Translational Grounding: Using Paraphrase Recognition and Generation to Demonstrate Semantic Abstraction Abilities of MultiLingual NMT

Jörg Tiedemann and Yves Scherrer
Department of Digital Humanities / HELDIG
University of Helsinki

Abstract

In this paper, we investigate whether multilingual neural translation models learn a stronger semantic abstraction of sentences than bilingual ones. We test this hypotheses by measuring the perplexity of such models when applied to paraphrases of the source language. The intuition is that an encoder produces better representations if a decoder is capable of recognizing synonymous sentences in the same language even though the model is never trained for that task. In our setup, we add 16 different auxiliary languages to a bidirectional bilingual baseline model (English-French) and test it with in-domain and out-of-domain paraphrases in English. The results show that the perplexity is significantly reduced in each of the cases, indicating that meaning can be grounded in translation. This is further supported by a study on paraphrase generation that we also include at the end of the paper.

1 Introduction

An appealing property of encoder-decoder models for machine translation is the effect of compressing information into dense vector-based representations to map source language input onto adequate translations in the target language. However, it is not clear to what extent the model actually needs to find semantic abstractions to perform that task; especially for related languages, it is often not necessary to acquire a deep understanding of the input to translate in an adequate way. The intuition that we would like to explore in this paper is based on the assumption that an increasingly difficult training objective will enforce stronger abstractions. In particular, we would like to see whether multilingual machine translation models learn representations that are closer to language-independent meaning representations than bilingual models do. Hence, our hypothesis is that representations learned from multilingual data sets covering a larger linguistic diversity better reflect semantics than representations learned from less diverse material.

Figure 1 illustrates this intuition in relation to the conceptual setup of machine translation and the classical Vauquois triangle (Vauquois, 1976). Encoder-decoder models reflect the idea of combining language understanding and generation, where the encoder maps the incoming signal to some internal representation, from which the decoder generates text in the target language. On the basis of this illustration, we expect multilingual models to build a stronger and more language-independent representation layer, which ought to be closer to the abstract meaning behind the input. In order to test this, we add linguistically diverse material to the training data and measure the abstractions that the model achieves when confronted with paraphrased sentences in one language.
Our basic framework consists of a standard attentional sequence-to-sequence model as commonly used for neural machine translation (Sennrich et al., 2017), with the multilingual extension proposed by Johnson et al. (2016). This extension allows a single system to learn machine translation for several language pairs, and crucially also for language pairs that have not been seen during training (this configuration is commonly referred to as zero-shot translation). We use Bible translations for training, in order to keep the genre and content of training data constant across languages, and to enable further studies on increasing levels of linguistic diversity. We propose different setups, all of which share the characteristics of having some source data in English and some target data in English. We can then evaluate these models on their capacity of recognizing and generating English paraphrases, or in other words, on their capacity of translating English sentences to English. Note that this approach is by no means restricted to English, but we selected this language for evaluation because we could more easily find paraphrased sentences as test material than in less resourced languages.

Starting with a base model using French–English and English–French training data, we select 16 additional languages as auxiliary information that are added to the base model, each of them separately.

2 Related Work

Paraphrase generation has been commonly treated as a monolingual machine translation problem, where the source and target languages happen to be the same (Quirk et al., 2004; Finch et al., 2004). For training such systems, large parallel monolingual corpora were required, and the attention of the research field shifted thus to mining such datasets, resulting in two of the most commonly used paraphrase datasets (Lin et al., 2014; Fader et al., 2013). More recently, Prakash et al. (2016) proposed to use sequence-to-sequence neural networks for monolingual paraphrase generation.

In another line of research, paraphrasing is viewed as a two-step translation process through some different pivot language: two strings $x_1$ and $x_2$ are considered paraphrases if they both translate to the same string $y$ in another language (Bannard and Callison-Burch, 2005). Paraphrases can be generated by first translating $x_1$ to $y$, and then translating $y$ back to the original language, yielding $x_2$. This approach permits the use of bilingual parallel training data, which are much easier to find than monolingual ones. The PPDB (Ganitkevitch et al., 2013) is a resource that has been created with this approach. Mallinson et al. (2017) propose to use sequence-to-sequence models for pivot-based paraphrase generation with multiple pivot languages, but create distinct models for each translation direction. We follow the same approach, but use the method of Johnson et al. (2016) to create a single model for various translation directions.

We view our approach as an instance of transfer learning, where the originally learned task is machine translation, but the target task is paraphrase generation. In the same spirit, Brad and Rebeđa (2017) show that monolingual models of paraphrase generation can be improved by training on related tasks such as entailment generation.

3 Experimental Setup

For our experiments, we use a standard attentional sequence-to-sequence model with BPE-based segmentation. We use the Nematus-style models (Sennrich et al., 2017) as implemented in MarianNMT (Junczys-Dowmunt et al., 2018). These models apply gated recurrent units (GRUs) in the encoder and decoder with a bi-directional RNN on the encoder side. The word embeddings have a dimensionality of 512 and the RNN dimensionality is set to 1,024. We enable layer normalization and we use one RNN layer in both, encoder and decoder.

In training we use dynamic mini-batches to automatically fit the allocated memory (3GB in our case) based on sentence length in the selected sample of data. The optimization procedure applies Adam (Kingma and Ba, 2015) with mean cross-entropy as the optimization criterion. We also enable length normalization, exponential smoothing, scaling dropout for the RNN layers with ratio 0.2 and also apply source and target word dropout with ratio 0.1. All of these values are recommended settings that have empirically been found in the related literature. For testing convergence, we use independent development data of roughly 1,000 test examples and BLEU scores to determine the stopping criterion, which is set to five subsequent failures of improving the validation score. The translations are done with a beam search decoder of size 12. The validation frequency is set to run each 2,500 mini-batches.

In contrast to traditional neural machine translation, we do not train separate models for each
source/target language combination, but rather learn a single model with data from both translation directions, using the appropriate language flags. For this multilingual setup, we follow Johnson et al. (2016) by adding language flags to the source text, e.g. `<eng>` to indicate that the decoder should produce English output. We place that label at the beginning of each source sentence and make sure that it will appear in the vocabulary of the source language. Because we always add training examples in both directions we, thus, enable translations from one language to the same language (for example, English to English), which allows us to treat the model as a paraphrase generator that is trained through transfer learning (or zero-shot) in the same way as Johnson et al. (2016) use it for translations between languages that are not seen in combination in the training data.

As usual, we want to avoid unknown words and, therefore, apply byte-pair encoding (BPE) (Sennrich et al., 2016) to work on subword levels and to keep the vocabulary at a manageable size. Here, we need to ensure the same segmentation at least for English as we want to test different combinations of language pairs and English as our primary language for the paraphrase tasks. Therefore, we opted for language-dependent BPE code tables that we train on the combination of all Bible variants of each particular language. The number of merge operations is set to 10,000 for each of the code tables. The vocabulary size then depends on the combination of languages that we use in training.

### 3.1 Training data and configurations

The main data we use for our experiments comes from a collection of Bible translations (Mayer and Cysouw, 2014) that includes over a thousand languages. For high-density languages like English and French, various alternatives are available (see Table 1). Using the Bible makes it possible to easily extend our work with additional languages representing a wide range of linguistic variation, while at the same time keeping genre and content constant across languages.

In our setup, we consider English to be some kind of pivot language and train models that learn to translate from and to English. The translation task, however, is the auxiliary task here and we are interested in exploring the ability of the model to understand English by measuring the perplexity of seeing paraphrased sentences in the same language without being trained on that task. Assuming that translation enforces semantic abstraction, we want to know how well the encoder can map surface forms to internal representations that discover semantic equivalence.

Our setup uses a base model that considers French as the only other target or source language. As additional auxiliary languages, we then apply the ones listed in Table 1, which also includes some basic statistics of the entire collection. We strove to create a diverse set of auxiliary languages that represent languages with large coverage, closely related languages and low-density languages that are partially quite different from English and French from a typological point of view.

In the general setup, we do not include any pairs of English Bible translations in our training data, as we do not want to evaluate a model that is specifically trained for a paraphrasing task. However, for comparison we also create a model that includes all pairs of English translation variants that will serve as an upper bound (or rather, a lower bound in terms of perplexity) for models that are trained without explicit paraphrase data.

In order to contrast different amounts of linguistic complexity to test our initial hypothesis, we train the following translation models:

**Bilingual model:** A model trained on all combinations of English and French Bible translations. Each sentence pair represents two training instances, one for English-to-French

---

| Language | Trans. | Verses | Tokens |
|----------|--------|--------|--------|
| English  | 19     | 234,173| 6,750,869|
| French   | 14     | 369,910| 10,529,929|
| Afrikaans| 5      | 75,974 | 2,329,773 |
| Albanian | 2      | 58,192 | 1,648,242 |
| Breton   | 1      | 1,781  | 44,316  |
| German   | 24     | 499,844| 13,712,459|
| Greek    | 7      | 87,218 | 2,357,095 |
| Frisian  | 1      | 29,173 | 852,582  |
| Hindi    | 1      | 122,363| 3,429,182 |
| Dutch    | 3      | 87,460 | 2,596,298 |
| Ossetian | 2      | 37,807 | 936,533  |
| Polish   | 5      | 52,668 | 1,248,108|
| Russian  | 5      | 75,904 | 1,727,536|
| Slovene  | 1      | 29,088 | 748,367 |
| Spanish  | 8      | 30,019 | 844,299  |
| Swedish  | 1      | 29,088 | 833,983  |

Table 1: Statistics about the Bible data in our collection: number of individual Bible translations, number of verses and number of tokens per language in the training data sets.
and one for French-to-English. We also include French-to-French training instances using identical sentences in the input and output, in order to guide the model to correctly learn the semantics of the language flags.\footnote{During our initial experiments, we realized that the language labels did not always pick up the information about the target language they are supposed to indicate. In the bilingual model, it is clear that the opposite language needs to be generated by the decoder, so it is sufficient for the model to identify the input language to determine the target language to be produced. This, however, creates a problem if we test the model with another task that it is never trained on, namely the generation of English translations from English input. The bilingual model simply refuses to produce any English output and ignores the language label completely, generating French translations instead. To counteract this problem, we added pairs of identical verses from all French Bible variants to the training data.}

**Trilingual models:** Translation models trained on all bilingual combinations of Bibles in three languages – English, French and another auxiliary language (in both directions) + identical French verse pairs.

**Multilingual model:** One model that includes all languages in our test set with training data in both directions (translating from and to English or French) + identical French verse pairs.

**Paraphrase model:** A model trained on combinations of English Bible translations (the supervised upper bound).

Note that all models cover the same English data. No new English data is added at any point and any change that we observe when testing with English paraphrase tasks is due to the auxiliary languages that we add to the model as a translational training objective.

We also intentionally leave out pairs of identical (or even paraphrased) English verses in our training data for two reasons: First of all, we are interested in a zero-shot scenario where no training examples are available for the task to be tested. Furthermore, we also want to avoid that the model learns to produce the identical string as a paraphrase of English input.

### 3.2 Test data

For our experiments, we apply test sets from two domains. One of them represents in-domain data from the Bible collection that covers 998 verses from the New Testament that we held out of training and development sets. Our second test set comes from a very different source, namely data collected from user-contributed translations that are on-line in the Tatoeba database.\footnote{https://tatoeba.org/eng/} They include everyday expressions with translations in a large number of languages. As the collection includes translation alternatives, we can treat them as paraphrases of each other. We extracted altogether 3,873 pairs of synonymous sentences in English.\footnote{These two datasets, in contrast to those presented in Section 2, can easily be extended to multilingual versions, which can then be tested on the translation task, as we do in Section 4.1.}

From both test data sources, we create a single-reference test set for paraphrase recognition and a multi-reference test set for paraphrase generation. The single-reference Bible test set uses the *Standard* English Bible as the source, and the *Common English Bible*\footnote{CEB is an ambitious new translation rather than a revision of other translations (see https://www.biblegateway.com).} as the reference. A few examples taken from the Bible test set are shown in Figure 2. The multi-reference Bible test set uses the *Amplified* Bible as the source (the first one on our list), and all 18 other English Bibles as the references.

The Tatoeba single-reference test set contains all 3,873 synonymous sentence pairs. For the multi-reference test set, we filtered the data to exclude near-identical sentence pairs by expanding contractions (like "I’m" to "I am") that are quite common in the data and removed all pairs that differ only in punctuation after that procedure. Furthermore, we merged alternatives of the same sentence into synonym sets and created, thus, a multi-reference corpus for testing. This set contains 2,444 sentences with their references. A few examples of the multi-reference corpus are shown in Figure 2.

### 4 Results

We evaluate the models on two tasks: (1) paraphrase recognition and (2) paraphrase generation. The following sections summarize our main findings in relation to these two tasks. However, before looking at paraphrasing, we also have a quick look at the actual performance in terms of machine translation in order to ensure that the models are proper translation models optimized for that task.

#### 4.1 Translation

Table 2 summarizes the BLEU scores when testing on heldout data from the in-domain corpus (Bible) and the out-of-domain corpus (Tatoeba). For the former we used heldout data from the English standard Bible and the New-World Bible for
The Spirit immediately drove him out into the wilderness. At once the Spirit forced Jesus out into the wilderness. And Simon and those who were with him searched for him, Simon and those with him tracked him down. And they began to beg Jesus to depart from their region. Then they pleaded with Jesus to leave their region.

What... you still don’t know how to drive? What? You don’t know how to drive a car yet? It is necessary for you to stop smoking. You must quit smoking. Are you sure? You must give up smoking. Do you think so? You must stop smoking. Are you certain?

Table 2: English to French translation quality in terms of BLEU scores, using the in-domain Bible test set (left half, single reference) and the out-of-domain Tatoeba test set (right half, multiple references). The columns marked with $\Delta$ show the absolute BLEU score difference compared to the baseline English–French model; improvements are highlighted in bold face.

| Training languages | Bible BLEU | $\Delta$ | Tatoeba BLEU | $\Delta$ |
|--------------------|------------|----------|--------------|----------|
| English–French     | 21.29      |          | 15.62        |          |
| + Afrikaans        | 21.14      | -0.15    | 16.49        | 0.87     |
| + Albanian         | 21.22      | -0.07    | 15.82        | 0.20     |
| + Breton           | 20.91      | -0.38    | 15.43        | -0.19    |
| + German           | 20.77      | -0.52    | 14.63        | -0.99    |
| + Greek            | 20.87      | -0.42    | 15.43        | -0.19    |
| + Frisian          | 21.59      | 0.30     | 15.52        | -0.10    |
| + Hindi            | 21.47      | 0.18     | 15.07        | -0.55    |
| + Italian          | 21.40      | 0.11     | 16.48        | 0.86     |
| + Dutch            | 21.18      | -0.11    | 16.30        | 0.68     |
| + Ossetian         | 20.84      | -0.45    | 17.11        | 1.49     |
| + Polish           | 21.05      | -0.24    | 17.18        | 1.56     |
| + Russian          | 21.00      | -0.29    | 15.49        | -0.13    |
| + Slovene          | 21.40      | 0.11     | 16.30        | 0.68     |
| + Spanish          | 20.81      | -0.48    | 15.11        | -0.51    |
| + Serbian          | 21.44      | 0.15     | 17.19        | 1.57     |
| + Swedish          | 20.64      | -0.65    | 16.85        | 1.23     |
| average            | 21.11      | -0.18    | 16.03        | 0.41     |

French. For Tatoeba, we created a multi-reference test corpus from the English-French translations in the database that includes 1,068 English sentences with a total of 7,998 translations into French.

There are at least two interesting patterns that can be seen from the translation results. First, the multilingual models are on par with the bilingual one on in-domain data. That means that we do not lose performance by adding new languages even though the model has to cover additional information. Note, however, that the system with all languages in one model causes a drop of more than one BLEU point (20.15% BLEU on the Bible test set), which shows the increasing problems with the capacity of such a model that needs to learn the translations between all language pairs with the same limited parameter space.

The second interesting observation is that the out-of-domain translation quality actually increases in the majority of the cases when adding an auxiliary language to the model. Note that there is no additional information for the given languages that we evaluate, not even in combination with the auxiliary languages that enter the training data. All models see the same English and French sentences, but possibly paired with other languages as well. An increase of up to 1.57 BLEU points is quite significant especially considering that we test a language pair with a good coverage in the training data and rather little auxiliary data that is added in most cases. This seems to be sufficient to provide an additional signal for increasing the abstraction capabilities of the model that is especially needed when shifting domains. Certainly, there is no consistent improvement in our results, which is probably due to the variety of styles that are used in Bible translations. That may influence translation results in various ways. The case of German is special because the amount of auxiliary data actually exceeds the number of examples available for the main task. It is not very surprising that the model is affected by this and the scores for translating into French go down significantly.

After this discussion we will now return to the main tasks we are interested in: paraphrase recognition and paraphrase generation. With those tasks we will more directly study the abstraction capabilities of the system.

4.2 Paraphrase Recognition

In this experiment, we would like to know how well our translation models are capable of handling paraphrased sentences. For this, we compute perplexity scores of the various models when observing English output sentences for given English input coming from our paraphrase test sets. The intuition is that models with a higher level of semantic abstraction in the encoder should be less surprised by seeing paraphrased sentences on the decoder side, which will result in a lower perplexity.

Let us first look at the in-domain data from our Bible test set. Figure 3 (left half) illustrates the reduction in perplexity when adding languages to our
bilingual model. The figure is sorted by decreasing perplexities. While the picture does not reveal any clear pattern about the languages that help the most, we can clearly see they all contribute to an improved perplexity in comparison to the bidirectional English-French model. Breton is clearly the least useful language, without doubt due to the size of that language in our collection. Note that a further 5% perplexity reduction over the best trilingual model is achieved by the model that combines all languages (perplexity of 7.23, which is very close to the lower bound of 6.05).

The picture is similar but with a slightly different pattern on out-of-domain data. Figure 3 (right half) shows the same plot for the Tatoeba test set with languages sorted in the same order as in the previous figure. Adding languages helps again, which is re-assuring, but the amount is less and further away from the lower bound (which is to be expected in this setup). Again, Breton is not helping as much. Furthermore, in the out-of-domain case, the model combining all languages actually does not improve the perplexity any further (the value of 42.63 is similar to other trilingual models), which is most probably due to the strong domain mismatch that influences the scores significantly.

To further demonstrate the problems of the bilingual model to learn a proper paraphrase model, we can also have a look at the learning curves in Figure 4. The plot clearly shows that the perplexity scores on paraphrase data do not follow the smooth line of the validation data in English and French whereas the models that include auxiliary languages have the capability to improve the model with respect to paraphrase recognition throughout the training procedure. The model that combines all languages achieves by far the lowest paraphrase perplexity. Learning curves of other trilingual models look very similar to the one included here.

### 4.3 Paraphrase Generation

This second experiment aims to test the capacity of the models to generate text in the same language as the input. The hypothesis is that the generated sentences will preserve the meaning of the input, but not necessarily the same form, such that the generated sentences can be viewed as genuine para-
Figure 4: Learning curves from three models (the bilingual English-French model, a trilingual model and a multilingual one): Perplexity on Bible data, English-French in validation (blue) and English paraphrases in testing (red). Note the different scales.

| Source | He slept soundly. | Eng-Fra Et il se prosterna devant soi. | +Bre And, behold, he rose up quickly. | +Deu And he began to sleep. | +Ell He was sleeping. | +ALL And when he had died, he was asleep. |
|--------|------------------|---------------------------------------|--------------------------------------|--------------------------|---------------------|------------------------|
| Source | She has no brothers. | Eng-Fra Elle n’a point de frères. | +Bre Or, elle n’a pas de frères. | +Deu For she has no brothers. | +Oss No, brothers. | +ALL You have no brothers. |

Figure 5: Examples of generated Tatoeba paraphrases.

Paraphrase generation could be achieved trivially by copying the input to the output. However, our models show very few cases of this behavior, as shown in Table 3. Identical output is slightly more prevalent in the out-of-domain Tatoeba data. These figures confirm that the risk of copying is effectively limited by the chosen training setup lacking English-English training pairs.

The very low identity scores of the base model and the Breton model result from their inability to generate the correct target language. In fact, even though the \texttt{<eng>} target language label is specified, and even though we have added French–French data during training (see Footnote 1), these models continue to produce French output (see Figure 5). Using English–English training data, in contrast, increases the amount of identical sentences dramatically (see last line of Table 3), which breaks the use of such models as a paraphrase generator.

Good paraphrase models should produce sentences that are as close as possible to one of the references, yet as different as possible from the source. The first part can be measured by common machine translation metrics such as BLEU (Papineni et al., 2002), which supports multiple references. The second part, which we have approximated with the simple identity score of Table 3, can be measured more accurately by specific paraphrase quality metrics such as PINC (Chen and Dolan, 2011), which computes the proportion of non-overlapping n-grams between the source and the generated paraphrase. Good paraphrases should thus obtain high BLEU as well as high PINC scores on some paraphrase test set.

Figure 6 plots BLEU scores against PINC scores for the two test sets (lowercased and ignoring punctuations), the alternative English translations in the heldout data from the Bible and the Tatoeba paraphrase set. We exclude the bilingual model and the Breton model from the graphs, as they have BLEU scores close to 0 and PINC scores close to 100% due to the output being generated in the wrong language.

The figures show a more or less linear correlation between BLEU and PINC. This is expected to a certain extent, as there is a clear trade-off between producing varied sentences (higher PINC) and preserving the meaning of the source sentence (higher BLEU). However, we find that the model containing all languages shows the overall best performance (e.g., according to the arithmetic mean of PINC and BLEU). This suggests that a highly multilingual model provides indeed more abstract internal representations that eventually lead to higher-quality paraphrases. We also conclude that additional languages with large and diverse (i.e., many different Bibles) datasets are better at preserving the meaning of the source sentence. However, there is no obvious language family or similarity effect.

The Tatoeba test set yields much lower BLEU scores than the Bible test set, due to the large num-
Figure 6: Paraphrase BLEU vs. PINC scores for the Bible test set (left) and the Tatoeba test set (right).

Source But even as he was on the road going down, his servants met him and reported, saying, Your son lives!
+NLD And as he was on the road, his servants went down with him, and reported, saying, Thy son lives!
+SPA But as it was on the road, his servants came to him and told him, "Your own Son lives!"
+ALL And while he was on the way, his servants came to him, saying, "Your son lives!"

Source Give attention to this! Behold, a sower went out to sow.
+AFR Pay attention to this! Behold, the sower went out to sow.
+ALL Take care of this. Behold, a sower went out to sow.
+BRE Give attention to this! For, look! un semeur sortit pour semer.
+DEU Listen to this! Behold, a sower went out to sow.

Figure 7: Examples of generated Bible paraphrases.

A considerable proportion of the test vocabulary refers to contemporary objects which obviously do not appear in the Bible training corpus, and it will thus be difficult for the model to generate adequate paraphrases. A few examples of sentences containing out-of-vocabulary words are shown in Figure 8. They indicate that the models are often able to identify the general meaning of the words and sentences, but they also call for a more generic evaluation of the semantic similarity of paraphrases than is done by n-gram overlap with reference paraphrases.

5 Conclusions

This paper presents a study on the semantic representations that can be learned from multilingual data sets. We show that additional linguistic diversity lead to stronger abstractions and we verify our intuitions with a paraphrase scoring task that measures perplexity of multilingual sequence-to-sequence models. We also investigate the ability of translation models to generate paraphrases and conclude that this is indeed possible with promising results even without diversified decoders. In the future, we will try to push the model further to approach truly language-independent meaning representation based on massively parallel data sets as additional translational grounding.
Acknowledgments

The work in this paper is supported by the Academy of Finland through project 314062 from the ICT 2023 call on Computation, Machine Learning and Artificial Intelligence. We would also like to acknowledge NVIDIA and their GPU grant.

References

Colin Bannard and Chris Callison-Burch. 2005. Paraphrasing with bilingual parallel corpora. In Proceedings of the ACL 2005, pages 597–604, Ann Arbor, Michigan.

Florin Brad and Traian Rebedea. 2017. Neural paraphrase generation using transfer learning. In Proceedings of the 10th International Conference on Natural Language Generation, pages 257–261, Santiago de Compostela, Spain.

David Chen and William Dolan. 2011. Collecting highly parallel data for paraphrase evaluation. In Proceedings of ACL 2011, pages 190–200, Portland, Oregon, USA.

Anthony Fader, Luke Zettlemoyer, and Oren Etzioni. 2013. Paraphrase-driven learning for open question answering. In Proceedings of ACL 2013, pages 1608–1618, Sofia, Bulgaria.

Andrew Finch, Taro Watanabe, Yasuhiro Akiba, and Eiichiro Sumita. 2004. Paraphrasing as machine translation. 11:87–111.

Juri Ganitkevitch, Benjamin Van Durme, and Chris Callison-Burch. 2013. PPDB: The paraphrase database. In Proceedings of NAACL 2013, pages 758–764, Atlanta, Georgia.

Melvin Johnson, Mike Schuster, Quoc V. Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda B. Viégas, Martin Wattenberg, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2016. Google’s multilingual neural machine translation system: Enabling zero-shot translation. CoRR, abs/1611.04558.

Marcin Junczys-Dowmunt, Roman Grundkiewicz, Tomasz Dwojak, Hieu Hoang, Kenneth Heafield, Tom Neckermann, Frank Seide, Ulrich Germann, Alham Fikri Aji, Nikolay Bogoychev, André F. T. Martins, and Alexandra Birch. 2018. Marian: Fast neural machine translation in C++. arXiv preprint arXiv:1804.00344.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In The International Conference on Learning Representations.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick. 2014. Microsoft COCO: Common objects in context. In Computer Vision – ECCV 2014, pages 740–755. Springer International Publishing.

Jonathan Mallinson, Rico Sennrich, and Mirella Lapata. 2017. Paraphrasing revisited with neural machine translation. In Proceedings of EACL 2017, pages 881–893, Valencia, Spain.

Thomas Mayer and Michael Cysouw. 2014. Creating a massively parallel Bible corpus. In Proc. of LREC, pages 3158–3163, Reykjavik, Iceland. European Language Resources Association (ELRA).

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of ACL 2002, pages 311–318, Philadelphia, Pennsylvania, USA.

Aaditya Prakash, Sadid A. Hasan, Kathy Lee, Vivek Datla, Ashqueil Qadir, Joey Liu, and Oladimeji Farri. 2016. Neural paraphrase generation with stacked residual LSTM networks. In Proceedings of COLING 2016, pages 2923–2934.

Chris Quirk, Chris Brockett, and William Dolan. 2004. Monolingual machine translation for paraphrase generation. In Proceedings of EMNLP 2004, pages 142–149, Barcelona, Spain.

Rico Sennrich, Orhan Firat, Kyunghyun Cho, Alexandra Birch, Barry Haddow, Julian Hitschler, Marcin Junczys-Dowmunt, Samuel Läubli, Antonio Valerio Miceli Barone, Jozef Mokry, and Maria Nadejde. 2017. Nematus: a toolkit for neural machine translation. CoRR, abs/1703.04357.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of ACL 2016, pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

B Vauquois. 1976. Automatic translation – a survey of different approaches. In Statistical Methods in Linguistics, pages 127–135. Presented at COLING 1976, Ottawa, Canada.