Phrase-level Adversarial Example Generation for Neural Machine Translation

Juncheng Wan\textsuperscript{1}, Jian Yang\textsuperscript{2}, Shuming Ma\textsuperscript{3}, Dongdong Zhang\textsuperscript{3}, Weinan Zhang\textsuperscript{1}, Yong Yu\textsuperscript{1}, Furu Wei\textsuperscript{3},
\textsuperscript{1}Shanghai Jiao Tong University
\textsuperscript{2}Beihang University
\textsuperscript{3}Microsoft Research Asia

jorgenwan@gmail.com; jiaya@buaa.edu.cn; \{shumma, dozhang, fuwei\}@microsoft.com; wnzhang@sjtu.edu.cn; yyu@apex.sjtu.edu.cn

Abstract
While end-to-end neural machine translation (NMT) has achieved impressive progress, noisy input usually leads models to become fragile and unstable. Generating adversarial examples as the augmented data is proved to be useful to alleviate this problem. Existing methods for adversarial example generation (AEG) are word-level or character-level. In this paper, we propose a phrase-level adversarial example generation (PAEG) method to enhance the robustness of the model. Our method leverages a gradient-based strategy to substitute phrases of vulnerable positions in the source input. We verify our method on three benchmarks, including LDC Chinese-English, IWSLT14 German-English, and WMT14 English-German tasks. Experimental results demonstrate that our approach significantly improves performance compared to previous methods.

1 Introduction
Recently, neural machine translation (NMT) has effectively improved translation quality. NMT has shown state-of-the-art performance for many language pairs (Wu et al., 2016; Hassan et al., 2018; Vaswani et al., 2017). Various architectures (Sutskever et al., 2014; Bahdanau et al., 2015; Gehring et al., 2017; Vaswani et al., 2017) bring many appealing properties. Most NMT systems heavily rely on high-quality parallel data and perform poorly in noisy input. With the noise rising in the source sentence, NMT tends to be more vulnerable (Szegedy et al., 2014; Goodfellow et al., 2015), due to the output prediction of the decoder easily intervened by the other words (Cheng et al., 2018). A slight disturbance like a random permutation can damage the translation quality dramatically (Belinkov and Bisk, 2018). Even replacing a word with a synonym in the source input, the NMT model can be cheated and the target output cannot be translated correctly.

To improve the robustness of the NMT model, previous works propose to construct the adversarial examples by manipulating hidden features or discrete text input. These adversarial examples are used as augmented data for the training of the NMT model. To attack hidden features, Cheng et al. (2018) added perturbations in the input at the feature level for adversarial stability training. To generate discrete adversarial input, Ebrahimi et al. (2018) employed differentiable string-edit operations to rank adversarial changes. Belinkov and Bisk (2018) and Vaibhav et al. (2019) emulated naturally occurring errors in clean data as synthetic noise. Cheng et al. (2019) proposed a gradient-based method to craft adversarial examples, considering the similarity between the gradient related to the translation loss of input and the embedding difference of words.

 precedent methods of adversarial example generation (AEG) are limited at the low level, like word-level, not considering the relationship between different words within a phrase. There is one example in Table 1. The word-level AEG method selects a vulnerable position then substitutes the corresponding word, omitting that the substituted word is in

| Original sentence | A cooked hot dog in a bun with ketchup and relish. |
|-------------------|---------------------------------------------------|
| Word-level AEG    | A cooked \textit{warm} dog in a bun with ketchup and relish. |
| Phrase-level AEG  | A cooked \textit{sausage rolls} in a bun with ketchup and relish. |

Table 1: An example of adversarial example generation (AEG). When the third position of the sentence “hot” is selected, word-level adversarial example generation method substitutes “hot” to “war”. The phrase-level method substitutes the whole phrase “hot dog” to “sausage rolls”.
a phrase. Sometimes, the examples of this kind of substitution can even harm the translation model.

Therefore, we propose a phrase-level adversarial example generation method. The method attacks vulnerable positions in the source input. Then, PAEG substitutes phrase wholly with phrase-level candidates, which are created from the word-level candidates by the pre-trained language model. Furthermore, we extend our method with a bidirectional generation method. As adversarial pairs of target-to-source translation are a kind of slight perturbation of the original data, they can be used to improve the robustness of the source-to-target translation. In practice, we generate adversarial examples after fixed intervals of model updating and use them as new augmented data for the training of the NMT model.

To verify the effectiveness of our method, we conduct experiments on the LDC Chinese-English, IWSLT14 German-English, and WMT14 English-German benchmarks. Experimental results demonstrate our method achieves significant improvements over the previous baselines including other adversarial examples generation methods.

2 Phrase-level Adversarial Example Generation

In this section, we formulate the problem of adversarial example generation mathematically. First, our proposed method provides reliable candidates with the pre-trained model. Then, we use the gradient-based method to select vulnerable positions and substitutes at phrase-level to generate adversarial examples. These examples are used as augmented data for the training of the NMT model. To further improve the performance, we extend our method to the bidirectional generation.

2.1 Problem Formulation

Let \( A = \{ (x, z), y \} \) denote the training data in NMT, where \((x, z)\) are the encoder input and the decoder input, \(y\) the corresponding decoder output. To generate the corresponding adversarial examples \( B = \{ (x', z'), y \} \), where only the input is slightly different from \(A\), we need to limit the adversarial input \((x', z')\) semantically close to the original data.

Adversarial examples aim to cheat the model, making it predict wrong words. Therefore, given real output words \(y\), we construct an input to make the model predict the incorrect word \(y' (y' \neq y)\).

The process of adversarial example generation in NMT can be formulated as solving the following optimization problem:

\[
\{(x', z') : \arg \max_{(x', z') \in (x,z)} P(x', z'; y, \theta), \quad \text{dist}((x', z'), (x, z)) < \epsilon \}
\]

where \(\text{dist}\) is a measure function of the input, such as the semantic distance of sentence embeddings or edit distance, \(P(x', z'; y, \theta)\) is the maximal probability that the model predicts a wrong word \(y'\) such that \(y' \neq y\) when the model is fed with \((x', z')\), \(\theta\) is the model parameters, and \(\epsilon\) is a sufficiently small distance.

2.2 Phrase Candidates from BERT

To guarantee the generated example \((x', z')\) is similar to the original example \((x, z)\), two aspects are taken into account. One aspect is that the information of sentences should not change a lot. The other is to guarantee that words are similar. Therefore, high-quality candidates for words or phrases to substitute should have similar semantic meaning to their original one and more fluent in the whole sentence.

To achieve this, one intuitive method is to substitute words with maximal prediction probability in the language model (LM), since LM predicts words based on the context. Cheng et al. (2019) uses a
bidirectional LM trained on the monolingual part of the parallel corpus. However, a high-quality LM often needs billions of monolingual data to train like BERT (Devlin et al., 2019). It is unbearable to spend much time and computational resources to train reliable LMs. Therefore, we propose to utilize the knowledge of the pre-trained model. In this paper, we use BERT as LM.

In our paper, we use the notation \( x_{ij} \) as the phrase from position \( i \) to \( j \) in sentence \( x \), \( \text{cand}(x_{ij}) \) as the phrase candidates of phrase \( x_{ij} \). When \( i = j \), \( x_{ij} \) indicates the word \( x_i \) and \( \text{cand}(x_{ij}) \) indicates the word candidates \( \text{cand}(x_i) \). Besides, we use \( D_n \) as the \( n \)-gram phrase dictionary and \( \bigcup \) the union set of all \( D_n \).

In the \( i \)-th position of the source input, we construct \( \text{cand}(x_i) \) by selecting the top \( n_s \) tokens with maximal prediction probability in BERT when fed with \( x \), where \( x_i \) is masked. For the target input side, candidates consist of two parts. The first part is from BERT, which provides with \( n_t \) candidates. The second part is from the trained NMT model, which provides with \( n_t^m \) candidates. In this way, the candidate set \( \text{cand}(z_j) \) of target input side consists of words fluent in the sentence and words conforming the translation of \( x \). In this paper, we set \( n_t = 10 \) and \( n_t^m = 5 \).

Given a phrase \( x_{ij} \), we construct phrase-level candidates \( \text{cand}(x_{ij}) \). We first build the set of all probable phrase candidates as the Cartesian product of all \( \text{cand}(x_k) \) \( (k = i, i + 1, \ldots, j) \). Then, we screen out unreasonable phrase candidates by the phrase dictionary \( D \). Candidates not in this dictionary are discarded.

To obtain the phrase dictionary \( D \), we introduce two methods. The first one is to use the syntax parser to parse the sentence into a syntax tree. Then, the leaf nodes of an \( n \)-leaf subtree is an \( n \)-gram phrase. The phrase dictionary \( D \) is the union of these \( n \)-gram phrase dictionary \( D_n \). The second method is to utilize the existing phrase extraction tool directly. In this paper, we take both of these two methods. The syntax parser we used is \texttt{nltk.parse} and \( n = 2, 3, 4 \). The phrase extraction tool we used is \texttt{TextBlob}.

### 2.3 Select Vulnerable Positions

Instead of randomly selecting positions, we propose that the adversarial examples should select the most vulnerable positions in the sentence. Given a certain sentence, some NMT models may get worse translations when certain words or phrases are substituted.

Given that we train an NMT model with parameters \( \theta_m \) and use negative log likelihood as the loss function with the input \( x \), \( z \) and the output \( y \), we can get the gradient vector \( \nabla e(x_i) \) of token \( x_i \) over the training loss:

\[
\nabla e(x_i) = \nabla \log P(y|x, z; \theta_m)
\]

(2)

where \( e(x_i) \) is the embedding vector of token \( x_i \).

Previous methods randomly choose positions in the source input. Since different positions have different gradient norms \( ||\nabla e(x_i)||_2 \), if the gradient norm is large, the position is more unstable. Therefore, positions with large gradient norm are more vulnerable. For the source input, we select the top \( \alpha_s |x| \) positions with maximal gradient norm, where \( \alpha_s \in (0, 1) \) is a ratio.

To construct the target input \( x' \), we teach the model how to defend the attack from the source \( x' \). It is a reason that we choose \( n^m_t \) candidates from the NMT model on the target side. Selected target side positions should have the target counterpart of substituted source words in \( x' \). For example, if we substitute the word “画” (draw) to “吃” (eat) in the source input “他爱画苹果。” (“he likes drawing apples.”), then we need to find the position of the corresponding translation “drawing” and substitute it to an English word related to “eating”, such as “eating”.

This process is the inverse process of attention in NMT. Following (Cheng et al., 2019), we sample \( \alpha_t |y| \) \( (\alpha_t \in (0, 1)) \) relevant words influenced by the perturbed words in the source input \( x' \) as by sampling function \( P(\cdot) \):

\[
P(j) = \frac{\sum_i M_{ij} \delta_{x_i \neq x'_j}, j = 1, \ldots, |y|}{\sum_k \sum_i M_{ik} \delta_{x_i \neq x'_j}, j = 1, \ldots, |y|}
\]

(3)

where \( M_{ij} \) is the value of attention matrix between token \( x_i \) and token \( y_j \) from NMT model, \( \delta_{x_i \neq x'_j} \) is 1 if \( x_i \neq x'_j \) and 0 otherwise.

### 2.4 Phrase-level Substitution

Since words in the same phrase have a close relationship, we substitute words at word-level and phrase-level in the adversarial example generation. There are two aspects to consider. First, as different phrases contain different numbers of words, the feature representation of a phrase should be irrelevant.
Algorithm 2: Bidirectional Generation

Input: \( \{ (x, z), y \} \) denotes source-to-target input and output. \( \{ (y, z'), x \} \) denotes target-to-source input and output. Gen is the adversarial examples generator.

Output: augmented source-to-target data \( D_t \) and target-to-source data \( D_r \).

1: Compute \( \{ g_{z, z'} \}_{i=1}^{N} \) with \( x, z, y \) by Eq. (2).
2: Initialize \( D_t \) with \( \{ (x, z_i), y \} \).
3: Initialize \( D_r \) with \( \{ (y, z_r), x \} \).
4: \( x', z_i' \leftarrow \text{Gen}(x, z_i) \)
5: \( y', z_r' \leftarrow \text{Gen}(y, z_r) \)
6: Add \( \{ (x', z_i'), y \} \) to \( D_t \).
7: Add \( \{ (y', z_r'), x \} \) to \( D_r \).
8: return \( (D_t, D_r) \)

The model is trained on the augmented dataset. For source-to-target training, we have three pairs respectively the original training data, the adversarial examples and the reversed adversarial examples with baseline.

We use the average function for \( f^e \) and \( f^g \) and cosine similarity as the similarity function. For source-to-target training, we have three pairs (the original training data, the adversarial examples and the reversed adversarial examples with baseline).

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Formally, we notate 
\[
(x, z_i, y) \rightarrow \text{encoder input and decoder output for source-to-target translation, (y, z_r, x) as the encoder input, decoder input and decoder output for target-to-source translation.}
\]
```

The phrase-level adversarial example generation process is shown in Algorithm 1. During the training of the NMT model, we generate adversarial examples periodically as augmented data. Note that we do not need training LMs for the source and target languages.

2.5 Bidirectional Generation

In practice, reversed adversarial examples from target-to-source translation can also be used as augmented data for the source-to-target translation. Therefore, we introduce a bidirectional generation method to boost our phrase-level adversarial example generation method.

Our bidirectional generation has two translation directions, source-to-target, and target-to-source. We use a universal encoder and decoder for these two directions as (Johnson et al., 2017). From the original data, we generate the adversarial examples for two directions. In each iteration, the adversarial examples are reversed and added to the dataset. The model is trained on the augmented dataset.

Formally, we notate \( (x, z_i, y) \) as the encoder input, decoder input and decoder output for source-to-target translation, \( (y, z_r, x) \) as the encoder input, decoder input and decoder output for target-to-source translation. After generating the adversarial examples, we get \( (x', z_i', y) \) and \( (y', z_r', x) \). Then, the adversarial examples input are reversed and added to the training data of the other direction. For source-to-target training, we have three pairs of data \( (x, z, y), (x', z_i', y), (z_r', y', y) \). They are respectively the original training data, the adversarial examples and the reversed adversarial examples from the other direction.

The phrase-level adversarial example generation of these two directions can help mutually during the training of the NMT model. Our bidirectional generation algorithm is shown in Algorithm 2.

3 Experiments

We evaluate our method on two datasets, LDC Chinese-English and IWSLT14 German-English translation datasets. Then, we compare our method with baselines. At last, we do a detailed analysis of the different components of our method.

3.1 Dataset

LDC Chinese-English Task This is a dataset of 1.2M training sequence pairs. The LDC numbers are 2002E17, 2002E18, 2004T08, 2005T10, 2005T34, 2006E17, 2006T06, and 2008T17. We choose the NIST 2006 as the validation set, which has 1664 sentences, and the NIST 2002, NIST 2003, NIST 2005, NIST 2008, NIST 2012 as the test sets, which contain 877, 919, 1082, 1357, 2190 sentences respectively.

IWSLT14 German-English Task This dataset comes from translated TED talks. This dataset contains roughly 160K pairs as the training set, 7K pairs as the validation set, and 7K pairs as the test

https://catalog.ldc.upenn.edu/byproject
### Table 2: Case-insensitive BLEU-4 scores (%) on LDC Zh→En task. Our method is compared with other baselines and *Transformer_base* model. Methods with “†” use adversarial examples for training.

| Method                        | MT06 | MT02 | MT03 | MT05 | MT08 | MT12 | Avg. |
|-------------------------------|------|------|------|------|------|------|------|
| Transformer (Vaswani et al., 2017) | 43.52 | 43.17 | 44.06 | 44.45 | 36.27 | 35.07 | 41.09 |
| Multilingual NMT (Johnson et al., 2017) | 43.54 | 43.46 | 44.63 | 44.40 | 36.13 | 35.00 | 41.19 |
| Word Dropout (Sennrich et al., 2016a)† | 43.96 | 44.02 | 44.55 | 44.70 | 36.49 | 35.33 | 41.51 |
| SwitchOut (Wang et al., 2018a)† | 43.83 | 44.36 | 45.02 | 44.85 | 36.53 | 35.45 | 41.67 |
| AdvGen (Cheng et al., 2019)† | 44.74 | 45.12 | 46.49 | 45.95 | 36.53 | 35.45 | 42.60 |
| PAEG (this work)†             | 45.49 | 45.76 | 47.58 | 46.83 | 38.18 | 36.91 | 43.46 |

### Table 3: Case-insensitive BLEU-4 scores (%) on IWSLT14 De→En task. Our method is compared with other baselines and *Transformer_small* model. Methods with “†” use adversarial examples for training.

| De → En                        | BLEU |
|-------------------------------|------|
| Transformer (Vaswani et al., 2017) | 34.20 |
| Multilingual NMT (Johnson et al., 2017) | 34.13 |
| NT²MT (Feng et al., 2018)     | 31.75 |
| LightConv (Wu et al., 2019)   | 34.80 |
| DynamicConv (Wu et al., 2019) | 35.20 |
| Word Dropout (Sennrich et al., 2016a)† | 34.72 |
| SwitchOut (Wang et al., 2018a)† | 34.83 |
| AdvGen (Cheng et al., 2019)†  | 35.25 |
| PAEG (this work)†             | 35.65 |

### Table 4: Case-insensitive BLEU-4 scores (%) on WMT14 En→De task. Our method is compared with other baselines and *Transformer_big* model. Methods with “†” use adversarial examples for training.

| En → De                       | BLEU |
|-------------------------------|------|
| Transformer (Vaswani et al., 2017) | 28.40 |
| Multilingual NMT (Johnson et al., 2017) | 29.11 |
| RNMT+ (Chen et al., 2018)     | 28.49 |
| LightConv (Wu et al., 2019)   | 28.90 |
| DynamicConv (Wu et al., 2019) | 29.70 |
| Word Dropout (Sennrich et al., 2016a)† | 29.30 |
| SwitchOut (Wang et al., 2018a)† | 29.40 |
| AdvGen (Cheng et al., 2019)†  | 30.01 |
| PAEG (this work)†             | 30.49 |

3.2 Training Details

Our backbone model is the Transformer model (Vaswani et al., 2017). The NMT model consists of a Transformer encoder and a Transformer decoder. The pre-trained LM is BERT-based⁴. We use nltk.parse to build the syntax tree and extract the phrases of length 2, 3, 4. Besides, we use TextBlob to extract the noun phrases and merge all phrases to build the phrase dictionary.

LDC Chinese-English Translation We use our in-house Chinese word-breaker toolkit to segment Chinese data. We use byte pair encoding (BPE) to encode sentences with a shared token vocabulary of 51K sub-word tokens. The size of the phrase vocabulary is 1.2M for Chinese and 0.9M for English. We limit the maximum sentence length up to 256 words. We apply Adam (Kingma and Ba, 2015) with $\beta_1 = 0.9$ and $\beta_2 = 0.98$ to train models for 80 epochs and select the best model parameters according to the model performance on the valid set. We use Transformer_base setting: embedding size as 512, feed-forward network (FFN) size as 2048, attention heads as 8, learning rate as 0.1, batch size as 6144, and dropout rate as 0.1. We use the warm-up strategy with 4000 warm-up steps. We report case-insensitive tokenized BLEU-4 scores with Moses⁵.

IWSLT14 German-English Translation We use BPE to encode sentences with a shared vocabulary of 10K sub-word tokens. The phrase vocabulary of German is of size 0.4M and English of size 0.4M. We limit the maximum sentence length up to 256 words. We apply Adam with $\beta_1 = 0.9$ and $\beta_2 = 0.98$ to train models for 100 epochs and

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⁴https://github.com/huggingface/transformers
⁵https://github.com/moses-smt/mosesdecoder/blob/master/scripts/tokenizer/tokenizer.perl
select the best model parameters according to the model performance on the valid set. We use Transformer_small setting: embedding size as 512, FFN size as 1024, attention heads as 4, learning rate as 0.1, batch size as 6144, and dropout rate as 0.3. We use the warm-up strategy with 4000 warm-up steps.

**WMT14 English-German Translation** We use BPE to encode sentences with a shared vocabulary of 10K sub-word tokens. The phrase vocabulary of German is of size 0.7M and English of size 0.4M. We limit the maximum sentence length up to 256 words. We apply Adam with $\beta_1 = 0.9$ and $\beta_2 = 0.98$ to train models for 50 epochs and select the best model parameters according to the model performance on the valid set. We use Transformer_big setting: embedding size as 1024, FFN size as 4096, attention heads as 16, learning rate as 0.1, batch size as 6144, and dropout rate as 0.1. We use the warm-up strategy with 4000 warm-up steps.

### 3.3 Comparisons to Baseline Methods

We compare our proposed method with NMT models without adversarial examples (Non-adv NMT) and NMT models using adversarial examples (Adv NMT). Our method gets significant translation improvement by statistical significance testing ($p < 0.05$) compared to relevant baselines.

**Non-adv NMT Multilingual NMT** (Johnson et al., 2017): We implement this method with the Transformer as the universal encoder and decoder. Special tags are added in the source input to determine which target language to output. **NT^2MT** (Feng et al., 2018): This model uses a phrase attention mechanism to discover the relation between source input phrases that target output phrases. The backbone model is LSTM. We report the maximal result with out-of-domain dictionaries in the paper. **RNMT+** (Chen et al., 2018): An enhanced version of RNN-based NMT model. **LightConv** (Wu et al., 2019): A lightweight convolution which can perform competitively to the standard Transformer. We report the best results in the paper. **DynamicConv** (Wu et al., 2019): A dynamic convolution which predicts separate convolution kernels based on the current time-step to determine the importance of context elements. We also report the best results in the paper. **Adv NMT Word Dropout** (Sennrich et al., 2016a): This method drops words randomly. We implement this method on the token level, as recommended by the paper. When a word occurs multiple times in a sentence, we drop out any number of its occurrences, and not just none or all. **SwitchOut** (Wang et al., 2018a): This method randomly replaces words in both the source sentence and the target sentence with other words from the vocabulary. We implement the hamming distance sampling method in the paper. **AdvGen** (Cheng et al., 2019): An adversarial example generation method at the word-level. This method uses doubly adversarial input, the adversarial source examples to attack the model and the adversarial target examples to defend the attack. We implement this method with the Transformer for the bidirectional LMs and the NMT model in the paper. For LDC Chinese-English task, we use the ratio $\alpha_s = 25\%, \alpha_t = 50\%$ in this paper. For IWSLT14 German-English and WMT14 English-German data, we select $\alpha_s = 20\%, \alpha_t = 20\%$ as the best ratio.

Table 2 demonstrates the comparisons between our method with the above five baseline methods on LDC Chinese-English translation task. First, we compare our method with the Transformer. On average, PAEG can improve +2.37 BLEU points significantly. Then, we compare our method with methods of training with adversarial examples. On average, adversarial example generation methods (AdvGen and PAEG) utilizing the training information of the model greatly surpass the other methods.

| Method                              | MT06  | MT02  | MT03  | MT05  | MT08  | MT12  | Avg.  |
|-------------------------------------|-------|-------|-------|-------|-------|-------|-------|
| PAEG                                | 45.49 | 45.76 | 47.58 | 46.83 | 38.18 | 36.91 | 43.46 |
| w/o bidirectional generation        | 45.52 | 45.53 | 46.96 | 46.72 | 38.10 | 36.85 | 43.24 |
| w/o phrase-level substitution       | 44.03 | 44.02 | 45.63 | 45.35 | 37.21 | 35.51 | 41.96 |
| w/o candidates from BERT            | 43.52 | 43.17 | 44.06 | 44.45 | 36.27 | 35.07 | 41.09 |

Table 5: Experiments on LDC Zh→En dataset to analyze the effect of different components of our method PAEG. We removed three components of PAEG step by step. The results show that phrase-level substitution is the most effective part.
(Word Dropout and SwitchOut). The reason is that the former approach is better at attacking vulnerable parts of the NMT model. Compared with the state-of-the-art adversarial example generation method AdvGen, PAEG gets an improvement of +0.86 BLEU points.

In Table 3, we compare our method with the above eight baseline methods on the IWSLT14 German-English translation task. Compared with the backbone model Transformer, PAEG gets the gain of +1.45 BLEU points. Compared with methods built on top of Transformer, NT²MT (Feng et al., 2018) with out-of-domain dictionaries suffers from worse backbone model (LSTM). Multilingual NMT (Johnson et al., 2017) has a similar performance with the Transformer model. Compared with the other methods of training with adversarial examples, PAEG has the best performance. PAEG gets +0.8~0.9 BLEU points improvement compared with adversarial example generation methods which do not leverage the training information of the model.

The comparisons on WMT14 English-German task are in Table 4. Compared with Transformer_big model, PAEG has a notable gain of +2.09 BLEU points. PAEG consistently outperforms all three baselines training with adversarial examples, having around +0.5~1.0 BLEU points improvement.

### 3.4 Ablation Studies

Our proposed method PAEG is mainly affected by three components, the use of the pre-trained model, the phrase-level substitution, and the bidirectional adversarial example generation. We analyze the different components of PAEG by ablation studies.

**Effect of Phrase-level Substitution** We use the phrase-level substitution and there is +1.28 BLEU points improvement in Table 5, which is significant. Substituting words randomly from the top 10 word-level candidates can not guarantee the consistency between words. What is worse is that random substitution may destroy the phrase structure and semantic consistency in the sentence.

For common languages, such as Chinese, English, and German, the ratio of phrases is non-negligible. Substituting at the phrase-level makes the adversarial input more fluent and thus limited to the smaller neighborhood of the real sample. In this way, our method can teach the model to defend the attack at the target side better.

| Method | Word-level | Phrase-level |
|--------|------------|--------------|
| NP(%)  | 18.69      | 20.11 (+1.42) |
| VP(%)  | 7.56       | 7.48 (-0.08)  |
| PP(%)  | 16.43      | 17.53 (+1.10) |
| ADJP(%)| 1.76       | 1.98 (+0.22)  |

Table 6: Experiments on LDC Zh→En dataset to compare the phrase-level AEG method to the word-level AEG method by the ratio of phrases in the hypothesis. We make the statistics of four kinds of phrases, including noun phrase (NP), verb phrase (VP), prepositional phrase (PP), and adjective phrase (ADJP).

| Method | Word-level | Phrase-level |
|--------|------------|--------------|
| 1-gram BLEU | 79.56     | 79.78 (+0.22) |
| 2-gram BLEU | 52.87     | 53.59 (+0.72) |
| 3-gram BLEU | 34.49     | 35.65 (+1.16) |
| 4-gram BLEU | 24.22     | 25.03 (+0.81) |

Table 7: Experiments on LDC Zh→En dataset to compare the phrase-level AEG method to word-level AEG method in n-gram BLEU scores. Phrase-level method improves n-gram \(n > 1\) BLEU scores significantly.

**Effect of Pre-trained Model** To find out the impact of the pre-trained model, we use BERT to generate pseudo data. In Table 5, with the use of the pre-trained model BERT, the Transformer model has +0.87 BLEU points improvement. This proves that BERT provides more reliable candidates by pre-training on amounts of data. Compared with the LMs trained on millions of monolingual data, BERT can significantly leverage the contextual information to make the candidates appear fluent in the sentence.

**Effect of Bidirectional Generation** In Table 5, we add the bidirectional generation method to PAEG and there is +0.22 BLEU points improvement. This shows that the bidirectional generation has slight improvements. The BLEU score improves the most in NIST 2003 test set (+0.62), which means that bidirectional generation may be useful for NIST 2003 test set.

### 3.5 Discussions

As mentioned above, phrase-level substitution shows remarkable improvement in the BLEU scores on average. In this subsection, we analyze the translation details and discuss the reason for such an improvement.

First, we make the statistics of the ratio of phrases \(\eta\) of the hypothesis in LDC Chinese-English translation in Table 6. In a text \(x\), the ratio
Adversarial training for neural networks has been studied recently (Szegedy et al., 2014; Goodfellow et al., 2015). Similar ideas are applied into natural language processing (Lamb et al., 2016; Li et al., 2017; Yang et al., 2018; Cheng et al., 2018, 2019, 2020; Namsy et al., 2020; Croce et al., 2020; Wang et al., 2020a; Zang et al., 2020; Ding et al., 2020). Specifically, adversarial example generation (Fadaee et al., 2017; Ebrahimi et al., 2018; Wang et al., 2018b; Cheng et al., 2020; Zou et al., 2020; Zheng et al., 2020; Hidey et al., 2020) is proved to be useful to train a robust NMT system. Recently, Cheng et al. (2019) adopted a gradient-based method to craft adversarial examples at word-level, using the adversarial source input to attack while the target input to defend the model.

Our bidirectional generation method is similar to multilingual NMT training. Multilingual NMT models (Dong et al., 2015; Luong et al., 2016; Johnson et al., 2017; Wang et al., 2020b; Zhang et al., 2020; Zhu et al., 2020; Siddhant et al., 2020) are trained over multiple language pairs with parameter sharing, such as using the same encoder or decoder for different source and target languages (Johnson et al., 2017), using one encoder and separate decoders to translate one source language to multiple target languages (Dong et al., 2015), and sharing an attention mechanism (Firat et al., 2016) across multiple language pairs for many-to-many translation. In this work, we use the adversarial examples generated from the other direction to improve the robustness of the original translation direction.

### 5 Conclusion

In this work, we propose a phrase-level adversarial example generation method. Our basic idea is to improve the fluency and stability of the generated sentences. We adopt a phrase-level strategy to substitute phrases by candidates from pre-
trained model BERT. Furthermore, we propose a bidirectional generation method to help the original translation direction. We verify our method on Chinese-English, German-English, and English-German corpus, and the results show that PAEG can improve translation quality significantly.

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