Robust Unsupervised Neural Machine Translation with Adversarial Training

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Abstract
Unsupervised neural machine translation (UNMT) has recently attracted great interest in the machine translation community, achieving only slightly worse results than supervised neural machine translation. However, in real-world scenarios, there usually exists minor noise in the input sentence and the neural translation system is sensitive to the small perturbations in the input, leading to poor performance. In this paper, we first define two types of noises and empirically show the effect of these noisy data on UNMT performance. Moreover, we propose adversarial training methods to improve the robustness of UNMT in the noisy scenario. To the best of our knowledge, this paper is the first work to explore the robustness of UNMT. Experimental results on several language pairs show that our proposed methods substantially outperform conventional UNMT systems in the noisy scenario.

1 Introduction

Neural machine translations (NMT) (Bahdanau et al., 2015; Vaswani et al., 2017) have set several state-of-the-art new benchmarks (Bojar et al., 2018; Barrault et al., 2019). Recently, unsupervised NMT (UNMT) has attracted great interest in the machine translation community (Artetxe et al., 2018; Lample et al., 2018a; Yang et al., 2018; Lample et al., 2018b; Sun et al., 2019). Typically, UNMT relies solely on monolingual corpora rather than bilingual parallel data in supervised NMT (SNMT) to model translations between the source language and target language and has achieved remarkable results on several translation tasks (Lample and Conneau, 2019). However, previous work only focus on how to build state-of-the-art UNMT systems on the clean data and ignore the robustness of UNMT on the noisy data. In the real-world scenario, there often exists minor noise in the input sentence. The translation model is sensitive to small perturbations in the input, leading to various errors. The existing neural translation system, which lacks of robustness, is difficult to be widely applied to the noisy-data scenario (noisy scenario in the following sections). Therefore, the robustness of neural translation system is not only worthy of being studied, but also very essential in the real-world scenario.

The robustness of SNMT (Belinkov and Bisk, 2018; Cheng et al., 2018; Cheng et al., 2019; Karpukhin et al., 2019) has been well-studied. However, they only focus on the effect of the word substitution for translation performance, and ignore the effect of word order for translation performance. In this paper, we first define these two types of noises, that is, word noise and word order noise. Then we empirically investigate the performance of UNMT and SNMT in this noisy scenario. Our empirical results show that the UNMT model outperformed the SNMT model, although both of their performances decreased significantly in this scenario. Moreover, we proposed adversarial training methods to alleviate poor performance in the noisy scenario. To the best of our knowledge, this paper is the first work to explore the robustness of UNMT. Experimental results on several language pairs show that the proposed strategies substantially outperform conventional UNMT systems in the noisy scenario.

This paper primarily makes the following contributions:

• We define two types of noises, i.e., word noise and word order noise, and empirically investigate the performance of UNMT in the noisy scenario.

* Haipeng Sun was an internship research fellow at NICT when conducting this work.
• We propose adversarial training methods to train a robust UNMT system, achieving up to 10 BLEU scores improvement for UNMT in the noisy scenario.

The remainder of the paper is organized as follows. In Section 2, the background of UNMT is briefly described. The generation of synthetic noisy sentence and the results of preliminary experiments are presented and analyzed in Section 3. In Section 4, we propose methods to train a robust UNMT system. Section 5 describes experiments and evaluates the performance of our proposed methods. Some related work is discussed in Section 6. We conclude the paper in Section 7.

2 Background of UNMT

There are four primary components of the state-of-the-art UNMT (Lample and Conneau, 2019): cross-lingual language model pre-training, denoising auto-encoder, back-translation, and sharing latent representations. Consider monolingual data \( \{X_i\} \) in language \( L_1 \) and \( \{Y_i\} \) in another language \( L_2 \). \(|X|\) and \(|Y|\) are the number of sentences in monolingual corpora \( \{X_i\} \) and \( \{X_i\} \) respectively. The encoders and decoders of \( L_1, L_2 \) are trained through denoising and back-translation. The objective function \( L_{all} \) of the entire UNMT model would be optimized as:

\[
L_{all} = L_D + L_B,
\]

where \( L_D \) is the objective function for denoising, and \( L_B \) is the objective function for back-translation.

**Cross-lingual language model pre-training**: It aims at building a universal cross-lingual encoder that can encode two monolingual sentences into a shared embedding space. The pre-trained cross-lingual encoder is then used to initialize the UNMT model.

**Denoising auto-encoder**: In contrast with the normal auto-encoder, denoising auto-encoder (Vincent et al., 2010) could improve the model learning ability by introducing noise in the form of random token deleting and swapping in this input sentence. The denoising auto-encoder, which encodes a noisy version and reconstructs it with the decoder in the same language, acts as a language model during UNMT training. It is optimized by minimizing the objective function:

\[
L_D = \sum_{i=1}^{|X|} - \log P_{L_1 \rightarrow L_1} (X_i | C(X_i)) + \sum_{i=1}^{|Y|} - \log P_{L_2 \rightarrow L_2} (Y_i | C(Y_i)),
\]

where \( \{C(X_i)\} \) and \( \{C(Y_i)\} \) are noisy sentences. \( P_{L_1 \rightarrow L_1} \) (\( P_{L_2 \rightarrow L_2} \)) denotes the reconstruction probability in the language \( L_1 \) (\( L_2 \)).

**Back-translation**: It (Sennrich et al., 2016a) is adapted to train a translation system across different languages based on monolingual corpora. The pseudo-parallel sentence pairs \( \{(Y_M(X_i), X_i)\} \) and \( \{(X_M(Y_i), Y_i)\} \) produced by the model at the previous iteration would be used to train the new translation model. The UNMT model would be improved through iterative back-translation. Therefore, the back-translation probability would be optimized by minimizing

\[
L_B = \sum_{i=1}^{|X|} - \log P_{L_2 \rightarrow L_1} (X_i | Y_M(X_i)) + \sum_{i=1}^{|Y|} - \log P_{L_1 \rightarrow L_2} (Y_i | X_M(Y_i)),
\]

where \( P_{L_1 \rightarrow L_2} \) and \( P_{L_2 \rightarrow L_1} \) denote the translation probability across the two languages.

**Sharing latent representations**: The same vocabulary is used for both languages. Encoders and decoders are shared for both languages, to help UNMT model to translate more fluently with synthetic source sentences benefiting from denoising training.

3 Preliminary Experiments

In this section, we first introduce the two primary types of noises in the corpus of UNMT. Then we empirically analyze the effect of these noises on UNMT.
3.1 Synthetic Noise Generation

A few studies of the SNMT robustness (Belinkov and Bisk, 2018; Karpukhin et al., 2019) focus on character-level noise, which affects the spelling of a single word. In this paper, we study the word-level noise, which affects the meaning of a word in one sentence. We refer to this noise as word noise in this paper. Moreover, we study the sentence-level noise, which affects the order of a whole sentence. We refer to this noise as word order noise in this paper.

**Word Noise:** We replace every word in the source sentence with an arbitrary word under a probability \(a\). A larger probability \(a\) results in that more words are replaced with arbitrary words.

**Word Order Noise:** Motivated by the input shuffling strategy (Lample et al., 2018a), we apply a random permutation \(\gamma\) to the source sentence to change the word order of the original sentence, to meet the condition:

\[
|\gamma(i) - i| \leq b, \forall i \in \{1, n\},
\]

where \(n\) denotes the length of the source sentence, and \(b\) is a hyper-parameter to control the magnitude of the word order adjustment. A larger \(b\) results in worse order in the source sentence.

To generate a random permutation verifying the above condition for a sentence of size \(n\), we generate a random array \(Q\) of size \(n\):

\[
Q_i = i + U(0, b),
\]

where \(U\) is the uniform distribution in the range from 0 to \(b\). Then, \(\gamma\) is defined to be the permutation that sorts the array \(Q\). We apply this permutation to adjust word order in order to generate synthetic noise. Note that the order will be changed only when \(b > 1\).

3.2 Noisy Scenario

As the cross-lingual language model pre-training, which need large-scale additional monolingual data, is introduced, the UNMT system performed similarly to SNMT system which only relies on parallel data in the clean scenario. To investigate the performance of UNMT and SNMT in the noisy scenario, we empirically choose English (En) -French (Fr) as the language pair to do stimulated experiments. The detailed experimental settings for UNMT are given in Section 5. For SNMT, we used 40 million sentences from WMT parallel news crawl datasets for En-Fr. We used fairseq toolkit\(^1\) and followed the default settings of transformer (base) model. The training data is clean and the test data contains synthetic noises described in Section 3.1.

![Figure 1: The UNMT and SNMT performance as the word noise \((a \text{ value})\) and word order noise \((b \text{ value})\) increases on the noisy En-Fr newstest2014 set.](image)

Figure 1 shows the trend in BLEU score of UNMT and SNMT systems as the ratio of word noise and word order noise in the source language input increases. As the ratio of noise in the source language input increased, the performance of both SNMT and UNMT decreased. Regarding these two systems, the UNMT system performed better than SNMT system by BLEU score in the noisy scenario. The

\(^1\)https://github.com/pytorch/fairseq
denoising auto-encoder from UNMT system, trained in the same language sentence, has slight ability to adjust word order and replace some wrong words. This specific training of UNMT system was better than SNMT at maintaining translation performance in the noisy scenario.

4 Methods

Based on previous empirical findings and analyses, we propose two adversarial training methods during denoising training to further improve the robustness of UNMT in this noisy scenario. In detail, adversarial training for word embedding (Word_AT) and adversarial training for positional embedding (Position_AT) are proposed to boost UNMT performance with the input of word noise and word order noise, respectively.

![Diagram](attachment:image.png)

**Figure 2:** (a) Architecture of the original transformer. (b) Architecture of transformer with adversarial perturbation for word embedding. (c) Architecture of transformer with adversarial perturbation for positional embedding. The transformer architecture is used for denoising and back-translation training. It should be noted that the adversarial perturbation is only added during denoising training.

4.1 Adversarial Training for Word Embedding

The adversarial training strategy (Miyato et al., 2017) has been applied to text classification. Motivated by this strategy, we apply adversarial training method to denoising training of UNMT. Regarding to the original denoising training, adversarial perturbation would be added to enhance the learning ability of denoising auto-encoder. As Figure 2(b) shows, adversarial perturbation is added to the word embedding as a combined word embedding before combining with the positional embedding, compared to the original transformer architecture as shown in Figure 2(a).

During every iteration of denoising training for language $L_1$, the worst case perturbation $\delta_{atx}$ for word embedding is added to train the denoising auto-encoder to be robust to such perturbation through minimizing

$$
L_{atx} = \sum_{i=1}^{|X|} - \log P_{L_1 \rightarrow L_1}(X_i | C(X_i) + \delta_{atx}),
$$

where $\delta_{atx}$ is a small perturbation in the source side. Actually, it is intractable to calculate the maximization of objective function as shown in Eq. 7. Following Miyato et al. (2017)’s method, the word adversarial perturbation $\delta_{atx}$ is approximated via the gradient of objective function as

$$
\delta_{atx} = \epsilon \frac{g_x}{\|g_x\|_2},
$$

where $\epsilon$ is a small perturbation.
\[ g_x = \nabla_x - \log P_{L_1 \rightarrow L_1}(X_i|C(X_i)), \]  
where \( g_x \) denotes the gradient of objective function, calculated by back-propagation algorithm. \( \epsilon \) is a hyper-parameter to control the magnitude of adversarial perturbation.

The word adversarial perturbation objective function for language \( L_2 \) is similarly optimized as

\[ L_{aty} = \sum_{i=1}^{|Y|} - \log P_{L_2 \rightarrow L_2}(Y_i|C(Y_i) + \delta_{aty}), \]  

\[ \delta_{aty} = \epsilon g_y / \|g_y\|_2, \]  

\[ g_y = \nabla_y - \log P_{L_2 \rightarrow L_2}(Y_i|C(Y_i)). \]  

Typically, to improve UNMT robustness, objective function \( L_{atx} \) and \( L_{aty} \) would be added during the UNMT denoising training process. The entire UNMT objective function is reformulated as follows:

\[ L_{all} = L_D' + L_B, \]  

\[ L_D' = L_D + L_{atx} + L_{aty}. \]

### 4.2 Adversarial Training for Positional Embedding

The positional embedding has been used to encode order information for the source sentence in the transformer architecture. To capture the order robustness, we propose adversarial training method based on the original positional embedding.

As Figure 2(c) shows, adversarial perturbation is added to the original positional embedding as a new positional embedding before combining with the word embedding, compared to the original transformer architecture as shown in Figure 2(a). The positional adversarial perturbation is then used to penalize the existing positional embedding of the source sentence to generate a new order positional embedding during UNMT denoising training. The positional adversarial perturbation objective function for language \( L_1 \) \((L_2)\) is similarly represented as Eq. 6 \(\text{Eq. 10}\).

### 4.3 UNMT with Adversarial Training Mechanism

Based on our proposed adversarial training methods to improve the robustness of UNMT, we design three UNMT systems with adversarial training: Word_AT, Position_AT, and Both_AT, all of which enrich robust information via adversarial perturbation.

**Word_AT:** The proposed adversarial perturbation is only applied to the word embedding of UNMT encoder during denoising training to improve the robustness of UNMT for the word noise.

**Position_AT:** The proposed adversarial perturbation is only applied to the positional embedding of UNMT encoder during denoising training to improve the robustness of UNMT for the word order noise.

**Both_AT:** To further improve the robustness of UNMT for these two types of noises, we simultaneously apply adversarial perturbation to the word embedding and positional embedding of UNMT encoder during denoising training.

### 5 Experiments

#### 5.1 Datasets

We considered two language pairs to do simulated experiments on the Fr↔En and German(De)↔En translation tasks. We used 50 million sentences from WMT monolingual news crawl datasets for each language. To make our experiments comparable with previous work (Lample and Conneau, 2019), we reported results on newstest2014 for Fr↔En and newstest2016 for De↔En.

For preprocessing, we followed the same method of Lample et al. (2018b). That is, we used a shared vocabulary for both languages with 60K subword tokens based on BPE (Sennrich et al., 2016b).
5.2 UNMT Settings
We used a transformer-based XLM toolkit\(^2\) and followed settings of Lample and Conneau (2019) for UNMT: 6 layers for the encoder and the decoder. The dimension of hidden layers was set to 1024. The Adam optimizer (Kingma and Ba, 2015) was used to optimize the model parameters. The initial learning rate was 0.0001, \(\beta_1 = 0.9\), and \(\beta_2 = 0.98\). The cross-lingual language model was used to pretrain the encoder and decoder of the whole UNMT model. We used the case-sensitive 4-gram BLEU score computed by multi-bleu.perl script from Moses (Koehn et al., 2007) to evaluate the test sets.

5.3 Main Results

| Word Noise | Word Order Noise | Method | En-Fr | Fr-En | En-De | De-En |
|------------|------------------|--------|-------|-------|-------|-------|
| No         | No               | Lample et al. (2018a) | 15.05 | 14.31 | n/a  | n/a  |
|            |                  | Artetxe et al. (2018) | 15.13 | 15.56 | 9.64 | 13.33 |
|            |                  | Lample et al. (2018b) | 27.60 | 27.68 | 20.23 | 25.19 |
|            |                  | Lample and Conneau (2019) | 33.40 | 33.30 | 26.40 | 34.30 |
| No         | No               | UNMT  | 37.25 | 34.32 | 26.61 | 34.24 |
|            |                  | +Word_AT | 37.68 | 34.88 | 27.55 | 34.39 |
|            |                  | +Position_AT | 37.72 | 34.75 | 27.48 | 34.41 |
|            |                  | +Both_AT | 37.81 | 34.90 | 27.61 | 34.43 |
| Yes        | No               | UNMT  | 25.35 | 22.32 | 14.40 | 26.29 |
|            |                  | +Word_AT | 32.90 | 30.46 | 24.09 | 30.42 |
|            |                  | +Position_AT | 25.85 | 23.11 | 15.82 | 27.16 |
|            |                  | +Both_AT | 33.52 | 31.19 | 24.95 | 30.58 |
| No         | Yes              | UNMT  | 26.52 | 23.20 | 15.83 | 27.52 |
|            |                  | +Word_AT | 27.48 | 24.02 | 16.33 | 28.48 |
|            |                  | +Position_AT | 35.44 | 33.29 | 25.72 | 31.86 |
|            |                  | +Both_AT | 36.29 | 33.78 | 25.86 | 32.58 |
| Yes        | Yes              | UNMT  | 21.78 | 19.03 | 11.35 | 22.89 |
|            |                  | +Word_AT | 26.02 | 22.49 | 16.07 | 26.14 |
|            |                  | +Position_AT | 25.07 | 22.02 | 15.39 | 25.77 |
|            |                  | +Both_AT | 32.30 | 30.75 | 22.59 | 29.08 |

Table 1: Performance (BLEU score) of UNMT in the different level of noisy scenarios. \(a = 0.1\) for word noise; \(b = 3\) for word order noise.

Table 1 shows the detailed BLEU scores of all UNMT systems in the different level of noisy scenarios on the Fr\(\leftrightarrow\)En and De\(\leftrightarrow\)En test sets. Our observations are as follows:

1) Our re-implemented baseline in this work outperformed the state-of-the-art method (Lample and Conneau, 2019), using clean input on the Fr\(\leftrightarrow\)En test set, and achieved performance comparable to the original method on the De\(\leftrightarrow\)En test sets. This indicates that it is a strong UNMT baseline system.

2) In the scenario that there is only word noise in the input, our proposed Word_AT method substantially outperformed the original baseline by approximately 7.4 BLEU scores. In the scenario that there is only word order noise in the input, our proposed Position_AT method substantially outperformed the original baseline by approximately 8.3 BLEU scores.

3) In the most noisy scenario containing the word noise and word order noise, the performance of the original UNMT system decreased significantly. Our proposed Word_AT and Position_AT method achieved average improvements of 4 and 3.3 BLEU scores, respectively. Moreover, Our proposed Both_AT method could further improve UNMT performance, achieving an average improvement of 10 BLEU scores. This demonstrates that our proposed methods effectively alleviate the noisy input issue.

\(^2\)https://github.com/facebookresearch/XLM
4) Our proposed adversarial training method could also slightly improve UNMT performance in the clean scenario, achieving an average improvement of 0.6 BLEU scores on all test sets. This indicates that the proposed method can improve the robustness of the UNMT in the clean scenario.

5.4 Discussion

We empirically investigated the performance of UNMT with Both_AT mechanism, using the noisy input with the different level of word noise and word order noise, respectively. Figure 3 shows the trend in BLEU score of UNMT baseline system and UNMT system with our proposed Both_AT mechanism as the ratio of word noise and word order noise in the input increases. Our proposed adversarial training method performed significantly better than the UNMT baseline system in the noisy scenario. Especially, the noisier the source language input is, the more obvious the gap between these two UNMT systems is. These demonstrate that our proposed adversarial training method is robust and effective.

Moreover, we analyze translation examples to further analyze the effectiveness of our proposed adversarial training method in the noisy scenario. Table 2 shows two translation examples, which were generated by UNMT baseline system and +Both_AT system, using clean and noisy input on the Fr-En dataset, respectively. For the first example, +Both_AT could adjust the wrong word order to the natural English word order. For the second example, +Both_AT could be better at mitigating the impact of missing words and noisy words. These examples indicate that our proposed +Both_AT system could be widely applied to the real-world noisy scenario.

6 Relate Work

Recently, UNMT (Artetxe et al., 2018; Lample et al., 2018a; Yang et al., 2018) that relies solely on monolingual corpora in each language via bilingual word embedding initialization, denoising auto-encoder, back-translation and sharing latent representations. Lample et al. (2018b) concatenated two bilingual corpora as one monolingual corpus and used monolingual embedding to initialize the embedding layer of UNMT, achieving remarkable results on some similar language pairs. Wu et al. (2019) proposed an extract-edit approach, to extract and then edit real sentences from the target monolingual corpora instead of back-translation. Sun et al. (2019) proposed an agreement method to train UNMT with bilingual word embedding agreement. More recently, Lample and Conneau (2019) and Song et al. (2019) introduced the pretrained cross-lingual language model to achieve state-of-the-art UNMT performance. However, previous work only focuses on how to build state-of-the-art UNMT systems and ignore the robustness of UNMT on the noisy data.

Actually, Belinkov and Bisk (2018) pointed that synthetic and natural noise both influenced the performance of NMT systems. Belinkov and Bisk (2018), Ebrahimi et al. (2018), and Karpukhin et al. (2019) designed character-level noise, which affects the spelling of a single word, to improve the model
Table 2: Comparison of translation results of baseline and +Both_AT system for clean and noisy input.

| Input Type            | Clean                                                                 | Noisy                                                                 | Reference                                      |
|-----------------------|-----------------------------------------------------------------------|----------------------------------------------------------------------|------------------------------------------------|
| Clean Input           | On est très excités, mais très tendus aussi.                          | On est très excités, très mais tendus aussi.                        | We were very excited, but also very tense.     |
| Reference             |                                                                       |                                                                        | +Both_AT on Clean Input: We’re very excited, but also very tense.   |
| +Both_AT on Clean Input| We’re very excited, but very tense too.                               |                                                                       | +Both_AT on Noisy Input: We’re very excited, very tense but also.    |
| Baseline on Noisy Input | We’re very excited, very tense but also.                               |                                                                       | +Both_AT on Noisy Input: We’re very excited, but also very tense.    |
| Baseline on Clean Input | We’re very excited, but very tense.                                   |                                                                       | +Both_AT on Noisy Input: We’re very excited, but also very tense.    |
| Baseline on Clean Input | We’re very excited, but very tense.                                   |                                                                       | +Both_AT on Noisy Input: We’re very excited, but also very tense.    |

Table 2: Comparison of translation results of baseline and +Both_AT system for clean and noisy input.

robustness. Meanwhile, both textual and phonetic embeddings were used to improve the robustness of NMT to homophone noises (Liu et al., 2019). Adversarial examples, generated by gradient-based method, attacked the translation model (Cheng et al., 2019). In contrast with this work, we applied adversarial perturbation to the denoising training of UNMT , instead of translation training, to enhance the learning ability of UNMT model.

Adversarial training method, first proposed in the computer vision (Goodfellow et al., 2015; Moosavi-Dezfooli et al., 2016), was applied to several natural language processing tasks (Miyato et al., 2017; Jia and Liang, 2017; Belinkov and Bisk, 2018; Ebrahimi et al., 2018).

7 Conclusion

In this paper, we mainly raise the issue of UNMT robustness on the noisy data since the robustness of UNMT has been never explored. Actually, neural translation model is sensitive to small perturbation, causing poor performance. We first define two types of noises and empirically investigate the performance of UNMT in the noisy scenario. Moreover, we propose adversarial training methods to train a robust UNMT system. Experimental results on several language pairs show that our proposed methods substantially outperform conventional UNMT systems in the noisy scenario. In the future, we will try to apply other machine learning methods to improve the robustness of UNMT system.

References

Mikel Artetxe, Gorka Labaka, Eneko Agirre, and Kyunghyun Cho. 2018. Unsupervised neural machine translation. In ICLR, Vancouver, Canada.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In ICLR, San Diego, CA, USA.

Loïc Barrault, Ondřej Bojar, Marta R. Costa-jussà, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Philipp Koehn, Shervin Malmasi, Christof Monz, Mathias Müller, Santanu Pal, Matt Post, and Marcos Zampieri. 2019. Findings of the 2019 conference on machine translation (WMT19). In WMT, Florence, Italy.

Yonatan Belinkov and Yonatan Bisk. 2018. Synthetic and natural noise both break neural machine translation. In ICLR, Vancouver, Canada.

Ondřej Bojar, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Philipp Koehn, and Christof Monz. 2018. Findings of the 2018 conference on machine translation (WMT18). In WMT, Belgium, Brussels.
Yong Cheng, Zhaopeng Tu, Fandong Meng, Junjie Zhai, and Yang Liu. 2018. Towards robust neural machine translation. In ACL, Melbourne, Australia.

Yong Cheng, Lu Jiang, and Wolfgang Macherey. 2019. Robust neural machine translation with doubly adversarial inputs. In ACL, Florence, Italy.

Javid Ebrahimi, Anyi Rao, Daniel Lowd, and Dejing Dou. 2018. HotFlip: White-box adversarial examples for text classification. In ACL, Melbourne, Australia.

Ian J. Goodfellow, Jonathon Shlens, and Christian Szegedy. 2015. Explaining and harnessing adversarial examples. In ICLR, San Diego, CA, USA.

Robin Jia and Percy Liang. 2017. Adversarial examples for evaluating reading comprehension systems. In EMNLP, Copenhagen, Denmark.

Vladimir Karpukhin, Omer Levy, Jacob Eisenstein, and Marjan Ghazvininejad. 2019. Training on synthetic noise improves robustness to natural noise in machine translation. In W-NUT@EMNLP, Hong Kong, China.

Diederik P Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In ICLR, San Diego, California.

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 ACL, Prague, Czech Republic.

Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. CoRR, abs/1901.07291.

Guillaume Lample, Alexis Conneau, Ludovic Denoyer, and Marc’Aurelio Ranzato. 2018a. Unsupervised machine translation using monolingual corpora only. In ICLR, Vancouver, Canada.

Guillaume Lample, Myle Ott, Alexis Conneau, Ludovic Denoyer, and Marc’Aurelio Ranzato. 2018b. Phrase-based & neural unsupervised machine translation. In EMNLP, Brussels, Belgium.

Hairong Liu, Mingbo Ma, Liang Huang, Hao Xiong, and Zhongjun He. 2019. Robust neural machine translation with joint textual and phonetic embedding. In ACL, Florence, Italy.

Takeru Miyato, Andrew M. Dai, and Ian J. Goodfellow. 2017. Adversarial training methods for semi-supervised text classification. In ICLR.

Seyed-Mohsen Moosavi-Dezfooli, Alhussein Fawzi, and Pascal Frossard. 2016. Deepfool: A simple and accurate method to fool deep neural networks. In CVPR, Las Vegas, NV, USA.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016a. Improving neural machine translation models with monolingual data. In ACL, Berlin, Germany.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016b. Neural machine translation of rare words with subword units. In ACL, Berlin, Germany.

Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. 2019. Mass: Masked sequence to sequence pre-training for language generation. In ICML, Long Beach, California, USA.

Haipeng Sun, Rui Wang, Kehai Chen, Masao Utiyama, Eiichiro Sumita, and Tiejun Zhao. 2019. Unsupervised bilingual word embedding agreement for unsupervised neural machine translation. In ACL, Florence, Italy.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In NIPS, Long Beach, CA, USA.

Pascal Vincent, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, and Pierre-Antoine Manzagol. 2010. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. JMLR, 11.

Jiawei Wu, Xin Wang, and William Yang Wang. 2019. Extract and edit: An alternative to back-translation for unsupervised neural machine translation. In NAACL, Minneapolis, Minnesota.

Zhen Yang, Wei Chen, Feng Wang, and Bo Xu. 2018. Unsupervised neural machine translation with weight sharing. In ACL, Melbourne, Australia.