How Do Source-side Monolingual Word Embeddings Impact Neural Machine Translation?

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Abstract

Using pre-trained word embeddings as input layer is a common practice in many natural language processing (NLP) tasks, but it is largely neglected for neural machine translation (NMT). In this paper, we conducted a systematic analysis on the effect of using pre-trained source-side monolingual word embedding in NMT. We compared several strategies, such as fixing or updating the embeddings during NMT training on varying amounts of data, and we also proposed a novel strategy called dual-embedding that blends the fixing and updating strategies. Our results suggest that pre-trained embeddings can be helpful if properly incorporated into NMT, especially when parallel data is limited or additional in-domain monolingual data is readily available.

1 Introduction

Leveraging the information encoded in pre-trained monolingual word embeddings (Bengio et al., 2003; Mikolov et al., 2013; Pennington et al., 2014; Bojanowski et al., 2017) is a common practice in various natural language processing tasks, for example: parsing (Dyer et al., 2015) (Kiperwasser and Goldberg, 2016), relation extraction (Peng et al., 2017), natural language understanding (Cheng et al., 2016a), sequence labeling (Ma and Hovy, 2016), and so on. While research in neural machine translation (NMT) seeks to make use of monolingual data by techniques such as back-translation (Sennrich et al., 2016a), the use of pre-trained monolingual word embeddings does not seem to be the standard practice.

In this paper, we study the interaction between the source-side monolingual word embeddings with NMT. Our goal is to understand whether they help translation accuracy, and how to integrate them into the model in the best way. Specifically, we seek to answer questions such as: (1) Should the embeddings be fixed or updated during NMT training? (2) Are embeddings more effective when bilingual training data is limited? (3) Does the amount or domain of monolingual data used to train the embeddings affect results significantly? We answered these questions with experiments on varying amounts of bilingual training data drawn from Chinese-English and German-English tasks.

Additionally, we proposed a simple yet effective strategy called dual-embedding, which combines a fixed pre-trained embedding with a randomly initialized embedding that is updated during NMT training. We found that this strategy generally improves BLEU under various data scenarios, and is an useful way to exploit pre-trained monolingual embeddings in NMT.

2 Related Work

Various works have explored the use of monolingual data in NMT. On using target side monolingual data, (Gulcehre et al., 2015) incorporated a pre-trained RNN language model, while (Sennrich et al., 2016a) trained an auxiliary model with reverse translation direction to construct pseudo parallel data. (Currey et al., 2017) copied target monolingual data to the source side and mix it with real parallel data to train a unified encoder-decoder model. It should be noted that although some of these techniques are very popular in practice, they are only capable of incorporating target-side monolingual data, and hence they are outside the immediate scope of this paper.

On using source side monolingual data, (Cheng et al., 2016b; Zhang and Zong, 2016) proposed self-learning for NMT, which learns the transla-
tion by reconstruction. Also, several works have shown promising results in incorporating pre-trained source-side word embedding into NMT systems. (Rios Gonzales et al., 2017) used sense embedding to improve word sense disambiguation abilities of the translation system. Most similar to our work is (Abdou et al., 2017), which used pre-trained word embedding to help training converge faster, and (Di Gangi and Federico, 2017), which studied the effect of source monolingual embedding for NMT, but focus on low resource settings; further, their gated sum approach to combining embeddings has similar motivation to our dual embedding strategy. The results and analysis in our work verifies most of the conclusions in their paper, while extending them by examining both low and high resource settings and providing additional answers to question of when and how are embeddings beneficial.

3 Strategies for Incorporating Pre-trained Embeddings

3.1 Initializing Embedding

We focus on simple strategies to incorporate pre-trained source-side monolingual embeddings in the NMT encoder. The goal is to require minimum modification of the standard NMT model. The simplest way is to initialize the NMT model with pre-trained embedding values – for each word in the source sentence of the training bitext, we look-up its pre-trained embedding and initialize the NMT encoder with it.

After initialization, there are two strategies during training. We can fix the embeddings to their initialized pre-trained values throughout training; in other words, NMT training optimizes parameters in the context encoding layers (e.g. LSTM), the attention layers, etc., but do not back-propagate into the embedding parameters. Example works adopting such strategy include (Dyer et al., 2015) and (Kiperwasser and Goldberg, 2016).

Alternatively, we can update the embeddings with all other NMT model parameters during training. Here, the pre-trained word embeddings only provide an initialization that is different from the baseline of random initialization. Updating the initialization allows embeddings to adjust to values that are suitable for the NMT overall objective, whereas fixing embeddings potentially allows generalization to test words that are not observed in the training data. Example works adopting such strategy include (Ma and Hovy, 2016) and (Peng et al., 2017).

3.2 Dual Embedding

To combine the benefit of both strategies introduced above, we propose dual embedding, as shown in Figure 1. Basically, we augment the original encoder-decoder architecture of NMT model with an extra word embedding of same size, which is concatenated with the original word embedding. While the original word embedding is randomly initialized, this extra embedding will be initialized by a pre-trained monolingual word embedding and fixed through out training. The idea behind this architecture is that we would like to learn a correction term over the original monolingual word embedding, rather than rewriting the monolingual word embedding altogether.

4 Experiments

We conducted experiments for Chinese-English (ZH-EN) and German-English (DE-EN) language pairs. For ZH-EN experiments, a collection of
LDC Chinese-English data with about 2.01 million sentence pairs was used as training set, while NIST OpenMT 2005 and OpenMT 2008 dataset were used as development set and test set, respectively. For DE-EN experiments, we used WMT 2016 data for training, newstest2008 as development set, and newstest2015 as test set. To investigate the effectiveness of pre-trained monolingual embedding on systems trained on different amount of bilingual data, we varied the amount of training data in the experiments by performing random sampling on the full parallel data; Table 1 shows the number and percentage of OOV word types for each training subset.

The monolingual data used for ZH-EN experiments is the XMU LDC monolingual data provided in WMT 2017 news translation evaluation (Bojar et al., 2017), while for DE-EN the German news crawl 2016 dataset was used as the monolingual data. To investigate whether monolingual data size is a significant factor in NMT translation quality, we experimented with two different kinds of monolingual word embeddings:

- **small**: only the source-side of the parallel corpus is used for pre-training
- **extended**: additionally, the monolingual corpus is used for pre-training

BPE was applied (Sennrich et al., 2016b) for both parallel and monolingual corpus with operation number 49,500, while total vocabulary size was set to 50,000.

We compared the following strategies to incorporate pre-trained monolingual word embeddings.

- **fixed** initialization: the source-side word embedding is fixed during training
- **update** initialization: the source-side word embedding is updated during training
- **dual** embedding: one half of the word embedding parameter contains the fixed pre-trained vector, while the other half is updated during training and acts as a correction term.

These were compared to the **baseline** of using random initialization.

A modified fork of OpenNMT-py\(^2\) (Klein et al., 2017) was used to run all NMT experiments, while fastText (Bojanowski et al., 2017) was used to build all the pre-trained monolingual word embedding, with embedding dimension 300. We used 2-layer LSTM for both the encoder and decoder, and the hidden dimension of LSTM was set to 1024. We updated the parameter with Adadelta (Zeiler, 2012) with learning rate 1.0, \(\epsilon = 1e^{-6}\) and \(\rho = 0.95\), and performed dropout on all the LSTM layers and embedding layers with a rate of 0.2. We trained all of our models for 20 epochs, the best model selected by the perplexity on the validation set will be used to decode on test set.

We evaluated our models with uncased BLEU calculated using `multi-bleu.perl` that comes with the Moses decoder (Koehn et al., 2007). We also performed pairwise significance testing (Koehn, 2004) between some key experimental setups.

### 4.1 Results

Figure 2 shows the training and development log-probability curve under 100k and unsampled Chinese-English training data\(^3\), respectively. We can see from the figure that adding pre-trained word embedding does not speedup convergence of the training process, which verifies the conclusion from (Abdou et al., 2017). However, our result extends over the previous work to show that while there is no change in the convergence speed, the objective function value (especially the development loss function value) at convergence is significantly higher when pre-trained word embedding is incorporated, which indicates stronger model is learned. We also notice that contrary to the general belief, pre-trained embedding initialization does not make the initial objective value significantly higher. This implies that fixing word embedding throughout the training process as what has been done in some other NLP literatures may not be a very good strategy for neural machine translation. The hypothesis is further verified by the result that follows.

Table 2 and Table 3 show the uncased BLEU scores and the significance of difference between some pairs of results. Comparing the results of fixed strategy and others, it can first be noticed that fixed initialization does not only almost consistently generate worst BLEU score among the three, but also significantly hurts the performance.

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\(^1\)To reduce variance introduced by BPE over different size of the training data, we used a single BPE model trained on the source-side monolingual data and a comparable sample of English news crawl 2014 monolingual data.

\(^2\)https://github.com/shuoyang3/OpenNMT-py/tree/mono_emb

\(^3\)The same plots were generated for German-English experiments and small embedding incorporations as well, and the trend looks very similar. Hence they are omitted to avoid repetitiveness.
over the baseline sometimes. This strengthens our hypothesis above. On the other hand, if we allow the source-side word embedding to be updated, we can observe improvements over the baseline more often. We hence conclude that pre-trained source-side monolingual word embedding cannot directly benefit NMT performance, and adjustment by NMT training is necessary for it to be beneficial to the NMT system performance.

Comparing the Chinese-English and German-English experiments, we notice that incorporating embeddings for German-English experiments yields significant improvements over baselines more often, mainly because of the improvements obtained by extended fixed embedding incorporation. We think this is due to fact that the German-English test set generally has higher pre-BPE OOV rate across different sample size of the parallel training data.

Comparing the results under different monolingual data scales, for Chinese-English experiments, the extended embedding always performs better than small embedding, while for German-English experiments, we got mixed results when comparing results with two different kinds of embeddings. This can be explained by the fact that the parallel training data has a minor domain mismatch from the monolingual training data (parliament proceedings vs. news). In terms of incorporation strategy, it can be observed that while the dual strategy is not very helpful with small word embeddings, improvements over update strategy can almost always be obtained with extended embeddings. We can also notice that under the German-English setting with extended embeddings, the different between update and dual embedding method is more often significant compared to that of Chinese-English experiments, signaling that dual embedding method is more robust to domain variances between monolingual data and bi-text.

Comparing the results obtained under different parallel training data scales, it can be observed that the benefit of source-side monolingual word embedding (compared to the baseline) seems to be decreasing along with the increasing amount of data, verifying the intuition that extra monolingual information is most useful under low-resource settings. On the other hand, the dual embedding model is able to obtain the largest performance gains over update initialization both for Chinese-English and the German-English training
data with extended embeddings. This indicates that the dual embedding model is able to get the best of both worlds as expected – it leverages more on the initialized word embedding at low resource settings, but is able to learn useful supplementary features when relatively large amount of parallel training data is available.

### 4.2 Analysis

**Qualitative Analysis**

Translation of test sets were examined manually to evaluate the qualitative improvements obtained by incorporating pre-trained word embeddings within NMT. In the case of small embedding, we have learned from significance test that many of these improvements are not statistically significant. But even for the significant ones, we didn’t observe very specific patterns for qualitative improvements.

In the case of extended embedding, however, we observed an specific improvement of the translation adequacy for rare words (mainly named entities) in the training data, and the usage of dual embedding model often brings further improvements in that aspect. Such improvement is evident in Table 4 when comparing the translation results from systems trained with unsampled parallel data (sentence 6-8 and sentence 14-16).

To further verify the observation above, we did a simple human evaluation where we take the translation output from Chinese-English systems trained on unsampled parallel data with extended embedding incorporation. We first took the singleton words (before BPE) in the unsampled parallel data and filtered the test sentences containing these singleton words. We then manually read the filtered and shuffled test sentences and answered the yes/no question: are the singleton words appeared in the sentence translated correctly in the test output? We chose to analyze singleton words rather than OOV words because (1) the translation of singleton words is less noisy; (2) if a word occurs in both the training set and the test set, it’s more likely to occur in the monolingual data and hence embedding incorporation will add extra information to translate these words. We found 226k singleton words in the training data and 134 occurrences of these words in the test data. The results is shown in the Table 5 and we can see that both update and dual incorporation method

![Table 2: Chinese-English experiment Results with Different Data Sizes. Asterisks are appended when the difference between update and dual method translation output is significant, and daggers are appended when difference between any system output and the baseline is significant. The significance level is \( p < 0.05 \).](image)

| Sentence Pairs | Baseline | small embedding | extended embedding |
|----------------|----------|-----------------|--------------------|
|                |          | fixed | update | dual | fixed | update | dual |
| 100,000        | 15.99    | 15.36† | 16.44 | 16.89† | 15.90 | 17.55† | 17.56† |
| 250,000        | 21.72    | 22.05 | 22.16 | 22.08 | 22.05 | 23.04† | 23.38† |
| 500,000        | 26.28    | 25.48† | 26.51 | 26.29 | 26.13 | 27.09† | 26.76† |
| 1,000,000      | 29.75    | 29.54 | 29.59 | 29.83 | 29.39 | 30.6† | 30.89† |
| 2,013,142      | 32.44    | 31.40† | 33.21† | 33.21† | 32.61 | 33.26† | 34.03† |

![Table 3: German-English experiment Results with Different Data Sizes. Asterisks are appended when the difference between update and dual method translation output is significant, and daggers are appended when difference between any system output and the baseline is significant. The significance level is \( p < 0.05 \).](image)

| Sentence Pairs | Baseline | small embedding | extended embedding |
|----------------|----------|-----------------|--------------------|
|                |          | fixed | update | dual | fixed | update | dual |
| 100,000        | 13.55    | 14.02† | 14.75† | 14.91† | 15.14† | 15.28† | 15.96*† |
| 250,000        | 20.11    | 20.18 | 20.92*† | 20.47 | 20.74† | 20.76† | 20.95† |
| 500,000        | 23.09    | 23.46 | 24.14† | 24.11† | 23.55† | 24.14† | 24.64*† |
| 1,000,000      | 26.17    | 25.95 | 26.29 | 26.21 | 26.27 | 26.19 | 26.59*† |
| 4,562,102      | 29.71    | 28.73† | 30.00† | 30.07 | 29.17† | 29.13† | 30.00*† |
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Table 4: Two translation snippets from the 100k sample and unsampled Chinese-English experiments with several named entities highlighted in corresponding colors. All the embedding incorporated are extended embeddings. The @@ symbol is the token breaking symbol produced by BPE processing.

| system         | accuracy |
|----------------|----------|
| baseline       | 29.10%   |
| update         | 32.09%   |
| dual           | 33.58%   |

Table 5: Human-evaluated singleton word translation accuracies on Chinese-English test set.

improves the singleton translation accuracy. This agrees with our observation as presented in Table 4.

On the other hand, while the BLEU scores improves significantly over baselines under the low-resource settings with extended embedding incor-
poration, we did notice that the systems with embedding incorporated tends to produce repetitive output more frequently (e.g. sentence 4 and 5), to which we don’t have a very good explanation. We conjecture that such problem could be remedied by coverage modeling techniques such as (Tu et al., 2016) and (Wu et al., 2016), but leave the verification of it as future work. We also acknowledge that the improvements on rare word translation is not obvious under low-resource settings (e.g. sentence 11-13) because translation outputs are often too noisy to tell much useful qualitative trend.
Figure 3: Sentence-Level BLEU Scatter Plot Between Baseline and Embedding-Incorporated Systems. The dots on the upper-left part of the red line corresponds to system output sentences that are better than the baseline, and vice versa.

Figure 4: Average Norm of Update on Word Embeddings Grouped by Word Frequency in Training Data
Quantitative Analysis

For quantitative analysis, we focus on the small-scale experiment (trained with 100k sample of parallel data) with extended embedding incorporation as they seem to pose most interesting improvements in terms of BLEU scores.

We started with computing the sentence-level BLEU with MultEval toolkit (Clark et al., 2011) and generating scatter plot of sentence-level BLEU score of the update and dual embedding system against the baseline system for each output sentence decoded on the test set, as shown in Figure 3. The purpose of this analysis is to examine the variance of output sentence before/after the embedding incorporation. It could first be noticed that across all embedding incorporation methods, the dots are shifted to the upper left side of the red line, which means sentence-level BLEU score tends to increase after incorporation. This agrees with the increase of corpus-level BLEU score in Table 2 and Table 3. On the other hand, all embedding incorporation methods incurs similar amount of variances in translation outputs, even on different language pairs. In terms of comparison across incorporation strategies, the update strategy seems to incur slightly more drastic BLEU scores changes (dots that are close to the right and upper part of the horizontal and vertical axes, respectively), but the difference is not significant enough to make a strong argument.

Another problem we are interested in is the norm of update on the word embeddings during the NMT training process. More specifically, for each words in the dictionary, we take their word embedding before/after the training process and compare the norm of their difference. Figure 4 shows the norm of update grouped by the word frequency in the training data. It should be noted that the norm of update is increasing roughly linearly along with the frequency of words up till 50000. This implies that for each iteration, unless the word has been seen extremely frequently, the norm of update performed on the word embedding is about the same on average. We also see that norm of update performed on dual incorporation strategy is consistently lower than update incorporation strategy. Because the pre-trained part of the embedding is fixed, and the dual strategy is essentially learning a correction term over the pre-trained word embedding rather than rewriting the pre-trained value completely, we conjecture that the fixed part of the dual embedding is preventing the updated part of the dual embedding to perform too much correction over its pre-trained value. This conservativeness in performing update may account for the extra robustness of dual embedding incorporation we observed in the qualitative analysis.

5 Conclusion

Our analysis on using source-side monolingual word embeddings in NMT indicates that (1) the source-side embeddings should be updated during NMT training; (2) the source-side embeddings are more effective when bilingual training data is limited, especially when OOV rates is high. Moreover, source-side embedding incorporation is also useful under some high-resource settings when incorporated properly; (3) the effect of source-side word embedding strengthens when extra monolingual data is provided for training, and the domain of the monolingual data also seems to matter.

We recommend that incorporating pre-trained embeddings as input become a standard practice for NMT when bilingual training data is scarce, especially when extra source-side monolingual data is available. While incorporating pre-trained embeddings at high-resource settings may also be helpful, we advise that extra caution should be used to ensure the monolingual data is in-domain, and appropriate incorporation strategy should be selected.

References

Mostafa Abdou, Vladan Gloncak, and Ondřej Bojar. 2017. Variable mini-batch sizing and pre-trained embeddings. In Proceedings of the Second Conference on Machine Translation. Association for Computational Linguistics, pages 680–686. http://aclweb.org/anthology/W17-4780.

Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. 2003. A neural probabilistic language model. Journal of machine learning research 3(Feb):1137–1155.

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching word vectors with subword information. Transactions of the Association of Computational Linguistics 5:135–146. http://aclweb.org/anthology/Q17-1010.

Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Shujian Huang, Matthias Huck, Philipp Koehn, Qun Liu, Varvara Logacheva, Christof Monz, Matteo Negri, Matt
Jianpeng Cheng, Li Dong, and Mirella Lapata. 2016a. Long short-term memory-networks for machine reading. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. EMNLP 2016, Austin, Texas, USA, November 1-4, 2016. pages 551–561. http://aclweb.org/anthology/D/D16/D16-1053.pdf.

Yong Cheng, Wei Xu, Zhongjun He, Wei He, Hua Wu, Maosong Sun, and Yang Liu. 2016b. Semi-supervised learning for neural machine translation pages 1965–1974. https://doi.org/10.18653/v1/P16-1185.

Jonathan H Clark, Chris Dyer, Alon Lavie, and Noah A Smith. 2011. Better hypothesis testing for statistical machine translation: Controlling for optimizer instability. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: short papers-Volume 2. Association for Computational Linguistics, pages 176–181.

Anna Currey, Antonio Valerio Miceli Barone, and Kenneth Heafield. 2017. Copied monolingual data improves low-resource neural machine translation. In Proceedings of the Second Conference on Machine Translation. Association for Computational Linguistics, pages 148–156. http://aclweb.org/anthology/W17-4715.

Mattia Antonino Di Gangi and Marcello Federico. 2017. Monolingual embeddings for low resourced neural machine translation. In Proceedings of the 14th International Workshop on Spoken Language Translation. pages 97–104.

Chris Dyer, Miguel Ballesteros, Wang Ling, Austin Matthews, and Noah A. Smith. 2015. Transition-based dependency parsing with stack long short-term memory. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). Association for Computational Linguistics, pages 334–343. https://doi.org/10.3115/v1/P15-1033.

Caglar Gulcehre, Orhan Firat, Kelvin Xu, Kyunghyun Cho, Loic Barrault, Hui-Chi Lin, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2015. On using monolingual corpora in neural machine translation. arXiv preprint arXiv:1503.03535.

Eliyahu Kiperwasser and Yoav Goldberg. 2016. Simple and accurate dependency parsing using bidirectional lstm feature representations. Transactions of the Association of Computational Linguistics 4:313–327. http://www.aclweb.org/anthology/Q16-1023.

Guillaume Klein, Yoon Kim, Yuntian Deng, Jean Senellart, and Alexander Rush. 2017. Opennmt: Open-source toolkit for neural machine translation pages 67–72. http://www.aclweb.org/anthology/P17-4012.

Philipp Koehn. 2004. Statistical significance tests for machine translation evaluation. In Proceedings of the 2004 conference on empirical methods in natural language processing.

Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, Chris Dyer, Ondrej Bojar, Alexandra Constantin, and Evan Herbst. 2007. Moses: Open source toolkit for statistical machine translation. In Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics Companion Volume Proceedings of the Demo and Poster Sessions. Association for Computational Linguistics, Prague, Czech Republic, pages 177–180. http://www.aclweb.org/anthology/P07-2045.

Xuezhe Ma and Eduard H. Hovy. 2016. End-to-end sequence labeling via bi-directional lstms-crf. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016, August 7-12, 2016, Berlin, Germany, Volume 1: Long Papers. http://www.aclweb.org/anthology/P/P16/P16-1101.pdf.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems. pages 3111–3119.

Nanyun Peng, Hoifung Poon, Chris Quirk, Kristina Toutanova, and Wen-tau Yih. 2017. Cross-sentence n-ary relation extraction with graph lstms. Transactions of the Association for Computational Linguistics 5:101–115. https://transacl.org/ojs/index.php/tacl/article/view/1028.

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for Computational Linguistics, Doha, Qatar, pages 1532–1543. http://www.aclweb.org/anthology/D14-1162.

Annette Rios Gonzales, Laura Mascarilla, and Rico Sennrich. 2017. Improving word sense disambiguation in neural machine translation with sense embeddings. In Proceedings of the Second Conference on Machine Translation. Association for Computational Linguistics, pages 11–19. http://aclweb.org/anthology/W17-4702.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016a. Improving neural machine translation models with monolingual data pages 86–96. http://www.aclweb.org/anthology/P16-1009.
Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016b. Neural machine translation of rare words with subword units pages 1715–1725. http://www.aclweb.org/anthology/P16-1162.

Zhaopeng Tu, Zhengdong Lu, Yang Liu, Xiaohua Liu, and Hang Li. 2016. Coverage-based Neural Machine Translation. arXiv.org.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. arXiv preprint arXiv:1609.08144.

Matthew D Zeiler. 2012. Adadelta: an adaptive learning rate method. arXiv preprint arXiv:1212.5701.

Jiajun Zhang and Chengqing Zong. 2016. Exploiting source-side monolingual data in neural machine translation. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Austin, Texas, pages 1535–1545. https://aclweb.org/anthology/D16-1160.