Learning Latent Representations for Speech Generation and Transformation

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Interspeech 2017
What to Expect in This Talk

1. A convolutional variational autoencoder framework to model a generative process of speech
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2. A method to associate learned latent representations with physical attributes, such as speaker identity and linguistic content
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1. A convolutional variational autoencoder framework to model a generative process of speech
2. A method to associate learned latent representations with physical attributes, such as speaker identity and linguistic content
3. Simple latent space arithmetic operations to modify speech attributes
Outline

1. Motivation
2. Background and Models
3. Latent Attribute Representations and Operations
4. Experiments
5. Conclusion
Motivation

• We want to learn a generative process of speech
  1. What are the factors that affect speech generation?
  2. How do these factors play a role in speech generation?
  3. How can we infer these factors from observed speech?
Motivation

• We want to learn a generative process of speech
  1. What are the factors that affect speech generation?
  2. How do these factors play a role in speech generation?
  3. How can we infer these factors from observed speech?

• Why do we want to learn a generative process?
  • Synthesis (1, 2)
  • Recognition and verification (3)
  • Voice conversion and denoising (1, 2, 3)
1. Motivations
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Generative Model Backgrounds

• “Shallow” generative models
  • Hidden Markov model-Gaussian mixture models (HMM-GMMs)

• “Deep” generative models
  • Generative adversarial networks (GANs)
    • model $p(x|z)$ and bypass the inference model (generator / discriminator)
  • Auto-regressive models (e.g. WaveNets)
    • model $p(x_t|x_{1:t-1})$ and abstain from using latent variables
  • Variational autoencoders (VAEs)
    • learn an inference model and a generative model jointly
Variational Autoencoders (VAEs)

• Define a probabilistic generative process between observation $x$ and latent variable $z$
  • $p(z)$, $p(x|z)$, and $q(z|x)$ are defined to be in some parametric family
• We define $p(x|z)$ (decoder) and $q(z|x)$ (encoder) to be diagonal Gaussians
  • Parameters (mean and variance) are described using some NN
• $p(z)$ is defined to be isotropic Gaussian with unit variance
Convolutional Neural Network Architecture

Encoder

Decoder

Conv1  Conv2  Conv3  FC1  Gauss  Sample  FC2  FC3  T-conv1  T-conv2  T-conv3 (Gauss)

$F$

$x$

$q(z|x)$

$z$

$p(x|z)$

$\mu_z$

$\sigma_z$

$\mu_x$

$\sigma_x$

*T-conv stands for transposed convolution
Experiment Setup

- Dataset: TIMIT (5.4hr) (standard 462 speaker sx/si training set)
- Speech Segment Dimension:
  - Unsupervised training (i.e., no use of phonetic transcription)
  - $T = 20$ frames (with shift of 8 frames)
  - $F = 80$ (FBank) or 200 (Log Magnitude Spectrogram)
- Training Objective: Variational Lower Bound
- Optimizer: Adam
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5. Audio Demo
6. Conclusion
Speech Reconstruction Illustration

- The trained VAE is able to reconstruct speech segments
- Examples from 10 instances of /aa/, /sh/, and /p/ (sampled at center of segment)
Latent Attribute Representations

- VAE is encouraged to model independent factors using different dimensions
  - Because the prior is assumed to be a diagonal Gaussian
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  • Because the prior is assumed to be a diagonal Gaussian
• We want to associate physical attributes with some dimensions
Latent Attribute Representations

- VAE is encouraged to model independent factors using different dimensions
  - Because the prior is assumed to be a diagonal Gaussian
- We want to associate particular dimensions with different physical attributes
Latent Attribute Representations

- Factors have normal distributions along their associated dimensions
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- For example, if we want to estimate the latent phone representation for /aa/:
Latent Attribute Representations

- Factors have normal distributions along their associated dimensions.
- For example, if we want to estimate the latent phone representation for /aa/:
  - We can estimate latent attribute by taking the mean latent representations.

Speaker A:

| /aa/ | -0.7 | 0.3 | -0.2 | 1.5 | 0.4 |

Speaker B:

| /aa/ | 1.1 | -0.4 | -0.2 | 1.5 | 0.4 |

Speaker C:

| /aa/ | 0.4 | 0.1 | -0.2 | 1.5 | 0.4 |

Average:

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Empirical Study of the Assumptions

- We compute latent attribute representations of two attributes:

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![Heatmap Diagram]
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• We compute latent attribute representations of two attributes:
• Compute the absolute cosine similarity between latent attribute representations
Arithmetic Operations to Modify Attributes

• The result suggests that we can modify a specific attribute without altering the others
  • Suppose we want to convert the voice from speaker A (light blue) to speaker B (dark blue)
  • We can do the following operations:
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Magnitude Spectrogram Reconstruction

- **Griffin and Lim algorithm** is used for waveform reconstruction
  - Iteratively estimate phase
Modify the Phoneme

- Modify /aa/ to /ae/, F2 goes up (back vowel -> front vowel)
Modify the Phoneme

- Modify /s/ to /sh/, cutoff goes down (alveolar -> palatal strident)
Modify the Speaker

- Modify a female to a male, pitch decreases
Modify the Speaker

- Modify a male to a female, pitch increases
Modify the Speaker for An Entire Utterance

- We choose an utterance from a male speaker (madc0)
  - Modify to another male speaker (mabc0), and a female speaker (fajw0)
- Each speaker has only 8 utterances in the set
  - ~4s/utterances
- Estimate the latent speaker representation using only 30s of speech
Modify the Speaker for An Entire Utterance

Original Speaker
(top) original spectrogram, (bottom) reconstructed spectrogram
Modify the Speaker for An Entire Utterance

Convert to Speaker mabc0
(top) original spectrogram, (bottom) modified spectrogram
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Convert to Speaker fajw0
(top) original spectrogram, (bottom) modified spectrogram
Quantitative Evaluation

• We train **discriminators for phone classification and speaker classification**

• **Posteriors** as the quantitative metric
  • Discriminators’ mean opinion score on the two attributes
  • Posterior of target attribute increases; posterior of source attribute decreases
  • Posteriors of irrelevant attributes unchanged
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• We present a CNN-VAE to model generation process of speech segments.
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• We demonstrate qualitatively and quantitatively the ability to modify speech attributes.
• We have applied the modification operation to data augmentation for ASR and achieved significant improvement for domain adaptation. (submitted to ASRU)
• For future work, we plan to investigate the use of VAE on voice conversion and speech de-noising under the setting of no parallel training data.
Thanks for Listening.
Q&A?

Paper, slides, samples and follow-up works can be found on
http://people.csail.mit.edu/wnhsu/