GENERATIVE SPEECH CODING WITH PREDICTIVE VARIANCE REGULARIZATION

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ABSTRACT
The recent emergence of machine-learning based generative models for speech suggests a significant reduction in bit rate for speech codecs is possible. However, the performance of generative models deteriorates significantly with the distortions present in real-world input signals. We argue that this deterioration is due to the sensitivity of the maximum likelihood criterion to outliers and the ineffectiveness of modeling a sum of independent signals with a single autoregressive model. We introduce predictive-variance regularization to reduce the sensitivity to outliers, resulting in a significant increase in performance. We show that noise reduction to remove unwanted signals can significantly increase performance. We provide extensive subjective performance evaluations that show that our system based on generative modeling provides state-of-the-art coding performance at 3 kb/s for real-world speech signals at reasonable computational complexity.

Index Terms— Speech, coding, WaveNet, regularization

1. INTRODUCTION
In recent years it has become possible to generate high-quality speech from a conditioning sequence with a very low information rate. This suggests that generative synthesis forms a natural basis for the coding and enhancement of speech. However, it has been found that generative synthesis is sensitive to the quality of the data used for training and the conditioning sequences used for training and inference. This can result in poor synthesized speech quality. In this paper, we discuss methods that significantly reduce the impact of distortions in the input signal on signal synthesis for speech coding.

WaveNet 1 first showed that the generation of high-quality speech from only a low-rate conditioning sequence, such as written text, is possible. WaveNet is based on an autoregressive structure that specifies a predictive distribution for each subsequent signal sample. While WaveNet uses a dilated convolution to determine the predictive distribution, other recurrent neural networks structures such as WaveRNN 2 and the WaveGRU structure that we use in this paper have also been used successfully for this purpose. Although autoregressive structures for synthesis are common, feedforward structures are used by, for example, Parallel WaveNet 3, WaveGlow 4, WaveGAN 5, and GANSynth 6. It is fair to state that while the more recent methods may have computational advantages, they do not surpass the basic synthesis quality of the original WaveNet approach.

The high quality of generative speech synthesis has led to a significant effort towards its usage for coding. In contrast to synthesis from text, synthesis for coding must be able to generate an unlimited range of voices and its conditioning is variable as it is computed from input signals that may suffer from a range of distortions. It was found that the synthesis of a wide range of voices with a single generative model is not a significant problem. Generative synthesis of a wide range of unknown voices with a single model results in only a minor reduction of speaker identifiability 7. However, variability in the conditioning leads to a reduced output speech quality that can not be improved significantly with straightforward measures such as training with noisy conditioning and undistorted target signals. Hence, despite extensive research, e.g., 8-12 generative synthesis based speech coding has not yet seen major practical applications.

The contribution of this paper consists of the identification of causes of the sensitivity to distortion, the development of methods to reduce this sensitivity, and subjective testing of the new methods confirming the improvements. We show that a major cause of the sensitivity is associated with an attribute of the log-likelihood (LL) objective function. The LL objective function incurs a high penalty if the model assigns a low probability to observed data. Hence, in the context of autoregressive structures, it encourages an overly broad predictive distribution when at least some training data are difficult to predict accurately from the past signal and conditioning, which is true for real-world training data. We mitigate this effect by including predictive variance regularization in the objective function.

We also show with experiments that input-noise suppression can improve performance significantly. It is well-known that a sum of low-order linear autoregressive processes is, in general, not a low-order autoregressive process. This suggests that linear autoregressive models are poor for sums of independent signals and our results indicate this also holds for nonlinear autoregressive models. Whereas traditional analysis-by-synthesis coding methods can compensate for model inadequacies, this is not true for generative synthesis based coding, explaining the effectiveness of noise suppression.

2. PROBLEM FORMULATION
In this section, we first describe how an autoregressive model is used to model a process. The method is as proposed in 1. We then discuss a common problem that occurs when training such sequences.

Consider a random process \( \{X_i\} \) consisting of real-valued random samples \( X_i \), with a time index \( i \in \mathbb{Z} \). The joint distribution of a finite sequence, \( p(x_i, \cdots, x_{i-N}) \), can be expressed as a product of conditional distributions:

\[
p(x_i, \cdots, x_{i-N}|\beta) = \prod_{j=0}^{N} p(x_{i-j}|x_{i-j-1}, \cdots, x_{i-N}, \beta),
\]

where \( \beta \) is conditioning information.

It follows from 1 that we can create an approximate realization of a random process by recursively sampling from a model of the predictive distribution \( p(x_{i+j}|x_{i-j-1}, \cdots, x_{i-N}, \beta) \) for sufficiently large \( N \). It is convenient to use a standard-form distribution \( q(x_i|\alpha) \)
with parameters α as a model predictive distribution. The standard-
form distribution can be a Gaussian or a logistic mixture, for ex-
ample. This formulation allows us to predict the model parameters with
deterministic neural network \( \phi : (x_{i-1}, \cdots , x_{i-N}, \beta, W) \mapsto \alpha \)
where \( W \) is a vector of network parameters. Thus, the predictive
distribution for sample \( x_i \) is now \( q(x_i | \phi(x_{i-1}, \cdots , x_{i-N}, \beta, W)) \).

To find the parameters \( W \), a reasonable objective is to min-
imize the Kullback-Leibler divergence between the ground truth
joint distribution \( p(x_i, \cdots , x_{i-N}) \) and the model distribution
\( q(x_{i-1}, \cdots , x_{i-N}) \), or, equivalently, the cross-entropy between these
distributions. The latter measure is tractable even though \( p \) is only
available as an empirical distribution. It follows from (1) and our
formulation of \( q(x_i | \alpha) \) that cross-entropy based estimation of the
parameters of \( \phi \) can be implemented using maximum-likelihood
based teacher forcing. For a database of \( M \) signal samples, the
maximum-likelihood estimate of \( W \) can be written as
\[
W^* = \arg \max_W \sum_{i=1}^{M} \log q(x_i | \phi(x_{i-1}, \cdots , x_{i-N}, \beta, W)). \tag{2}
\]

Note that (2) leads to rapid training as it facilitates parallel imple-
mentation. For sufficiently large \( N \) and \( M \), the LL objective pro-
vides an upper bound on the differential entropy rate as
\[
h(x_i | x_{i-j}, \cdots , x_{i-N}) \leq -\frac{1}{M} \sum_{i=1}^{M} \log q(x_i | \phi(x_{i-1}, \cdots , x_{i-N}, W)), \tag{3}
\]
where, for notational convenience, we considered the unconditioned
case. Conversely, (3) can be interpreted as a lower bound on a mea-
sure of uncertainty associated with the model predictive distribution.
This lower bound is associated with the process itself and not with
the model.

Although the differential entropy rate is subadditive for summed
signals, predictive models tend not to work well for summed signals.
In general, a model of summed signals is essentially multiplicative in
the required model configurations. It is well-known that the sum of
finite-order linear autoregressive models is, in general, not a finite-
order autoregressive model [13]. It is relatively straightforward to
reduce this problem with noise suppression.

A more difficult problem relates to well-known drawbacks of the
Kullback-Leibler divergence and, hence, the LL objective of (2). When
the model distribution \( q \) vanishes in the support region of the
groundtruth \( p \), the Kullback-Leibler divergence diverges. In (2) this
manifests itself as a severe penalty for training data \( x_i \) that have
a low model probability \( q(x_i | \phi(x_{i-1}, \cdots , x_{i-N}, \beta, W)) \). Hence,
a few nonrepresentative outliers in the training data may lead the
training procedure to equate the predictive model distribution with
heavy tails. Such tails lead to signal synthesis with a relatively high
entropy rate during inference. In audio synthesis this corresponds to
a noisy synthesized signal. Hence it is desirable to counter the
severity of the penalty for low probability training data.

We can identify a second relevant drawback to the ML object-
ive. When the ML objective function is used, the model distribution
should converge to the groundtruth distribution with increasing
database size. However, in practice the stochastic nature of the train-
ing data and the training method results in inaccuracies and this in
turn means the method attempts to minimize the impact of such
errors. For example, the implicit description of pitch by the predictive
distribution may be inaccurate. A predictive model distribution with
heavy tails for voiced speech then increases the likelihood of training
data as it reduces the impact of the model pitch deviating from the
groundtruth pitch. From this reasoning we conclude that it is desir-
able to account for the audibility (perception) of distortions, leading
to empirically motivated refinements of the objective function.

The problems associated with the LL objective have been con-
sidered earlier in different contexts. The vanishing support problem
described above was addressed in the context of generative adver-
sarial networks (GANs) [14], where the implicit Jensen-Shannon
objective function of the original method and the more general f-
divergence based method [15] suffer, at least in principle, from sim-
ilar problems. The support problem in GANs can be removed by
using the 1-Wasserstein distance [16] or with maximum mean dis-
crepancy (MMD) [17, 18]. However, as these measures require as
input two empirical distributions, these methods are natural for static
distributions and not for dynamic predictive distributions. The meth-
ods also do not facilitate adjustment to account for perception. An
existing approach that attempts to compensate for overly broad pre-
dictive distributions is to lower the “temperature” during inference,
e.g., [19]. The predictive distribution is typically raised to a power,
then renormalized. This approach does not account for the implicit
cost penalty in the basic training objective.

3. OBJECTIVE FUNCTIONS FOR PREDICTIVE DISTRIBUTION MODELS

In this section, we discuss two related approaches that modify the
maximum likelihood criterion to obtain improved performance.
Both approaches aim to reduce the impact of data points in the train-
ing set that are difficult to predict. The methods remove the need
for heuristic modifications during inference. While the principles of
our methods are general, we apply them to the mixture of logistics
distribution that we use in our coding scheme (cf. section 4).

3.1. Encouragement of low-variance predictive distributions

We now discuss how to add a term to the objective function that
encourages low-variance predictive distributions. In this approach
we define the overall objective function for the weights \( W \) given a
database \( \{x\} \) as
\[
J(\{x\}, W) = J_{LL}(\{x\}; W) + \nu J_{var}(\{x\}, W) \tag{4}
\]
where the log likelihood over the database, \( J_{LL}(\{x\}; W) = \sum \log q(x_i | \phi(x_{i-1}, \cdots , x_{i-N}, W)) \), is combined with a vari-
ance regularization term \( J_{var}(\{x\}, W) \) that is defined below and
where \( \nu \) is a constant that must be tuned.

3.1.1. Predictive variance computation

The variance of the predictive distribution is an instantaneous para-
meter that varies over a database and \( J_{var}(\{x\}, W) \) must be an
average over the predictive distributions. The predictive distribution
of each sample has a distinct variance and the averaging method can
be selected to have properties that are advantageous for the specific
application. As noted in section 2 the predictive distribution is a
standard-form distribution \( q(x | \alpha) \).

The predictive distribution \( q(x | \alpha) \) is commonly a mixture dis-
bution. Hence we must find an expression for the variance of a mix-
ture distribution. We first note that the mean of a mixture distribu-
tion is simply
\[
\mu = E_q[X] = \sum_{k=1}^{K} \gamma_k E_{q_k}[X] = \sum_{k=1}^{K} \gamma_k \mu_k, \tag{5}
\]
where $E_q$ is expectation over $q$ and $q_k = \tilde{q}(\cdot; \mu_k, s_k)$, with $\tilde{q}$ a mixture component. The variance of the mixture distribution is

$$E_q[(X - E_q[X])^2] = \sum_{k=1}^{K} \gamma_k (\sigma^2_k + \mu^2_k - \mu^2).$$

(6)

We now consider the specific case of a mixture of logits in more detail. The logistic distribution for component $k$ is:

$$\tilde{q}(x; \mu_k, s_k) = \frac{e^{-\frac{x-\mu_k}{s_k}}}{1 + e^{-\frac{x-\mu_k}{s_k}}}.$$  

(7)

where $s_k$ is the scale and $\mu_k$ is an offset. It is easily seen that the logistic distribution is symmetric around $\mu$ and that hence, $\mu$ is the distribution mean. The variance of the logistic distribution is

$$E_{X\sim\tilde{q}}[(X - E_{X\sim\tilde{q}}[X])^2] = \frac{s_k^2}{3}.$$  

(8)

We can now write down the variance of the mixture of logistics model by combining (6) and (8):

$$\sigma^2 = \sum_{k=1}^{K} \gamma_k (\frac{s_k^2}{3} + \mu^2_k) - \sum_{k=1}^{K} \gamma_k \mu_k)^2.$$  

(9)

### 3.1.2. Regularization terms

The most obvious approach for reducing the prediction variance is to use the prediction variance $\sigma^2$ directly as variance regularization in the objective function (7):

$$J_{\text{var}}(\{x\}, W) = Edata[\sigma^2_q],$$

(10)

where $E_{\text{data}}$ indicates averaging over the database. That is, we encourage selection of weights $W$ of the network $\phi$ that minimize $\sigma^2_q$.

Straightforward optimization of (10) over a database may result in the prediction variance being reduced mainly for signal regions where the conditional differential entropy $\tilde{h}$ is large. The conditional differential entropy can be decomposed into the sum of a scale-independent term and a logarithmic scale (signal variance) dependency. For speech the scale-independent term is large for unvoiced segments while the scale-dependent term is large for voiced speech (as it is relatively loud).

For signals that have uniform overall signal variance, it may be desirable to encourage low predictive variance only for regions that have relatively low conditional differential entropy. (For speech that would correspond to encouraging low variance for voiced speech only.) This can be accomplished by a monotonically increasing concave function of the predictive variance. The logarithm is particularly attractive for this purpose as it is invariant with scale: the effect of a small variance getting smaller equals that of a large variance getting smaller by the same proportion. We then have:

$$J_{\text{var}}(\{x\}, W) = Edata[\log(\sigma_q + a)],$$

(11)

with $a$ providing a floor.

### 3.2. Baseline distribution approach

For completeness we describe an alternative method for preventing the vanishing support problem of the Kullback-Leibler divergence by using a "baseline" distribution. To this purpose consider a mixture distribution of the form

$$q_{\text{train}}(x; \phi) = \gamma_0 \tilde{q}(x; \phi) + \sum_{k=1}^{K} \gamma_k \tilde{q}(x; \phi(x_{i-1}, \cdots, x_{i-N}, \beta, W_k),$$

(12)

where the parameters $\gamma_0$ and $\alpha_0$ are set by the designer and where the first term is omitted during inference (the other terms must be renormalized by a factor $\frac{1}{1-\gamma_0}$). By selecting $\gamma_0$ to provide an overly broad distribution, the distribution used for inference will be of low variance.

### 4. SYSTEM ARCHITECTURE

In this section we describe the architecture of our coding scheme. The parameter settings of the scheme is provided in section 5.1.

Let us consider an input signal with a sampling rate $S$ Hz. To avoid the need for modeling summed independent signals, the input is pre-processed with a real-time TasNet [20][21]. The encoder first converts the signal into a sequence of log mel spectra (e.g., [22]). A set of subsequent log mel-spectra are stacked into a supervector that is subjected to a Karhunen-Loève transform (KLT) that is optimized off-line. The transformed stacked log mel spectra are encoded using split vector quantization with a small number of coefficients per split. No other information is encoded.

The decoder first decodes the bit stream into a sequence of quantized log mel spectra. These spectra form the input to the conditioning stack, which consists of a set of 1D convolutional layers, all except the first with dilations. The output is a vector sequence with a sampling rate equal to that of the mel spectra of the encoder and a dimensionality equal to the state of the GRU unit discussed below.

The autoregressive network consists of a multi-band WaveGRU, which is based on gated recurring units (GRU) [23]. For our $N$-band WaveGRU, $N$ samples are generated simultaneously at an update rate of $S/N$ Hz, one sample for each frequency band. For each update, the state of the GRU network is projected onto an $N \times K \times 3$ dimensional space that defines $N$ parameter sets, each set corresponding to a mixture of logistics for a band. The value of a next signal sample for each band is then drawn by first selecting the mixture component (a logistics distribution) according to its probability and then drawing the sample from this logistic distribution by transforming a sample from a uniform distribution. For each set of $N$ samples a synthesis filter-bank produces $N$ subsequent time-domain samples, which results in an output with sampling rate $S$ Hz.

The input to the WaveGRU consists of the addition of an autoregressive and conditioning components. The autoregressive component is a projection of the last $N$ frequency-band samples projected onto a vector of the dimensionality of the WaveGRU state. The second component is the output of the conditioning stack (dimensionality of the WaveGRU state), repeated in time to obtain the correct sampling rate of $S/N$ Hz.

The training of the WaveGRU network and the conditioning stack is performed simultaneously using teacher forcing. That is, the past signal samples that are provided as input to the GRU are ground-truth signal samples. The objective function , combining log likelihood (cross entropy) and variance regularization, is used for each subsequent signal sample. For our implementation with variance regularization, we found the baseline distribution not to aid performance significantly, and it was omitted from the experiments.
Our experiments had two goals. The first is to show the effect of predictive variance regularization and noise suppression. The second is to show that our contributions enable a practical system.

5.1. System configuration

We tested eight systems, all variants based on a single baseline system operating on 16 kHz sampled signals. It is conditioned using a sequence of 160-dimensional log mel spectra computed from 80 ms windows at an update rate of 50 Hz. The system uses four frequency bands, each band sampled at 4 kHz. The conditioning stack consists of a single non-causal input layer (expanding from 160 channels to 512 channels), three dilated causal convolutional layers with kernel size two, and three upsampling transpose convolutional layers (kernel size two). The overall algorithmic delay is 90 ms. The conditioning outputs are tiled to match the GRU update frequency. The GRU state dimensionality is 1024, and eight mixture-of-logistics components are used for the predictive distribution per band.

The systems were trained from randomly initialized weights $W$ for 7.5 million steps, using a mini-batch size of 256. The target signal was from a combination of clean [24, 25] and noisy sources [26], including large proprietary TTS datasets. Additional noise was added from [27], with random SNR between 0 and 40 dB SNR.

Table 1 shows the combinations of coder attributes that were used. We briefly discuss each attribute. The variance regularization included refinements that further improved its performance: it was applied to the first two bands only and $\nu$ in (4) was made proportional to a voicing score. The noise suppression system was a version of ConvTasNet [21]. The weight pruning attribute was selected to enable implementation on consumer devices. For the three GRU matrices, we used block-diagonal matrices with 16 blocks, which uses 93% fewer weights than a fully connected model. For other hidden layers, we applied iterative magnitude pruning to remove 92% of the model weights [28]. The pruning makes the codec with TasNet run reliably on a Pixel 2 phone in single-threaded mode. The system was quantized with 120 bits per supervector, each supervector containing two log mel spectra, for an overall rate of 3 kb/s. The quantization was a two-dimensional vector-quantization of the KLT coefficients.

5.2. Testing procedure

To evaluate the absolute quality of the different systems on different SNRs a Mean Opinion Score (MOS) listening test was performed. Except for data collection, we followed the ITU-T P.800 [29] (ACR) recommendation. The data was collected using a crowd-sourcing platform with the requirements on listeners being native English speakers and using headphones. The evaluation dataset is composed of 30 samples from the Noisy VCTK dataset [30]: 15 clean and 15 augmented with additive noise at various SNRs (2.5, 7.5 and 12.5 dB). Each utterance for each system was rated about 200 times and the average and 95% confidence interval were calculated per SNR.

5.3. Results

The quality for the systems of Table 1 is shown in Figs. 1 and 2. The MOS with 95% confidence intervals are given for four SNRs.

Fig. 1 displays the effect of predictive variance regularization and noise suppression (TN) without weight pruning and quantization. Predictive variance regularization results in a significant quality improvement and reduces the sensitivity to noise in the input signal. Noise suppression aids performance when noise is present.

Fig. 2 shows the quality for pruned and quantized systems. For this case, the improvement due to variance regularization is particularly large for clean signals. The effect of noise suppression (TN) varies in an unexpected manner with SNR. This likely results from an interaction between noise suppression and quantization. It may be related to noise suppression reducing signal variability and quantization reducing noise on its own.

As a reference, Fig. 2 provides the performance of the Opus codec [31] operating at 6 kb/s and the EVS codec [32] operating at 5.9 kb/s (for fairness with disabled DTX). It is seen that the proposed fully practical 3 kb/s WaveGRU codec performs significantly better than Opus at 6 kb/s and similarly to EVS operating at 5.9 kb/s.

6. CONCLUSION

We have developed a robust speech codec using neural-network based signal synthesis that encodes speech at 3 kb/s. Our system is suitable for, for example, low-rate video calls, and fits in consumer devices as evidenced by our implementation running on a wide range of mobile phones including the Pixel 2. Our experiments show that its quality is similar or better than state-of-the-art conventional codecs operating at double the rate. Our main contribution is that we addressed the impact of variability and distortion inherent in real-world input to practical speech codecs. We identified as causes for poor performance i) the inherent emphasis of outliers by the maximum likelihood criterion and ii) the difficulty of modeling a sum of multiple independent sources. We resolved these problems with predictive variance regularization and noise suppression.

| System label   | b      | v      | t      | vt     | q      | qv     | qt     | qvt    |
|----------------|--------|--------|--------|--------|--------|--------|--------|--------|
| var. regularization | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      |
| TasNet noise supp. | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      |
| 3 kb/s quantization | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      |
| 93% pruning | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      |
7. REFERENCES

[1] A. v. d. Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu, “Wavenet: A generative model for raw audio,” arXiv preprint arXiv:1609.03499, 2016.

[2] N. Kalchbrenner, E. Elsen, K. Simonyan, S. Noury, N. Casagrande, E. Lockhart, F. Stimberg, A. v. d. Oord, S. Dieleman, and K. Kavukcuoglu, “Efficient neural audio synthesis,” arXiv preprint arXiv:1802.08435, 2018.

[3] A. v. d. Oord, Y. Li, I. Babuschkin, K. Simonyan, O. Vinyals, K. Kavukcuoglu, G. Driessche, E. Lockhart, L. Cobo, F. Stimberg et al., “Parallel WaveNet: Fast high-fidelity speech synthesis,” in International conference on machine learning. PMLR, 2018, pp. 3918–3926.

[4] R. Prenger, R. Valle, and B. Catanzaro, “Waveglow: A flow-based generative network for speech synthesis,” in 2019 IEEE Int. Conf. Acoust Speech Signal Processing (ICASSP). IEEE, 2019, pp. 3617–3621.

[5] C. Donahue, J. McAuley, and M. Puckette, “Adversarial audio synthesis,” arXiv preprint arXiv:1802.04208, 2018.

[6] J. Engel, K. K. Agrawal, S. Chen, I. Gulrajani, C. Donahue, and A. Roberts, “GANSynth: Adversarial neural audio synthesis,” arXiv preprint arXiv:1902.08710, 2019.

[7] W. B. Kleijn, F. S. Lim, A. Luebs, J. Skoglund, F. Stimberg, Q. Wang, and T. C. Walters, “WaveNet based low rate speech coding,” in 2018 IEEE Int. Conf. Acoust Speech Signal Processing (ICASSP). IEEE, 2018, pp. 676–680.

[8] J. Klejsa, P. Hedelin, C. Zhou, R. Feijin, and L. Villemoes, “High-quality speech coding with sample RNN,” in 2019 IEEE Int. Conf. Acoust Speech Signal Processing (ICASSP). IEEE, 2019, pp. 7155–7159.

[9] C. Gárbacea, A. van den Oord, Y. Li, F. S. Lim, A. Luebs, O. Vinyals, and T. C. Walters, “Low bit-rate speech coding with VQ-VAE and a WaveNet decoder,” in 2019 IEEE Int. Conf. Acoust Speech Signal Processing (ICASSP). IEEE, 2019, pp. 735–739.

[10] J.-M. Valin and J. Skoglund, “A Real-Time Wideband Neural Vocoder at 1.6kb/s Using LPCNet,” in Proc. Interspeech 2019, 2019, pp. 3406–3410.

[11] F. S. Lim, W. B. Kleijn, M. Chinen, and J. Skoglund, “Robust low rate speech coding based on cloned networks and wavenet,” in 2020 IEEE Int. Conf. Acoust Speech Signal Processing (ICASSP). IEEE, 2020, pp. 6769–6773.

[12] R. Feijin, J. Klejsa, L. Villemoes, and C. Zhou, “Source coding of audio signals with a generative model,” in 2020 IEEE Int. Conf. Acoust Speech Signal Processing (ICASSP). IEEE, 2020, pp. 341–345.

[13] C. W. J. Granger and M. J. Morris, “Time series modelling and interpretation,” Journal of the Royal Statistical Society: Series A (General), vol. 139, no. 2, pp. 246–257, 1976.

[14] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in Advances in neural information processing systems, 2014, pp. 2672–2680.

[15] S. Nowozin, B. Cseke, and R. Tomioka, “f-GAN: Training generative neural samplers using variational divergence minimization,” in Advances in neural information processing systems, 2016, pp. 271–279.

[16] M. Arjovsky, S. Chintala, and L. Bottou, “Wasserstein GAN,” arXiv preprint arXiv:1701.07875, 2017.

[17] Y. Li, K. Swersky, and R. Zemel, “Generative moment matching networks,” in International Conference on Machine Learning, 2015, pp. 1718–1727.

[18] C.-L. Li, W.-C. Chang, Y. Cheng, Y. Yang, and B. Póczos, “MMD GAN: Towards deeper understanding of moment matching network,” in Advances in Neural Information Processing Systems, 2017, pp. 2203–2213.

[19] S. Kim, S.-g. Lee, J. Song, J. Kim, and S. Yoon, “FloWaveNet: A generative flow for raw audio,” arXiv preprint arXiv:1811.02155, 2018.

[20] Y. Luo and N. Mesgarani, “Conv-TasNet: Surpassing ideal time–frequency magnitude masking for speech separation,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 27, no. 8, pp. 1256–1266, 2019.

[21] S. Sonning, C. Schüldt, H. Erdogan, and S. Wisdom, “Performance study of a convolutional time-domain audio separation network for real-time speech denoising,” in 2020 IEEE Int. Conf. Acoust Speech Signal Processing (ICASSP). IEEE, 2020, pp. 831–835.

[22] D. O’Shaughnessy, Speech Communications: Human And Machine (IEEE). Universities press, 1987.

[23] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, “Empirical evaluation of gated recurrent neural networks on sequence modeling,” arXiv preprint arXiv:1412.3555, 2014.

[24] J. S. Garofolo, D. Graff, D. Paul, and D. Pallett, “CSR-I (WSJ0) Other,” Other. Harvard Dataverse, Tech. Rep., 2016. [Online]. Available: https://doi.org/10.7910/DVN/ZVU9HF.

[25] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “Librispeech: an ASR corpus based on public domain audio books,” in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2015, pp. 5206–5210.

[26] R. Ardila et al., “Common voice: A massively-multilingual speech corpus,” arXiv preprint arXiv:1912.06670, 2019.

[27] E. Fonseca, J. Pons, X. Favory, F. Font, D. Bogdanov, A. Ferraro, S. Oramas, A. Porter, and X. Serra, “Freesound datasets: a platform for the creation of open audio datasets,” in Proc. 18th Int. Society Music Information Retrieval Conference (ISMIR 2017), Suzhou, China, 2017, pp. 486–493.

[28] M. Zhu and S. Gupta, “To prune, or not to prune: exploring the efficacy of pruning for model compression,” arXiv preprint arXiv:1710.01878, 2017.

[29] Recommendation ITU-T P.800 Methods for subjective determination of transmission quality, ITU-T Std., Aug 1996.

[30] C. Valentini-Botinhao, “Noisy speech database for training speech enhancement algorithms and its models,” University of Edinburgh. School of Informatics. Centre for Speech Technology Research (CSTR), Tech. Rep., 2016.

[31] J. M. Valin, K. Vos, and T. Terriberry, Definition of the Opus Audio Codec, IETF Std., Sept 2012, RFC: 6717.

[32] C. Dietz et al., “Overview of the EVS codec architecture,” in 2015 IEEE Int. Conf. Acoust Speech Signal Processing (ICASSP). IEEE, 2015, pp. 5698–5702.