A Reinforced Generation of Adversarial Samples for Neural Machine translation

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Abstract

Neural machine translation systems tend to fail on less decent inputs despite its great efficacy, which may greatly harm the credibility of these systems. Fathoming how and when neural-based systems fail on such cases is critical for industrial maintenance. Instead of collecting and analyzing bad cases using limited handcrafted error features, here we investigate this issue by generating adversarial samples via a new paradigm based on reinforcement learning. Our paradigm could expose pitfalls for a given performance metric, e.g. BLEU, and could target any given neural machine translation architecture. We conduct experiments of adversarial attacks on two mainstream neural machine translation architectures, RNN-search and Transformer. The results show that our method efficiently produces stable attacks with meaning-preserving adversarial samples. We also present a qualitative and quantitative analysis for the preference pattern of the attack, showing its capability of pitfall exposure.

1 Introduction

Neural machine translation (NMT) based on the encoder-decoder framework, such as RNN-Search (Bahdanau, Cho, and Bengio, 2014; Luong, Pham, and Manning, 2015, RNNSearch) or Transformer (Vaswani et al., 2017, Transformer), has achieved remarkable progress and become a de-facto in various machine translation applications. However there are still pitfalls for a well-trained neural translation system, especially when applied to less decent real-world inputs compared to training data. For example, typos may severely deteriorate system outputs (Table 1). Moreover, recent studies show that a neural machine translation system can also be broke by synthetic noisy inputs (Belinkov and Bisk 2017, Lee et al. 2018). Due to the black-box nature of a neural system, it has been a challenge to fathom when and how it tends to fail.

Instead of analyzing a system based on reported bad cases, researchers seek to apprehend such errors in advance. A straightforward strategy (Zhao et al. 2018) is to induce a set of handcrafted error features which are likely to cause system failures. Such strategy is very expensive because it requires the expert knowledge for both linguistics and the targeted neural architecture. Handcrafted features are also less applicable because some common errors in deep learning systems can be hard to formulate, while some others are very specific to certain architectures.

Instead of designing error features, recent researchers adopt ideas from adversarial learning (Goodfellow, Shlens, and Szegedy 2014) to generate adversarial samples to mine NLP system pitfalls (Cheng et al., 2018a; Ebrahimi, Lowd, and Dou 2018; Zhao, Dua, and Singh 2017). Adversarial samples are minor perturbed inputs which keep the semantic meaning of the input, yet yield degraded outputs. Despite of the success for continuous input, e.g. images, there are two major issues for generating adversarial samples in NLP tasks.

One issue is to generate discrete tokens for natural language, e.g. words or characters. Cheng et al. (2018a) follow the adversarial learning paradigm in computer vision to learn perturbed continuous representation, then sample discrete tokens accordingly. However, there is no guaranteed correspondence between the perturbed representation and valid tokens. Therefore, sampling may generate tokens departing from perturbed representation, which undermines the generation process. Ebrahimi, Lowd, and Dou (2018) turn to a search paradigm by a brute-force search for perturbations directly on the token level. To lead the search, a gradient-based surrogate loss must be designed upon every token modification indicating pitfalls. However, this paradigm is inefficient due to the formidable computation for gradients over every modified input. Furthermore, surrogate losses defined upon each token risks being invalidated by any perturb that changes tokenization, which will affect

| in   | ye lu sa leng fa sheng zi sha bao zha shi jian |
| out  | suicide bombing in jerusalem                  |
| in   | ye lu sa leng fa sheng zi sha bao shi jian   |
| out  | eastern jerusalem explores a case of eastern europe |

Table 1: Fragility of neural machine translation. A typo leaving out a Chinese character “zha” leads to significant change in English translation. Both “bao” and “bao zha” mean “bombing” in English.
In Two man are playing on the street corner.
Adv in Two men are playing frisbee in the park.
Out Zwei Man spielan einer Spielen.
Adv out Zwei Man spielen frisbee im park.

Table 2: Example of undesirable perturbation in adversarial samples for machine translation in [Zhao, Dua, and Singh 2017], though it yields very different output compare to the origin, it does not indicate malfunction in system.

the search process.

Another issue is to keep the semantics of original inputs. Different from the fact that minor noises on images does not change the semantics, sampling discrete tokens from arbitrary perturbed representation [Cheng et al. 2018a] may generate tokens with very different meanings and lead to ill-perturbed samples (Table 2). Searching for the perturbed input also requires a semantic constraint of the search space, for which handcrafted constraints are employed [Ebrahimi, Lowd, and Dou 2018]. Though constraints can also be introduced by multitask modeling with additional annotations [Zhao, Dua, and Singh 2017], this is still not sufficient for tasks requiring strict semantic equivalence, such as machine translation.

In this paper, we adopt a novel paradigm that generates more reasonable tokens and secures semantic constraints as much as possible. Our contributions can be summarized as the following:

- We develop a reinforcement learning [Sutton and Barto 2018] RL paradigm, which learns to perform discrete perturbations on token level, aiming for direct overall degradation. That is, the victim translation model is regarded as an interactive environment for an agent with the aim to directly maximize its final degradation on specific translation evaluation.
- We combine a GAN-style [Goodfellow et al. 2014] discriminator in environment for the terminal signal in our architecture to further constrain semantics, which is free of additional annotations. Experiments show that our approach not only achieves semantic constrained adversarial samples but also effective attacks for machine translation.
- Since our method does not need to inspect inner of the victim architecture and free of feature engineering targeting architectures, it is viable among analysis of different machine translation models. Furthermore, our method outclasses the state-of-the-art adversarial sample generation in efficiency.
- We also present some analysis upon the state-of-the-art Transformer based on its attack, showing our method’s competence in system pitfall exposure.

2 Preliminaries

Neural Machine Translation

The most popular architectures for neural machine translation are RNN-search [Bahdanau, Cho, and Bengio 2014] and Transformer [Vaswani et al. 2017]. Generally they share the paradigm to learn the conditional probability \( P(Y | X) \) of a target translation \( Y = [y_1, y_2, ..., y_n] \) given a source input \( X = [x_1, x_2, ..., x_n] \). A typical NMT architecture consists of an encoder, a decoder and attention networks. The encoder encodes the source embedding \( X_{emb} = [emb_1, emb_2, ..., emb_n] \) into hidden representation \( H = [h_1, h_2, ..., h_n] \):

\[
H = f_{enc}(X_{emb}; \theta_{enc})
\]

where \( \theta_{enc} \) denotes the encoder parameter set, and \( f_{enc} \) denotes the encoder network. Then a decoder with attention network \( f_{dec} \) attently access source hidden representations for an auto-regressive generation of each \( y_i \) until the end of sequence symbol (EOS) is generated:

\[
P(y_i | y_{<i}, X) = \text{softmax}(f_{dec}(y_{i-1}, s_t, c_t; \theta_{dec}))
\]

where \( c_t \) is the attentive result for current decoder state \( s_t \) among \( H \).

Actor-Critic for Reinforcement Learning

Reinforcement learning [Sutton and Barto 2018] is a widely used machine learning technique which follows the paradigm of explore and exploit. Unlike supervised learning, that is to collect training signals through stochastic policies (explore) and reinforce reward-oriented policies (exploit). Thus reinforcement learning is apt for learning policy in many challenging tasks which are hard to supervise (e.g. games [Mnih et al. 2015]). It is also used for direct optimization for non-derivative learning objectives [Wu et al. 2018; Bahdanau et al. 2016] in NLP.

Actor-critic [Konda and Tsitsiklis 2000] is one of the most popular reinforcement learning architectures where the agent consists of separate policy and value networks called actor and critic. They both take in environment state \( s_t \) at each time step as input, while actor determines an action \( a_t \) among possible action set \( A \) and critic yields value estimation \( V_t(s_t) \). In general, the agent is trained to maximize discounted rewards \( R_t = \sum_{i=k}^{\infty} \gamma^i r_{t+i} \) for each state, where \( \gamma \in (0, 1) \) is the discount factor. Such goal can be further derived as individual losses applied to actor and critic. Thus the actor policy loss \( L^a_{\pi} \) on step \( t \) is:

\[
L^a_{\pi}(\theta_{\pi}) = \log P(a_t | s_t) A_t(s_t, a_t); a_t \in A
\]

where \( \theta_{\pi} \) denotes actor parameters, \( A_t(s_t, a_t) \) denotes general advantage function [Schulman et al. 2015] on state \( s_t \) for action \( a_t \) given by \( \sum_{i=0}^{\infty} \gamma^i r_{t+i} + \gamma^k V(s_{t+k}) - V(s_t) \), which can be further derived as:

\[
A_t(s_t, a_t) = \gamma A_{t+1}(s_{t+1}, a_{t+1}) + r_t + \gamma V_{t+1}(s_{t+1}) - V_t(s_t)
\]

On the other hand, critic learns to estimate expected discounted rewards \( R_t \) via minimizing a temporal difference loss \( L^v \) on each step \( t \):

\[
L^v(\theta_v) = \frac{1}{2}(r_t + \gamma R_{t+1} - V_t(s_t))^2
\]

where \( \theta_v \) denotes critic parameter.
Figure 1: Overall, the victim NMT model is regarded as a part of the environment which yields a rewards indicating degradation based on agent’s modification on inputs. Discriminator provides survival signals by determining whether SRC is ill-perturbed. The agent sequentially decides whether to attack on a token from left to right until it reaches the end of sequence or terminated by the discriminator in the environment.

One of the reasons for a vanilla reinforcement learning model to fail is that the early failure of exploration before exploit optimum policy during training. Maximum entropy actor-critic (Ziebart, 2010) promotes policy entropy to ensure training exploration, that is, to also maximize policy entropy $H^\pi$ of a stochastic actor during learning. Thus the total loss becomes:

$$L(\theta) = \sum_t (\alpha L^F_t - \beta H^\pi(\cdot|s_t))$$

where $\alpha$ and $\beta$ are hyper parameters for value loss and entropy coefficients.

Adversarial Samples in NLP

A general adversarial sample generation can be described as the learning process to find a perturbation $\delta$ on input $X$ that maximize system degradation $L_{adv}$ within a certain constraint $C(\delta)$:

$$\arg\max_\delta L_{adv}(X + \delta) - \lambda C(\delta)$$

where $\lambda$ denotes the constraint coefficient. $L_{adv}$ is determined by the goal of the attack. With the perturbed representation, tokens with the nearest embedding are sampled as the results. However, currently popular adversarial generation for NLP is to search by maximizing a surrogate gradient-based loss:

$$\arg\max_{1 \leq i \leq n, x' \in \text{vocab}} L_{adv}(x_0, x_1, \ldots, x'_i, \ldots, x_n)$$

where $L_{adv}$ is a differentiable function indicating adversarial object. Due to its formidable search space, this paradigm simply perturb on a small ratio of token positions and greedy search by brute force among candidates.

3 Approach

In this section, we will describe our reinforced generation of adversarial samples (Figure 1) in details.

Environment

We encapsulate the victim translation model with a reward process as an environment $Env$ for an reinforced agent to interact.

Environment State $Env$ is initialized with $N$ sequences $SRC = [src_0, src_1, \ldots, src_N]$ with similar length, which are processed based on victim translation’s vocabulary and tokenization. It is essential to train on batches of sequences to stabilize reinforced training and avoid early exploration failure, which will be further explained in the reward process. Each sequence $src_i = [x_1, x_2, \ldots, x_n]$ is concatenated with $BOS, EOS$, which indicates the begin and end of the sequence. Finally, the batch is padded to same length with a mask indicating valid inputs. The state of the $Env$ is described as $s_t = (SRC, t)$, where time step $t \in [1, n]$ also indicates the token position to be perturbed by the agent. Environment will consecutively update $s_t$ and yield reward signals until $t$ reaches the end, or intermediate terminated. That is, all sequences in $SRC$ is determined as ill-perturbed during reward process. Once the $Env$ is terminated, it finishes the current episode and reset its state with a new batch of sequences as $SRC$.

Reward Process with Discriminator

Reward process is only used during training an agent. It consists of a survival reward $r_{\text{survive}}$ on every step and a final reward $r_{\text{degrade}}$ concerning an overall metric if the agent survives till the end. Overall, we denote reward as:
where \( a, b \) are hyper parameters that keeps the overall \( r_{\text{survive}} \) and \( r_{\text{degrade}} \) within similar magnitude.

Instead of direct optimization of the constrained adversarial loss in Eq.6, we model discriminator \( D \)’s output as survival rewards similar to that in gaming [Mnih et al., 2015]. That is, the agent must survive for its goal by also fooling \( D \) which attempts to terminate ill-perturbed modifications. We define ill-perturbed source by determining whether it still matches original target \( tgt \). We do not follow traditional discriminator training in GAN using original source and perturbed source as inputs, because it promotes agent to do nothing for survival which will result in early training failure.

**Discriminator** As it is shown in Figure 1(b), discriminator \( D \) consists of bi-directional GRU encoders for both source and target sequence. Their corresponding representation is averaged and concatenated before passed to a feedforward layer with 0.5 dropout. Finally, the output distribution is calculated by a softmax layer.

Once \( D \) determines the pair as positive, its corresponding possibility is regarded as the reward, otherwise 0:

\[
    r_{\text{survive}} = \begin{cases} 
    P(\text{positive}|(s_{\text{src}}, tgt); \theta_d), & \text{positive} \\
    0, & \text{otherwise}
    \end{cases} \tag{9}
\]

As long as the environment survives, it yields averaged reward among samples from \( SRC \) (Eq.8) to mitigate rewards’ fluctuation that destabilize training. Note that \( D \) can be too powerful during early training stage compared to agent’s actor that it can easily terminate an exploration. Therefore, we must train on batches and determine an overall terminal signal as aforementioned to ensure early exploration.

**Discriminator Training** Similar to GAN training, environment’s \( D \) must be updated as the agent updates. During its training, the agent’s parameter is freezed to provide training samples. We treat original pair \((s_{\text{src}}, tgt)\) as positive sample, while \((s_{\text{src}}', tgt)\) as negative. For every \( D \) training epoch, we randomly choose half of the batch and perturb its source using current agent as negative samples. After few epochs of updates, we randomly generate a new batch of pairs from parallel data likewise to test accuracy. \( D \) is updated at most \( step_D \) epochs, or its test accuracy reaches \( acc_{\text{bound}} \).

Environment only yields -1 as overall terminal rewards when all sequences in \( SRC \) is immediately terminated. For samples classified as negative during survival, their

\[
    r_t = \begin{cases} 
    -1, & \text{terminated} \\
    \frac{1}{n} \sum_N a \cdot r_{\text{survive}}, & \text{survive \& } t \in [1, n) \\
    \frac{1}{n} \sum_N (a \cdot r_{\text{survive}} + b \cdot r_{\text{degrade}}), & \text{survive \& } t = n \tag{8}
    \end{cases}
\]

follow-up rewards and actions are masked as 0. If the environment survives until the end, it yields additional averaged \( r_{\text{degrade}} \) as final rewards for an episode. We adopt the relative degradation like [Michel et al., 2019], that is:

\[
    r_{\text{degrade}} = \frac{\text{score}(y) - \text{score}(y')}{\text{score}(y)} \tag{10}
\]

where \( y \) and \( y' \) denote original and perturbed output, and score is a translation metric. If \( \text{score}(y) \) is zero, we return zero as \( r_{\text{degrade}} \). To calculate score we retokenize perturbed \( SRC \) by victim models vocabulary and tokenizer before translation.

**Agent**

We choose actor-critic framework [Konda and Tsitsiklis, 2000] for the agent. As it is shown in Figure 1(c), agent’s actor and critic shares the same input layers and encoder, but later processed by individual feedforward layers and output layers. Actor takes in \( SRC \) and current token with its surrounding \((x_{t-1}, x_t, x_{t+1})\), then yields a binary distribution
to determine whether to attack a token on step \(t\), while critic emits a value \(V(s_t)\) for every state. Once the actor decides to perturb a specific token, this token will be replaced by another token in its candidate set.

**Candidate Set** We collect at most \(K\) candidates for each token in victim’s vocabulary within a distance \(c\). \(c\) is the averaged Euclidean distance of \(K\)-nearest embedding for all tokens in victim vocabulary. For those without a nearby candidate, we assign UNK as its candidate. Because we note that there shall always be candidates for a token in test scenarios that are beyond victim’s vocabulary. Once the Agent choose to replace a token with UNK, we generate a valid token that is also UNK to victim’s vocabulary using homophone.

**Agent Training & Adversarial Generation** The agent is trained by Algorithm 1 where we apply asynchronous learning with an additional global agent with its parameter set \(\theta^g\) to ensure stability (Mnih et al., 2015).

Since agent is required to explore with stochastic policy during training, it will first sample based on its actor’s output distribution on whether to perturb the current position, then randomly choose among corresponding candidates. Agent and discriminator take turns to update. If \(acc_D\) does not reach over a certain convergence boundary\((> 0.5)\) within \(patience\_round\) continuous learning rounds of agent and discriminator, we assume the model is converged and save the model at \(patience\_round - 1\) as final results.

To generate adversarial samples, the agent will take in source sequences and decide whether to perturb on each position from left to right. As agent’s critic learns to estimate expected future rewards for a step, only when it yields positive value will agent perturb, otherwise it indicates an undesirable perturbation, thus the agent is muted.

### 4 Experiments

**Data Set**

Because of diversity in translation, it’s better to testify generated samples on translation tasks with multiple references, thus we perform all our experiments on Zh→En translation task, which provides a relative strong baseline for victim model and multiple test references.

We train our agent using only parallel data that is used for victims’ training. Our training set consists of about 1.3 million sentence pairs from LDC\(^2\). For subword level translation, we apply byte pair encoding (Sennrich, Haddow, and Birch, 2015; BPE) for both source and target languages with the vocabulary size of 37k. For word level translation, we use NLPIR-ICTCLAS for Chinese tokenization and Moses tokenizer for English tokenization, and adopt 30k as vocabulary size for both source and target language. We adopt NIST test sets\(^3\) for Zh→En translation and then generate adversarial samples for these sources for analysis.

**Victim Model**

We choose the state-of-the-art RNN-search and Transformer as victim translation models. For RNN-search, we train a subword level model and strictly follow the architecture in Bahdanau, Cho, and Bengio (2014) with GRU as recurrent units on every layer and 80 as maximum sequence length. As for Transformer, we train both word-level and subword-level model and strictly follow the architecture and the hyper parameter settings in Vaswani et al. (2017) with 128 as maximum sequence length. For above models, we apply the same batch scheme and Adam optimizer following Vaswani et al. (2017) with MT03 as validation set.

**Baseline Attack**

We choose the search-based adversarial generation which is currently widely applied in various robustness machine translation system as our baseline. We generally follow the strategy of Ebrahimi, Lowd, and Dou (Michel et al., 2018; 2019) which is applicable for both RNN-search and Transformer. More specifically, the \(L_{adv}\) in Eq.7 is derived as:

\[
\arg\max_{1 \leq i \leq n, \text{emb}' \in \text{vocab}} \left| \text{emb}' - \text{emb} \right| \nabla_{\text{emb}} L_{adv},
\]

\[
L_{adv}(X', Y) = \sum_{t=1}^{|Y|} \log(1 - P(y_t|X', y_1, ..., y_{t-1})),
\]

where each \(P(y_t|X)\) is calculated by Eq.8 given a corresponding reference, therefore we choose the first reference given by corresponding test set during generation. For every source sequence, a small ratio of positions are sampled for search. Then we greedy search\(^4\) the corresponding loss upon those positions with given candidates. For better comparison, we adopt the candidate set used in our model instead of naive KNN candidates. Both baseline and our model share the same UNK generation strategies.

**Experiment Details**

We adopt commonly accepted translation metric BLEU as score in Eq.9. We use 50 sequence pairs per batch both in environment initialization and training of discriminator and agent. The \(step_D\) and \(step_A\) are set as 80 and 120. \(acc\_bound\) for discriminator training is set to 0.85. The \(\alpha\) and \(\beta\) in Eq.8 are set to 0.5 and 10. The dimension of feed-forward layers in agent’s critic and discriminator are all 128 with 0.5 dropout rate.

For reinforcement learning, we set discount factor \(\gamma\) to 0.99, \(\alpha\) and \(\beta\) in Eq.8 to 0.5 and 0.05 respectively. As for the stop criterion, we set \(patience\_round\) to 15 with convergence boundary for \(acc_D\) to 0.52. The agent is trained with Adafactor(Shazeer and Stern, 2018), which is a memory-efficient Adam based on matrix factorization. The learning rate for Agent’s optimizer is initiated as 0.001 and scheduled by rsqrt with 100 steps of warmup.

\(^3\) Three times the average convergence episodes to train a discriminator with initial agent by the given batch size.
|                | BLEU | HE | chrF1 | RD |
|----------------|------|----|-------|----|
| Transformer-word |     |    |       |    |
| Search (0.2)    | 39.75 | 0.82 | 0.184 |
| Search (0.3)    | 32.42 | 3.22 | 0.210 |
| Ours            | 28.83 | 2.45 | 0.77  | 0.275 |
| Transformer-BPE |     |    |       |    |
| Search (0.2)    | 43.38 | 0.89 | 0.210 |
| Search (0.4)    | 27.27 | 2.91 | 0.80  | 0.371 |
| Ours            | 31.35 | 3.66 | 0.80  | 0.277 |
| RNN-search-BPE  |     |    |       |    |
| Search (0.2)    | 39.38 | 3.87 | 0.89  | 0.192 |
| Search (0.4)    | 26.13 | 2.82 | 0.79  | 0.336 |
| Ours            | 31.18 | 3.60 | 0.83  | 0.208 |

Table 3: Experiment results. Note that sequence length for word level system is shorter, thus we search by ratio 0.3 which shares similar chrF1 with search on subword level system with ratio 0.4. An ideal adversarial sample generation must achieve degradation with respect to higher semantic similarity with origin inputs (HE).

Our agent takes around 50 hours to converge on a single nvidia 1080. Note that higher ace_bound and lower convergence boundary for D indicates higher semantic constraints, which will increase training time. Unlike baseline, the generation in our model request only source from NIST test sets as inputs, which is a big advantage under monolingual scenarios.

Results

We adopt sacreBLEU to test case-insensitive BLEU. For adversarial sample evaluation, we follow Michel et al. (2019) to use character-level F1 score (chrF1) to indicate modification rates of the inputs when reporting relative degradation (RD) of BLEU. Since the search paradigm attacks by a predefined ratio indicating modification rate, while our reinforced agent actively determines the modification, we compare the search results with similar F1 score. We also test source semantic similarity with human evaluation (HE) ranging from 0 to 5 used by Michel et al. (2019) by randomly sample 20% of total sequences from each results mixed with corresponding baseline results for double-blind test.

As it is shown in Table 3, our model can stably generate adversarial samples without significant change in semantics with the same training setting for different models, while search methods must tune for proper ratio of modification, which can hardly strike a balance between semantic constraints and degradation.

For word level translation (Transformer-word), both search results and our methods share similar chrF1, however they achieve degradation with lower human evaluation scores, while our method achieves degradation more effectively with higher human evaluation. For subword level Transformer (Transformer-BPE), our model achieves significantly more BLEU degradation with very little sacrifice in semantics compared to search (0.2), while search (0.4) shares the similar modification rate with tremendous loss in human evaluation. For subword level RNN-search, our model also achieves similar degradation compared to search (0.2), while search (0.4) with similar modification rate still suffers tremendous loss in human evaluation while achieving the most degradation.

5 Analysis

Efficiency

As it is shown in Figure 2, given same amount of memory cost, our method is significantly more efficient compared to search paradigm. Gradient computation with respect to every modified source sequence can cost greatly in time or space for a state-of-the-art system, which could be even worse for systems with recurrent units. When it comes to mass production of adversarial samples for a victim translation system, our method can also generate by given only monolingual inputs, while search methods must be given same amount of well-informed targets.

Attack Patterns

To further analyze pitfalls, we first adopt LTP POS tagger to label NIST test sets, then check the modification rate for each POS. To ensure the reliability of our analysis, we run three sets of experiments on both baseline and our agent with similar modification rate targeting state-of-the-art Transformer with BPE, and collect overall results.

As it is shown in Figure 3, our reinforced paradigm shows specific preference upon certain POS tags, indicating pitfalls of a victim translation system, while search paradigm distributed almost evenly upon different POS tags. Note that unlike existing work relying on feature engineering, we have no error features implemented for agents. However, our agent can still spot error patterns by favoring some of the POS, such as Ni (organization name), Nh (person name), Ni (location name), M (numbers), which are commonly accepted as hard-to-translate parts. Moreover, the agent also tend to favor K (suffix) more, which is less noticed. Moreover, as it is shown in Table 4, our method is less likely
to perturb some easily-modified semantics (e.g. numbers), while search occasionally generate very different tokens to achieve degradation. Thus our agent can lead to more insightful and plausible analyses for neural machine translation than search by system gradient.

### 6 Related Work

Cheng et al. (2018a) and Cheng et al. (2018b) applied continuous perturbation learning on token’s embedding and then manage a lexical representation out of a perturbed embedding. Zhao, Dua, and Singh (2017) learned such perturbation on the encoded representation of a sequence, and then decode it back as an adversarial sample. These methods are applicable for simple NLP classification tasks, while failing machine translation which requires higher semantic constraints. Zhao, Dua, and Singh (2017) further attempted to constrain semantic in such paradigm by introducing multi-task modeling with accessory annotation, which further limits applicability.

On the other hand, Ebrahimi, Lowd, and Dou (2018) and Cheng, Jiang, and Macherey (2019) regarded it as a search problem by maximizing surrogate gradient losses. Due to the formidable gradient computation, such methods are less viable to more complex neural architectures. Cheng, Jiang, and Macherey (2019) introduced a learned language model to constrain generation. However, a learned language model is not apt for adversarial samples involving common typos or UNK. Another pitfall of this paradigm is that surrogate losses defined by a fixed tokenization for non-character level systems, risks being invalidated once the attack changes tokenization. Therefore, Ebrahimi, Lowd, and Dou (2018) simply focused on char-level systems, while Michel et al. (2019) specially noted to exclude scenarios in their search paradigm where attack changes tokenization.

### 7 Conclusion

We propose a new paradigm to generate adversarial samples for neural machine translation, which is capable of exposing translation pitfalls without handcrafted error features. Experiments show that our method achieves stable degradation
with meaning preserving adversarial samples over different victim models.

Please notice that our method can generate adversarial samples efficiently from monolingual data. As a result, mass production of adversarial samples for victim model’s analysis and further improvement of robustness become convenient, which we leave as the future work.

References

Bahdanau, D.; Brakel, P.; Xu, K.; Goyal, A.; Lowe, R.; Pineau, J.; Courville, A.; and Bengio, Y. 2016. An actor-critic algorithm for sequence prediction. *arXiv preprint arXiv:1607.07086*.

Bahdanau, D.; Cho, K.; and Bengio, Y. 2014. Neural machine translation by jointly learning to align and translate. *CoRR*.

Belinkov, Y., and Bisk, Y. 2017. Synthetic and natural noise both break neural machine translation. *arXiv preprint arXiv:1711.02173*.

Cheng, M.; Yi, J.; Zhang, H.; Chen, P.-Y.; and Hsieh, C.-J. 2018a. Seq2sick: Evaluating the robustness of sequence-to-sequence models with adversarial examples. *arXiv preprint arXiv:1803.01128*.

Cheng, Y.; Tu, Z.; Meng, F.; Zhai, J.; and Liu, Y. 2018b. Towards robust neural machine translation. *arXiv preprint arXiv:1805.06130*.

Cheng, Y.; Jiang, L.; and Macherey, W. 2019. Robust neural machine translation with doubly adversarial inputs. *arXiv preprint arXiv:1906.02443*.

Ebrahimi, J.; Lowd, D.; and Dou, D. 2018. On adversarial examples for character-level neural machine translation. *arXiv preprint arXiv:1806.09030*.

Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; and Bengio, Y. 2014. Generative adversarial nets. In *Advances in neural information processing systems*, 2672–2680.

Goodfellow, I. J.; Shlens, J.; and Szegedy, C. 2014. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*.

Konda, V. R., and Tsitsiklis, J. N. 2000. Actor-critic algorithms. In *Advances in neural information processing systems*, 1008–1014.

Lee, K.; Firat, O.; Agarwal, A.; Fannjiang, C.; and Sussillo, D. 2018. Hallucinations in neural machine translation. *NIPS 2018 Workshop IRASL*.

Luong, M.; Pham, H.; and Manning, C. D. 2015. Effective approaches to attention-based neural machine translation. In *EMNLP*.

Michel, P.; Li, X.; Neubig, G.; and Pino, J. M. 2019. On evaluation of adversarial perturbations for sequence-to-sequence models. *arXiv preprint arXiv:1903.06620*.

Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A. A.; Veness, J.; Bellemare, M. G.; Graves, A.; Riedmiller, M.; Fidjeland, A. K.; Ostrovski, G.; et al. 2015. Human-level control through deep reinforcement learning. *Nature* 518(7540):529.

Schulman, J.; Moritz, P.; Levine, S.; Jordan, M.; and Abbeel, P. 2015. High-dimensional continuous control using generalized advantage estimation. *arXiv preprint arXiv:1506.02438*.

Sennrich, R.; Haddow, B.; and Birch, A. 2015. Neural machine translation of rare words with subword units. *arXiv*.

Shazeer, N., and Stern, M. 2018. Adafactor: Adaptive learning rates with sublinear memory cost. *arXiv preprint arXiv:1804.04235*.

Sutton, R. S., and Barto, A. G. 2018. *Reinforcement learning: An introduction*. MIT press.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, Ł.; and Polosukhin, I. 2017. Attention is all you need. In *NIPS*.

Wu, L.; Tian, F.; Qin, T.; Lai, J.; and Liu, T.-Y. 2018. A study of reinforcement learning for neural machine translation. *arXiv preprint arXiv:1808.08866*.

Zhao, Y.; Zhang, J.; He, Z.; Zong, C.; and Wu, H. 2018. Addressing troublesome words in neural machine translation. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 391–400.

Zhao, Z.; Dua, D.; and Singh, S. 2017. Generating natural adversarial examples. *arXiv preprint arXiv:1710.11342*.

Ziebart, B. D. 2010. *Modeling purposeful adaptive behavior with the principle of maximum causal entropy*. Ph.D. Dissertation, figshare.