Generative Model-Based Text-to-Speech Synthesis

Heiga Zen (Google London)

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Outline

Generative TTS

Generative acoustic models for parametric TTS

- Hidden Markov models (HMMs)
- Neural networks

Beyond parametric TTS

- Learned features
- WaveNet
- End-to-end

Conclusion & future topics

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Conclusion & future topics

Text-to-speech as sequence-to-sequence mapping

Automatic speech recognition (ASR)

 → “Hello my name is Heiga Zen”

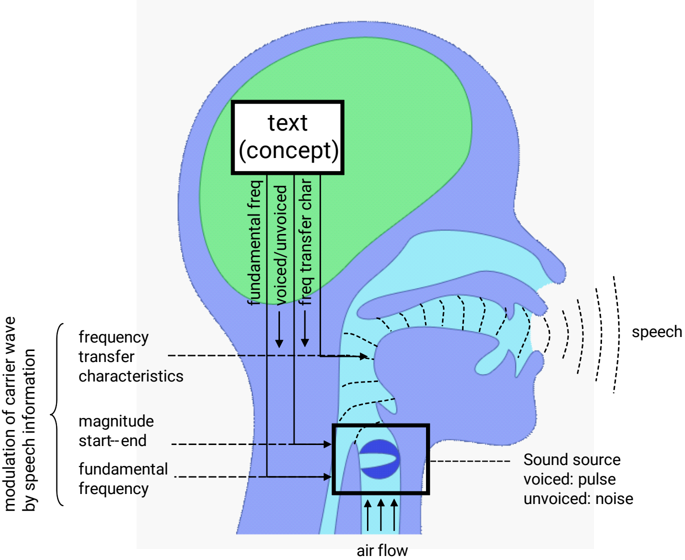
Machine translation (MT)

“Hello my name is Heiga Zen” → “Ich heiße Heiga Zen”

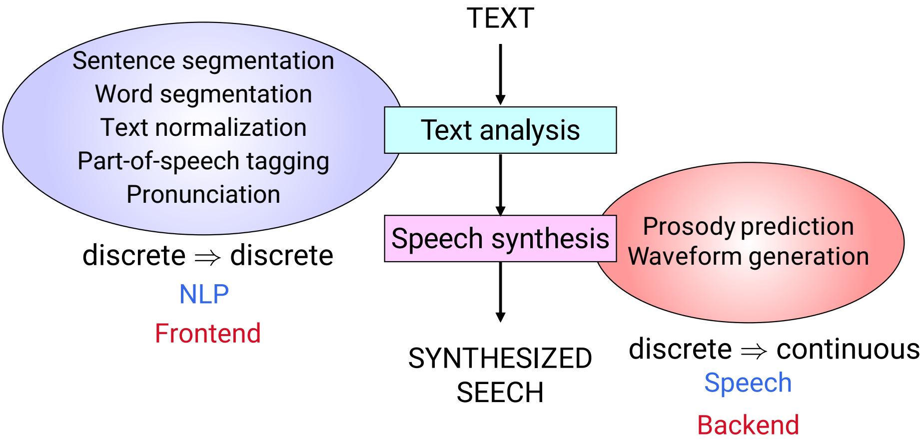
Text-to-speech synthesis (TTS)

“Hello my name is Heiga Zen” → 

Speech production process

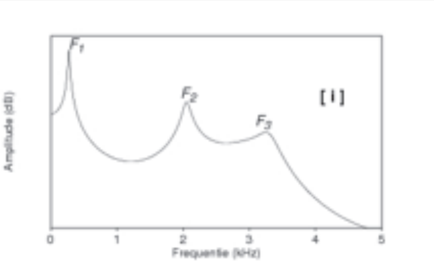


Typical flow of TTS system



Speech synthesis approaches

Rule-based, formant synthesis [1]



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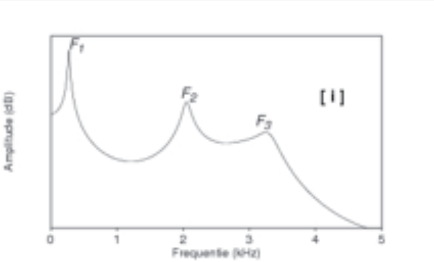
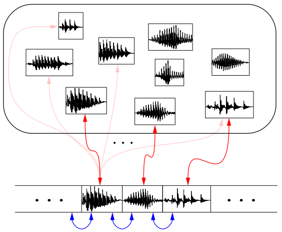


Sample-based, concatenative synthesis [2]



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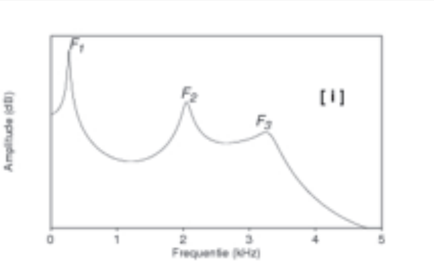

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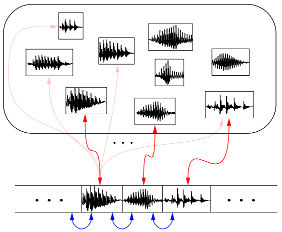
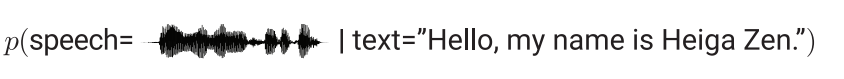


Model-based, generative synthesis



Probabilistic formulation of TTS

Random variables

$\mathcal{X}$	Speech waveforms (data)	Observed
$\mathcal{W}$	Transcriptions (data)	Observed
w	Given text	Observed
x	Synthesized speech	Unobserved

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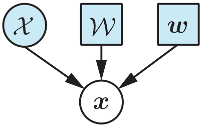
$\mathcal{W}$	Transcriptions (data)	Observed
$\boldsymbol{w}$	Given text	Observed
$\boldsymbol{x}$	Synthesized speech	Unobserved

Synthesis

- Estimate posterior predictive distribution
  $\rightarrow p(\boldsymbol{x} \mid \boldsymbol{w}, \mathcal{X}, \mathcal{W})$
- Sample $\bar{\boldsymbol{x}}$ from the posterior distribution



Probabilistic formulation

Introduce auxiliary variables (*representation*) + factorize dependency

$$p(\boldsymbol{x} \mid \boldsymbol{w}, \mathcal{X}, \mathcal{W}) = \iiint \sum_{\forall \boldsymbol{l}} \sum_{\forall \mathcal{L}} \{ p(\boldsymbol{x} \mid \boldsymbol{o}) p(\boldsymbol{o} \mid \boldsymbol{l}, \lambda) p(\boldsymbol{l} \mid \boldsymbol{w})$$

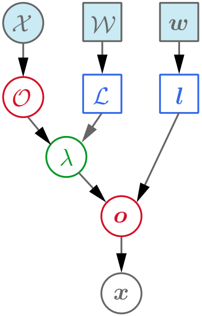
$$p(\mathcal{X} \mid \mathcal{O}) p(\mathcal{O} \mid \mathcal{L}, \lambda) p(\lambda) p(\mathcal{L} \mid \mathcal{W}) / \, p(\mathcal{X}) \} d\boldsymbol{o} d\mathcal{O} d\lambda$$

where

$\mathcal{O}, \boldsymbol{o}$: *Acoustic features*

$\mathcal{L}, \boldsymbol{l}$: *Linguistic features*

λ: *Model*



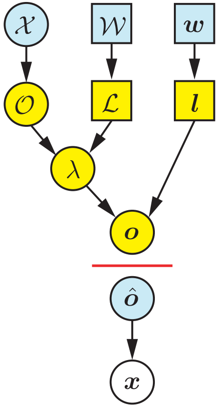
Approximation (1)

Approximate {sum & integral} by best point estimates (like MAP) [3]

$$p(\boldsymbol{x} \mid \boldsymbol{w}, \mathcal{X}, \mathcal{W}) \approx p(\boldsymbol{x} \mid \hat{\boldsymbol{o}})$$

where

$$\{\hat{\boldsymbol{o}}, \hat{\boldsymbol{l}}, \hat{\mathcal{O}}, \hat{\mathcal{L}}, \hat{\lambda}\} = \arg\max_{\boldsymbol{o}, \boldsymbol{l}, \mathcal{O}, \mathcal{L}, \lambda} \{ p(\boldsymbol{x} \mid \boldsymbol{o}) p(\boldsymbol{o} \mid \boldsymbol{l}, \lambda) p(\boldsymbol{l} \mid \boldsymbol{w}) p(\mathcal{X} \mid \mathcal{O}) p(\mathcal{O} \mid \mathcal{L}, \lambda) p(\lambda) p(\mathcal{L} \mid \mathcal{W}) \}$$



Approximation (2)

Joint $\rightarrow$ Step-by-step maximization [3]

$$\hat{\mathcal{O}} = \arg\max_{\mathcal{O}} p(\mathcal{X} \mid \mathcal{O})$$ Extract *acoustic features*

$$\hat{\mathcal{L}} = \arg\max_{\mathcal{L}} p(\mathcal{L} \mid \mathcal{W})$$ Extract *linguistic features*

$$\hat{\lambda} = \arg\max_{\lambda} p(\hat{\mathcal{O}} \mid \hat{\mathcal{L}}, \lambda) p(\lambda)$$ Learn *mapping*

$$\hat{\boldsymbol{l}} = \arg\max_{\boldsymbol{l}} p(\boldsymbol{l} \mid \boldsymbol{w})$$ Predict *linguistic features*

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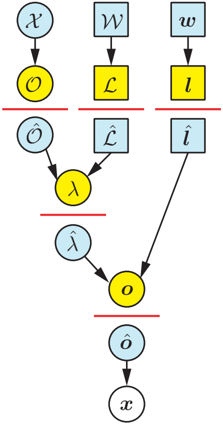
$$\bar{\boldsymbol{x}} \sim f_{\boldsymbol{x}}(\hat{\boldsymbol{o}}) = p(\boldsymbol{x} \mid \hat{\boldsymbol{o}})$$ Synthesize waveform



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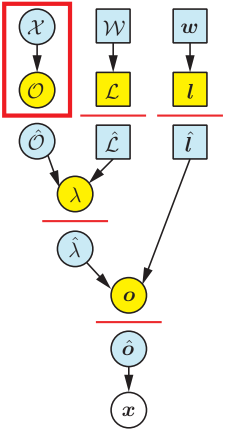

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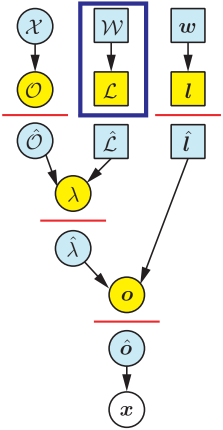

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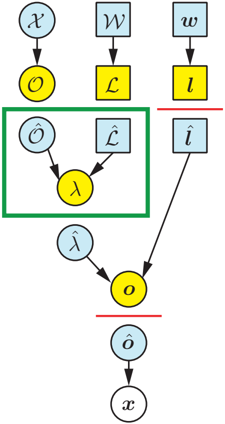

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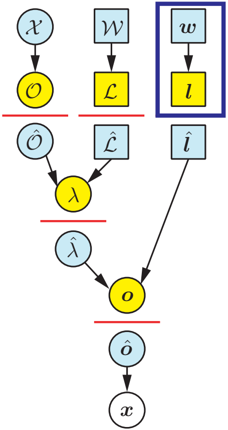

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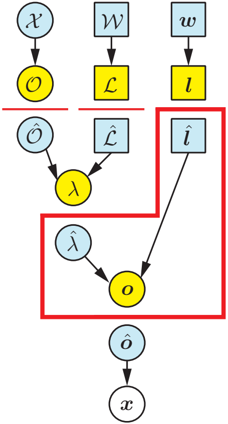

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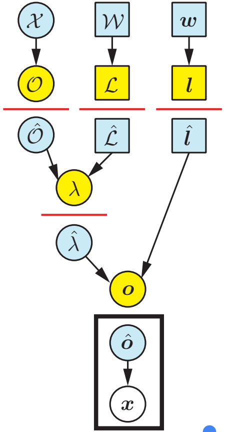

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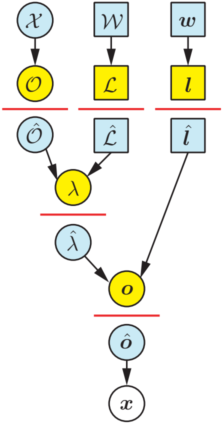
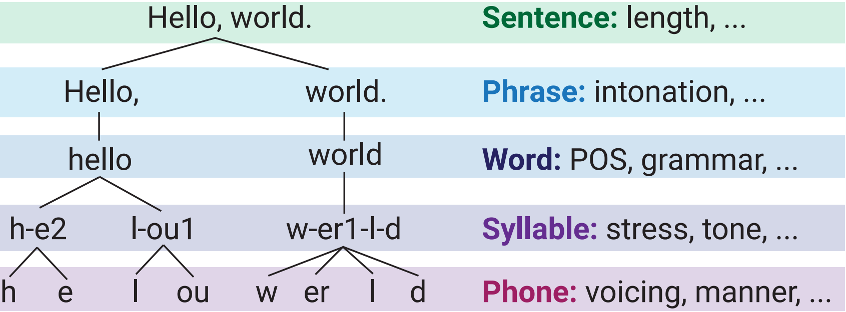


Representations: acoustic, linguistic, mapping

Representation – Linguistic features



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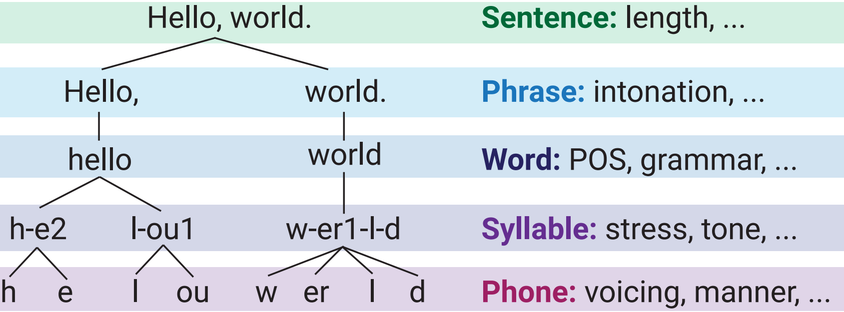
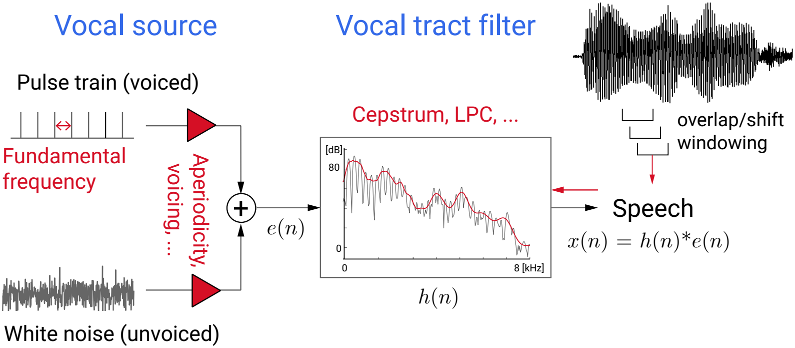


→ Based on knowledge about spoken language

- Lexicon, letter-to-sound rules
- Tokenizer, tagger, parser
- Phonology rules

Representation – Acoustic features

Piece-wise stationary, source-filter generative model $p(x \mid o)$



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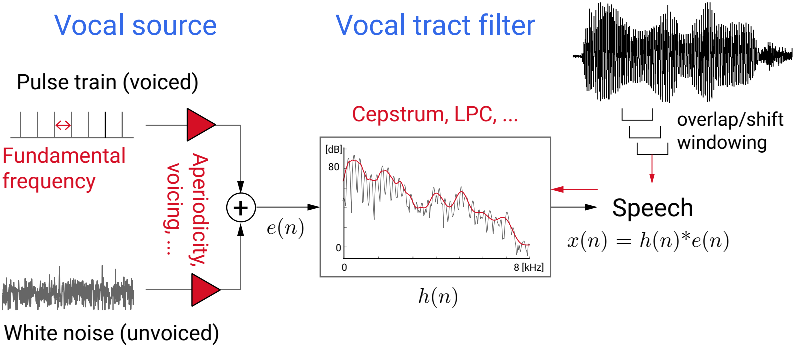

$\rightarrow$ Needs to solve inverse problem

- Estimate parameters from signals
- Use estimated parameters (e.g., cepstrum) as acoustic features

Representation – Mapping

Rule-based, formant synthesis [1]

$$\hat{\mathcal{O}} = \arg\max_{\mathcal{O}} p(\mathcal{X} \mid \mathcal{O})$$ Vocoder analysis

$$\hat{\mathcal{L}} = \arg\max_{\mathcal{L}} p(\mathcal{L} \mid \mathcal{W})$$ Text analysis

$$\hat{\lambda} = \arg\max_{\lambda} p(\hat{\mathcal{O}} \mid \hat{\mathcal{L}}, \lambda) p(\lambda)$$ ***Extract rules***

$$\hat{\boldsymbol{l}} = \arg\max_{\boldsymbol{l}} p(\boldsymbol{l} \mid \boldsymbol{w})$$ Text analysis

$$\hat{\boldsymbol{o}} = \arg\max_{\boldsymbol{o}} p(\boldsymbol{o} \mid \hat{\boldsymbol{l}}, \hat{\lambda})$$ ***Apply rules***

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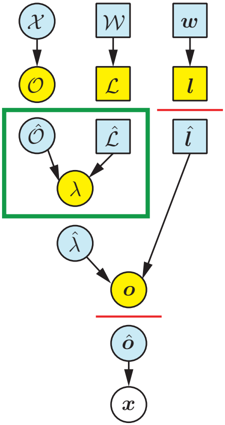

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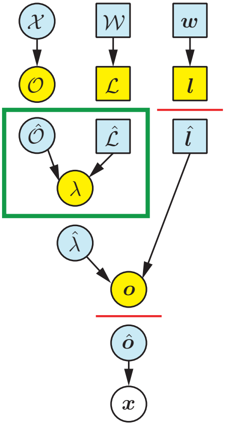

$\rightarrow$ Hand-crafted rules on knowledge-based features

Representation – Mapping

HMM-based [4], statistical parametric synthesis [5]

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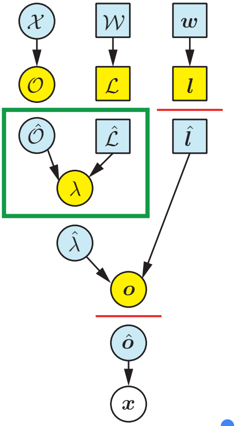

Representation – Mapping

HMM-based [4], statistical parametric synthesis [5]

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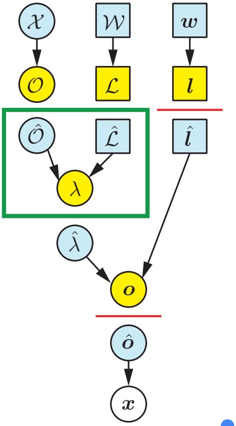

$\rightarrow$ Replace rules by HMM-based generative acoustic model

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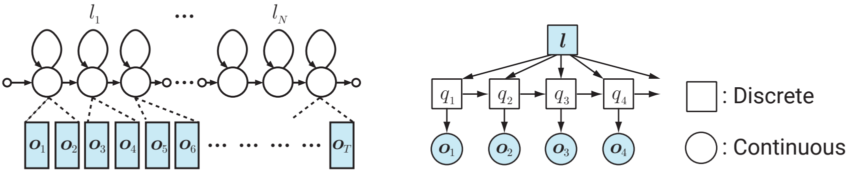
Conclusion & future topics

HMM-based generative acoustic model for TTS

- Context-dependent subword HMMs
- Decision trees to cluster & tie HMM states $\rightarrow$ *interpretable*



$$p(\boldsymbol{o} \mid \boldsymbol{l}, \lambda) = \sum_{\forall \boldsymbol{q}} \prod_{t=1}^{T} p(\boldsymbol{o}_t \mid q_t, \lambda) P(\boldsymbol{q} \mid \boldsymbol{l}, \lambda)$$

q_t: hidden state at t

$$= \sum_{\forall \boldsymbol{q}} \prod_{t=1}^{T} \mathcal{N}(\boldsymbol{o}_t; \boldsymbol{\mu}_{q_t}, \boldsymbol{\Sigma}_{q_t}) P(\boldsymbol{q} \mid \boldsymbol{l}, \lambda)$$

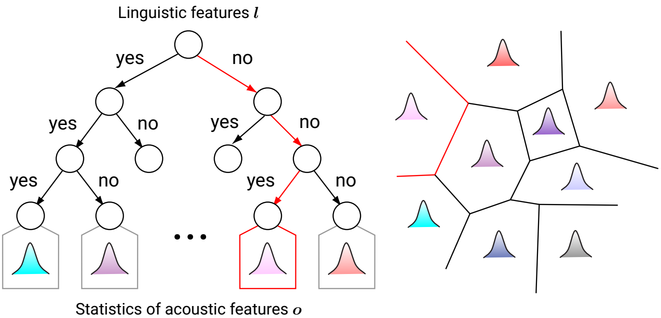
HMM-based generative acoustic model for TTS

- Non-smooth, step-wise statistics
  $\rightarrow$ Smoothing is essential
- Difficult to use high-dimensional acoustic features (e.g., raw spectra)
  $\rightarrow$ Use low-dimensional features (e.g., cepstra)
- Data fragmentation
  $\rightarrow$ Ineffective, local representation

A lot of research work have been done to address these issues

Alternative acoustic model

HMM: Handle variable length & alignment
Decision tree: Map linguistic → acoustic



Regression tree: linguistic features → Stats. of acoustic features

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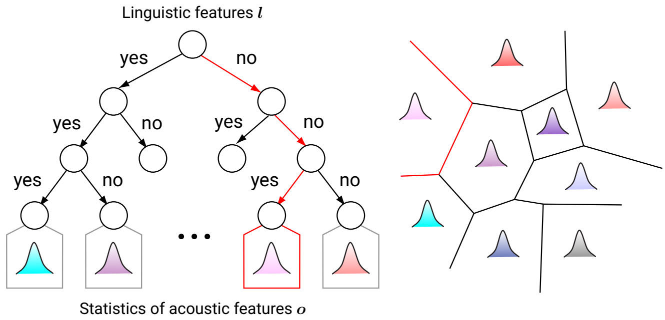
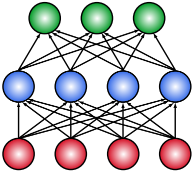
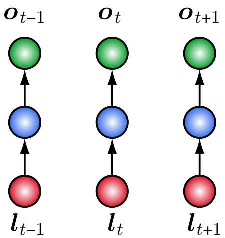


Regression tree: linguistic features $\rightarrow$ Stats. of acoustic features

Replace the tree w/ a general-purpose regression model
$\rightarrow$ **Artificial neural network**

FFNN-based acoustic model for TTS [6]



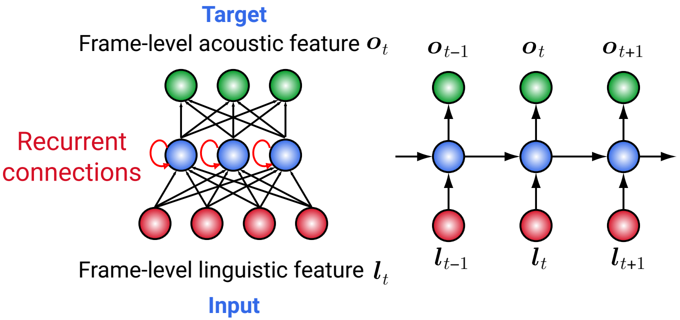


$$\boldsymbol{h}_t = g\left(\boldsymbol{W}_{hl}\boldsymbol{l}_t + \boldsymbol{b}_h\right) \qquad \hat{\lambda} = \arg\min_{\lambda} \sum_t \|\boldsymbol{o}_t - \hat{\boldsymbol{o}}_t\|_2$$

$$\hat{\boldsymbol{o}}_t = \boldsymbol{W}_{oh}\boldsymbol{h}_t + \boldsymbol{b}_o \qquad \lambda = \{\boldsymbol{W}_{hl}, \boldsymbol{W}_{oh}, \boldsymbol{b}_h, \boldsymbol{b}_o\}$$

$\hat{\boldsymbol{o}}_t \approx \mathbb{E}\left[\boldsymbol{o}_t \mid \boldsymbol{l}_t\right] \rightarrow$ Replace decision trees & Gaussian distributions

RNN-based acoustic model for TTS [7]



$$\boldsymbol{h}_t = g\left(\boldsymbol{W}_{hl}\boldsymbol{l}_t + \boldsymbol{W}_{hh}\boldsymbol{h}_{t-1} + \boldsymbol{b}_h\right) \qquad \hat{\lambda} = \arg\min_{\lambda} \sum_t \|\boldsymbol{o}_t - \hat{\boldsymbol{o}}_t\|_2$$

$$\hat{\boldsymbol{o}}_t = \boldsymbol{W}_{oh}\boldsymbol{h}_t + \boldsymbol{b}_o \qquad \lambda = \{\boldsymbol{W}_{hl}, \boldsymbol{W}_{hh}, \boldsymbol{W}_{oh}, \boldsymbol{b}_h, \boldsymbol{b}_o\}$$

FFNN: $\hat{\boldsymbol{o}}_t \approx \mathbb{E}\left[\boldsymbol{o}_t \mid \boldsymbol{l}_t\right]$ RNN: $\hat{\boldsymbol{o}}_t \approx \mathbb{E}\left[\boldsymbol{o}_t \mid \boldsymbol{l}_1, \ldots, \boldsymbol{l}_t\right]$

NN-based generative acoustic model for TTS

- Non-smooth, step-wise statistics
  $\rightarrow$ RNN predicts smoothly varying acoustic features [7, 8]
- Difficult to use high-dimensional acoustic features (e.g., raw spectra)
  $\rightarrow$ Layered architecture can handle high-dimensional features [9]
- Data fragmentation
  $\rightarrow$ Distributed representation [10]

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  $\rightarrow$ Distributed representation [10]

NN-based approach is now mainstream in research & products

- Models: FFNN [6], MDN [11], RNN [7], Highway network [12], GAN [13]
- Products: e.g., Google [14]

Outline

Generative TTS

Generative acoustic models for parametric TTS

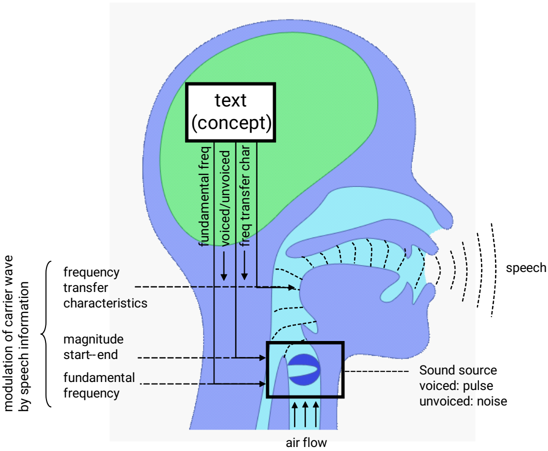
- Hidden Markov models (HMMs)
- Neural networks

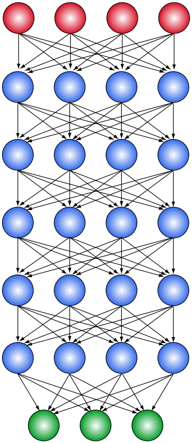
Beyond parametric TTS

- Learned features
- WaveNet
- End-to-end

Conclusion & future topics

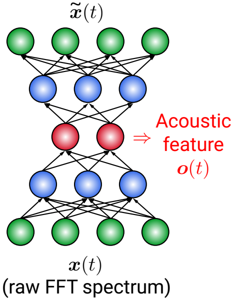
NN-based generative model for TTS

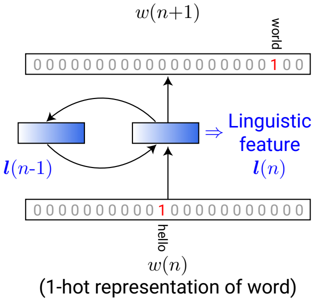




Text → Linguistic → (Articulatory) → Acoustic → Waveform

Unsupervised feature learning





- Speech: auto-encoder at FFT spectra [9, 15] $\rightarrow$ positive results
- Text: word [16], phone & syllable [17] $\rightarrow$ less positive

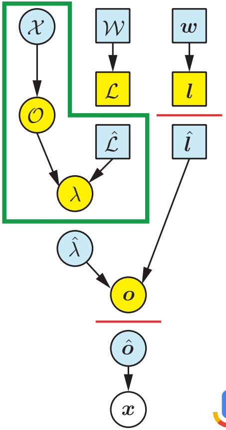
Relax approximation
Joint acoustic feature extraction & model training

Two-step optimization $\rightarrow$ Joint optimization

$$\begin{cases} \hat{\mathcal{O}} = \arg\max_{\mathcal{O}} p(\mathcal{X} \mid \mathcal{O}) \\ \hat{\lambda} = \arg\max_{\lambda} p(\hat{\mathcal{O}} \mid \hat{\mathcal{L}}, \lambda) p(\lambda) \end{cases}$$

$$\Downarrow$$

$$\{\hat{\lambda}, \hat{\mathcal{O}}\} = \arg\max_{\lambda, \mathcal{O}} p(\mathcal{X} \mid \mathcal{O}) p(\mathcal{O} \mid \hat{\mathcal{L}}, \lambda) p(\lambda)$$



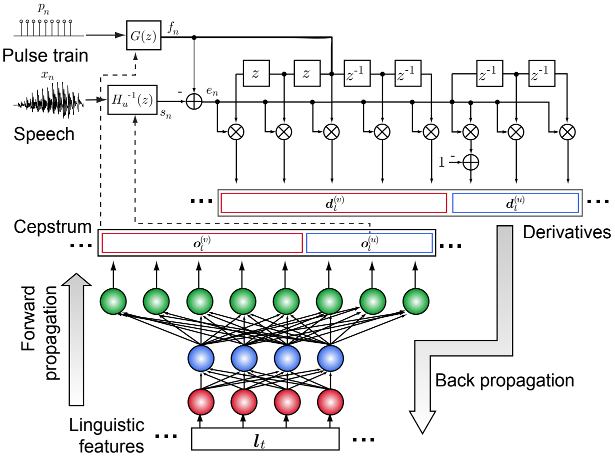
Joint source-filter & acoustic model optimization

- HMM [18, 19, 20]
- NN [21, 22]

Relax approximation

Joint acoustic feature extracion & model training

Mixed-phase cepstral analysis + LSTM-RNN [22]



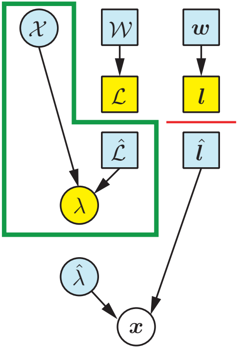
Relax approximation
Direct mapping from linguistic to waveform

No explicit acoustic features

$$\{\hat{\lambda}, \hat{\mathcal{O}}\} = \arg\max_{\lambda, \mathcal{O}} p(\mathcal{X} \mid \mathcal{O}) p(\mathcal{O} \mid \hat{\mathcal{L}}, \lambda) p(\lambda)$$

$$\Downarrow$$

$$\hat{\lambda} = \arg\max_{\lambda} p(\mathcal{X} \mid \hat{\mathcal{L}}, \lambda) p(\lambda)$$



Generative models for raw audio

- LPC [23]
- WaveNet [24]
- SampleRNN [25]

WaveNet: A generative model for raw audio

Autoregressive (AR) modelling of speech signals

$$\boldsymbol{x} = \{x_0, x_1, \dots, x_{N-1}\} \quad \text{: raw waveform}$$

$$p(\boldsymbol{x} \mid \lambda) = p(x_0, x_1, \dots, x_{N-1} \mid \lambda) = \prod_{n=0}^{N-1} p(x_n \mid x_0, \dots, x_{n-1,} \lambda)$$

WaveNet: A generative model for raw audio

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WaveNet [24]

$\rightarrow p(x_n \mid x_0, \dots, x_{n-1}, \lambda)$ is modeled by *convolutional NN*

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WaveNet [24]

$\rightarrow p(x_n \mid x_0, \ldots, x_{n-1}, \lambda)$ is modeled by *convolutional NN*

Key components

- *Causal dilated convolution*: capture long-term dependency
- *Gated convolution + residual + skip*: powerful non-linearity
- *Softmax at output*: classification rather than regression

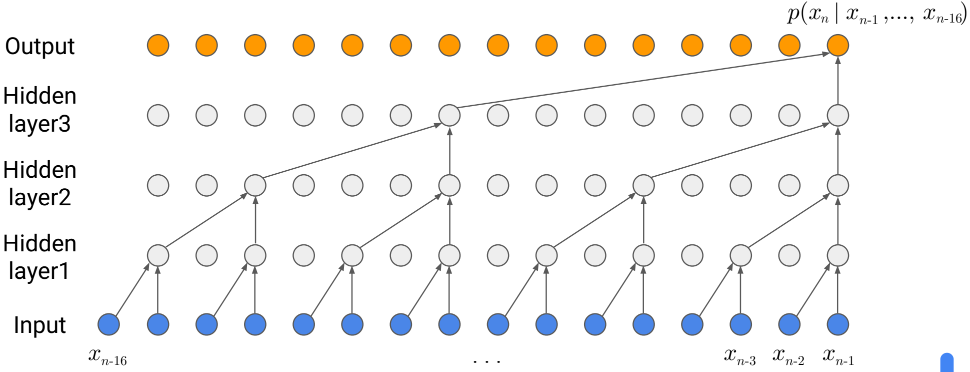
WaveNet – Causal dilated convolution

100ms in 16kHz sampling = 1,600 time steps

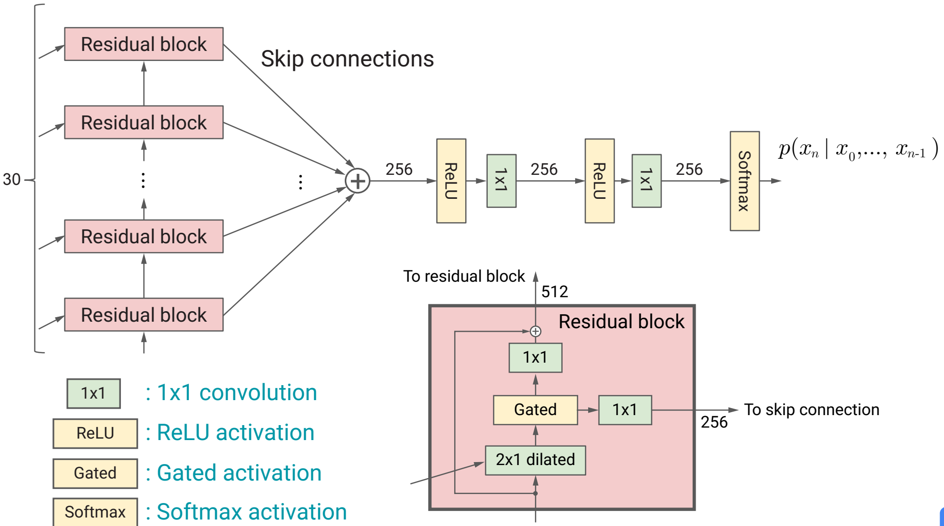
$\rightarrow$ Too long to be captured by normal RNN/LSTM

Dilated convolution

Exponentially increase receptive field size w.r.t. # of layers



WaveNet – Non-linearity

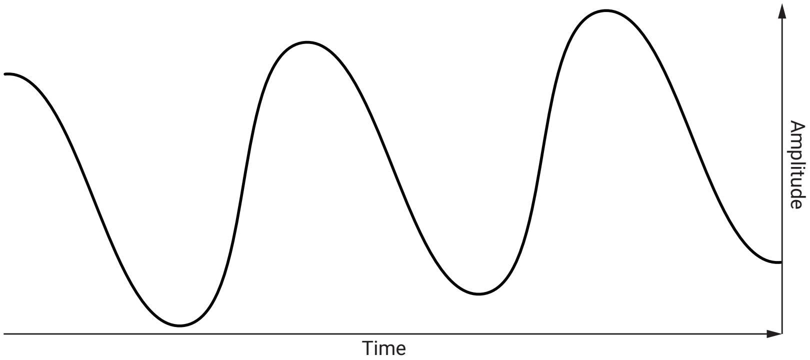


1x1 : 1x1 convolution

ReLU : ReLU activation

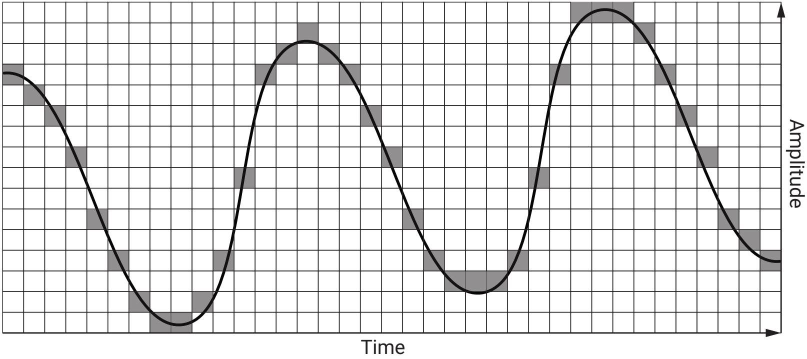
Gated : Gated activation

Softmax : Softmax activation



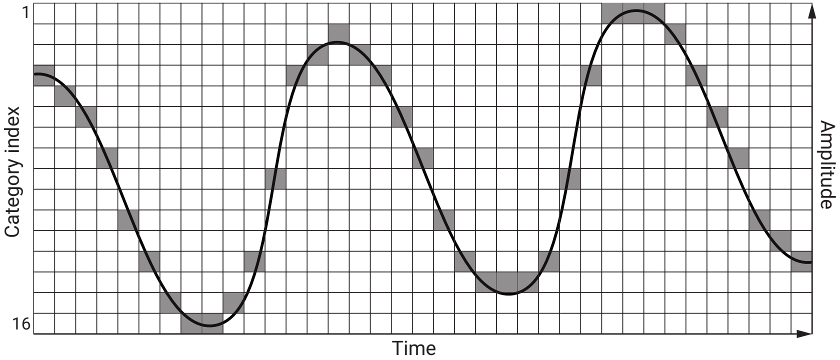
Analog audio signal

WaveNet – Softmax



Sampling & Quantization

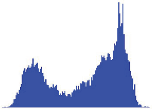
WaveNet – Softmax



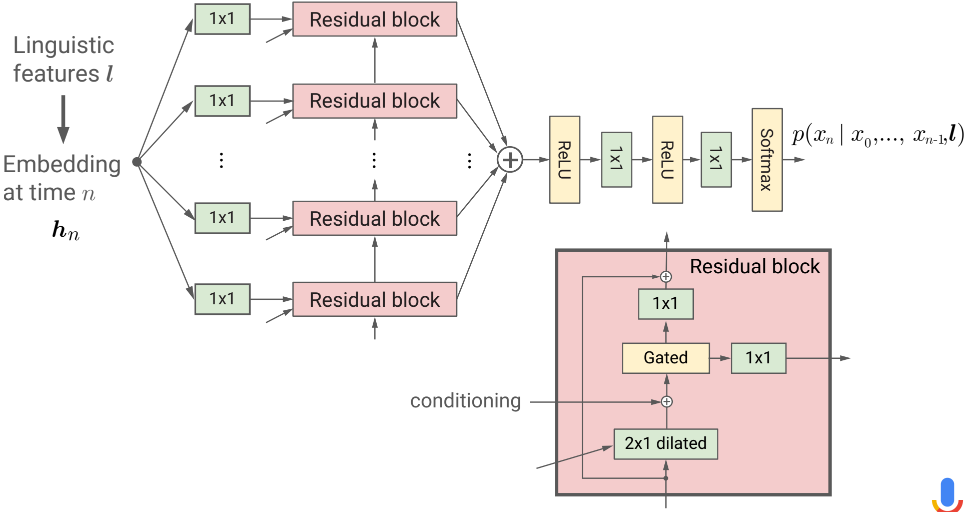
Categorical distribution → Histogram

- Unimodal
- Multimodal
- Skewed

...



WaveNet – Conditional modelling



WaveNet vs conventional audio generative models

Assumptions in conventional audio generative models [23, 26, 27, 22]

- Stationary process w/ fixed-length analysis window
  $\rightarrow$ Estimate model within 20–30ms window w/ 5–10 shift
- Linear, time-invariant filter within a frame
  $\rightarrow$ Relationship between samples can be non-linear
- Gaussian process
  $\rightarrow$ Assumes speech signals are normally distributed

WaveNet

- Sample-by-saple, non-linear, capable to take additional inputs
- Arbitrary-shaped signal distribution

SOTA subjective naturalness w/ WaveNet-based TTS [24]

HMM LSTM Concatenative WaveNet

Relax approximation
Towards Bayesian end-to-end TTS

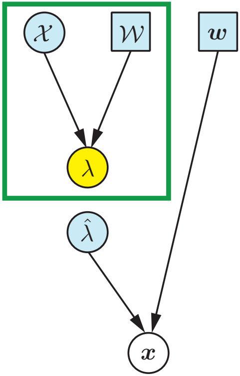
Integrated end-to-end

$$\begin{cases} \hat{\mathcal{L}} = \arg\max_{\mathcal{L}} p(\mathcal{L} \mid \mathcal{W}) \\ \hat{\lambda} = \arg\max_{\lambda} p(\mathcal{X} \mid \hat{\mathcal{L}}, \lambda) p(\lambda) \end{cases}$$

$$\Downarrow$$

$$\hat{\lambda} = \arg\max_{\lambda} p(\mathcal{X} \mid \mathcal{W}, \lambda) p(\lambda)$$

Text analysis is integrated to model



Relax approximation

Towards Bayesian end-to-end TTS

Bayesian end-to-end

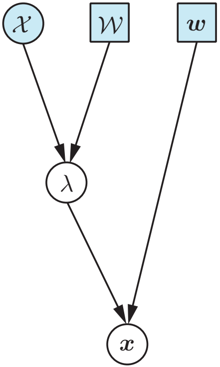
$$\begin{cases} \hat{\lambda} = \arg\max_{\lambda} p(\mathcal{X} \mid \mathcal{W}, \lambda) p(\lambda) \\ \bar{\boldsymbol{x}} \sim f_{\boldsymbol{x}}(\boldsymbol{w}, \hat{\lambda}) = p(\boldsymbol{x} \mid \boldsymbol{w}, \hat{\lambda}) \end{cases}$$

$$\Downarrow$$

$$\bar{\boldsymbol{x}} \sim f_{\boldsymbol{x}}(\boldsymbol{w}, \mathcal{X}, \mathcal{W}) = p(\boldsymbol{x} \mid \boldsymbol{w}, \mathcal{X}, \mathcal{W})$$

$$= \int p(\boldsymbol{x} \mid \boldsymbol{w}, \lambda) p(\lambda \mid \mathcal{X}, \mathcal{W}) d\lambda$$

$$\approx \frac{1}{K} \sum_{k=1}^{K} p(\boldsymbol{x} \mid \boldsymbol{w}, \hat{\lambda}_k) \quad \leftarrow \text{Ensemble}$$



Marginalize model parameters & architecture

Outline

Generative TTS

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- Hidden Markov models (HMMs)
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Beyond parametric TTS

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- End-to-end

Conclusion & future topics

Generative model-based text-to-speech synthesis

- Bayes formulation + factorization + approximations
- Representation: *acoustic features*, *linguistic features*, *mapping*
  - Mapping: Rules $\rightarrow$ HMM $\rightarrow$ NN
  - Feature: Engineered $\rightarrow$ Unsupervised, learned
- Less approximations
  - Joint training, direct waveform modelling
  - Moving towards integrated & Bayesian end-to-end TTS

Naturalness: Concatenative $\leq$ *Generative*

Flexibility: Concatenative $\ll$ *Generative* (e.g., multiple speakers)

Beyond “text”-to-speech synthesis

TTS on conversational assistants

- Texts aren’t fully contained
- Need more context
  - Location to resolve homographs
  - User query to put right emphasis

Beyond “text”-to-speech synthesis

TTS on conversational assistants

- Texts aren’t fully contained
- Need more context
  - Location to resolve homographs
  - User query to put right emphasis

We need representation that can

organize the world information & make it accessible & useful

from TTS generative models ☺

Beyond "generative" TTS

Generative model-based TTS

- Model represents process behind speech production
  - Trained to minimize error against human-produced speech
  - Learned model $\rightarrow$ ***speaker***

Beyond “generative” TTS

Generative model-based TTS

- Model represents process behind speech production
  - Trained to minimize error against human-produced speech
  - Learned model $\rightarrow$ ***speaker***

- Speech is for communication
  - Goal: maximize the amount of information to be received

Missing “listener”

$\rightarrow$ “listener” in training / model itself?

Thanks!

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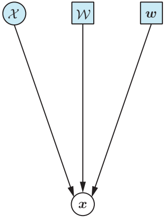
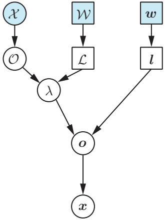
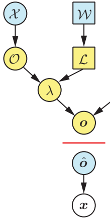


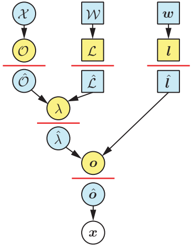
(1) Bayesian



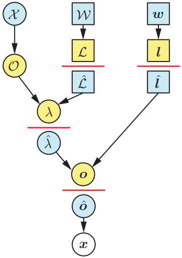
(2) Auxiliary variables
+ factorization



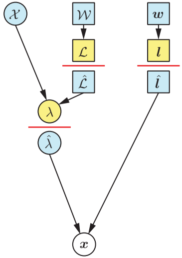
(3) Joint maximization



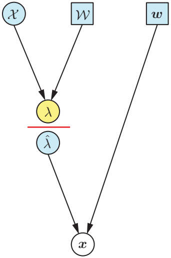
(4) Step-by-step maximization
e.g., statistical parametric TTS



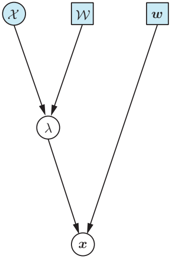
(5) Joint acoustic feature
extraction + model training



(6) Conditional WaveNet
-based TTS



(7) Integrated end-to-end



(8) Bayesian end-to-end