Improving Robustness of Machine Translation with Synthetic Noise

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Abstract

Modern Machine Translation (MT) systems perform consistently well on clean, in-domain text. However human generated text, particularly in the realm of social media, is full of typos, slang, dialect, idiolect and other noise which can have a disastrous impact on the accuracy of output translation. In this paper we leverage the Machine Translation of Noisy Text (MTNT) dataset (Michel and Neubig, 2018) to enhance the robustness of MT systems by emulating naturally occurring noise in otherwise clean data. Synthesizing noise in this manner we are ultimately able to make a vanilla MT system resilient to naturally occurring noise and partially mitigate loss in accuracy resulting therefrom.

1 Introduction

Machine Translation (MT) systems have been shown to exhibit severely degraded performance when presented with translation of out-of-domain or noisy data (Luong and Manning, 2015; Sakaguchi et al., 2016; Belinkov and Bisk, 2017). This is particularly pronounced in systems trained on clean, formalized parallel data such as Europarl (Koehn, 2005), are tasked with translation of unedited, human generated text such as is common in domains such as social media, where accurate translation is becoming of widespread relevance (Michel and Neubig, 2018).

Improving the robustness of MT systems to naturally occurring noise presents an important and interesting task. Recent work on MT robustness (Belinkov and Bisk, 2017) has further demonstrated the need to build or adapt systems that are resilient to such noise.

We approach the problem of adapting to noisy data through two primary research questions:

1. Can we artificially synthesize the types of noise common to social media text in otherwise clean data?

2. Are we able to improve the performance of vanilla MT systems on noisy data by leveraging artificially generated noise?

In this work we present two primary methods of synthesizing natural noise in accordance with the types of noise identified in prior work (Eisenstein, 2013; Michel and Neubig, 2018) as naturally occurring in internet and social media based text.

We present a series of experiments based on the Machine Translation of Noisy Text (MTNT) data set (Michel and Neubig, 2018) through which we demonstrate improved resilience of a vanilla MT system by adaptation using artificially noised data.

The primary contributions of this work are our Synthetic Noise Induction model which specifically introduces types of noise unique to social media text and the introduction of back translation (Sennrich et al., 2015a) as a means of emulating target noise.

2 Related Work

Szegedy et al. (2013) demonstrate the fragility of neural networks to noisy input. This fragility has been shown to extend to MT systems (Belinkov and Bisk, 2017; Khayrallah and Koehn, 2018) where both artificial and natural noise are shown to negatively affect performance.

Human generated text on the internet and social media are a particularly rich source of natural noise (Eisenstein, 2013; Baldwin et al., 2015) which causes pronounced problems for MT (Michel and Neubig, 2018).

Robustness to noise in MT can be treated as a domain adaptation problem (Koehn and Knowles, 2017) and several attempts have been made to

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handle noise from this perspective. Notable approaches include training on varying amounts of data from the target domain (Li et al., 2010; Axelrod et al., 2011), Luong and Manning (2015) suggest the use of fine-tuning on varying amounts of target domain data, and Barone et al. (2017) note a logarithmic relationship between the amount of data used in fine-tuning and the relative success of MT models.

Other approaches to domain adaptation include weighting of domains in the system objective function (Wang et al., 2017) and specifically curated datasets for adaptation (Blodgett et al., 2017). Kobus et al. (2016) introduce a method of domain tagging to assist neural models in differentiating domains. Whilst the above approaches have shown success in specifically adapting across domains, we contend that adaptation to noise is a nuanced task and treating the problem as a domain adaptation task may fail to fully account for the varied types of noise that can occur in internet and social media text.

Experiments that specifically handle noise include text normalization approaches (Baldwin et al., 2015) and (most relevant to our work) the artificial induction of noise in otherwise clean data (Sperber et al., 2017; Belinkov and Bisk, 2017).

3 Data

To date, work in the adaptation of MT to natural noise has been restricted by a lack of available parallel data. Michel and Neubig (2018) introduce a new data set of noisy social media content and demonstrate the success of fine-tuning which we leverage in the current work. The dataset consists of naturally noisy data from social media sources in both English to French and English to Japanese pairs.

In our experimentation we utilize the subset of the data for English to French which contains data scraped from Reddit[1]. The data set contains training, validation and test data. The training data is used in fine-tuning of our model in certain settings outlined below and all results are reported on the MTNT test set for French-English. We additionally use other datasets including Europarl (EP) (Koehn, 2005) and TED talks (TED) (Ye et al., 2018) for training our models as described in §5.

[1] www.reddit.com

Training Data	# Sentences	Pruned Size
Europarl (EP)	2,007,723	1,859,898
Ted talk (TED)	192,304	181,582
Noisy Text (NTMT)	19,161	18,112

Table 1: Statistics about different datasets used in our experiments. We prune each dataset to retain sentences with length ≤ 50.

4 Baseline Model

Our baseline MT model architecture consists of a bidirectional Long Short-Term Memory (LSTM) network encoder-decoder model with two layers. The hidden and embedding sizes are set to 256 and 512, respectively. We also employ weight-tying (Press and Wolf, 2016) between the embedding layer and projection layer of the decoder.

For expediency and convenience of experimentation we have chosen to deploy a smaller, faster variant of the model used in Michel and Neubig (2018), which allows us to provide comparative results across a variety of settings. Other model parameters reflect the implementation outlined in Michel and Neubig (2018).

In all experimental settings we employ Byte-Pair Encoding (BPE) (Sennrich et al., 2015b) using Google's SentencePiece[2].

5 Experimental Approaches

We propose two primary approaches to increasing the resilience of our baseline model to the MTNT data, outlined as follows:

5.1 Synthetic Noise Induction (SNI)

For this method, we inject artificial noise in the clean data according to the distribution of types of noise in MTNT specified in Michel and Neubig (2018). For every token we choose to introduce the different types of noise with some probability on both French and English sides in 100k sentences of EP. Specifically, we fix the probabilities of error types as follows: spelling (0.04), profanity (0.007), grammar (0.015) and emoticons (0.002). To simulate spelling error, we randomly add or drop a character in a given word. For grammar error and profanity, we randomly select and insert a stop word or an expletive and its translation on either side. Similarly for emoticons, we randomly select an emoticon and insert it on both sides. Algorithm 1 elaborates on this procedure.

[2] https://github.com/google/sentencepiece

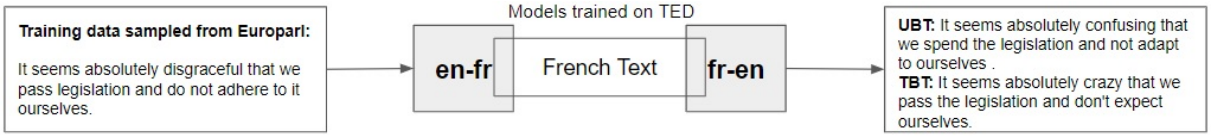

Figure 1: Pipeline for injecting noise through Back-Translation. For comprehension purposes we show the process through an English sentence. For generating actual noisy data for training, we use French sentences as input with reversed model order.

Algorithm 1 Synthetic Noise Induction

Inputs: $[(p_1, \eta_1), (p_2, \eta_2) \cdots (p_k, \eta_k)]$ ▷ pairs of noise probabilities and noise functions

procedure ADD_NOISE(fr, en)

$o = 1 - \sum_i p_i$ ▷ probability of keeping original

$D = [o, p_1, p_2, \cdots, p_k]$ ▷ Discrete densities

$j \leftarrow Select\_Index(Draw(D))$ ▷ noise type

if $j \neq 0$ **then** ▷ not original

$(fr, en) \leftarrow \eta_j(fr, en)$ ▷ add noise to words

return fr, en

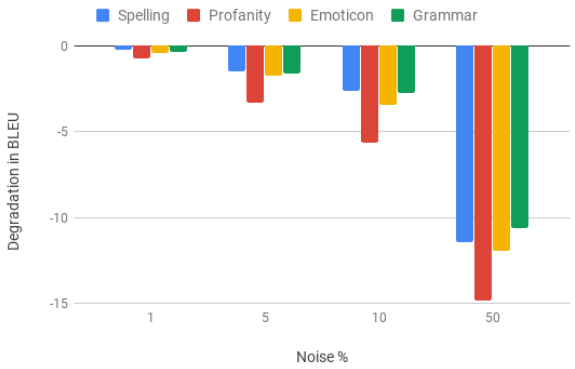

Figure 2: The impact of varying the amount of Synthetic Noise Induction on BLEU.

5.2 Noise Generation Through Back-Translation

We further propose two experimental methods to inject noise into clean data using the back-translation technique (Sennrich et al., 2015a).

5.2.1 Un-tagged back-translation (UBT)

We first train both our baseline model for fr-en and an en-fr model using TED.We subsequently take 100k french sentences from EP and generate a noisy version thereof by passing them sequentially through the trained models as shown in Figure 1. We hypothesize that the resulting translation will be inherently noisy as a result of imperfect translation of the intervening MT system.

5.2.2 Tagged back-translation (TBT)

The intuition behind this method is to generate noise in clean data whilst leveraging the particular style of the intermediate corpus. Both models are trained using TED and MTNT as in the preceding setting, save that we additionally append a tag in front on every sentence while training in accordance with Kobus et al. (2016), to indicate the origin data set of each sentence.

6 Results

We present quantitative results of our experiments in Table 3 below.

Of specific note is the apparent correlation between the amount of in-domain training data and the resulting BLEU score. The tagged back-translation technique produces the most pronounced increase in BLEU score being +6.07 points. This represents a particularly significant result given that we do not fine-tune the baseline model on in-domain data. We attribute this gain to the quality of the noise generated.

The results for all our proposed experimental methods further imply that out-of-domain clean data can be leveraged to make the existing MT models robust on a noisy dataset. However, simply using clean data is not that beneficial as can be seen from the experiment involving FT Baseline w/ TED-100k.

7 Analysis

In this section we present qualitative analysis of both methods introduced above.

Figure 2 illustrates the relative effect of varying the level of SNI on the BLEU score as evaluated on the newsdiscuss2015[3] dev set. From this we note that the relationship between the amount of noise and the effect on BLEU score appears to be linear. We also note that most negative effect is

[3] http://www.statmt.org/wmt15/test.tgz

	Output
REFERENCE	*> And yes, I am an idiot with a telephone in usb-c... F*** that's annoying, I had to invest in new cables when I changed phones.*
Baseline (trained on Europarl)	*And yes, I am an eelot with a phone in the factory ... P***** to do so, I have invested in new words when I have changed telephone.*
FT w/ NTMT-train-20k	*> And yes, I am an idiot with a phone in Ub-c. Sh**, it's annoying that, I have to invest in new cable when I changed a phone.*
FT w/ EP-100k-TBT	*- And yes, I'm an idiot with a phone in the factory... Puard is annoying that, I have to invest in new cables when I changed phone.*
FT w/ EP-100k-TBT + NTMT-train-20k	*> And yes, I am an idiot with a phone in USb-c... Sh** is annoying that, I have to invest in new cables when I changed a phone.*

Table 2: Output comparison of decoded sentences across different models. Profane words are censored.

	Training data	BLEU
Baselines		
Baseline	Europarl (EP)	14.42
+ FT w/	NTMT-train-10k	22.49
+ FT w/	NTMT-train-20k	23.74
Baseline FT w/	TED-100k	10.92
+ FT w/	NTMT-train-20k	24.10
Synthetic Noise Induction		
Baseline FT w/	EP-100k-SNI	13.53
+ FT w/	NTMT-train-10k	22.67
+ FT w/	NTMT-train-20k	25.05
Un-tagged Back Translation		
Baseline FT w/	EP-100k-UBT	10.13
+ FT w/	NTMT-train-10k	22.75
+ FT w/	NTMT-train-20k	24.84
Tagged Back Translation		
Baseline FT w/	EP-100k-TBT	20.49
+ FT w/	NTMT-train-10k	**23.89**
+ FT w/	NTMT-train-20k	**25.75**

Table 3: BLEU scores are reported on NTMT test set. NTMT valid set is used for fine-tuning in all the experiments. + FT denotes fine-tuning of the Baseline model of that particular sub-table, being continued training for 30 epochs or until convergence.

obtained by including profanity. Our current approach involves inserting expletives at random positions in a given sentence. However we note that the latter approach may under-represent the nuanced linguistic usage of the latter in natural text, which may result in its above-mentioned effect on accuracy.

Table 2 shows the decoded output produced by different models. We find that the output produced by our best model is reasonably successful at imitating the language and style of the reference. The output of *Baseline + FT w/ EP-100k-TBT* is far superior than that of *Baseline*, which highlights the quality of obtained back translated noisy EP through our tagging method.

We also consider the effect of varying the amount of supervision which is added for fine-tuning the model. From Table 4 we note that

	Output
REFERENCE	*Voluntary or not because politicians are *very* friendly with large businesses.*
FT w/ EP-100k-TBT	*Whether it's voluntarily, or invoiseally because the fonts are *èsn* friends with the big companies.*
FT w/ EP-100k-TBT + NTMT-train-10k	*Whether it's voluntarily, or invokes because the politics are *rès* friends with big companies.*
FT w/ EP-100k-TBT + NTMT-train-20k	*Whether it's voluntarily, or invisible because the politics are *very* friends with big companies.*

Table 4: Output comparison of decoded sentences for different amount of supervision. Here * denotes presence in the reference.

the *Baseline + FT w/ EP-100k-TBT* model already produces a reasonable translation for the input sentence. However, if we further fine-tune the model using only 10k NTMT data, we note that the model still struggles with generation of *very*. This error dissipates if we use 20k NTMT data for fine-tuning. These represent small nuances which the model learns to capture with increasing supervision.

To better understand the performance difference between UBT and TBT, we evaluate the noised EP data. Figure 1 shows an example where we can clearly see that the style of translation obtained from TBT is very informal as opposed to the output generated by UBT. Both the outputs are noisy and different from the input but since the TBT method enforces the style of MTNT, the resulting output is perceptibly closer in style to the MTNT equivalent. This difference results in a gain of 0.9 BLEU of TBT over UBT.

8 Conclusion

In this paper we introduce two novel methods of improving the resilience of vanilla MT systems to noise occurring in internet and social media text. Namely a method of emulating specific types of noise and the use of back-translation to create artificial noise.

Both of these methods are shown to increase system accuracy when used in fine-tuning without the need for the training of a new system and for large amounts of naturally noisy parallel data.

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