Does Speech enhancement of publicly available data help build robust Speech Recognition Systems?

Bhavya Ghai, Buvana Ramanan, Klaus Mueller

1Department of Computer Science, Stony Brook University, USA
2Nokia Bell Labs, Murray Hill, USA
{bghai,mueller}@cs.stonybrook.edu, buvana.ramanan@nokia-bell-labs.com

Abstract

Automatic speech recognition (ASR) systems play a key role in many commercial products including voice assistants. Typically, they require large amounts of clean speech data for training which gives an undue advantage to large organizations which have tons of private data. In this paper, we have first curated a fairly big dataset using publicly available data sources. Thereafter, we tried to investigate if we can use publicly available noisy data to train robust ASR systems. We have used speech enhancement to clean the noisy data first and then used it together with its cleaned version to train ASR systems. We have found that using speech enhancement gives 9.5% better word error rate than training on just noisy data and 9% better than training on just clean data. It’s performance is also comparable to the ideal case scenario when trained on noisy and it’s clean version.

Introduction

Automatic speech recognition (ASR) can be understood as a process to convert audio signal to text. ASR systems are a critical part of all voice assistants like Siri, Cortana, etc. Technology giants like Google, Amazon, etc. leverage tons of private data to build state-of-the-art ASR systems. This makes it really difficult for other players to reproduce similar performance. In this paper, we are trying to investigate if we can use publicly available data to train ASR systems which can compete with the state of the art. If true, it will empower startups, academics, etc. to build competent ASR systems. Publicly available speech data like Youtube may be contaminated with ambient noise and background music which makes it difficult to be used for training ASR systems. Hence, we propose speech enhancement techniques to clean the noisy data first and then use the original and its enhanced(cleaned) version to train ASR systems.

Speech enhancement (SE) is a well studied problem which aims to enhance audio quality by getting rid of contamination’s such as white noise, background music, etc. Different GAN based models like SEGAN, FSEGAN, etc. have been shown to perform well for speech enhancement. In this work, we have used SEGAN [Pascual, Bonafonte, and Serra 2017] which operates at waveform level to remove noise from given noisy speech signal. SEGAN uses CNNs instead of RNNs for its encoder and decoder modules which makes it faster. It operates end to end with raw audio signal so it’s free of any assumptions made for feature extraction. Lastly, authors have also shared its code which makes it more reproducible. Hence, we chose SEGAN over other speech enhancement techniques.

There are different processing stages to go about building noise robust ASR systems. Deep learning approaches to build robust ASR systems can be classified into 3 groups i.e. front-end, back-end & joint front- and back-end techniques [Zhang et al. 2018]. In the front-end setting, speech enhancement and recognition system are independent from each other. Noisy speech is first enhanced during preprocessing and then recognizer is trained on the enhanced speech. In the back-end setting, noisy speech is fed in as it is and the recognizer is optimized such that it outputs the correct corresponding text. Lastly, In joint front- and back-end setting, speech enhancement and recognizer are considered as a single block and trained end-to-end. In this work, we have focused on the front-end and back-end approach as shown in Fig. 1.

Figure 1: Our Approach: We use publicly available noisy data and its cleaned version to train ASR model.

One of the most popular approach for back-end setting is multi-condition training. Multi-condition training is a technique which helps make more robust recognition system by training on multiple acoustic variants of the training dataset. In our case, we propose to use publicly available noisy speech along with its cleaned variant(via SE) for building ASR systems.

Dataset

Existing datasets for speech enhancement are pretty limited in size. ASR systems trained on such datasets mightn’t
As shown in Fig. 2 DeepSpeech model trained on clean data performs well on clean test set but lags on noisy test set. Similarly, when trained on noisy data, DeepSpeech model performs better on noisy test set but lags on clean test set. Finally, DeepSpeech model trained on clean+noisy mixture outperforms other two cases on both clean and noisy test set. So clearly, training with noisy and clean version helps.

Since we mightn’t always have the clean version of publicly available data, we replaced clean speech with enhanced speech. Noisy speech combined with it’s enhanced speech by SEGAN performed significantly well for ASR systems.

Conclusions & Future Work

Our work shows that publicly available data together with Speech enhancement models can be leveraged to build robust ASR systems. Next, we intend to test our approach with other SE models like FSEGAN, Wave-u-net, etc. It will also be interesting to test how back-end approach compares with end-to-end approach. Overall, we believe this work will motivate larger research on building state of the art ASR systems from public available/found data.

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