joulin et al., 2018; Ruder et al., 2019) and pushes it further than unseen language pairs — examining the transferability of a multilingual NMT when it is applied to a new test language. Despite the debate on whether cross-lingual word embeddings are vital when transferring information in zero-shot translation, it is generally acknowledged that cross-lingual word embeddings is beneficial for the model's transferability. Thus we will use cross-lingual word embeddings as the source of transfer knowledge to the test languages and leave the translation model's shared parameters to model the interrelationships between the training languages.

We hypothesize that a multilingual NMT model trained with pre-trained cross-lingual word embeddings should transfer reasonably even to a completely unknown language. Although from the experiment results, cross-lingual word embeddings transfer only marginally between closely related languages. Our findings are in line with Aji et al. (2020) and indicate that some regularization is necessary to transfer the embedding layers between languages. Furthermore, when using aligned pre-trained word embeddings as the only transferable knowledge source, the performance will be negatively affected by the transformed output vector space, which needs to be countered in the future.

The rest of the thesis is organized below:

Chapter 2 talks about the background and previous works when working in the transferability of multilingual word embeddings scope, including information about word embeddings, multilingual translation and related works from others. Chapter 3 introduces our experiment method, whose result are discussed and analyzed in

Chapter 4. Finally, Chapter 5 gives out our conclusion. We also show samples of our multilingual NMT model in Appendix A.

2. Background

2.1. Word Embeddings

2.1.1. Representing Words in Vectors

In Natural Language Processing, people need to convert the natural representation of words into forms that are more efficient for computers to process. The idea started with statistical language modeling, which was introduced to Machine Translation in the early nighties (Brown et al., 1990), followed by Bengio et al. (2003) who powered statistical langauge modeling with neural networks. Mikolov, Chen, et al. (2013) introduced Word2Vec, which encapsulates words and their latent information into vectors. Besides the benefit that it simplifies representation and storage of words for computers, it enables the possibilities to calculate words and their semantic meanings just as vectors.

Take an example of vocabulary $V = \{\text{water}, \text{hydrogen}, \text{oxygen}\}$, if we convert these words into vectors, we could have an equation of

$$\vec{w} = \vec{h} + \vec{o} \tag{2.1}$$

where $\vec{w} = \text{vec}(\text{water})$, $\vec{h} = \text{vec}(\text{hydrogen})$ and $\vec{o} = \text{vec}(\text{oxygen})$. From either the individual word (vector) prespective and the united equation prespective, Equation 2.1 is meaningful mathematically and semantically.

Mathematically, we can observe a small geometric angle between $\vec{h}$ and $\vec{o}$. From the cosine similarity definition below,

$$\text{sim}(x, y) = \cos(\theta) = \frac{x \cdot y}{||x||||y||}$$

the smaller the angle θ between $\vec{h}$ and $\vec{o}$ is, the higher their cosine similarity is. In other words, when θ is zero, the cosine similarity $\text{sim}(x, y) \in [0, 1]$ will also approach its upper bound one. Also, as illustrated in Figure 2.1, vector $\vec{w}$ is roughly the sum of vector $\vec{h}$ and $\vec{o}$.

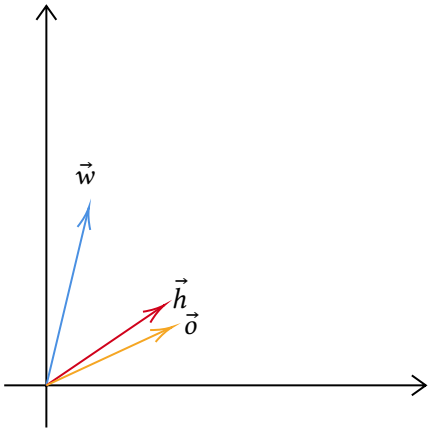

Figure 2.1.: Illustraion of a vector space where Equation 2.1 exists.

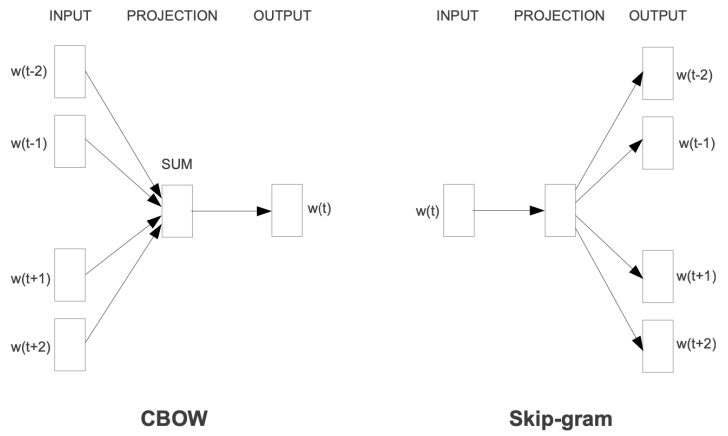

Figure 2.2.: The Skip-gram and the CBOW model. (Mikolov, Le, et al., 2013)

Semantically, words "hydrogen" and "oxygen" are similar since they point to two chemical elements. Adding them together is like how people would ignite the mixture of hydrogen and oxygen to produce water.

To turn words into vectors, one could use a simple one-hot encoding. Like in the example above we could make $\vec{w} = [1, 0, 0]$. However, these one-hot vectors cannot capture any latent semantic information between different words, nor to reflect the inflections between stems and their variants. Such as the word "hydrogen" and its stem "hydro-".

Recent vectorized word representations (word embeddings) were learned through neural networks. Compared to the naive one-hot vectors, word embeddings contains affluent information that links word together. One of the examples is Word2Vec, which learns word representations through a Skip-gram model or a Continuous Bag of Words (CBOW) model (Mikolov, Sutskever, et al., 2013). Both models are shown in Figure 2.2.

The Skip-gram model

The Skip-gram model can produce vector representations that are good at predicting the words surrounding the target word w within the context size of C. The probability of a context word $w_k \in \{w_{-C}, w_{-C+1}..., w_{C-1}, w_C\}$ given a target word w is:

$$P(w_k|w) = \frac{\exp({v'_{w_k}}^\top v_w)}{\sum_{i=1}^{|V|} \exp(v_i'^\top v_w)}$$

Here $|V|$ means the size of the whole vocabulary from the corpus. v stands for the input vector representations and it is initialized by one-hot vectors. v' is the desired output vector, who will be updated throughout the whole neural network training process.

The Continuous Bag of Words model (CBOW)

The CBOW model works like the other side of the coin. It predicts the target word w based on a bunch of context words $w_k \in \{w_{-C}, w_{-C+1}..., w_{C-1}, w_C\}$ within the window size C, as the formula below:

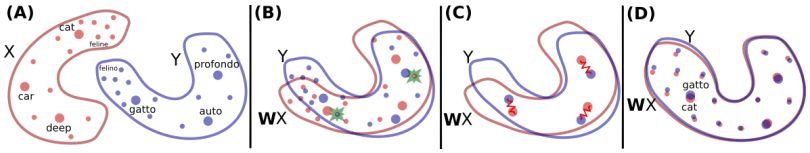

Figure 2.3.: Aligning bilingual vector spaces. (Conneau et al., 2017)

$$P(w|w_k) = \frac{\exp({v'_w}^\top \bar{v}_{w_k})}{\sum_{i=1}^{|V|} \exp({v'_{w_i}}^\top \bar{v}_{w_k})}$$

Here $\bar{v}_{w_k}$ means the sum of the context word w_k's vectorized representation, while v'_w means the input vector representations of word w, same as the one in the Skip-gram model.

By definition, the difference between these two models is that the CBOW model predicts the target word from multiple given context words, while the Skip-gram model predicts the context words from one given center word. In practice, the Skip-gram model is better at predicting rare words, while frequent words have advantages over rare words in the CBOW model. The Skip-gram model is arguably the most popular method to learn word embeddings, especially when learning less frequent words in the corpus (Levy et al., 2015).

2.1.2. Multilingual Word Embeddings

Learned from approaches like the Skip-gram model or the CBOW model, vectorized word representations tend to cluster words with similar semantics (Mikolov, Le, et al., 2013). It then becomes attractive to see whether we could fit two or more languages into the same vector space. Word embeddings that consist of more than one language are called multilingual word embeddings.

In the multilingual scenario, alignment in two different vector spaces is vital in order to make word embeddings from different languages comparable. Figure 2.3 illustrated the alignment method from Conneau et al. (2017). Suppose there is a set of word pairs $\{x_i, y_i\}$ where $i \in \{1, ..., n\}$, the two vector spaces were aligned by a rotation matrix $W \in \mathbb{R}^{d \times d}$ as shown in process **(B)**, where we try to optimize the formula

$$\min_{W \in \mathbb{R}^{d \times d}} \frac{1}{n} \sum_{i=1}^{n} \ell(Wx_i, y_i)$$

Here ℓ is the loss function and it is usually the square loss function $\ell(x, y) = ||x - y||^2$. Then W is further refined in process **(C)**, where we choose frequent words as anchor points and minimize the distance between each correspondent anchor points by an energy function. After this, the refined W is then used to map all words in the dictionary during the inference process. We obtain the translation $t(i)$ of a given source word i in the formula

$$t(i) = \arg\min_{j \in \{1,...,N\}} \ell(Wx_i, y_j)$$

Despite the mathematically proven theoretical feasibility, we need data to drive the alignment process. Lexicon is the most common form of such seed parallel data, though there are other kinds of alignment using data from sentence or documents (Ruder et al., 2019).

By using word-level information, we can start with a pivot language (usually English) and map each other monolingual word embeddings by looking the same word up in a

dictionary (Mikolov, Le, et al., 2013). Sentence-level parallel data is similar to the role of corpora in Machine Translation (MT) since they both contain mapped sentences (Hermann and Blunsom, 2013). Document-level information is usually topic-aligned or class-aligned, such as data of the same Wikipedia item (Vulić and Moens, 2013).

Recent development in word alignment has showed possibilities for less supervision and smaller seed data size to initiate the alignment process (Ruder et al., 2019). Though it is still unclear if multilingual word embedding alignment can run without parallel data or supervison (Dyer, 2019), there are evidences that even distant language pairs have an accurate linear mapping (Mikolov, Le, et al., 2013). If such linear mapping does exist for every language in the word, and if it can be accquired through deep learning, people could build machine translation systems that are able to translate words in unseen languages.

2.1.3. fastText

In this work, we have chosen fastText aligned word vectors[1] (Joulin et al., 2018) as the vectorized word representation. They are based on the pre-trained monolingual vectors computed from the Wikipedia corpus using fastText (Bojanowski et al., 2016).

fastText is an extension of the original Word2Vec methods, which uses sub-words to augment low-frequency and unseen words. Take word `low-key` as an example. As a whole word, its possibility in a given document would be much lower than its components, `low` and `key`. fastText learns its vectorized representation from a smaller n-gram sub-word level. It divides the whole word `low-key` into sub-words units (assume $n = 3$)

<lo, low, ow-, w-k, -ke, key, ey>

Each sub-word has its own vectorized representation learned through a CBOW or Skip-gram model as in Word2Vec. The word vector for the whole word unit `<low-key>` is then the sum of all of its sub-word vectors. Hence its rareness would be compensated by two more frequent subwords `low` and `key`, even if it might not appear in the training document at all.

In addition to the advantage in representing rare words, fastText aligned word embeddings also has a large collection of languages available out of the box, making it attractive to cross-lingual word embedding experiments. In the following Section 3.2, some experiment languages have no publically available pre-trained aligned word embeddings in other formats except fastText. Thus fastText was selected in this thesis to save effort on training and alignemnt multilingual word embeddings, making it possible to concentrate more on experiments themselves.

2.2. Multilingual Neural Machine Translation (MNMT) Systems

2.2.1. Multilingual Neural Machine Translation

Neural Machine Translation (NMT) uses neural networks to learn the translation relationship between a source and a target language. It has outperformed the traditional Statistical Machine Translation (SMT) in some machine translation assignments and has enabled some new possibilities in this field. One of these new applications is multilingual Neural Machine Translation. As shown in Figure 2.4, the system has an encoder and a decoder consisting of several layers of LSTM network spread parallelly on multiple GPUs. An attention module serves as the connection bridge between the

[1] https://fasttext.cc/docs/en/aligned-vectors.html

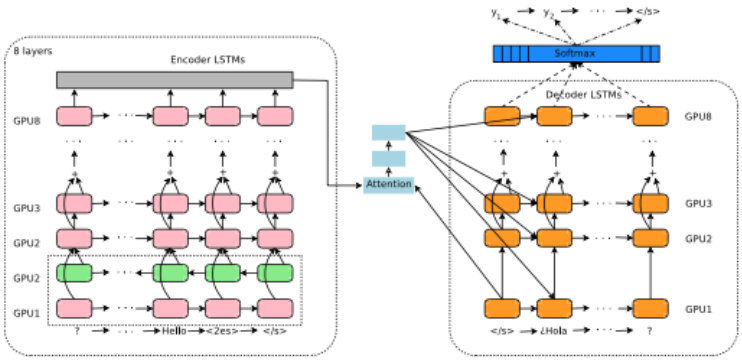

Figure 2.4.: Google's MNMT Architecture (M. Johnson et al., 2016; Wu et al., 2016)

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encoder and the decoder. It emphasizes which part of the source sentence is more relevant to the current translation context, especially when translating long sentences. (Wu et al., 2016). Multilingual NMT uses the same attentional encoder-decoder model but trains it on a multilingual corpus with additional artificial tokens to indicate the target language (M. Johnson et al., 2016).

The benefit of such a multilingual NMT system does not necessarily stop at higher translation performance between common languages like English, French, or Spanish; it also leverages additional information from high resource languages to low resource languages (Zoph et al., 2016). Such information leverage could be viewed as a special form of transfer learning (Zoph et al., 2016), which may happen both in the horizontal or vertical direction (Lakew et al., 2019): In the horizontal direction, knowledge transfers from pre-trained data (such as word embeddings or language models) to the raw test data; in the vertical direction, knowledge transfers from languages to languages, which could either transfer from high resource to low resource languages or from seen languages to unseen languages. The latter is called zero-shot translation.

2.2.2. Zero-shot Machine Translation Systems

Zero-shot translation stands for translation between language pairs invisible to the multilingual NMT system during the training time. For example, building a multilingual NMT system with German-English and French-English training language pairs while testing its performance on a German-French scenario. In 2016, M. Johnson et al. (2016) first published their result on a zero-shot MT system. Their multilingual MT system includes an encoder, a decoder, and an attention module. It requires no change to a standard NMT system except introducing an additional token at the beginning of each source sentence to denote the translation target language. Ha et al. (2016) also showed that their universal encoder and decoder model is capable of zero-shot MT. Translation between unseen language pairs is attractive, especially for low-resource language pairs. Compared with a pivot based system, zero-shot translation eliminates the need for a bridging language, or *interlingua*, as an intermediary of the source and target language. However, zero-shot translation still underperforms than pivot-based translation.

Two reasons could explain the gap between a zero-shot system and a pivot based system, language bias (Arivazhagan et al., 2019; Ha et al., 2016, 2017) and poor generalization (Arivazhagan et al., 2019). Language bias means that the MT system tends to decode the target sentence into the wrong language during inference, usually copying

the source language or the bridging language Ha et al. (2016). It could be the consequence of always translating all source languages into the bridging language, making the model difficult to learn to translate to the desired target language (Arivazhagan et al., 2019).

The other potential reason for the worse performance of a zero-shot system is poor generalization. When a zero-shot system is trained purely on the end-to-end translation objective, the model prefers to overfit the supervised translation direction features than learn more transferable language features. There is no guarantee that the model would discover language invariant representations as there is no explicit incentive to learn language invariant features, resulting in the intermediate encoder representations are too specific to individual languages (Arivazhagan et al., 2019).

To fix these two problems, there has been work on improving the preprocessing process (Lakew et al., 2018), parameter sharing (Blackwood et al., 2018; Firat et al., 2016), additional loss penalty functions (Arivazhagan et al., 2019) and pre-training modules using external information (Baziotis et al., 2020). In some of the improvements, zero-shot system could achieve better performance than pivot based systems.

2.3. Previous Work

The transferability of multilingual neural machine translation models is vital from both the theoretical and practical perspectives. The theoretical importance of these models come to the way that they find the correspondence between language pairs (M. Johnson et al., 2016; Lu et al., 2018). The practical importance is due to their effective use for the translation of low-resource languages (Nguyen and Chiang, 2017; Zoph et al., 2016). M. Johnson et al. (2016) shows that multilingual NMT trained on a massive training set can generalize reasonably well in the zero-shot learning setting. This capability is further examined by Aharoni et al. (2019), demonstrating that multilingual NMT models transfer better when trained on a massive training set. Kim et al. (2019) shows that multilingual NMT models can be transferred to a new language when their embedding spaces are realigned to the embeddings of the new language.

In terms of the application of pre-trained aligned word embeddings in a multilingual NMT system, there are some successful applications, such as using the aligned embeddings as the embedding layer (Artetxe et al., 2017; Neishi et al., 2017), as the substitution of a supervised dictionary (Conneau et al., 2017), or as an external supplementary extension (Di Gangi and Federico, 2017). There are even cases where people successfully trained a MT system using very little or none parallel data (Conneau et al., 2017) and heavily rely on aligned word embeddings. Nevertheless, in most MT systems, using pre-trained word embeddings purely as the embedding layer will not outperform other models such as Transformers (Vaswani et al., 2017) and its other evolutions, largely because the training data for an MT system is usually several orders of magnitude larger than the monolingual pre-trained word embeddings. Typically pre-trained word embeddings are mainly introduced in MT systems dealing with low-resource languages.

For NMT systems focused on low resource language, Qi et al. (2018) looked into the question of when and why are pre-trained word embeddings useful. They found that pre-trained word embeddings are consistently useful for all languages. The gains would be more visible if the source and target language are similar, such as languages within the same family. Also, pre-trained word embeddings work well only on MT systems with moderate performance. Pre-trained word embeddings can not work when there is not enough data to train a basic MT system. Finally, aligned word embeddings

are useful in a multilingual MT system. For bilingual MT systems, pre-trained word embeddings do not necessarily need to be aligned.

Moreover, aligned word embeddings do not work well for morphologically rich languages such as Russian and Belarusian. Qi et al. (2018) argues that this may be mainly due to the sparsity in the word embeddings files. Plus, most of the previous works target zero-shot language pairs, not on completely unseen languages. For language pairs $A \rightarrow$ EN and EN $\rightarrow B$, they are all interested in the unseen language pair $A \rightarrow B$. For language pairs that include an unseen language C, whether it is on the source side, or the target side, it remains to see how universal word embeddings could help translate in this scenario.

It is then interesting to see how far can aligned word embeddings could go beyond known languages. As mentioned in Section 2.2.2, zero-shot translation analyzed this question by testing the multilingual NMT system on unseen language pairs — language in either source or target side of the translation is known to the system, but their paired combination remains unknown. In this work, we would like to take a step further to see how aligned word embeddings would work for zero-resource languages – Languages that are entirely unseen to the multilingual NMT setting.

3. Methodalogy

In this chapter, we will perform experiments in a universal word embedding based multilingual NMT system to see the transferability of the model on the test languages.

3.1. Theoratical Feasibility

As mentioned in Section 2.1.2, Mikolov, Le, et al. (2013) showed that there is a linear relationship between similar word embeddings in different languages. For each word pairs, assume their vector representations are $\{x_i, y_i\}_{i=1}^{n}$, we could calculate a transformation matrix W such that Wx_i approximates to y_i. In practice, people can learn W by optimizing the following target function.

$$\min_{W} \sum_{i=1}^{n} ||Wx_i - y_i||^2$$

Mikolov, Le, et al. (2013) also showed their result in the word/phrase translation task for the approximated word embedding mappings. For some subsets of words, around 70% of word embeddings match precisely with each other according to the P@5 score. If we relax the cosine similarity threshold to 0.6, the P@5 score would be as high as 90%.

To convert words into vectors to be calculated in the neural network, NMT systems should treat each word as a word embedding. The value of these word embeddings could be learned directly during translation, but then the initialization is a crucial step since poor initialization could lead to slow converge or worse local minima (Glorot and Bengio, 2010). The situation could be even more challenging when translating with very few parallel corpora since there is no data to help the embedding layer converge to its ideal state. Hence the word embedding mapping technique above becomes appealing.

Qi et al. (2018) explored how effective it is by using aligned pre-trained word embeddings in an NMT system. They found that regardless of languages, alignment is useful as long as it is applied in a multilingual setting. They believe that since both the source and the target side vector spaces are already aligned, the NMT system will learn how to transform a similar fashion from the source language to the target language.

Therefore, translating a completely unseen language is to test the transferability from known languages to an unknow language. It can be viewed as the question below — Given a vector space Z that consists of aligned word embeddings $\{a_i, b_i, c_i, ...\}$, how much does the NMT system knows about an unseen language A if it was only trained on the remaining languages? In theory, since the word embeddings are clustered by their semantic meanings in the same vector space Z, we should be able to build loose mappings between the semantic centers from both the source and the target sides. The generalization ability of the system is the key to answer this question. Hence we conducted some experiments below.

3.2. Experiment Settings

To get a basic multilingual MT system running, we chose English (EN), German (De), and French (FR) to be the training languages. Let C donate the final corpus, l donates the language-specific corpus fragment and Z is the set of corresponding candidate languages, the training language set is then $Z_{TRAIN} = l_{EN}, l_{DE}, l_{FR}$. For the test language set, we picked up Swedish (SV), Hungarian (HU), and Hebrew (HE) being his test languages. Therefore $Z_{TEST} = l_{SV}, l_{HU}, l_{HE}$.

For each experiment, the author trained a basic multilingual NMT system using a training corpus C_{TEST} with all three training languages, including all six directions from the cartesian product without duplicates as below.

$$C_{\text{TRAIN}} = \{x \times y \mid x, y \in Z_{\text{TRAIN}} \text{ and } x \neq y\} \tag{3.1}$$

The equation below means that the multilingual NMT system is tested on the test corpus with all three training languages and one of the test language. The test corpus consists of both translation directions of three different training language and that only test language.

$$C_{\text{TEST}} = \{(x, y) \cup (y, x) \mid x \in Z_{\text{TRAIN}} \text{ and } y \in Z_{\text{TEST}}\} \tag{3.2}$$

we designed the experiments and picked up the training and target languages based on Language Similarity. Qi et al. (2018) observed that pre-trained word embeddings are useful for languages from the same language family. The closer their relationship is, the higher the performance improvement is. Aligned word embeddings will also be beneficial if applied in a multilingual NMT system consisting of languages from the same language family.

3.2.1. Corpus and Preprocessing

we have used the TED talk subtitle corpus from Qi et al. (2018) [1] to train the multilingual NMT. The whole corpus has roughly 2.7×10^6 sentences split into three parts, train, dev, test at the ratio of $0.95 : 0.025 : 0.025$.

To build up the corpus for each experiment, the author has modified the original script from Qi et al. (2018) and added a few customized features. In short, the script will extract shared sentences from each part of the split corpus to form up a common intersection used in training, developing, and testing. Since the experiments consist of languages that are relatively common in the TED project, this fine-tuned corpus is not too different from the original corpus, hence after all the sizes for the train, dev, and test split were kept.

For preprocessing, since the original TED corpus is already tokenized by Moses. Then the system Neubig et al. (2018) turned all of the text into lower cases and applied a sentence length filter to remove any long sentences with more than 60 words. This sentence length filter prevents inferior performance in training. After that, when building the i2w and w2i index for the pre-trained embeddings, we have also removed any words that are less frequent than two times to stop the system from overfitting by low-frequency words. All of the preprocess functions are built upon the built-in XNMT preprocess features (Neubig et al., 2018).

3.2.2. Neural Network

The neural network is a modified version of the one from Qi et al. (2018), which is built with XNMT Neubig et al. (2018). The only change is doubling the encoding layer to a

[1] https://github.com/neulab/word-embeddings-for-nmt

2-layer-bidirectional LSTM network, thus having more parameters to accommodate the additional information in a multilingual scenario. Everything else is the same as the original experiment settings, including the encoder-decoder model with attention (Bahdanau et al., 2014) with a beam size of 5, trained using batches of size 32, dropout set to 0.1, the Adam optimizer (Kingma and Ba, 2014) and the evaluation metric BLEU score (Papineni et al., 2002). The initial learning starts at 0.0002 and decays by 0.5 when development BLEU score decreases (Denkowski and Neubig, 2017).

3.2.3. Embeddings

As metioned in Section 2.1.3, the embeddings used in the experiments are fastText aligned word embeddings[2]. They are based on the pre-trained vectors on Wikipedia[3] using fastText (Bojanowski et al., 2016). The alignment is performed using RCSLS as in Joulin et al. (2018).

Each of the fastText word embedding file is language-specific and contains word embeddings in 300 dimensions. We concatenated different language files to build up multilingual word embedding files for the multilingual NMT system. If there is a shared word w with two different vector values $\vec{v_a}$ and $\vec{v_b}$ in different embedding files, the average value of both vectors $\vec{v_{mean}}$ will be the new vector.

$$\vec{v_{mean}} = (\vec{v_a} + \vec{v_b})/2 \tag{3.3}$$

In this way, there are possibilities that both of the unique semantic values in the two words w_a and w_b could be lost, as there are cases that word with distant meaning share the same spelling in different languages. However, people could also argue that many words with the same spelling do have a similar meaning. For example, the word `café` means the same thing in English and French, as English borrowed that word from French. Later in the experiment, there will also be a different attempt where the system treats each word as a unique word even though they might share the same spelling. Both of the results will be available below.

[2] https://fasttext.cc/docs/en/aligned-vectors.html
[3] https://www.wikipedia.org/

4. Results and Analysis

As anticipated, Swedish will get the best result among all three test languages. Its performance could even be on the same level as the baseline multilingual NMT consists of only the training languages — EN, DE, and FR. The other two test languages' performance will not be close to the Swedish one, and they could be less than 10 BLEU scores.

In the results shown in Table 4.1, Swedish, Hungarian and Hebrew all got unpredicted low BLEU scores. The expected high perfromance from Swedish did not appear in the experiment result. All of the three languages only achieved around 1 BLEU score. Also, since the system hardly translates any of the languages, it is hard to tell the relationship between language similarity and the model's performance. Nevertheless, the relatively low results on the test languages compared with the training languages indicate that cross-lingual embeddings are not rich enough for the model transfer in machine translation. However, when it comes to a random setting with no pre-trained embeddings, we see that the translation model trained with cross-lingual embeddings performs substantially better (Avg BLEU=1.2) than a model trained with random embeddings (BLEU=0.1).

In XNMT, one can also see the individual precision scores form 1 to 4 grams in the translation text. By looking at that details, all three languages had a significantly better unigram precision score than their bigram, trigram, and quadgram precision score. The bigram precision score in Swedish was about half of its unigram scores. The precison score on trigrams and quadgrams are close to 0 on all languages, which again is a sign showing the multilingual NMT system has little transferability from known training languages to an unknown test language.

To increase the transferability from known languages to unknown languages, we have tried various techniques, such as increasing dropout rate. We have observed small improvements (average 0.5 BLEU score increase), but since this technique improves the zero-shot performance at the cost of supervised translation directions Arivazhagan et al. (2019), we decided to explore other approaches in below.

4.1. The Effect of Source/Target Language Annotation

Previous initial results opened up some follow up experiments to see what could be improved. The first improvement is to alter the way the target language annotation in the source sentences, inspired by Blackwood et al. (2018). In the original corpus building script, it will add a custom `__{lang_id}__` token at the front of each source

Language	BLEU	1gram	2gram	3gram	4gram
EN+DE+FR	29.22	0.57	0.34	0.24	0.16
SV	1.12	0.16	0.02	0.00	0.00
HU	1.12	0.18	0.02	0.00	0.00
HE	1.02	0.16	0.02	0.00	0.00

Table 4.1.: Initial results for SV, HU and HE on the baseline system (Target language annotation only, dropout=0.3, trained on mixed language branch corpus.)

Languages	TGT	SRC	Full
EN+DE+FR	29.22	17.59	28.73
SV	1.12	0.00	1.16
HU	1.12	0.00	1.12
HE	1.02	0.00	1.02

Table 4.2.: BLEU scores for different language annotations (Target only, source only and full annotation)

sentence, as suggested by M. Johnson et al. (2016). A sentence in the annotated source text whose target language is German would look like

```
__de__ and we struggle with how to deal with them .
```

Later two other tokens — a single source token and a source token together with a target token, were added into the experiments. Hence a sentence in English would look like this.

```
__en__ and we struggle with how to deal with them .
```

When it needs to be translated into German, the annotation would then become

```
__en__ __de__ and we struggle with how to deal with them .
```

The results are in Table 4.2. Adding a source token together with the target token did not change the overall result much, but removing the target token had a negative impact on the final BLEU score. This discovery is in line with previous claims and results (Blackwood et al., 2018; M. Johnson et al., 2016), as the multilingual NMT system requires a target token at the beginning of each sentence to help identify the target language. The difference between different langauge annotations indicated that a word embedding based multilingual NMT system would also automatically learn the source language during training. People should only annotate the target language into the source text.

4.2. The Effect of Language Similarity

Previous hypothesis believes that Swedish will perform better the Hungarian and Hebrew for its closer relationship to the training languages. To deeper undetstand the question, we have further designed experiments to see if language similarity will improve the results.

The additional experiments will still use Swedish as the test langauge while remove French as the training language to homogenize the training language set more towards Swedish. In the previous training language set, French is the only training language that is Romanic. By replacing French with Danish, all of the training languages are now Germanic, as well as the test language Swedish. We have also included two more Germanic languages as the training language, Dutch (NL) and Norwegian (NO). We began with experiment trained on English, German and Danish, and added the additional training languages one by one in the next two expriments. Everything else is the same. The results are shown in Table 4.3.

As the results shows, the system gained most improvements when Danish and Norwegian were added. Despite Dutch and Swedish are both Germanic languages, Dutch does not help the multilingual NMT system to learn how to translate from

Language	BLEU	1gram	2gram	3gram	4gram
EN+DE+FR	1.12	0.16	0.02	0.00	0.00
EN+DE+DA	4.1	0.28	0.07	0.02	0.01
+NL	3.3	0.23	0.05	0.02	0.00
+NO	4.7	0.31	0.07	0.03	0.01

Table 4.3.: Results for langauge similarity tested on the Swedish language. Three other Germanic languages DA, NL and NO were added one by one into the training corpus.

Swedish or into Swedish a lot. This confirms that close languages would benefit each other more than distant languages in a multilingual NMT systemn using pre-trained word embeddings (Qi et al., 2018).

Swedish, Danish and Norwegian have deep historical relations to each other. As a result, these languages share many vocabularies as well as grammar and syntax ruls. To study how much of such kind of benefit were brought by shared vocabluaries or their similar syntax, each word in the training corpus was tagged by its source language token to distinguish its origins. Punctuations are not distinguished among languages, which means they don't receive a language-specific token. The word embeddings also tagged to point it to the correct source word. A Swedish sentence that needs to be translated into German is then

```
__de__ <<sv>>och <<sv>>vi <<sv>>kämpar <<sv>>med <<sv>>dem .
```

The assumption behind the word origin token is that, if the result suffers when each word differs by its origin language, the multilingual NMT system would primarily translate by shared vocabularies between language; if its results still holds after the modificaiton, it would primarily learn translation from shared syntax information instead.

The system has obtained 1.7 BLEU score on the EN+DE+FR to SV experiment. It showed that if each word is no longer allowed to be shared between languages the models's performance would dramatically decrease, hence most of the improvements were brought by the fact that Swedish, Danish and Norwegian have a large amount of common vocabluaries. On the other side, it also indicates that the system didn't learn too much syntactic information during training. Even though these languages have similar grammar structures, the system didn't catch it very well, otherwise we would see smaller BLEU score gap between the results as the close grammar relationship will be preserved in the embedding layer. The multilingual NMT system here primarily learns lexicon translation.

4.3. The Effect of the Transformed Vector Space

In addition to the low language similarity between the training languages and the test languages (except in the case of Swedish), we also hypothesis that the poor transferability is due to transformed vector space in the translation model. We believe that after a series of linear opeartion from the neural network onto the word embeddings, the output vector space is no longer aligned with the input vector space.

The whole experiment is based on the hypothesis that our NMT system have already learned the genrally mapping between words in the source vector space and the ones in the target vector space, even though the correct word in the target word space hasn't been seen by the system during training. However since every aligned word embeddings are grouped by their semantics, the correct target word should also be around the wrong output word.

Language	BLEU	1gram	2gram	3gram	4gram
EN+DE+DA → SV	0.65	0.14	0.01	0.00	0.00
SV → EN+DE+DA	6.00	0.33	0.08	0.03	0.01

Table 4.4.: Results for individual translation direction between EN+DE+DA and SV.

By looking closely from the predicted translation in Table 4.1, we have observed the contrary — Almost non of the words in the output text got translated to the correct word in the desired languages. They were either translated into one of the training languages, or were entirely copied directly from the source text, see Appendix A. The BLEU score gains were from punctuations and a small collection of words shared between languages (e.g. property nouns).

Taking a step further, when analyze both translation directions there are other traces to support our transformed vector space hypothesis. We have conducted comparisions on both directions on the Swedish language experiment, as shown in Table 4.4. When tranlsating from SV to the combined EN+DE+DA text, we could achieve almost 6 BLEU scores, which is much better than the nearly zero score when translating from the other direction. Also compared to the combined precision scores on the same experiment from Table 4.3, the results of the translation direction EN+DE+DA to SV contributed almost nothing to the combined translation performance.

Thus, it is highly possible to suspect the output vectors from the model's decoder have been altered and are no longer in the same vector space as the input word embeddings. In this case, the transformed vector space has also made less sense to search for the correct word vector neighbours close to the predicted ouput vector in the output vector space. However, there opens a new possible to translate from completely unknown languages to known languages. We could perform a lexicon replacement based on the Euclidean distance between words in the unknown language and one of the known languages, then feed the processed text into a translation model which has already been trained on known languages. During the whole process, the unknown langauge remains untouched by the translation model hence it still qualifies as zero-resource translation. We will discuss the lexicon replacement process below.

4.3.1. Lexicon Replacement By Euclidean Distance

Suppose we now have a vector space S that contains aligned word embeddings in the unknown language and the known languages, respectively. We donate them as W_x and W_k For each $w_x \in W_x$ there exists at least one mapping to a target word in the known languages $w_k \in W_k$. We are looking for that specific w_k that are with in a specific radius of the original w_s. The distance should still be relatively small so that w_s and w_k are both considered to be a effective translation of each other.

In theory to determine the nearyby neighbour w_k we can use different kinds of metrics. Here we have chosen to use the Euclidean distance where determines the distance between w_s and w_k as

$$d(w_s, w_k) = \sqrt{\sum_{i=1}^{n} (w_{s_i} - w_{k_i})^2} \tag{4.1}$$

The distance d is a variable here and its value needs to be determined as well. Hence there are experiments to test the distance argument d by different experiments, ranging from $d = 0.25$ to $d = 5$.

The algorithm is described in Algorithm 1

Input: hypothesis H, source language embeddings E_s, target language embeddings E_t, distance threshold D
Result: Updated hypothesis H' with words being replaced by their neighbors in the desired language
Build kd-tree T from E_s **for** $l \in H$ **do** each line l in the source hypothesis H
  for $w \in l$ **do** each word w in line l
    if *w is a punctuation* **then**
      skip w;
    else if *w is an unknown word* **then**
      skip w;
    else
      query distance $d(w, w')$ for w in T;
      if $d < D$ **then**
        replace w with the correspoding w'
      end
    end
  end
end

Algorithm 1: Pesudo code for output hypothesis word subsitution. Each word in the NMT output hypothesis that are not in the desired language will be replaced by its cloeset neighbour in that language.

Performing a distance query on a vector space that has more than 3×10^6 vectors is slow, especially when all these vectors are considered to be high dimensional vectors. The code was implemented with SciPy (Virtanen et al., 2019). There are algothrims like KD-tree (Maneewongvatana and Mount, n.d.) that could reduce the calcualtion time for low-dimensional vectors, but for vectors that are higher than 20 dimentions it is not necessarily faster than brutal force.[1] On the other hand, based on the Johnson–Lindenstrauss theorem (W. B. Johnson and Lindenstrauss, 1984), a vector space should have at least more than 300 dimensions to distinguish 1×10^6 vectors in it. As the aligned vector space in fastText contains more than 3×10^6 words, the dimensions could not be compressed any more or you are at risk of not be able to distinguish each word. All in all, the script is slow at subsitute every word in the output hypothesis into the correspoding one in the desired language.

We have performed the lexicon replacement experiment on the SV ↔ EN+DE+DA text from the same TED text corpus (Qi et al., 2018), feeded into an already trained tranlsation model based on the NO ↔ EN+DE+DA corpus, using NO as the pivot language. When applying the previously mention Algorithm 1 on the SV ↔ EN+DE+DA text, we replace all of the source text started without the target langauge token `__SV__`. In other words, we translate all of the source sentence in Swedish to Norwegian first, leaving all of the other source sentences (sentences in EN, DE or DA) untouched. The target translation reference is also remained as is.

The BLEU scores are shown in Table 4.5. In order to demostate the difference of applying the same algorithm on the input and the output vector space, we have also selected result from $d = 0$ to $d = 4$ and compared them with the results when Algorithm 1 was performed on the output vector space. The comparision is in Figure 4.1.

From both Table 4.5 and Figure 4.1, we can see a noticeable improvement over the baseline result as the BLEU score doubled. Even compared with the SV ↔ EN+DE+DA

[1] As descibed on the API document, "High-dimensional nearest-neighbor queries are a substantial open problem in computer science.", https://docs.scipy.org/doc/scipy/reference/generated/scipy.spatial.KDTree.html

d value	BLEU	1gram	2gram	3gram	4gram
SV ↔ EN+DE+DA	4.1	0.28	0.07	0.02	0.01
No replacement	2.99	0.27	0.05	0.02	0.00
0.25	2.99	0.27	0.05	0.02	0.00
0.5	2.99	0.27	0.05	0.02	0.00
1	6.18	0.34	0.10	0.04	0.01
2	6.17	0.34	0.10	0.04	0.01
3	6.17	0.34	0.10	0.04	0.01
4	6.17	0.34	0.10	0.04	0.01
0	6.00	0.33	0.08	0.03	0.01

Table 4.5.: Results for the lexicon replacement experiments with different d thresholds. Tested on SV text using NO as the pivot language on the NO ↔ EN+DE+DA translation model. $d = 0$ stands for no threshold control (replace every word).

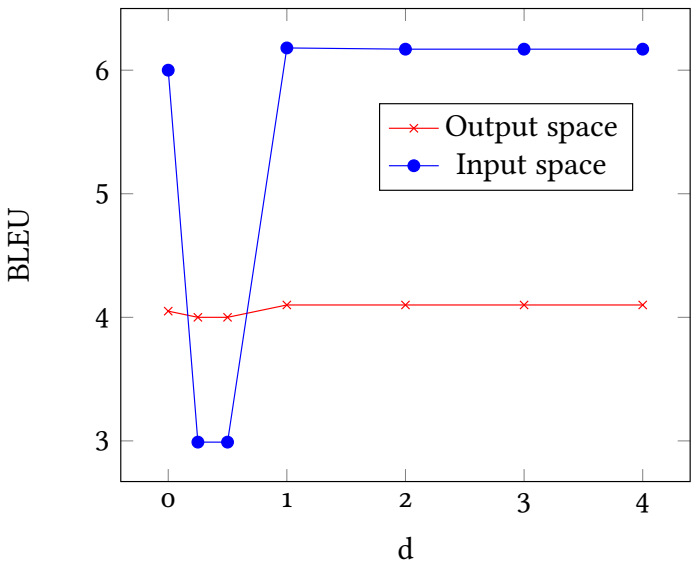

Figure 4.1.: BLEU scores for the lexicon replacement algorithm applied on both the input and the output vector space.

model, the result from the lexicon replacement experiment is still leading ahead for about 2 BLEU scores. Thus it demostrates that our lexicon replacement hypothesis is effective within the input vector space.

Moreover, the value d will affect the translation model. As we increase d from 0.5 to 1 we see a big tranlation quality improvement. On the other side, increasing d after $d = 1$ will have no positive impact on the model's performance. When we set $d = 0$ to remove the threshold control its performance even dropped around 0.2 points, mostly due to the lowered bigram precison score. We conclude that there is a sweet spot for the d value, though its accurate value needs to be fine tuned to adapt different source and pivot language combinations.

Finally, when comparing the results of lexicon replacement on the input vector space and the results on the output vector space, we confirmed the output vector space did changed during the translation tranining process by the model's neural network. Unlike the input vector space, excuting lexicon replacement on the output space does not have a leap on the BLEU score no matter how the distance threshold d changes. Hence it is not worth to perform operations like lexicon replacement on the output vector space.

5. Conclusion and Future Work

In this thesis, we have explored the transferring and generalizability of cross-lingual word embeddings on unknown languages. From the achievement of zero-shot machine translation, we took a step further and expected moderate performance from those word embeddings as if they would transfer knowledge learned from the test languages onto other completely unknown languages. However, our experiment results suggested that only slight knowledge transfer happened between closely related languages, which echoes back to some of the findings that the embedding layer along in a multilingual NMT system is not enough to handle the knowledge transfer (Aji et al., 2020).

To increase cross-lingual word embeddings' transferability in a multilingual NMT architecture similar to M. Johnson et al. (2016), there should be some additional alignment in the output vector space between the source and the target languages. During the training process, the neural network has never seen any positive examples from the test language. Therefore its output weight on the test language has been continuously deducted, which resulted in a transformed output vector space. Such output space is no longer aligned with the input vector space, hence connections between different languages solely rely on shared vocabularies. As a result, only very similar languages such as Swedish, Norwegian and Danish benefited in our experiments.

As we have demonstrated in our lexicon replacement experiments, a solution to align the deviated input and output embedding spaces is to add regularization to the multilingual model's loss function base on the divergence of the two vector spaces. Another potential solution to be explored is to supplement the translation model with language level information such as language embeddings (Littell et al., 2017; Malaviya et al., 2017) together with the cross-lingual embeddings. Language level information could also answer more questions remained in our study. Together with some previous studies (Aji et al., 2020; Qi et al., 2018), we believe the transferability of cross-lingual word embeddings is related to the similarity between the source and the target language, but how to measure the language similarity and link it to the transferability of the embedding layers could be an exciting topic.

Finally, it is worth exploring how other sets of embeddings would enhance the transferability of cross-lingual word embeddings. For example, to try the multilingual contextualized cross-lingual embeddings Devlin et al. (2019) and see if it would benefit the transferability by adding contextual information, or the multilingual sub-word embeddings Heinzerling and Strube (2017) if it would perform better by aligning more words between different languages.

A. Example Output from the Multilingual NMT Model

A.1. Results from the Initial Experiment

This sample output is taken from the SV ↔ EN+DE+FR experiment, described in Section 3.2. Its perfromance result is in Table 4.1.

We haved sampled 20 sentences from the output file. Each of the languages (SV, EN, DE and FR) as the target translation langauge has 5 examples.

Seg. id	Score	Segment comparison: Deletion Insertion Shift
1	211/273= 77%	Src: __sv__ by the end of this year , there 'll be nearly a billion people on this planet that actively use social networking sites . MT: en fin de cette année , il y aura presque un milliard de personnes sur cette planète qui utilisent activement les sites de réseaux sociaux . Ref: i slutet av detta år kommer det finnas närmare en miljard människor på denna planet som aktivt använder sociala nätverk på internet .
2	123/141= 87%	Src: __sv__ the one thing that all of them have in common is that they 're going to die . MT: the one thing that all of them are in common is that they 're going to . Ref: det enda alla dessa människor har gemensamt är att de kommer att dö .
3	208/226= 92%	Src: __sv__ while that might be a somewhat thought , i think it has some really profound implications that are worth exploring . MT: je pense que c' est un peu , je pense qu' il y a des implications très profondes qui sont . Ref: trots att det kan vara en något morbid tanke , tycker jag det har några djupgående konsekvenser som är värda att utforska .
4	269/355= 76%	Src: __sv__ what first got me thinking about this was a blog postearlier this year by derek k. miller , who was a science and technology journalist who died of cancer . MT: ce qui m' a dit , ce qui m' a fait réfléchir , c' était un blog de blog avant cette année par derek 26 miller , qui était un journaliste scientifique et de technologie qui est mort du cancer . Ref: det som först fick mig att tänka på detta var ett bloginlägg från tidigare i år , av derek k miller , en vetenskaps- och teknikjournalist som dog i cancer .
5	175/219= 80%	Src: __sv__ and what miller did was have his family and friends write a post that went out shortly after he died . MT: et ce que miller a fait , il y avait sa famille et amis , écrire un post qui a duré peu après qu' il est mort . Ref: det miller gjorde var att han bad familj och vänner skriva ett inlägg som publicerades kort efter hans död .
6	244/305= 80%	Src: __en__ i slutet av detta år kommer det finnas närmare en miljard människor på denna planet som aktivt använder sociala nätverk på internet . MT: now , i 've been able to the following line of conventional income , which is , which are of the lower planet , including , , internet . Ref: by the end of this year , there 'll be nearly a billion people on this planet that actively use social networking sites .
7	139/163= 85%	Src: __en__ det enda alla dessa människor har gemensamt är att de kommer att dö . MT: now , as common as the , , , , , , , . Ref: the one thing that all of them have in common is that they 're going to die .
8	223/271= 82%	Src: __en__ trots att det kan vara en något tanke , tycker jag det har några djupgående konsekvenser som är värda att utforska . MT: can actually be able to make , making sure that it would be used to think of the , , , . Ref: while that might be a somewhat morbid thought , i think it has some really profound implications that are worth exploring .

9	391/427= 92%	Src: *__en__ det som först fick mig att tänka på detta var ett blogginlägg från tidigare i år , av derek k miller , en vetenskaps- och som dog i cancer .* MT: now , you know , you know , you know , you know , you know , you know , you know , you know , you know , it 's common about the that i 've been doing right now in terms of that i do right now , and av : dan k kong , he said , " " . Ref: what first got me thinking about this was a blog post authored earlier this year by derek k. miller , who was a science and technology journalist who died of cancer .
10	225/271= 83%	Src: *__en__ det miller gjorde var att han bad familj och vänner skriva ett inlägg som publicerades kort efter hans död .* MT: so miller , he saw 's 's bad samaritan , and he said , " he said , " he said , " i had an of earlier earlier earlier , by the end of hans . Ref: and what miller did was have his family and friends write a post that went out shortly after he died .
11	194/239= 81%	Src: *__de__ i slutet av detta år kommer det finnas närmare en miljard människor på denna planet som aktivt använder sociala nätverk på internet .* MT: ich ford , , die , die planet , die die im internet . Ref: zum ende dieses jahres wird es nahezu eine milliarde menschen auf diesem planeten geben , die aktiv soziale netzwerke nutzen .
12	102/106= 96%	Src: *__de__ det enda alla dessa människor har gemensamt är att de kommer att dö .* MT: . Ref: was sie alle eint , ist , dass sie sterben werden .
13	228/263= 87%	Src: *__de__ trots att det kan vara en något tanke , tycker jag det har några djupgående konsekvenser som är värda att utforska .* MT: können auch sein , die . Ref: das scheint ein morbider gedanke zu sein , doch ich finde , er liefert einige ziemlich profunde implikationen , die eine nähere betrachtung rechtfertigen .
14	270/328= 82%	Src: *__de__ det som först fick mig att tänka på detta var ett blogginlägg från tidigare i år , av derek k miller , en vetenskaps- och som dog i cancer .* MT: , die , die ich , gestern derek miller , im . Ref: ich denke darüber nach , seit ich dieses jahr einen blog-eintrag von derek k. miller gelesen habe , der wissenschafts- und technologiejournalist war und der an krebs gestorben ist .
15	184/244= 75%	Src: *__de__ det miller gjorde var att han bad familj och vänner skriva ett inlägg som publicerades kort efter hans död .* MT: miller machte die schlechte frau , die , die , die ein . Ref: und miller brachte seine familie und freunde dazu , einen eintrag zu schreiben , der kurz nach seinem tod veröffentlicht wurde .
16	265/336= 79%	Src: *__fr__ i slutet av detta år kommer det finnas närmare en miljard människor på denna planet som aktivt använder sociala nätverk på internet .* MT: j' ai pris la place de la ligne de ligne de la ligne de données , qui les choses en ligne , en gros la planète de la planète , qui l' internet de l' internet . Ref: d' ici la fin de cette année , il y aura près d' un milliard de personnes sur cette planète qui utilisent activement les sites de réseaux sociaux .

17	151/193= 78%	Src:	*__fr__ det enda alla dessa människor har gemensamt är att de kommer att dö .*
		MT:	la **plupart des gens** qui ont **eu lieu** en **train de départ , les l' utilisation des de .**
		Ref:	la **chose** qu' **elles** ont **toutes** en **commun est qu' elles vont mourir .**
18	265/313= 85%	Src:	*__fr__ trots att det kan vara en något tanke , tycker jag det har några djupgående konsekvenser som är värda att utforska .*
		MT:	**les peuvent** être **en , en fait , en fait , en fait , les taux** de **les** d' **une certaine façon d' une autre manière .**
		Ref:	**alors que ça pourrait** être **une pensée quelque peu morbide , je pense qu' elle a** de **très profondes implications qui valent** d' **être explorées .**
19	346/419= 83%	Src:	*__fr__ det som först fick mig att tänka på detta var ett blogginlägg från tidigare i år , av derek k miller , en vetenskaps- och som dog i cancer .*
		MT:	**une fois , l'** automne **ordinaire , en** fait **, , en train de faire face à l' origine des classiques , des , j' ai** parlé **, le titre** d' un **chien , en le chien connu** du cancer **.**
		Ref:	**ce qui m'** a fait **penser à ça au dé**part **est une entrée** d' un **blog écrite il y a quelques mois par derek k. miller , qui était un journaliste scientifique et technologique qui est mort** du cancer **.**
20	238/286= 83%	Src:	*__fr__ det miller gjorde var att han bad familj och vänner skriva ett inlägg som publicerades kort efter hans död .*
		MT:	**le** miller a **fait de l' origine des de mauvaises , qui les gens qui ont suivi l' impression d' une étude d' origine de l' origine de hans .**
		Ref:	miller a **demandé à sa famille et** ses **amis d' écrire une entrée** qui **a été mise en ligne peu après sa mort .**

A.2. Results from the Language Similarity Experiment

This sample output is taken from the SV ↔ EN+DE+DA experiment, described in Section 4.2. Its perfromance result is in Table 4.3.

We haved sampled 20 sentences from the output file. Each of the languages (SV, EN, DE and DA) as the target translation langauge has 5 examples.

Seg. id	Score	Segment comparison: Deletion Insertion Shift
1	196/252= 78%	Src: *__sv__ by the end of this year , there 'll be nearly a billion people on this planet that actively use social networking sites .* MT: **am ende dieses jahres wird es fast eine milliarde menschen auf diesem** planeten **geben , die** aktiv **soziale nutzen .** Ref: **i slutet av detta år kommer det finnas närmare** en **miljard människor på denna** planet **som** aktivt **använder sociala nätverk på internet .**
2	72/119= 61%	Src: *__sv__ the one thing that all of them have in common is that they 're going to die .* MT: det **ene af dem** alle har **i fælles er** at de **vil dø .** Ref: det **enda** alla **dessa människor** har **gemensamt är** att de **kommer att dö .**
3	157/237= 66%	Src: *__sv__ while that might be a somewhat thought , i think it has some really profound implications that are worth exploring .* MT: **mens** det **måske er** en **smule** tanke **, tror jeg , at** det har **nogle virkelig dybe der** er **værd** at **udforske .** Ref: **trots att** det **kan vara** en **något morbid** tanke **, tycker jag** det har **några djupgående konsekvenser som är värda** att **utforska .**
4	186/323= 58%	Src: *__sv__ what first got me thinking about this was a blog postearlier this year by derek k. miller , who was a science and technology journalist who died of cancer .* MT: **hvad først fik** mig **til at tænke over** dette var **en** tidligere **dette** år **af** derek **kenobi** miller **, som var en** videnskab **og** journalist **der døde af kræft .** Ref: **det som först fick** mig **att tänka på** detta var **ett blogginlägg från** tidigare **i** år **, av** derek **k** miller **, en** vetenskaps- **och** teknikjournalist **som dog i** cancer **.**
5	117/214= 55%	Src: *__sv__ and what miller did was have his family and friends write a post that went out shortly after he died .* MT: **og hvad** miller gjorde var **, at hans** familie **og** venner skriver **en der gik ud** efter **, efter han døde .** Ref: **det** miller gjorde var **att han bad** familj **och** vänner skriva **ett inlägg som publicerades kort** efter **hans död .**
6	169/240= 70%	Src: *__en__ i slutet av detta år kommer det finnas närmare en miljard människor på denna planet som aktivt använder sociala nätverk på internet .* MT: **in** the early **years , it happens to be a of** planet **as** active **in the internet .** Ref: **by** the **end of this year , there 'll be** nearly **a billion people on this** planet **that** actively **use social** networking **sites .**
7	93/167= 56%	Src: *__en__ det enda alla dessa människor har gemensamt är att de kommer att dö .* MT: **it like regular beings who** have **the evidence** that they 're going to **be .** Ref: **the one** thing **that all of them** have **in common is** that they 're going to **die .**
8	204/284= 72%	Src: *__en__ trots att det kan vara en något tanke , tycker jag det har några djupgående konsekvenser som är värda att utforska .* MT: **the of** that **can prove** a thought **, i 'm sure that** this has **consistent consequences , which represents the of the .** Ref: **while** that **might be** a **somewhat morbid** thought **,** i **think it** has **some really profound implications that are worth exploring .**

9	203/322= 63%	Src:	*__en__ det som först fick mig att tänka på detta var ett blogginlägg från tidigare i år , av derek k miller , en vetenskaps- och som dog i cancer .*
		MT:	what struck me was the of the , the was the in the year , av derek 's miller , a , who was in cancer .
		Ref:	what first got me thinking about this was a blog post authored earlier this year by derek k. miller , who was a science and technology journalist who died of cancer .
10	185/245= 76%	Src:	*__en__ det miller gjorde var att han bad familj och vänner skriva ett inlägg som publicerades kort efter hans död .*
		MT:	the miller was doing his fear of his bad samaritan , and the meeting of the was the conversation as the beginning of his accident .
		Ref:	and what miller did was have his family and friends write a post that went out shortly after he died .
11	179/257= 70%	Src:	*__de__ i slutet av detta år kommer det finnas närmare en miljard människor på denna planet som aktivt använder sociala nätverk på internet .*
		MT:	ich habe jahre , die einen auf dem planeten , wie die aktiven des internets .
		Ref:	zum ende dieses jahres wird es nahezu eine milliarde menschen auf diesem planeten geben , die aktiv soziale netzwerke nutzen .
12	90/135= 67%	Src:	*__de__ det enda alla dessa människor har gemensamt är att de kommer att dö .*
		MT:	es ist die , wie menschen die haben , die sie werden .
		Ref:	was sie alle eint , ist , dass sie sterben werden .
13	232/277= 84%	Src:	*__de__ trots att det kan vara en något tanke , tycker jag det har några djupgående konsekvenser som är värda att utforska .*
		MT:	, dass es ein , ist , dass es eine solche folgen hat , die die des .
		Ref:	das scheint ein morbider gedanke zu sein , doch ich finde , er liefert einige ziemlich profunde implikationen , die eine nähere betrachtung rechtfertigen .
14	221/322= 69%	Src:	*__de__ det som först fick mig att tänka på detta var ett blogginlägg från tidigare i år , av derek k miller , en vetenskaps- och som dog i cancer .*
		MT:	es hat mich , die mich , dass die im jahr alt war , derek e. miller , ein als hund im krebs .
		Ref:	ich denke darüber nach , seit ich dieses jahr einen blog-eintrag von derek k. miller gelesen habe , der wissenschafts- und technologiejournalist war und der an krebs gestorben ist .
15	168/248= 68%	Src:	*__de__ det miller gjorde var att han bad familj och vänner skriva ett inlägg som publicerades kort efter hans död .*
		MT:	das miller machte sich , dass er schlechte , , wie die kurz nach seinem kopf .
		Ref:	und miller brachte seine familie und freunde dazu , einen eintrag zu schreiben , der kurz nach seinem tod veröffentlicht wurde .
16	166/236= 70%	Src:	*__da__ i slutet av detta år kommer det finnas närmare en miljard människor på denna planet som aktivt använder sociala nätverk på internet .*
		MT:	jeg år efter at en på planet som aktivt på internettet .
		Ref:	når dette år er ovre vil der være næsten én milliard mennesker på denne planet som aktivt bruger sociale netværkssider .
17	91/120= 76%	Src:	*__da__ det enda alla dessa människor har gemensamt är att de kommer att dö .*
		MT:	det som har de kommer til .
		Ref:	den ting de alle har til fælles er at de alle dør .

18	184/255= 72%	Src:	*__da__ trots att det kan vara en något tanke , tycker jag det har några djupgående konsekvenser som är värda att utforska .*
		MT:	, at det kan en , så vil det mig konsekvenser som .
		Ref:	selvom det måske er en temmelig morbid tanke , mener jeg at det har nogle meget vidtrækkende konsekvenser som er værd at undersøge .
19	170/306= 56%	Src:	*__da__ det som först fick mig att tänka på detta var ett blogginlägg från tidigare i år , av derek k miller , en vetenskaps- och som dog i cancer .*
		MT:	det som fik mig til at huske , var i år , derek k miller , en som hund i kræft .
		Ref:	det som først fik mig til at tænke over dette var et blog-indlæg forfattet af derek k. miller tidligere i år , en journalist indenfor videnskab og teknologi , som døde af kræft .
20	112/206= 54%	Src:	*__da__ det miller gjorde var att han bad familj och vänner skriva ett inlägg som publicerades kort efter hans död .*
		MT:	det miller gjorde var han dårligt , som kort efter hans .
		Ref:	hvad miller gjorde var at få hans familie og venner til at skrive et indlæg som udkom kort efter hans død .

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