An Approach to Improve Robustness of NLP Systems against ASR Errors

Tong Cui, Jinghui Xiao, Liangyou Li, Xin Jiang, Qun Liu
Huawei Noah’s Ark Lab
{cuitong5, xiaojinghui4, liliangyou, Jiang.xin, qun.liu}@huawei.com

Abstract
Speech-enabled systems typically first convert audio to text through an automatic speech recognition (ASR) model, and then feed the text to downstream natural language processing (NLP) modules. The errors of the ASR system can seriously downgrade the performance of the NLP modules. Therefore, it is essential to make them robust to the ASR errors. Previous work has shown it is effective to employ data augmentation methods to solve this problem by injecting ASR noise during the training process. In this paper, we utilize the prevalent pre-trained language model to generate training samples with ASR-plausible noise. Compare to the previous methods, our approach generates ASR noise that better fits the real-world error distribution. Experimental results on spoken language translation (SLT) and spoken language understanding (SLU) show that our approach effectively improves the system robustness against the ASR errors and achieves state-of-the-art results on both tasks.

1 Introduction
In recent years, speech-enabled systems have become more and more widely used, particularly in the spoken dialog system and spoken language translation system. Voice assistants, like Amazon Alexa and Apple Siri, are widely used in smartphones to obtain information and control devices. With simultaneous interpretation systems, people can hold a meeting with each other or watch live shows with automatically translated subtitles.

Usually, a pipeline process is exploited to build the speech-enabled system. First, audio is converted into text by an automatic speech recognition (ASR) system. Then, the text is fed into downstream modules for different tasks. The errors of the ASR system in the first stage would propagate to the downstream modules and degrade their performance. Belinkov and Bisk (2017) show that even a small perturbation in the ASR system could corrupt a machine translation (MT) system. Table 1 shows some practical examples of machine translation errors due to ASR noise.

| Speech | Because I was having four heart attacks at the same time. |
|--------|----------------------------------------------------------|
| ASR    | Because I was having. For heart attacks. At the same time, |
| Ref    | 因为我同时有四次心脏病发作。                                          |
| MT     | 因为有心脏病，同时。                                          |

Table 1: An English-Chinese translation example with ASR errors. In this example, “having four” is mis-recognized as “having. For”, which causes the MT model produce erroneous translation.

A simple but effective way to deal with ASR errors is to train the downstream tasks with samples containing ASR noise. It’s still a pipeline process without introducing additional inference time. Di Gangi et al. (2019b) use both clean manual transcriptions and noisy ASR outputs of audio paired with translation text to train MT models robust to ASR noise. However, corpora are scarce and hard to obtain. To address this problem, data augmentation methods are used to generate training samples containing ASR-plausible errors. Some heuristic rules are used in prior works, like homophones (Li et al. 2018), similar pronunciation (Tsintekov, Metze, and Dyer 2014) or confusion n-gram pairs harvested from aligned ASR-reference text pairs (Wang et al. 2020b). However, these methods ignore the contextual information in sentences, making the generated samples sub-optimal. Moreover, a predefined threshold value is used for the ratio or amount of words to be replaced, which does not fit real-world ASR error distributions, such as the proportion of errors on different words.

In this paper, we propose a novel data augmentation method leveraging a PLM to generate text containing ASR-plausible errors. Inspired by the success of PLMs on natural language generation tasks such as paraphrasing (Witteveen and Andrews 2019) and poetry generation (Liao et al. 2019), we fine-tune GPT-2 (Radford et al. 2019) on a limited size of clean-noisy pairs to obtain a noise generator which is then used to add noise to input text of downstream tasks. The contributions of this paper are threefold.

- Firstly, we propose a novel data augmentation method using pre-trained language models to generate samples containing ASR-plausible errors.
- Secondly, we conduct experiments on both SLT and SLU. To our best knowledge, this is the first work that applies

---

Copyright © 2021, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.
to multiple downstream tasks. Experimental results show that our approach effectively improves system robustness against ASR noise and achieves state-of-the-art.

• Thirdly, we contribute a large dataset containing ASR results of 3 popular public English speech corpus, recognized by a commercial ASR system. We will make the data publicly available soon.

2 Background

Training language models has become a popular way of creating models suitable for transfer learning in the field of NLP (Mikolov et al. 2013; Peters et al. 2018). While these models are initially trained in a self-supervised manner to predict the next word or the masked word in a sequence, they can be fine-tuned and used for a variety of downstream NLP tasks such as text classification, question answering, and text generation.

More recently, large language models (Devlin et al. 2018; Radford et al. 2018) using transformer (Vaswani et al. 2017) architectures are achieving state-of-the-art results for many of these tasks while using less supervised data than previously needed. One of these large language models that has proven to be very good at text generation (Liao et al. 2019; Witteveen and Andrews 2019) is GPT-2 (Radford et al. 2019), which is a direct scale-up of GPT (Radford et al. 2018), with more than 10X the parameters and trained on more than 10X the amount of data.

Here we will introduce transformer and GPT briefly before introducing our method.

2.1 Transformer

A standard Transformer layer contains a Multi-Head Attention (MHA) layer and a Feed-Forward Network (FFN). For the $t$-th Transformer layer, suppose the input to it is $X \in \mathbb{R}^{n \times d}$ where $n$ and $d$ are the sequence length and hidden state size. Suppose there are $N_H$ attention heads in each layer, with head $h$ parameterized by $W_h^Q \in \mathbb{R}^{d \times d_h}$, $W_h^K \in \mathbb{R}^{d \times d_h}$, $W_h^V \in \mathbb{R}^{d \times d_h}$, and output of each head is computed as:

$$\text{Attn}^h_{W_h^Q,W_h^K,W_h^V}(X) = \text{Softmax}(\frac{QK^T}{\sqrt{d_h}})VW_h^O$$

$$= \text{Softmax}(\frac{1}{\sqrt{d}}XW_h^QW_h^KX^TW_h^VW_h^O)$$

In multi-head attention, $N_h$ heads are computed in parallel to get the final output:

$$\text{MHAttn}_{W,h}^Q,W_h^K,W_h^V,W_h^O = \sum_{h=1}^{N_h} \text{Attn}^h_{W_h^Q,W_h^K,W_h^V}(X).$$

The FFN layer is parameterized by two matrices $W_1 \in \mathbb{R}^{d \times d_{ff}}$ and $W_2 \in \mathbb{R}^{d_{ff} \times d}$ where $d_{ff}$ is the number of neurons in the intermediate layer of FFN. With a slight abuse of notation, we still use $X \in \mathbb{R}^{n \times d}$ to denote the input to FFN, the output is then computed as:

$$\text{FFN}(X) = \text{GeLU}(XW_1 + b_1)W_2 + b_2$$

where $b_1$, $b_2$ are the bias in the two linear layers.

2.2 GPT

Given an unsupervised corpus of tokens $U = \{u_1, ..., u_n\}$, a standard language modeling objective is to maximize the following likelihood:

$$L_1(U) = \log P(u_{i|u_{i-k}, ..., u_{i-1}; \theta})$$

where $k$ is the size of the context window, and the conditional probability $P$ is modeled using a neural network with parameters $\theta$.

GPT uses a multi-layer transformer decoder for the language model, which is a variant of the transformer. This model applies a multi-headed self-attention operation over the input context tokens followed by position-wise feedforward layers to produce an output distribution over target tokens:
\[
h_0 = UW_e + W_p \]
\[
h_i = \text{transformer\_block}(h_{i-1}) \forall i \in [1, n] \quad (5)
\]
\[
P(u) = \text{Softmax}(h_n W_c^T) \quad (6)
\]
where \( U = (u_k, \ldots, u_1) \) is the context vector of tokens, \( n \) is the number of layers, \( W_e \) is the token embedding matrix, and \( W_p \) is the position embedding matrix.

### 3 Method

Instead of using heuristics as previous data augmentation methods do, we make use of deep learning techniques, especially pre-trained language models, to generate samples with ASR noise. First, we collect clean-noisy pairs from speech corpora and the ASR results of them by pairing the erroneous ASR results with the golden transcriptions of the same audio. Then, we fine-tune GPT-2 on these pairs to get a noise generation model. Thirdly, we use the generation model to generate noisy input text of downstream tasks. Finally, we pair the generated noisy text with the ground truth label as augmented data and train a robust NLP model. Figure 2 illustrates the architecture of our method.

#### 3.1 Clean-noisy pairs collecting

Firstly, we get the speech corpus, which includes both audio recordings of human speech and the corresponding transcriptions. Secondly, we put the audio into an ASR system to get the recognized results. Finally, we compare the ASR results with golden transcriptions in token-level and filter out exactly matched pairs.

#### 3.2 Noise generation model training

The clean-noisy text pairs provide a supervised signal to train a generation model to inject ASR noise to input text. Recently, pre-trained language models show great capability and achieve significant improvements both in the discriminative task and the generative task of natural language processing. We take the GPT model (Radford et al. 2018) and fine-tune it on these clean-noisy pairs. In detail, we concat clean text and noisy text with a [SEP] token as the separator, and end it with a [EOS] token as shown below:

```latex
\text{The valet} left the room. [SEP] \text{The valley} left the room. [EOS]
```

Figure 2: An example of training data for the noise generation model.

The learning objective is to maximize the probability of observed sequence \( X = \{x_1, x_2, \ldots, x_{|X|}\} \):

\[
P(X) = \sum_{1 \leq i \leq |X|} \log p(x_i | x_1, \ldots, x_{i-1}) \quad (8)
\]

where \( p(x_i | x_1, \ldots, x_{i-1}) \) is the conditional probability of the token \( x_i \), given all the historical tokens. The training is done in a small number of update steps to avoid overfitting the training data.

#### 3.3 Noise generation and filtering

After the PLM is fine-tuned, we use the model to augment the training data of downstream NLP systems. We feed clean text followed by a [SEP] token into the model, and it generates noisy text token-by-token to get the noisy text. The process is ended when reaching the [EOS] token.

During decoding, instead of beam-search, we apply Nucleus Sampling (Holtzman et al. 2019) strategy to improve the diversity of generation. At each step, only the most probable tokens with probabilities that add up to \( p \) or higher are kept for generation, from which a specific token is sampled.

In practice, we find that too much generated noise may harm the performance of NLP systems and it is necessary to filter them out. We propose a scoring metric called Phone Edit Rate (PER) to evaluate the noisiness of the generated samples:

\[
\text{PER}(O, G) = \frac{\text{Levenshtein}(\text{Phone}(O), \text{Phone}(G))}{\text{Len}(\text{Phone}(O))} \quad (9)
\]

where \( O \) is the original text and \( G \) is the generated text. \( \text{Phone}[] \) is a function that transforms a piece of text to its phonetic sequence. We calculate PER for each of the generated text, and filter out samples whose PER is larger than a given threshold. Table 2 shows an example of generated noisy texts and the PER value of each one.

#### 3.4 Robust NLP model training

For each sentence in the clean training data, we generate \( n_{aug} \) augmented sentences and pair them with the ground truth labels to get the noisy training data. Then we use both the clean and the noisy training data to train the NLP model such that the NLP model can tolerate real-world ASR noise. In this paper, we adopt two kinds of NLP models. One is machine translation, which is a classical sequence to sequence task. The other is language understanding, which we treat as a classification task.

### 4 Experiments

We evaluate our method on both SLT and SLU. We use a commercial ASR system throughout our experiments.

#### 4.1 Baselines

**Rule-based confusion substitution (RS)** Following the work of Li et al. [2018], Tsvetkov, Metze, and Dyer [2014], we randomly replace words with similarly pronounced words to construct noisy samples. First, we transform a word to its phonetic sequence using cmu-dict, then we generate candidates to replace for each word whose edit distance of phonetic sequence is less than a threshold.

1We use CMU Pronouncing Dictionary http://www.speech.cs.cmu.edu/cgi-bin/cmudict for the transformation.
The priest tied the knot.

| Text_{clean}          | Text_{noisy}         | PER  |
|-----------------------|----------------------|------|
| The priest tied the knot. | The priest told the knot. | 0.13 |
| DH AH0 P R IY1 S T T AY1 D DH AH0 N AA1 T | DH AH0 P R IY1 S T T OW1 L D DH AH0 N AA1 T |      |
| The priest down the knot | The priest to you, you. | 0.2  |
| DH AH0 P R IY1 S T D AW1 N DH AH0 N AA1 T | DH AH0 P R IY1 S T T UW1 Y UW1 Y UW1 | 0.467|
| The priest tied the night. | The priest tied the knot. Dot. | 0.067|
| DH AH0 P R IY1 S T T AY1 D DH AH0 N AA1 T | DH AH0 P R IY1 S T T AY1 D DH AH0 UNK | 0.2  |

Table 2: An example of noisy text generated by our method. In each cell, the first line is text, the second line is the phoneme sequences of the text transformed by cmu-dict. OOV words are transform to UNK.

Statistic-based confusion substitution (SS) Following the work of (Wang et al. 2020b), first we use scikit-learn to align the pair of clean text and noisy text mentioned in 4.1. Then we extract confusion pairs and count their frequencies.

In both RS and SS, for a clean sentence, we randomly select a proportion of positions and replace the word/n-gram \( w \) at each position with one of its candidates \( \tilde{w} \) by the following distribution:

\[
P(\tilde{w}) = \frac{W(\tilde{w})}{\sum_{\tilde{w}' \in V(w)} W(\tilde{w}')}
\]

where \( V(w) \) is the candidate set of \( w \). \( W \) is the weight of candidate. We count the term frequency from a large corpus as \( W \) for RS and use the confusion frequency for SS. Table 3 shows some examples of RS and SS.

| original | candidates | weight |
|----------|------------|--------|
| RS       | good       | 534636 |
|          | could      | 70     |
|          | goode      | 912456 |
|          | would      | 3776   |
|          | hood       | 26279  |
|          | should     | 885926 |
| SS       | what is    | 1      |
|          | uh what’s  | 15     |
|          | what’s     | 11     |
|          | EMPTY      | 4      |
|          | and        | 2      |

Table 3: Examples of RS and SS. EMPTY refers to empty string, which means the original n-gram is deleted.

4.2 Implementation details

Clean-noisy pairs collecting We collect some popular speech corpora for our experiments. For English, we adopt

- Common Voice,
- tatoeba_audio,
- and LJSpeech-1.1.

All of them contain the audio recordings of speech and their corresponding transcriptions.

| Name          | #Hours | #Recordings | Language |
|---------------|--------|-------------|----------|
| Common Voice  | 1488   | 854,444     | En       |
| tatoeba_audio | -      | 300,076     | En       |
| LJSpeech-1.1  | 24     | 13,100      | En       |

Table 4: Statistic of collected speech corpora.

We put the audio recordings of the above corpora into the ASR system and get recognized results. When we compare ASR results with golden transcriptions, punctuation and casing errors are ignored. Finally, we obtain about 930k pairs of golden transcriptions and the text with ASR noise.

Noise generation model training We use HuggingFace Transformers for model training and prediction. We fine-tune on GPT-2 small with 117M parameters released by OpenAI (Radford et al. 2019). The learning rate is set to 5e-5, and the batch size is set to 96. We train the model for 80,000 steps. Linear schedule is adopted for learning rate decay. We dump a model every 2000 steps and choose the model with the smallest perplexity on MSLT En-Zh dev set.

Noise generation and filtering We set \( p \) to 0.9 and softmax temperature to 1.0 for Nucleus Sampling. For PER calculation, we use cmu-dict to transform english sentences to phoneme sequences, out-of-vocabulary words to UNK. Table 2 shows an example of generated text and corresponding phone sequences.

4.3 Experiments: Spoken Language Translation

Following the work of (Di Gangi et al. 2019b), we first train a standard MT model with clean data. Then we augment the

- https://commonvoice.mozilla.org/en/datasets
- https://tatoeba.org/eng/downloads
- https://keithito.com/LJ-Speech-Dataset/
- https://github.com/huggingface/transformers
Datasets We verify our approach on two SLT tasks: English-German and English-Chinese.

For En-De, we replicate the setup of (Vaswani et al. 2017), based on WMT’14 training data with 4.5M sentence pairs. For En-Zh, we pre-process the WMT’17 training data following (Hassan et al. 2018) and obtain 19.4M sentence pairs.

We test En-De and En-Zh on CoV oST-2 (Wang, Wu, and Pino 2020) and MSLT (Federmann and Lewis 2017). Table 5 shows statistics of the test sets. We use the same ASR system to recognize all of the test sets. In addition, MSLT En-Zh test set comes with its own ASR results, we also evaluate performance on that. For En-De, we measure case-sensitive tokenized BLEU (Papineni et al. 2002). For En-Zh, we measure detokenized BLEU (Post 2018) following Hassan et al. (2018).

Settings All of the following experiments are carried out based on the Transformer base Model (Vaswani et al. 2017).

We train the En-De model following the settings of (Vaswani et al. 2017) and En-Zh following the settings of (Hassan et al. 2018). We train 100k steps for En-De and 300K steps for En-Zh. We average the 5 checkpoints performing best on the validation set to create the final model. During decoding, we use a beam size of 4 for En-De and 5 for En-Zh following (Ghazvininejad et al. 2019). We train the MT models on 8 NVIDIA V100 GPUs.

In the data augmentation phase, we generate 5 noisy sentences for each source sentence and filter out sentences very noisy by setting PER threshold to 1.0, then we randomly select $n_{aug} = 1$ sentence. For RS and SS, we set substitute proportion to 0.1 and generate 1 noisy sentence for each clean sentence as well.

Then, we continue training 100k steps for the En-De model and 200k steps for the En-Zh model on both clean and noisy training data.

Results The experimental results are shown in the Table 6.

Firstly, the baseline model performs well on the test sets without ASR noise, but it suffers a great performance drop on the noisy test sets. The results are consistent with conclusions of prior work (Li et al. 2018; Di Gangi et al. 2019) that the machine translation system is fragile to noise.

Secondly, our proposed method significantly outperforms both RS and SS on both En-De and En-Zh test sets with ASR noise. The performance of RS is equivalent or slightly worse than the baseline model, indicating that the ASR noise produced by RS does not fit the real-world ASR noise distribution. The performance of SS is better than the baseline model on all of the test sets because it harvests real ASR pairs, but the improvement is marginal due to the simple substitution strategy. Our method significantly improves the performance of MT models on ASR results, it improves BLEU score by 2.6/1.8 in CoV oST-v2 En-De/En-Zh, 3.8/6.3 in MSLT En-De/En-Zh. Figure 3 shows the evolution of BLEU scores during training. At the same iteration, our results are consistently higher than both RS and SS. Moreover, our method achieves significant improvement (4.5 BLEU scores) on MSLT En-Zh with a different ASR system. It indicates that our method can produce some common ASR errors shared across different ASR systems, which can be used to improve model robustness to general ASR errors.

Lastly, in most cases, the models trained with augmented data will degrade performance slightly on clean input. The performance drop caused by our method is competitive to other data augmentation methods. We even get a better result on MSLT En-Zh clean set.

The effect of noisiness In this section, we study the effect of the noisiness of augmented data on final performance. We use different PER threshold $\alpha$ to filter generated noisy texts. Larger $\alpha$ tends to involve noisier texts. The result is shown in Table 7. We find that if the noisiness is too low, the model is less robust to ASR noise, if the noise is too much, the model performance downgrades on clean data and ASR results. The performance on MSLT test set is more sensitive to $\alpha$ than on CoVST-v2.

A Case Study In Table 8, we provide a realistic example to illustrate the advantage of our robust MT system on erroneous ASR output. In this case, the word "classic" is
### Table 6: BLEU scores for the results of MT models on manual transcriptions and ASR results of test sets. “Clean” refers to models trained on clean training data. “+SS”, “+RS”, “+Ours” refer to models trained on augmented data. “ASR-other” refers to the ASR results provided by MSLT dataset.

|                | En-Zh | En-De |
|----------------|-------|-------|
|                | CoVoST-v2 | MSLT | CoVoST-v2 | MSLT |
| Manual ASR     | Manual | ASR   | Manual ASR | ASR   |
| Clean          | 50.5  | 28.2  | 45.3  | 34.1  | 34.0  | 17.2  | 26.2 | 13.9 |
| +RS            | 50.5  | 28.2  | 45.3  | 26.7  | 31.6  | 34.1  | 17.0 | 13.7 |
| +SS            | 50.3  | 29.7  | 44.4  | 28.9  | 35.8  | 34.0  | 18.0 | 14.3 |
| +Ours          | 50.2  | **30.8** | 44.4  | **32.0** | 38.6  | 34.0  | **19.0** | **26.6** | **20.2** |

|                | CoVoST-v2 | MSLT |
|----------------|------------|------|
|                | α          | Manual ASR | Manual ASR |
| +Ours          | 0.5        | 34.2 | 18.9 | 26.4 | 19.7 |
|                | 1.0        | **34.4** | **19.0** | **26.6** | **20.2** |
|                | inf        | 34.1 | 18.9 | 25.9 | 18.6 |

Table 7: Effect of different PER threshold α on BLEU scores of MSLT En-De test set.

misrecognized as "class. Sick". The baseline MT model as well as other models trained with augmented data can hardly avoid the translation of "class" and "sick" which are frequent characters with explicit word senses. In contrast, our model avoids translating "class" and "sick" which will corrupt the translation completely and produces a more fluent and meaningful translation. We consider that the robustness improvement is mainly attributed to our proposed ASR-specific noise training.

#### 4.4 SLU

**Datasets** We use the following two SLU datasets. (1) Fluent Speech Commands (FSC) (Lugosch et al. [2019]): English speech commands related to personal assistant services. (2) DSTC-2 (Henderson, Thomson, and Williams [2014]): human-computer dialogs in a restaurant domain collected using Amazon Mechanical Turk. We follow the same data preprocessing steps as in (Weng et al. [2020]; Wang et al. [2020b]) for DSTC-2. Statistics of the two datasets are summarized in Table 9.

Each sample of FSC has exactly one intent, while DSTC-2 has multiple intents, thus we treat them as multiclassification and multi-label classification problems respectively. We use the clean transcriptions of train sets to train intent recognition models, and use ASR results of test sets to evaluate model performance. We use our ASR system for FSC. Since DSTC-2 doesn’t come with audio records, we use the self-contained ASR results recognized for testing.

**Settings** We use fasttext (Joulin et al. [2016]) for intent classification. We use softmax loss for FSC and one-vs-all loss for DSTC-2. We set word vector dimension to 20 and word-Ngram to 2. For DSTC-2, we set the probability threshold to 0.5 and choose up to 3 intents. We use accuracy to evaluate performance of FSC and multi-label accuracy/F1-score (Sorower [2010]) for DSTC-2. We randomly run 5 times and report the average score.

We use EDA (Wei and Zou [2019]) as another baseline to compare. EDA is a general data augmentation method for text classification. It adopts simple operations like insert/replace/drop/swap on clean sentences without considering ASR errors. By contrast, our method is designed for dealing with ASR errors specifically. We generate 4 noisy samples for each of the clean sentences.

**Results** The main results are shown in Table 10. Our method significantly improves the performance on ASR test sets and outperforms other methods.

### Table 8: For the same erroneous ASR output, translations of the baseline En-Zh MT model and robustly trained MT models including 2 baseline data augmentation methods and our method.

|                | Speech                  |
|----------------|-------------------------|
| Clean          | Yeah. Classic margherita pizza, besides the cauliflower. |
| +RS            | is the,同学们，除了花椰菜，还有不舒服的玛格丽特披萨。 |
| +SS            | is the,同学们，除了花椰菜之外，还有不健康的玛格丽特披萨。 |
| +Ours          | 除了花椰菜，还有玛格丽特的披萨。 |

|                | ASD             |
|----------------|-----------------|
| Clean          | yeah, class. Sick marguerite pizza. Besides the cauliflower, |
| +RS            | is the,同学们，除了花椰菜，还有不舒服的玛格丽特披萨。 |
| +SS            | is the,同学们，除了花椰菜之外，还有不健康的玛格丽特披萨。 |
| +Ours          | 除了花椰菜，还有玛格丽特的披萨。 |

### Table 9: Statistics of the SLU datasets.

|                | #Train | #Dev | #Test | #intents |
|----------------|--------|------|-------|----------|
| FSC            | 23,132 | 3,118| 3,793 | 31       |
| DSTC-2         | 10,886 | 3,560| 9,160 | 28       |

Speech: Yeah. Classic margherita pizza, besides the cauliflower.

ASR: Yeah, class. Sick marguerite pizza. Besides the cauliflower,

Ref: 除去花椰菜，是经典的玛格丽特比萨。
|        | FSC | DSTC2-live* | DSTC2-batch* |
|--------|-----|-------------|--------------|
|        | Acc | Acc F1      | Acc F1       |
| clean  | 93.8 | 84.2 85.1  | 81.2 82.3    |
| +noisy | 98.5 | 86.5 87.5  | 83.7 84.8    |
| +EDA   | 94.8 | 84.5 85.4  | 81.6 82.7    |
| +RS    | 94.1 | 84.4 85.3  | 81.4 82.4    |
| +SS    | 94.6 | 82.5 83.6  | 80.1 81.3    |
| +Ours  | 97.0 | 85.2 86.0  | 82.3 83.4    |

Table 10: Accuracy (%) and F1-score on ASR results of FSC and DSTC-2 test sets. * DSTC-2 contains two sets of ASR results recognized by the ASR system in live mode and a less accurate batch mode. We conduct experiment on both. +noisy means adding the ASR results of train sets, which act as an upper-bound of model performance.

EDA consistently improves performance on both FSC and DSTC-2. RS and SS only show slight improvements on FSC. They downgrade performance on DSTC-2. Our method improves performance on all test sets by a large margin. From the improvements on DSTC-2, which uses a different ASR system than ours, we can conclude the same as previous section (section 4.3), that our method can benefit model robustness to various ASR errors. Augmenting the training data with ASR results of audio recordings yields the best performance as “+noisy” shows. However, such data is expensive to obtain in production.

5 Related Work

It is necessary to improve the robustness of NLP models against ASR errors in speech-enabled systems. Prior work mainly focuses on these directions.

Data augmentation Data augmentation is simple and attractive because it does not modify the existing model architecture or introduce additional latency during inference time.

Li et al. (2018) proposed four strategies to craft ASR-specific noise training examples mainly based on word substitution, among which homophone-based substitution achieves the best performance.

Tsvetkov, Metze, and Dyer (2014) proposed a rule-based method to firstly transform a word n-gram to its phonetic sequence, and then apply random edits on that phonetic sequence, and finally transform back to another word n-gram.

Wang et al. (2020b) used a data-driven approach rather than heuristic rules to simulate ASR errors. First, it collects pairs of ASR hypothesis and corresponding reference text. Then these pairs are aligned at word-level by minimizing the Levenshtein distance. Then it counts n-gram confusion frequencies from these aligned pairs. Then, the confusion matrix is used to replace n-grams in the clean text to generate noisy text. Moreover, to make the generated noise match the ASR’s error distribution it uses a heuristic to control the substitution process.

Our work is mostly related to Wang et al. (2020b), however, we use a novel language generator to generate noisy samples instead of simple substitution.

Feature enhancement Some work uses phone features to enhance input representation. Li et al. (2018); Liu et al. (2018) adopted phone features by concating/adding Chinese Pinyin embedding to token embedding in the input layer of transformer model to make Zh-En translation model more robust to homophone errors.

End-to-End approach The end-to-end approach seems promising to handle error propagation in traditional pipelined systems. The main issue is training data in the form of speech paired with downstream task ground truth, eg. translation target or intent/slot labels is extremely rare. Some works (Lugosch et al. 2019; Huang et al. 2020; Wang et al. 2020a) attempted to use end-to-end training for SLT/SLU task. Wang, Wu, and Pino (2020); Lugosch et al. (2019); Di Gangi et al. (2019a) contributed some useful data resources to support end-to-end research. However, for now, pipelined systems are still mainstream in production.

ASR error correction and n-best reranking Weng et al. (2020) used an error correction module to correct errors in ASR outputs before sending them to downstream NLP models. Li et al. (2020) tried to leverage n-best ASR hypotheses to deal with ASR noises. Corona, Thomason, and Mooney (2017) reranked n-best ASR hypotheses using language models and sent the 1-best hypothesis to downstream NLP models.

6 Conclusion

Speech-enabled systems are fragile to ASR noise. In this paper, We propose a simple yet effective data augmentation method to improve the robustness of NLP systems against ASR errors. Experimental results show that our method significantly improves the performance of machine translation tasks and intent classification tasks compared to previous data augmentation methods. In the future, we would like to explore more powerful PLMs proposed in recent years (Lewis et al. 2019; Bao et al. 2020) for better noise generation, and evaluate our method on more languages such as Chinese and German.

References

Bao, H.; Dong, L.; Wei, F.; Wang, W.; Yang, N.; Liu, X.; Wang, Y.; Piao, S.; Gao, J.; Zhou, M.; et al. 2020. Unilmv2: Pseudo-masked language models for unified language model pre-training. arXiv preprint arXiv:2002.12804.

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

Corona, R.; Thomason, J.; and Mooney, R. 2017. Improving black-box speech recognition using semantic parsing. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 2: Short Papers), 122–127.
Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Di Gangi, M. A.; Cattoni, R.; Bentivogli, L.; Negri, M.; and Turchi, M. 2019a. MuST-C: a multilingual speech translation corpus. In 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 2012–2017. Association for Computational Linguistics.

Di Gangi, M. A.; Enyedi, R.; Brusadin, A.; and Federico, M. 2019b. Robust Neural Machine Translation for Clean and Noisy Speech Transcripts. arXiv preprint arXiv:1910.10238.

Federmann, C.; and Lewis, W. D. 2017. The Microsoft Speech Language Translation (MSLT) Corpus for Chinese and Japanese: Conversational Test data for Machine Translation and Speech Recognition. In Proceedings of the 16th Machine Translation Summit (MT Summit XVI). Nagoya, Japan. URL http://aamt.info/app-def/S-102/mtsummit/2017/wp-content/uploads/sites/2/2017/09/MTSummitXVI_ResearchTrack.pdf.

Ghazvininejad, M.; Levy, O.; Liu, Y.; and Zettlemoyer, L. 2019. Mask-predict: Parallel decoding of conditional masked language models. arXiv preprint arXiv:1904.09324.

Hassan, H.; Aue, A.; Chen, C.; Chowdhary, V.; Clark, J.; Federmann, C.; Huang, X.; Junczys-Dowmunt, M.; Lewis, W.; Li, M.; et al. 2018. Achieving human parity on automatic chinese to english news translation. arXiv preprint arXiv:1803.05567.

Henderson, M.; Thomson, B.; and Williams, J. D. 2014. The second dialog state tracking challenge. In Proceedings of the 15th annual meeting of the special interest group on discourse and dialogue (SIGDIAL), 263–272.

Holtzman, A.; Buys, J.; Du, L.; Forbes, M.; and Choi, Y. 2019. The curious case of neural text degeneration. arXiv preprint arXiv:1904.09751.

Huang, Y.; Kuo, H.; Thomas, S.; Kons, Z.; Audhkhasi, K.; Kingsbury, B.; Hoory, R.; and Picheny, M. 2020. Leveraging Unpaired Text Data for Training End-To-End Speech-to-Intent Systems. In ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 7984–7988.

Joulin, A.; Grave, E.; Bojanowski, P.; and Mikolov, T. 2016. Bag of Tricks for Efficient Text Classification. arXiv preprint arXiv:1607.01759.

Lewis, M.; Liu, Y.; Goyal, N.; Ghazvininejad, M.; Mohamed, A.; Levy, O.; Stoyanov, V.; and Zettlemoyer, L. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

Li, M.; Ruan, W.; Liu, X.; Soldaini, L.; Hamza, W.; and Su, C. 2020. Improving spoken language understanding by exploiting asr n-best hypotheses. arXiv preprint arXiv:2001.05284.

Li, X.; Xue, H.; Chen, W.; Liu, Y.; Feng, Y.; and Liu, Q. 2018. Improving the robustness of speech translation. arXiv preprint arXiv:1811.00728.

Liao, Y.; Wang, Y.; Liu, Q.; and Jiang, X. 2019. GPT-based Generation for Classical Chinese Poetry. arXiv preprint arXiv:1907.00151.

Liu, H.; Ma, M.; Huang, L.; Xiong, H.; and He, Z. 2018. Robust neural machine translation with joint textual and phonetic embedding. arXiv preprint arXiv:1810.06729.

Lugosch, L.; Ravanelli, M.; Ignoto, P.; Tomar, V. S.; and Bengio, Y. 2019. Speech model pre-training for end-to-end spoken language understanding. arXiv preprint arXiv:1904.03670.

Mikolov, T.; Sutskever, I.; Chen, K.; Corrado, G. S.; and Dean, J. 2013. Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems, 3111–3119.

Papineni, K.; Roukos, S.; Ward, T.; and Zhu, W.-J. 2002. BLEU: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting of the Association for Computational Linguistics, 311–318.

Peters, M. E.; Neumann, M.; Iyyer, M.; Gardner, M.; Clark, C.; Lee, K.; and Zettlemoyer, L. 2018. Deep contextualized word representations. arXiv preprint arXiv:1802.05365.

Post, M. 2018. A call for clarity in reporting BLEU scores. arXiv preprint arXiv:1804.08771.

Radford, A.; Narasimhan, K.; Salimans, T.; and Sutskever, I. 2018. Improving language understanding by generative pre-training.

Radford, A.; Wu, J.; Child, R.; Luan, D.; Amodei, D.; and Sutskever, I. 2019. Language models are unsupervised multitask learners. OpenAI Blog 1(8): 9.

Sorower, M. S. 2010. A literature survey on algorithms for multi-label learning. Oregon State University, Corvallis 18: 1–25.

Tsvetkov, Y.; Metze, F.; and Dyer, C. 2014. Augmenting translation models with simulated acoustic confusions for improved spoken language translation. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, 616–625.

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 Advances in neural information processing systems, 5998–6008.

Wang, C.; Wu, A.; and Pino, J. 2020. CoVoST 2: A Massively Multilingual Speech-to-Text Translation Corpus. arXiv preprint arXiv:2007.10310.

Wang, C.; Wu, Y.; Liu, S.; Yang, Z.; and Zhou, M. 2020a. Bridging the Gap between Pre-Training and Fine-Tuning for End-to-End Speech Translation. In AAAI, 9161–9168.

Wang, L.; Fazel-Zarandi, M.; Tiwari, A.; Matsoukas, S.; and Polymenakos, L. 2020b. Data Augmentation for Training Dialog Models Robust to Speech Recognition Errors. arXiv preprint arXiv:2006.05635.
Wei, J.; and Zou, K. 2019. Eda: Easy data augmentation techniques for boosting performance on text classification tasks. *arXiv preprint arXiv:1901.11196*.

Weng, Y.; Miryala, S. S.; Khatri, C.; Wang, R.; Zheng, H.; Molino, P.; Namazifar, M.; Papangelis, A.; Williams, H.; Bell, F.; and Tur, G. 2020. Joint Contextual Modeling for ASR Correction and Language Understanding. In *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 6349–6353.

Witteveen, S.; and Andrews, M. 2019. Paraphrasing with large language models. *arXiv preprint arXiv:1911.09661*.