COMPARING THE BENEFIT OF SYNTHETIC TRAINING DATA FOR VARIOUS AUTOMATIC SPEECH RECOGNITION ARCHITECTURES

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ABSTRACT

Recent publications on automatic-speech-recognition (ASR) have a strong focus on attention encoder-decoder (AED) architectures which tend to suffer from over-fitting in low-resource scenarios. One solution to tackle this issue is to generate synthetic data with a trained text-to-speech system (TTS) if additional text is available. This was successfully applied in many publications with AED systems, but only very limited in the context of other ASR architectures. We investigate the effect of varying pre-processing, the speaker embedding and input encoding of the TTS system w.r.t. the effectiveness of the synthesized data for AED-ASR training. Additionally, we also consider internal language model subtraction for the first time, resulting in up to 38% relative improvement. We compare the AED results to a state-of-the-art hybrid ASR system, a monophone based system using connectionist-temporal-classification (CTC) and a monotonic transducer based system. We show that for the later systems the addition of synthetic data has no relevant effect, but they still outperform the AED systems on LibriSpeech-100h. We achieve a final word-error-rate of 3.3%/10.0% with a hybrid system on the clean/noisy test-sets, surpassing any previous state-of-the-art systems on Librispeech-100h that do not include unlabeled audio data.

Index Terms— speech recognition, text-to-speech, semi-supervised training, architecture comparison

1. INTRODUCTION

Many publications \cite{1, 2, 3} have shown that ASR systems using an AED architecture can achieve similar performance on large corpora compared to other methods such as hidden-markov-model (HMM) based hybrid models \cite{4}. CTC models \cite{5, 6} or recurrent neural network Transducer (RNN-T) models \cite{7, 8}. For smaller corpora however, they usually suffer from a much stronger performance loss \cite{4, 9}. To increase the effectiveness of attention-based ASR systems different methods were proposed, such as data augmentation techniques like SpecAugment \cite{10}, various regularization techniques \cite{11}, generating synthetic data from additional text \cite{12, 13, 14, 15, 16} or using unlabeled speech data \cite{9, 16, 17}.

In this work we will make use of SpecAugment and a Tacotron-2 \cite{18} style TTS system to boost the performance of ASR systems on LibriSpeech-100h \cite{19}, which is a quite common task to test the performance of synthetic data or semi-supervised training approaches. LibriSpeech-360h and LibriSpeech-500h are then used as text-only or audio-only data. In this context we experiment with different text encoding, speaker encoding and a novel approach to improve on the stability issues in autoregressive TTS systems. These issues are caused by the nature of the ASR data in contrast to TTS targeted data \cite{13, 20}. It was shown in \cite{20} that the stability does not only depend on the used TTS system, but also on the quality and processing style of the data. LibriSpeech contains many utterances with unnaturally long pauses, which are causing stability issues in TTS, also referred to as "bias-problem" \cite{21}. While it is impossible to have an objective metric for TTS quality without using human ratings, \cite{22} presented two objective metrics which give an indication for stability issues.

Most previous publications on generating synthetic data for LibriSpeech-100h only aimed at improving a single AED system \cite{12, 13, 14, 15}. In this work, we will use four fundamentally different architectures to show the effects of synthetic data. For RNN-T systems, there is prior work on domain adaptation with TTS \cite{23} and a recent publication on improving LibriSpeech \cite{24} by using synthetic data. The four state-of-the-art baselines we present are an AED system, a hybrid ASR system, a CTC system and a monotonic RNN-T system. One objective of this paper is to determine how much we can close the gap between an AED system and a hybrid system by adding synthetic data under fair conditions. To the best of our knowledge no recent publication shows strong results with a hybrid ASR system on LibriSpeech-100h, with the previous best results being reported in \cite{4}. We wanted to see if models without label context such as the hybrid and the CTC acoustic models can improve with synthetic data, and if yes, how much. In \cite{14} it was shown that synthetic data and language model fusion have orthogonal effects. As ASR...
systems with label context such as AED and RNN-T benefit from subtracting an estimated internal language model (ILM) \cite{25,26,27,28,29}, we investigate if the benefits of synthetic data from additional text are retained when using ILM subtraction methods for AED systems.

We make general versions of the used RETURNN\cite{30} and RASR\cite{31} toolkit configuration files available online. All experiments in this work were managed with Sisyphus\cite{32}.

2. SPEECH RECOGNITION

2.1. Attention-based ASR

The AED system is inspired by previous work on attention-based ASR systems using bidirectional long-short-term-memory (BLSTM)\cite{33} layers as encoder and decoder \cite{34,35}. Our encoder consists of 2 convolutional layers followed by 6 BLSTM layers with 1024 dimensions per direction. We use time downsampling via max-pooling layers with a factor of 6. We apply regularization techniques for both encoder and decoder similar to \cite{11}. We apply a dropout of 30\% to the LSTM input and 30\% drop-connect to the recurrent hidden-to-hidden weight matrices. Our decoder consists of a Zoneout-LSTM layer \cite{37} with a dimension of 1000. We apply 30\% attention dropout and embedding dropout, as well as using $10^{-3}$ weight decay and 0.1 label smoothing. We use byte-pair-encoding (BPE)\cite{38} as output labels with a vocabulary size of 2k. We add CTC as additional loss on top of the encoder for training stability.

2.2. Hybrid ASR

The hybrid ASR system used in this paper follows the train-clean-100 model presented in \cite{4}. The initial alignment is created by using a Gaussian-mixture-model (GMM) that is as described in Section 2.1.1 of the aforementioned paper. The hybrid BLSTM acoustic model (AM) consists of 8 BLSTM-layers with 1024 hidden units per direction. The model uses 12k classification and regression tree (CART)\cite{39} based labels and is trained with standard cross-entropy loss. We do not use dropout or L2 constraints for the hybrid training. The BLSTM network is implemented in RETURNN, the GMM-training and the decoder in RASR.

2.3. CTC ASR

Similar to the monotonic RNN-T model presented in \cite{40}, our CTC model uses a 6-Layer BLSTM network, with a factor 2 max-pooling layer applied between the third and fourth layer. Each LSTM layer has a hidden dimension of 512 per direction and includes an L2 loss and dropout of 0.1 for regularization. The CTC labels consists of the CMU/Dict\cite{1} phonemes with and without an additional end-of-word labeling symbol “#”, and a unified silence/blank symbol. This results in a total number of 139 labels. The BLSTM network is implemented in RETURNN. The state machine for Baum-Welch loss computation used during training and the decoder are implemented in RASR.

2.4. RNN-Transducer ASR

The monotonic RNN-T model also follows \cite{40}, using the same encoder model and labels as the CTC model. The prediction network is a 2-layer LSTM with 1024 dimensions each, so other than in \cite{40} the model uses the complete history for the prediction network. During training three different losses are used. First, the model includes a CTC loss on the encoder output states which is the same as in the CTC model. Then, there is both a normal CE loss with the aligned labels as target, but also a segmental loss which excludes blank positions.

2.5. Language Modeling

For the attention-based setup we trained a 24-layer Transformer language model (LM) following the setup described in \cite{41}. The BPE-perplexity of the final model on the dev-sets is 18.6, which would be equivalent to 73.6 on word-level. For the hybrid and CTC setup, we use a 2-layer LSTM network with a hidden dimension of 4096 and an output vocabulary of 200k, as a Transformer network is computationally too expensive in these scenarios. The word-level perplexity on the dev-sets is 60.

3. SPEECH SYNTHESIS

The synthesis system consists of an LSTM-based encoder-decoder architecture with a location-sensitive attention. This architecture is commonly referred to as “Tacotron-2” \cite{18}. The setup closely follows \cite{14}, with a different variation of input and speaker embedding as well as minor changes. The Zoneout-LSTM in the encoder was replaced by our native CUDA LSTM implementation and a dropout layer for increased training and decoding speed. For the decoder, we kept the 2-layer Zoneout-LSTMs, but used a hidden dimension of 768. To convert the log-mel features of the TTS system into audio-signals, we use a separately trained 2-layer BLSTM to convert the features first back into linear STFT features \cite{14}. The linear features are transformed into raw-waveforms with the Griffin & Lim \cite{42} algorithm and stored as .ogg files. We found out that the usage of .ogg files has no effect on the ASR training. Also, the synthetic data is required to be stored in audio waveform instead of features, as the different ASR systems have independent and varying feature pipelines.
3.1. Input Encoding

In this work we experimented with character embeddings as well as phoneme embeddings. The phoneme representations are based on the CMU pronunciation dictionary. We use Sequitur [43] to generate the phoneme representations for words not part of the dictionary.

3.2. Silence Preprocessing

The LibriSpeech corpus has an utterance structure that is not beneficial for TTS systems [20]. Especially longer silence parts that occur within an utterance can severely influence the model performance. In this paper we compare two approaches for silence pre-processing, namely threshold-based silence filtering and a newly introduced GMM alignment-based silence filtering. For threshold-based filtering we use the FFMPEG silence-remove filter with a (silence-)threshold of -40dB. For the GMM-based silence pre-processing we train a simple GMM-HMM model starting from a linear alignment. It uses 16-dimensional MFCC features with first and second derivatives as well as energy features, as in [4]. The alignment and the mixture densities are updated over 75 iterations, followed by 10 iterations splitting and re-estimating the mixture densities. A final alignment is used to determine all silence frames. We extract timestamps for all silence regions, and remove those parts excluding a predefined amount $\Delta t$ at the silence region borders from the audio files. This means for a silence region from, e.g., 2s to 4s in an utterance we would remove the audio from 2.25s to 3.75s if $\Delta t = 0.5s$, or all of it if $\Delta t = 0s$. If any, we keep only silence between words, not before or after the utterance.

3.3. Speaker Modeling

For controlling the speaker characteristics of the TTS system, we compare a supervised and an unsupervised approach. For the supervised speaker embeddings we simply add a 256-dimensional look-up table for all 251 speakers of the training corpus. As unsupervised method we use a reference encoder with global style tokens (GST) [44]. The reference encoder and the GST network are implemented as described in [14].

4. EXPERIMENTS

All our experiments are conducted by using LibriSpeech-100h as training data for the TTS and the baseline ASR systems, and the text of LibriSpeech-360h for synthesizing additional training data. We choose this scenario, as this is a very common task for semi-supervised training, and allows to compare our results with previous literature [12, 14, 15, 16]. The best checkpoints are determined by the minimum of the negative log-likelihood score on a holdout set consisting of a subset of dev-clean and dev-other. All systems use SpecAugment [2] in training. Note that we optimized the parameters and training settings for each of the different ASR architectures presented individually in order to achieve the respective best performance on LibriSpeech-100h. The scales for language model integration were tuned on dev-clean/dev-other.

4.1. Evaluation Methods

As evaluation method for our ASR systems we use word error rate (WER). For the evaluation of our TTS systems we use two metrics as proposed in [22]: Word Deletion Rate (WDR) and Unaligned Duration Ratio (UDR). The WDR is defined as the relative amount of non-generated words by the TTS, which is the deletion rate in WER evaluation. The UDR is given by the ratio of not aligned audio segments of a length greater than a certain threshold, which was defined to be one second. For further details on these metrics refer to [22].

Table 1. UDR and WDR measured on dev-clean and test-clean when synthesized with TTS models using the respective preprocessed data. Values are averaged over 4 different trained models each.

| Pre-Proc. | UDR [%] | WDR [%] |
|-----------|---------|---------|
| Threshold | 9.8     | 3.5     |
| GMM 0.0   | 0.0     | 2.9     |
| GMM 0.5   | 0.0     | 3.0     |

4.2. Stability Analysis of the TTS

For each trained TTS system, we synthesized the text of LibriSpeech dev-clean and test-clean and computed the UDR and WDR using existing ASR systems. For the UDR, we used a GMM-HMM ASR model and ran a forced-alignment on the synthesized data to label each frame as “speech” or “silence/noise”. Following [22], we use one second as threshold for allowed non-aligned-audio. To compute the WDR, we use an attention-based LibriSpeech-960h ASR system [4], with a WDR on dev-clean and test-clean of 0.5%. In the first set of experiments we trained 12 different TTS systems by adjusting 3 different conditions:

- Input encoding:
  - Lower cased characters (char)
  - CMUDict-style phonemes with stress (phon)
- Speaker Encoding
  - Trained look-up table (look-up)
  - Reference encoder with Global-Style-Token (GST)
- Silence Pre-Processing
  - Threshold-based with -40dB (Threshold)
  - GMM-HMM alignment w. 0.0s silence (GMM 0.0s)
  - GMM-HMM alignment w. 0.5s silence (GMM 0.5s)
Table 2. Results on LibriSpeech-100h with an AED model without external LM. The TTS models for data generation used a fixed look-up table and phoneme inputs.

| Syn. Data | Silence Pre-Proc. | Added Data | WER [%] |
|-----------|-------------------|------------|---------|
|           | [Δt]/[s]          | [h]        |         |
| No        |                   |            | dev     | test    |
|           | Threshold         | 330        | 8.1     | 21.6    |
|           | GMM               | 0.5        | 5.7     | 19.7    |
|           |                   | 0.0        | 5.6     | 19.8    |
|           |                   | 278        | 5.7     | 19.5    |
| Oracle    |                   | 360        | 4.5     | 14.8    |

First, we used the UDR to determine if using the GMM-HMM alignment to remove excessive silence helps to reduce long noise and silence sections in the synthesized audio. Table 1 shows the results with UDR and WDR for each silence pre-processing method, averaged over the remaining conditions (speaker and input encoding). By using the GMM-HMM alignment for silence pre-processing, the UDR can be reduced to an absolute zero, so there are no unaligned noise or silence parts above one second remaining in the synthesized audio. This also means that the TTS system always stops correctly at the end of an utterance. The WDR is reduced by up to 0.6%, meaning fewer words are dropped during synthesis, but is still higher than the original 0.5%. This indicates that the TTS still suffers from either early stopping or skipped words.

Table 3. Comparison of different TTS systems. The WER score is the AED system performance after synthesizing LibriSpeech-360h and using it for training. * means averaged over all possible TTS models and respective ASR training.

| Silence Pre-Proc. | Speaker | Input Type | WDR [%] | WER [%] |
|-------------------|---------|------------|---------|---------|
| [Δt]/[s]          |         |            | dev + test | test     |
| Threshold         | *       | *          | 3.5     | 6.2     |
| GMM               | *       | *          | 2.9     | 6.1     |
| 0.5               | *       | *          | 3.0     | 6.2     |

4.3. Synthetic data for Attention-Encoder-Decoder ASR

As AED systems use less resources in training and decoding we first tested the quality of the different TTS systems with our AED-ASR baseline. The baseline is trained for 250 sub-epochs with a partitioning factor of 3, resulting in about 83 full epochs. We reset the learning rate to the maximum at sub-epoch 80 for all experiments. When adding synthetic data, we take the checkpoint of sub-epoch 80 of the baseline as starting point to reduce the training variance for the experiments. For the remaining 170 sub-epochs we oversample the real data 3 times, having 3 · 100h of real data matched with ~300h of synthetic data. With a partitioning of factor 9 this results in 83 epochs of training on LibriSpeech-100h, and about 19 epochs for the synthetic data. The results for the baseline, synthetic data from 3 different TTS systems, and the oracle performance can be found in Table 2. We see a notable jump in WER of about 2% absolute when adding the synthetic training data. The term oracle refers to using the original LibriSpeech-360h audio files instead of the synthesized one. To see the effect of the different TTS systems better, we also combined all important conditions and created synthetic data. The evaluation of the different conditions can be seen in Table 3. For each condition, we average over all possible variants for the other conditions, i.e. for the first line we took the average of the 4 experiments with threshold silence pre-processing combined with look-up or GST embedding and character or phoneme encoding. The results indicate that only the speaker embedding has a notable effect on the final ASR performance, although we observe an increased stability by using the GMM silence pre-processing method. We conclude that the ASR does not suffer from noisy or incorrect sequences, but instead they have a regularization effect on the training. For those 12 experiments, we picked 4 to also test different data ratios 1:3 and 2:3, which can be found in Table 4. Here we confirmed that the AED model with oversampling LibriSpeech-100h by factor 3 is performing best.

4.3.1. Internal Language Model Subtraction

Internal language model (ILM) subtraction is a method to remove the label prediction bias of ASR models that use a label prediction context such as AED systems and RNN-T systems. The first methods were presented in [25, 26, 27] and exten-
5. DISCUSSION

To put the performance of our systems into perspective, we show a full comparison of the best systems of each category in Table 6. Only the AED system improved significantly by using synthesized data from additional text, which is in line with previous publications that only show improvements for AED systems. One exception is [24] which uses an RNN-T ASR system reporting up to 12.5% improvements on LibriSpeech, but the TTS system includes additional training data which means the TTS can learn additional acoustic information. In our case, when relying only on the LibriSpeech-100h dataset as parallel data, we had no improvements with the two label context-independent models (CTC and hybrid ASR) and the context-dependent RNN-T. This indicates that the TTS system cannot produce a larger variety of audio features compared to the existing data. We observed in other experiments that AED systems did not improve when synthesizing exactly the same text that is already used for the baseline training. Similar behavior was also found in [13], and it was shown in [14, 16] that training with synthetic data is complementary to using SpecAugment. Our conclusion was that the improvements for AED systems shown in many publications are due to the improved decoder. The large improvements by reducing the influence of encoder states based on synthetic data, as done with the $\alpha$-factor in [16], further backed this hypothesis. Now that we see equivalent improvements when using ILM subtraction for AED-ASR and no improvements with RNN-T models, we conclude that it is not the internal language model of the decoder that benefits most from the synthetic data, but rather the attention mechanism. It was also previously shown in [14] that the effect of synthetic data from additional text and external language model fusion of the same text have independent effects. Another possibility is that RNN-T systems might not need a large label context [40, 46], and thus cannot benefit from more textual data. Investigating if the label type plays a role in the effect of synthetic data can be future work.

We also compare our systems to other publications. The system from [9] is to our knowledge the best existing LibriSpeech-100h AED system without additional data, but uses non-constrained computational resources for training, meaning...
Table 6. Comparison of different systems on LibriSpeech-100h from literature and the results for each architecture described in this paper. Synthetic data describes the TTS used to generate the synthetic data, which is always based on the transcriptions of LibriSpeech-360h. Except for [4], all systems include SpecAugment.

| Architecture       | Encoder Model     | Label Type | LM            | Synthetic Data | WER [%] |
|--------------------|-------------------|------------|---------------|----------------|---------|
|                    |                   |            |               |                | clean | clean | other | other |
| Attention Enc.-Dec.| LAS - BLSTM [9]   | 16k WPM    | -             | -              | 5.3   | 16.5  | 5.5   | 16.9  |
|                    | ESPNet - Transformer [15] | 5k SPM     | LSTM          | VAE-TTS        | 10.3  | 24.0  | 11.2  | 24.9  |
|                    |                  |            |               |                | 5.8   | 16.0  | 7.0   | 17.0  |
|                    | ESPNet - Transformer [16] | characters | LSTM         | x-vector TTS   | 14.3  | 36.4  | 14.4  | 36.9  |
|                    |                  |            |               |                | 8.9   | 23.0  | 8.6   | 24.1  |
|                    |                  |            |               | x-vector TTS + α | 4.5   | 15.8  | 4.7   | 15.9  |
|                    | RETURNNN - BLSTM [ours] | 2k BPE    | Transformer   | lookup-TTS*    | 8.1   | 21.6  | 8.2   | 22.6  |
|                    |                  |            | + ILM sub.    |                | 4.6   | 13.7  | 5.3   | 14.8  |
|                    | RETURNNN - BLSTM [ours] | 12k CART  | 4-gram        |                | 5.0   | 19.5  | 5.8   | 18.6  |
| Hybrid             | RETURNNN - BLSTM [ours] | 12k CART  | LSTM          |                | 4.9   | 14.7  | 5.6   | 15.3  |
|                    |                  |            |               | lookup-TTS*    | 3.0   | 9.3   | 3.4   | 10.0  |
|                    | RETURNNN - BLSTM [ours] | phonemes (w. EOW) | Transformer | | 3.3 | 10.8 | 3.8 | 11.3 |
|                    |                    |            | 4-gram        |                | 5.0   | 15.4  | 5.6   | 16.1  |
|                    |                    |            | LSTM          |                | 3.3   | 11.4  | 3.8   | 12.4  |
|                    |                    |            |               | lookup-TTS*    | 3.2   | 11.6  | 3.6   | 12.5  |
|                    |                    |            |                |                | 3.3   | 10.4  | 3.6   | 11.7  |
|                    |                    |            |                | lookup-TTS*    | 3.1   | 10.4  | 3.6   | 11.1  |

* results are averaged over multiple runs with varying silence pre-processing, see Section 4.2

the model is trained on 32 TPUs for 10 days. The system presented in [16] has the weakest baseline, but shows the largest improvements by using a TTS system with x-vector [47] speaker embeddings and the scaling of the synthetic encoder states. As seen in section 4.3, only changing the speaker embedding had a notable effect. Investigating why the speaker embedding method is important although the encoder parts of ASR systems do not seem to benefit from synthetic data can be future work, together with finding objective performance markers for the quality of synthetic data different from UDR and WDR.

6. CONCLUSION

In this work we presented four state-of-the-art ASR systems for LibriSpeech-100h and tried to improve the performance of each by using synthetic data from a TTS system trained on the same data. By using the alignment of a GMM-HMM system for silence removal, we were able to improve the stability of an autoregressive TTS system with respect to unaligned duration rate and word deletion rate. We found that an increase in the stability of the TTS systems is not needed to generate useful synthetic data to be used in AED-ASR training. For the first time we apply synthetic data from a TTS system to an attention-encoder-decoder, hybrid, CTC and a RNN-T system in a direct comparison, and show that only the AED system can be significantly improved by using synthetic data. We show that we can get up to 38% relative improvements by adding synthetic data to the AED-ASR system, even when using internal language model subtraction. This indicates that the benefit of adding synthetic data from additional text is mostly related to improving the robustness of the attention mechanism for sequence mapping, and not related to improving the internal language model of the decoder. Nevertheless, the improvement on AED systems is currently not sufficient to close the performance gap to a strong hybrid baseline presented in this work, which outperforms any other system in literature under the same data conditions with a word-error-rate of 3.3%/10.0% on test-clean and test-other respectively.

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8. REFERENCES

[1] Gabriel Synnaeve, Quan tong Xu, Jacob Kahn, Tatiana Likhomanenko, Edouard Grave, Vinceel Pratap, Anu roop Sriram, Vitality Lipchitchinsky, and Ronan Collobert, “End-to-end ASR: from supervised to semi-supervised learning with modern architectures,” in ICML 2020 Work shop: Self-supervision in Audio and Speech, July 2020.

[2] Daniel S Park, William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D Cubuk, and Quoc V Le, “SpecAugment: A simple data augmentation method for automatic speech recognition,” in Interspeech 2019.

[3] Shigeki Karita, Nanxin Chen, Tomoki Hayashi, Takaaki Hori, Hirofumi Inaguma, Ziyan Jiang, Masao Someki, Nelson Enrique Yalta Soplin, Ryuichi Yamamoto, Xiaofei Wang, Shinnji Watanabe, Takenori Yoshimura, and Wangyou Zhang, “A comparative study on transformer vs RNN in speech applications,” in 2019 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), 12 2019, IEEE.

[4] Christoph Lüscher, Eugen Beck, Kazuki Irie, Markus Kitza, Wilfried Michel, Albert Zeyer, Ralf Schlüter, and Hermann Ney, “RWTH ASR systems for librispeech: Hybrid vs attention,” in Interspeech 2019. September 2019, ISCA.

[5] Alex Graves, Santiago Fernández, and Faustino Gomez, “Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks,” in In Proceedings of the International Conference on Machine Learning, ICML 2006, 2006, pp. 369–376.

[6] Alex Graves and Navdeep Jaitly, “Towards end-to-end speech recognition with recurrent neural networks,” in Proceedings of the 31st International Conference on Machine Learning, Eric P. Xing and Tony Jebara, Eds., Beijing, China, 22–24 Jun 2014, vol. 32, of Proceedings of Machine Learning Research, pp. 1764–1772, PMLR.

[7] Alex Graves, “Sequence transduction with recurrent neural networks,” CoRR, vol. abs/1211.3711, 2012.

[8] Wei Han, Zhengdong Zhang, Yu Zhang, Jiahui Yu, Chung-Cheng Chiu, James Qin, Anmol Gulati, Ruoming Pang, and Yonghui Wu, “Con textnet: Improving convolutional neural networks for automatic speech recognition with global context,” in Interspeech 2020. October 2020, ISCA.

[9] Daniel S. Park, Yu Zhang, Ye Jia, Wei Han, Chung-Cheng Chiu, Bo Li, Yonghui Wu, and Quoc V. Le, “Improved noisy student training for automatic speech recognition,” in Interspeech 2020. October 2020, ISCA.

[10] Daniel S. Park, William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D. Cubuk, and Quoc V. Le, “SpecAugment: A simple data augmentation method for automatic speech recognition,” CoRR, vol. abs/1904.08779, 2019.

[11] Z. Tüske, G. Saon, Kartik Audhkhasi, and Brian Kingsbury, “Single- headed attention based sequence-to-sequence model for state-of-the-art results on switchboard-300,” in INTERSPEECH, 2020.

[12] Murali Karttich Baskar, Shinnji Watanabe, Ramon Astudillo, Takaaki Hori, Lukáš Burget, and Jan Černocký, “Semi-supervised sequence-to-sequence ASR using unpaired speech and text,” in Interspeech 2019. September 2019, ISCA.

[13] Andrew Rosenberg, Yu Zhang, Bhuvana Ramabhadran, Ye Jia, Pedro Moreno, Yonghui Wu, and Zelin Wu, “Speech recognition with augmented synthesized speech,” in 2019 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), 12 2019, IEEE.

[14] Nick Rossenbach, Albert Zeyer, Ralf Schlüter, and Hermann Ney, “Generating synthetic audio data for attention-based speech recognition systems,” in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), January 2020, number 9052899, pp. 7069–7073, IEEE.

[15] Aleksandr Laptev, Roman Korostik, Aleksey Svishchev, Andrei Andrusenko, Ivan Medennikov, and Sergey Rybin, “You do not need more data: Improving end-to-end speech recognition by text-to-speech data augmentation,” 2020 13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), October 2020.

[16] Murali Karttich Baskar, Lukas Burget, Shinnji Watanabe, Ramon Fernandez Astudillo, and Jan Honza Černocký, “Eat: Enhanced ASR-TTS for self-supervised speech recognition,” in ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP); 6 2021, IEEE.

[17] Jacob Kahn, Ann Lee, and Awni Hannun, “Self-training for end-to-end speech recognition,” in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). May 2020, IEEE.

[18] Jonathan Shen, Ruoming Pang, Ron J. Weiss, Mike Schuster, Navdeep Jaitly, Zongheng Yang, Zhifeng Chen, Yu Zhang, Yuxuan Wang, Rj Skerrv-Ryan, Rf A. Saurous, Yannis Agiomvrgiannakis, and Yonghui Wu, “Natural TTS synthesis by conditioning wavenet on MEL spectrogram predictions,” in ICASSP 2018 - 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). April 2018, IEEE.

[19] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, “Librispeech: An asr corpus based on public domain audio books.,” pp. 5206–5210, 2015.

[20] Heiga Zen, Viet Dang, Rob Clark, Yu Zhang, Ron J. Weiss, Ye Jia, Zhifeng Chen, and Yonghui Wu, “LibriTTS: A corpus derived from librispeech for text-to-speech,” in Interspeech 2019. September 2019, ISCA.

[21] Rui Liu, Berrak Sisman, Jingdong Li, Feilong Bao, Guangli Gao, and Haizhou Li, “Teacher-student training for robust tacotron-based TTS,” in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). May 2020, IEEE.

[22] Jonathan Shen, Ye Jia, Mike Chrzanowski, Yu Zhang, Isaac Elias, Heiga Zen, and Yonghui Wu, “Non-attentive tacotron: Robust and controllable neural TTS synthesis including unsupervised duration modeling,” CoRR, vol.abs/2010.04301v3, October 2020.

[23] Jinyu Li, Rui Zhao, Zhong Meng, Yanqing Liu, Wenning Wei, Sarangarajan Parthasarathy, Vadim Mazalov, Zhenghao Wang, Lei He, Sheng Zhao, and Yifan Gong, “Developing RNN-T models surpassing high-performance hybrid models with customization capability,” in Interspeech 2020, ISCA, 10 2020, ISCA.

[24] Amin Fazeli, Wei Yang, Yulan Liu, Roberto Barra-Chicote, Yixiong Meng, Roland Maas, and Jasha Droppo, “Synthas: Unlocking synthetic data for speech recognition,” CoRR, vol.abs/2106.07803, 2021.

[25] Erik McDermott, Hasim Sak, and Ehsan Variani, “A density ratio approach to language model fusion in end-to-end automatic speech recognition,” in 2019 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), 2019, pp. 434–441.

[26] Ehsan Variani, David Rybach, Cyril Allauzen, and Michael Riley, “Hybrid autoregressive transducer (HAT),” in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 5 2020, IEEE.

[27] Zhong Meng, S. Parthasarathy, Eric Sun, Yashesh Gaur, Naoyuki Kanda, Liang Lu, Xie Chen, Rui Zhao, Jinyu Li, and Y. Gong, “Internal language model estimation for domain-adaptive end-to-end speech recognition,” 2021 IEEE Spon Spoken Language Technology Workshop (SLT), pp. 243–250, 2021.

[28] Mohammad Zeineldeen, Aleksandr Glushko, Wilfried Michel, Albert Zeyer, Ralf Schlüter, and Hermann Ney, “Investigating methods to improve language model integration for attention-based encoder-decoder asr models,” in Interspeech, Aug. 2021, To appear.

[29] Albert Zeyer, André Merboldt, Wilfried Michel, Ralf Schlüter, and Hermann Ney, “Librispeech transducer model with internal language model prior correction,” CoRR, vol.abs/2104.03006, 2021.
Patrick Doetsch, Albert Zeyer, Paul Voigtlaender, Ilia Kulikov, Ralf Schlüter, and Hermann Ney, “Returnn: The RWTH extensible training framework for universal recurrent neural networks,” in 2017 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2017, New Orleans, LA, USA, March 5-9, 2017, pp. 5345–5349.

Simon Wiesler, Alexander Richard, Pavel Golik, Ralf Schlüter, and Hermann Ney, “RASRNN: The RWTH neural network toolkit for speech recognition,” in ICASSP 2014 - 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). May 2014, IEEE.

Jan-Thorsten Peter, Eugen Beck, and Hermann Ney, “Sisyphus, a workflow manager designed for machine translation and automatic speech recognition,” in Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018: System Demonstrations, Brussels, Belgium, October 31 - November 4, 2018, pp. 84–89.

Sepp Hochreiter and Jürgen Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, no. 8, 1997.

Albert Zeyer, Kazuki Irie, Ralf Schlüter, and Hermann Ney, “Improved training of end-to-end attention models for speech recognition,” in Interspeech 2018, September 2018, ISCA.

Albert Zeyer, Parnia Bahar, Kazuki Irie, Ralf Schlüter, and Hermann Ney, “A comparison of transformer and lstm encoder decoder models for asr,” in IEEE Automatic Speech Recognition and Understanding Workshop, Sentosa, Singapore, Dec. 2019, pp. 8–15.

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov, “Dropout: A simple way to prevent neural networks from overfitting,” J. Mach. Learn. Res., vol. 15, no. 1, pp. 1929–1958, Jan. 2014.

David Krueger, Tegan Maharaj, János Kramár, Mohammad Pezeshki, Nicolas Ballas, Nan Rosemary Ke, Anirudh Goyal, Yoshua Bengio, Aaron Courville, and Chris Pal, “Zoneout: Regularizing RNNs by randomly preserving hidden activations,” CoRR, vol. abs/1606.01305v4, June 2016.

Rico Sennrich, Barry Haddow, and Alexandra Birch, “Neural machine translation of rare words with subword units.” in Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Aug. 2016, pp. 1715–1725, Association for Computational Linguistics.

Steve J Young, “The general use of tying in phoneme-based HMM speech recognisers,” in ICASSP, 1992.

Wei Zhou, Simon Berger, Ralf Schlüter, and Hermann Ney, “Phoneme based neural transducer for large vocabulary speech recognition,” in ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 6 2021, IEEE.

Kazuki Irie, Albert Zeyer, Ralf Schlüter, and Hermann Ney, “Language modeling with deep transformers,” in Interspeech 2019. September 2019, ISCA.

Daniel W. Griffin, Douglas S. Deadrick, and Jae S. Lim, “Speech synthesis from short-time fourier transform magnitude and its application to speech processing,” in ICASSP ’84, San Diego, California, USA, March 19-21, 1984, pp. 61–64.

Maximilian Bisani and Hermann Ney, “Joint-sequence models for grapheme-to-phoneme conversion,” Speech Communication, vol. 50, no. 5, pp. 434–451, May 2008.

Yuxuan Wang, Daisy Stanton, Yu Zhang, RJ Skerry-Ryan, Eric Battenberg, Joel Shor, Ying Xiao, Fei Ren, Ye Jia, and Rif A. Saurous, “Style tokens: unsupervised style modeling, control and transfer in end-to-end speech synthesis,” CoRR, vol. abs/1803.09017v1, March 2018.

Tatiana Likhomanenko, Qiantong Xu, Jacob Kahn, Gabriel Synnaeve, and Ronan Collobert, “slimIPL: Language-model-free iterative pseudo-labeling,” CoRR, vol. abs/2010.11524v1, October 2020.