UNIVERSITY OF CAMBRIDGE

# MLMI14: Waveform Level Synthesis

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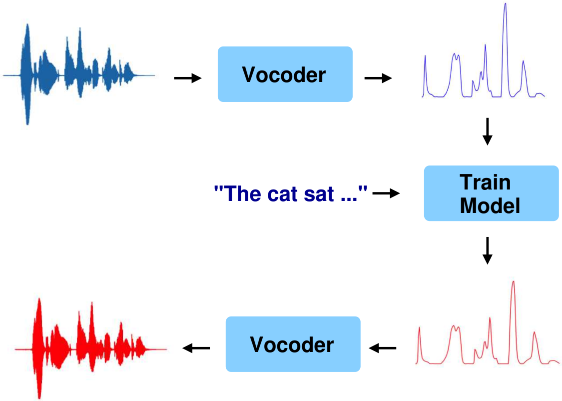
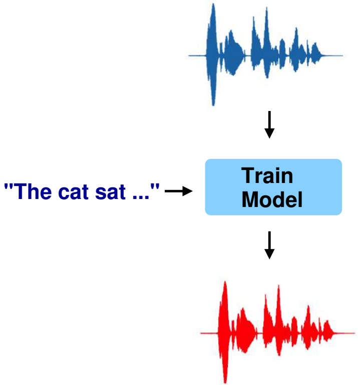
Lent 2021

# Statistical Parametric Synthesis [13]




- Quality of vocoder fundamentally limits performance

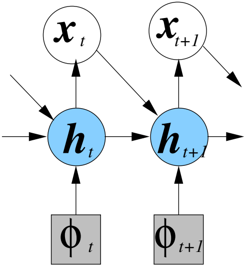
# Waveform Level Synthesis [19]




- Challenges:
  - 16KHz/24KHz predictions
  - long-span dependencies
  - 16KHz/24KHz labels

# Long-Span Dependencies

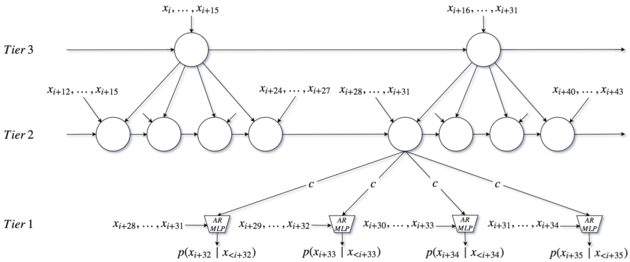
- Speech events act over about 250ms (roughly)
    - 5ms frame rate: this is 50 frames
    - 16Hz samples: this is 4000 samples




- Consider recurrent model:
    - history vector representation
    - rule-of-thumb < 100 samples
      6ms history!
    - insufficient history memory

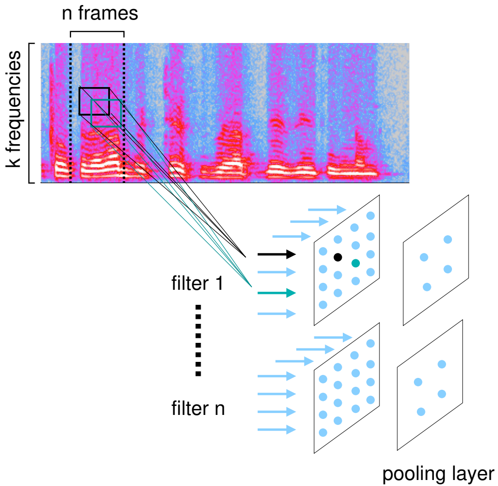
Alternative model (probably) required!

# Clockwork RNNs and SampleRNN [15, 10]




- Use a hierarchical RNN architecture - multiple tiers
  - each tier operates at a different timsescale: in diagram
    Tier1: 16KHz  Tier2: 4KHz  Tier3: 1KHz
  - like an (analogue) clock: hours, minutes, seconds
- Allows long-term dependencies in RNN architectures

# Convolutional Neural Networks [12]



## Convolutional Neural Networks [25]

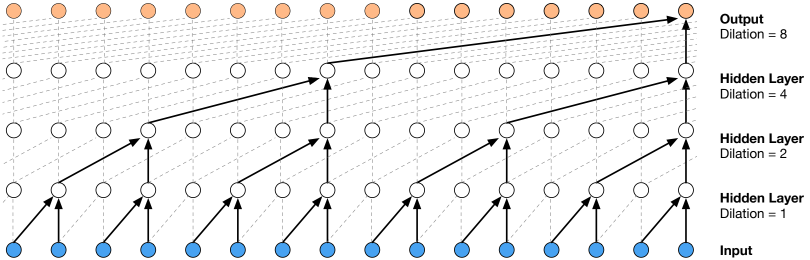
- Various parameters control the form of the CNN:
  - number (depth): how many filters to use
  - receptive field (filter size): height/width/depth ($h \times w \times d$)
  - stride: how far filter moves in the convolution
  - dilation: "gaps" between filter elements
  - zero-padding: do you pad the edges of the "image" with zeroes
- Filter output can be stacked to yield depth for next layer
- To illustrate the impact consider 1-dimensional case - default:
  - zero-padding, stride=1, dilation=0

sequence: $1, 2, 3, 4, 5, 6$ filter: $1, 1, 1$

default: $3, 6, 9, 12, 15, 11$ no padding: $6, 9, 12, 15$

dilation=1: $4, 6, 9, 12, 8, 10$ stride=2: $3, 9, 15$

# WaveNet Neural Vocoder [19]




- Use CNN acting over the one-dimensional waveform sequence
  - dilation used to control growth in number of parameters
  - different dilations at different levels
- A gated activation function is used (layer $k$, filter $f$)

$$\tanh\left(\mathbf{w}_f^{(k)} * \boldsymbol{x}_{1:T}\right) \odot \boldsymbol{\sigma}\left(\mathbf{w}_g^{(k)} * \boldsymbol{x}_{1:T}\right)$$

# Training Criterion

- Simplest training criterion - minimise

$$\mathcal{L}(\boldsymbol{\theta}) = -\sum_{t=1}^{T} \log(p(x_t|\mathbf{x}_{1:t-1};\boldsymbol{\theta})) \propto \sum_{t=1}^{T} \frac{(\hat{x}_t - x_t)^2}{\sigma^2}$$

  - $\hat{x}_t = f(\mathbf{x}_{1:t-1};\boldsymbol{\theta})$ is the prediction
  - Gaussian noise added to systematic system - is this good?
- Adopt "ASR-style" estimation - run as classification
  - quantise the values to predict $x_t \rightarrow x_t^{\mathrm{q}}$ ($\mu$-law)
  - minimise the cross-entropy to the real target $\mathbf{x}_{1:T} \rightarrow \mathbf{x}^{\mathrm{q}}_{1:T}$

$$\mathcal{L}(\boldsymbol{\theta}) = -\sum_{t=1}^{T}\sum_{k=1}^{K} \delta(\omega_k, x_t^{\mathrm{q}}) \log(P(\omega_k|\mathbf{x}_{1:t-1};\boldsymbol{\theta}))$$

# Quantising or Not?

- Quantising the waveform allows classification training
  - no assumption about Gaussian cost functions (important)
- Training criterion interesting mix of quantised and continuous

$$\mathcal{L}(\boldsymbol{\theta}) = -\sum_{t=1}^{T}\sum_{k=1}^{K}\delta(\omega_k, x_t^{\text{q}})\log(P(\omega_k|\boldsymbol{x}_{1:t-1};\boldsymbol{\theta}))$$

  - predict quantised value $x_t^{\text{q}}$
  - history is continuous $\boldsymbol{x}_{1:t-1}$
- Sample generation follows simple process:
  - obtain discrete distribution $P(x_t^{\text{q}}|\hat{\boldsymbol{x}}_{1:t-1};\boldsymbol{\theta})$
  - sample from discrete distribution to yield $\hat{x}_t^{\text{q}}$
  - convert from discrete to continuous $\hat{x}_t^{\text{q}} \rightarrow \hat{x}_t$
  - append to history $\hat{\boldsymbol{x}}_{1:t} = \{\hat{\boldsymbol{x}}_{1:t-1}, \hat{x}_t\}$, $t = t+1$, repeat

# Conditional Synthesis

- The models described so far have no conditioning on the text
  - generates speech like sound, but not speech
- Additional information (beyond context labels) used:
  - duration: LSTM-RNN-based phone duration
  - log-F0: autoregressive CNN-based log-F0 prediction models
- Add conditioning vector $\boldsymbol{\lambda}$ yields information about
  - text context $\boldsymbol{\lambda}_{1:T}^{(q)}$: up-sampled phonetic information from text
  - speaker $\boldsymbol{\lambda}^{(s)}$: speaker representation
- Activation function then has the form (ignoring gating term)
  - for filter $f$ of layer $k$

$$\tanh\left(\mathbf{w}_f^{(k)} * \boldsymbol{x}_{1:T} + \boldsymbol{v}_f^{(k)} * \boldsymbol{\lambda}_{1:T}^{(q)} + \left[\boldsymbol{u}_f^{(k)\mathsf{T}}\boldsymbol{\lambda}^{(s)}\right]_{1:T}\right) \odot \boldsymbol{\sigma}\left(\ldots\right)$$

  - where $[\ldots]_{1:T}$ indicates repeating the output from 1 to $T$

# Parallel Wavenet

# Parallel WaveNet [20]

- WaveNet generates high quality samples
  - but orders of magnitude too much latency
  - limits sampling frequency to 16KHz
  - only able to support 8-bit resolution

- Rather than swapping neural vocoder
  - modified output distribution to support 16-bit resolution
  - modified synthesis to allow parallel generation of samples
  - different architectures for training and synthesis

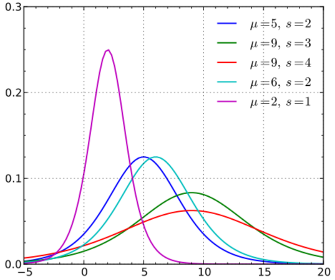
# Output Distribution: Logistic Distribution

- Interested in a distribution $\mathbb{L}(x;\mu,s)$ where

$$\int_{-\infty}^{a}\mathbb{L}(x;\mu,s)dx=\sigma\left(\frac{a-\mu}{s}\right);\quad \sigma(x)=\frac{1}{1+\exp(-x)}$$

  - $\sigma()$ is the logistic function - a valid CDF

- This is the Logistic distribution




- the form of the PDF is then

$$\mathbb{L}(x;\mu,s)=\frac{\exp((x-\mu)/s)}{s\left(1+\exp((x-\mu)/s)\right)^2}$$

- $\mu$ is the mean (location) of the distribution
- $s>0$ is the scale parameter

# Discretized Logistic Mixture Likelihood [16]

- Modelling using a softmax for the distribution limiting
  - doesn't scale well with the number of bin values
- Using the CDF of Logistic distributed variables

$$\int_a^b \mathbb{L}(x; \mu, s)dx = \sigma\left(\frac{b-\mu}{s}\right) - \sigma\left(\frac{a-\mu}{s}\right)$$

- Extending to a mixture model yields and examining a bin value

$$P(x^{\mathrm{q}}|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{s}) = \sum_{m=1}^{M} \pi_m \left(\sigma\left(\frac{x^{\mathrm{q}} + 0.5 - \mu_m}{s_m}\right) - \sigma\left(\frac{x^{\mathrm{q}} - 0.5 - \mu_m}{s_m}\right)\right)$$

  - recognises that bins 127 and 129 are near 128
  - allows expansion of targets with increasing cost

# Parallel Generation: Inverse Autoregressive Flows (IAFs) [9]

- Generate $T$, independent Logistic distributed, samples $\boldsymbol{z}_{1:T}$
  - apply (causal) transformation from $\boldsymbol{z}_{1:T} \to \boldsymbol{x}_{1:T}$

$$\log(p(\boldsymbol{x}_{1:T})) = \log(p(\boldsymbol{z}_{1:T})) - \log\left(\left|\frac{d\boldsymbol{x}_{1:T}}{d\boldsymbol{z}_{1:T}}\right|\right); \quad x_t = f(\boldsymbol{z}_{1:t})$$

  - possible to show that (from the causal aspect of transform)

$$\log\left(\left|\frac{d\boldsymbol{x}_{1:T}}{d\boldsymbol{z}_{1:T}}\right|\right) = \sum_{t=1}^{T} \log\left(\frac{\partial f(\boldsymbol{z}_{1:t})}{\partial z_t}\right)$$

- The following transformation is applied

$$x_t = z_t f_{\mathrm{s}}(\boldsymbol{z}_{1:t-1};\boldsymbol{\theta}) + f_{\mu}(\boldsymbol{z}_{1:t-1};\boldsymbol{\theta})$$

  - $f_{\mathrm{s}}(\boldsymbol{z}_{1:t-1};\boldsymbol{\theta})$: scale parameter prediction from $\boldsymbol{z}_{1:t-1}$
  - $f_{\mu}(\boldsymbol{z}_{1:t-1};\boldsymbol{\theta})$: location parameter prediction from $\boldsymbol{z}_{1:t-1}$

## Inverse Autoregressive Flows (IAFs) (cont)

- As $z_t$ is Logistic ($\mathbb{L}(0,1)$) distributed this means that

$$p(x_t|\boldsymbol{z}_{1:t-1};\boldsymbol{\theta}) = \mathbb{L}(x_t; f_\mu(\boldsymbol{z}_{1:t-1};\boldsymbol{\theta}), f_{\rm s}(\boldsymbol{z}_{1:t-1};\boldsymbol{\theta}))$$

  - $f_\mu(\boldsymbol{z}_{1:t-1};\boldsymbol{\theta})$ and $f_{\rm s}(\boldsymbol{z}_{1:t-1};\boldsymbol{\theta})$ from WaveNet style network
- Allows all samples $\boldsymbol{x}_{1:T}$ to be generated in parallel
  - $x_t$ no explicit dependence on previous generated samples $\boldsymbol{x}_{1:t-1}$
  - $x_t$ only depends on the noise samples $\boldsymbol{z}_{1:t-1}$
  - can generate $\boldsymbol{x}_{1:T}$ in parallel given $\boldsymbol{z}_{1:T}$ - Parallel WaveNet
- Transforms random sequence $\boldsymbol{z}_{1:T}$ to structured $\boldsymbol{x}_{1:T}$
  - too challenging to achieve with a single "flow"
  - stack multiple flows together for parallel WaveNet

# Training: Probability Density Distillation [20]

- Training parallel WaveNet directly is slow
  - training log-likelihood calculation is sequential (see IAF)
  - WaveNet training efficient (prediction $x_t$ uses real data $\boldsymbol{x}_{1:t-1}$)
- Given a trained WaveNet $p_{\mathtt{w}}()$ train $p(\boldsymbol{x};\boldsymbol{\theta})$ to minimise

$$\mathcal{L}(\boldsymbol{\theta}) = \mathcal{D}_{\mathtt{kl}}(p()||p_{\mathtt{w}}()) = \sum_{\boldsymbol{x}\in\mathcal{X}} p(\boldsymbol{x};\boldsymbol{\theta})\log\left(\frac{p(\boldsymbol{x};\boldsymbol{\theta})}{p_{\mathtt{w}}(\boldsymbol{x})}\right)$$

  - $\mathcal{X}$ is the set of all waveforms
  - contrast to teacher-student training

$$\mathcal{L}(\boldsymbol{\theta}) = \sum_{\boldsymbol{x}\in\mathcal{X}} p_{\mathtt{w}}(\boldsymbol{x})\log\left(\frac{p_{\mathtt{w}}(\boldsymbol{x})}{p(\boldsymbol{x};\boldsymbol{\theta})}\right)$$

- Two terms in criterion (both can be computed efficiently)
  - student entropy
  - cross-entropy

# Student Entropy

- Student entropy for a sequence of length $T$

$$\sum_{\boldsymbol{x}_{1:T} \in \mathcal{X}} p(\boldsymbol{x}_{1:T};\boldsymbol{\theta}) \log\left(p(\boldsymbol{x}_{1:T};\boldsymbol{\theta})\right) = -\mathbb{E}\left\{\sum_{t=1}^{T} \log\left(p(x_t|\boldsymbol{z}_{1:t-1};\boldsymbol{\theta})\right)\right\}_{p(\boldsymbol{z}_{1:T})}$$

$$= \mathbb{E}\left\{\sum_{t=1}^{T} \log\left(f_{\mathrm{s}}(\boldsymbol{z}_{1:t-1};\boldsymbol{\theta})\right)\right\}_{p(\boldsymbol{z}_{1:T})} + 2T$$

  - uses equality for entropy of a logistic distribution
  - can be computed without generating samples

# Cross-Entropy (to WaveNet model)

- The cross-entropy term has the following form

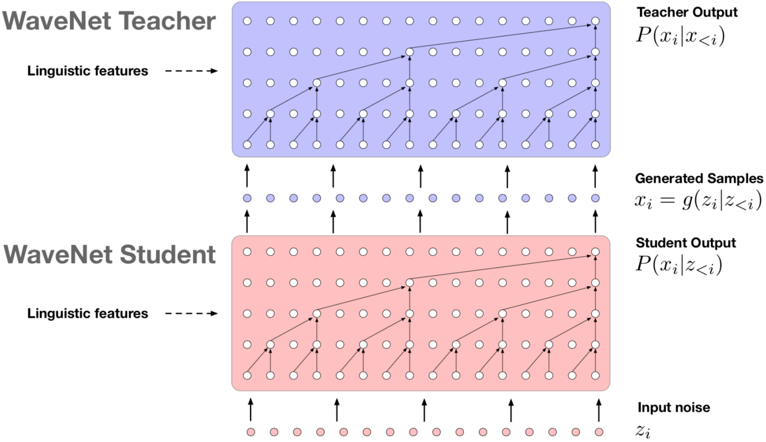
$$\sum_{\boldsymbol{x}_{1:T}\in\mathcal{X}} p(\boldsymbol{x}_{1:T};\boldsymbol{\theta})\log\left(p_{\mathtt{w}}(\boldsymbol{x}_{1:T})\right)$$

  - this requires drawing sample sequences from $p(\boldsymbol{x};\boldsymbol{\theta})$
- For a $T$ length sequence this can be written as (see paper)

$$\sum_{t=1}^{T}\mathbb{E}\left\{p(x_t|\boldsymbol{x}_{1:t-1};\boldsymbol{\theta})\log\left(p_{\mathtt{w}}(x_t|\boldsymbol{x}_{1:t-1})\right)\right\}_{p(\boldsymbol{x}_{1:t-1};\boldsymbol{\theta})}$$

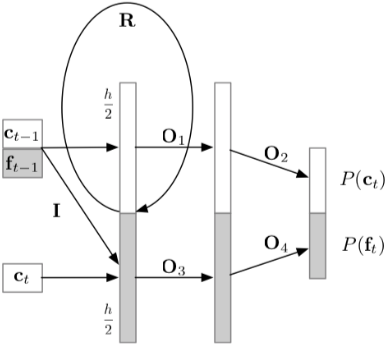
  - this is efficient (see paper!)

# Probability Density Distillation Overview



# WaveRNN

# WaveRNN [6]




- Modification to original WaveNet configuration
  - simplified (recurrent) architecture
  - split representation coarse ($\boldsymbol{c}_t$) and fine ($\boldsymbol{f}_t$)
  - efficient, improved, resolution

# WaveRNN Diagram Notation

- Split the 16-bit output into:
  - coarse, $\boldsymbol{c}_t$ 8 most significant bits
  - fine, $\boldsymbol{f}_t$ 8 least significant bits (conditioned on coarse)
- Diagram (from paper) uses notation
  - $\boldsymbol{O}_1$ and $\boldsymbol{O}_2$: "coarse" weight matrices
  - $\boldsymbol{O}_3$ and $\boldsymbol{O}_4$: "fine" weight matrices
  - $\mathbf{I}$ weight matrix (not identity!) from paper
- For the network layers
  - first layer recurrent (variant on GRU)
  - second layer ReLU
  - third layer soft-max

(Additional speed-ups descibed in paper: sparse WaveRNN)

# WaveRNN Architecture

- Split the prediction 16-bit prediction into 2 parts

$$\boldsymbol{x}_t = \begin{bmatrix} \boldsymbol{c}_t \\ \boldsymbol{f}_t \end{bmatrix}$$

  - coarse $\boldsymbol{c}_t$ (8 bits - 256 levels): top 8 bits of waveform

$$\boldsymbol{c}_t = \mathcal{F}_{\text{c}}(\boldsymbol{x}_{t-1}, \boldsymbol{h}_{t-1}) = \mathcal{F}_{\text{c}}(\boldsymbol{c}_{t-1}, \boldsymbol{f}_{t-1}, \boldsymbol{h}_{t-1})$$

  - fine $\boldsymbol{f}_t$ (8 bits - 256 levels): bottom 8 bits of waveform

$$\boldsymbol{f}_t = \mathcal{F}_{\text{c}}(\boldsymbol{c}_{t-1}, \boldsymbol{f}_{t-1}, \boldsymbol{h}_{t-1}, \boldsymbol{c}_t)$$

# WaveRNN Coarse Generation

- Equations can be split into distinct parts (ignoring biases)

$$\begin{aligned} P(\boldsymbol{c}_t) &= \mathtt{softmax}(\mathbf{O}_2\mathtt{relu}(\mathbf{O}_1\mathbf{z}_t^{\mathrm{c}})) \\ \boldsymbol{z}_t^{\mathrm{c}} &= \boldsymbol{u}_t^{\mathrm{c}} \odot \boldsymbol{h}_{t-1}^{\mathrm{c}} + (\mathbf{1} - \boldsymbol{u}_t^{\mathrm{c}}) \odot \boldsymbol{e}_t^{\mathrm{c}} \\ \boldsymbol{e}_t^{\mathrm{c}} &= \mathtt{tanh}(\boldsymbol{r}_t^{\mathrm{c}} \odot (\mathbf{W}_{\mathrm{e}}^{\mathrm{c}}\boldsymbol{h}_{t-1}) + \mathbf{W}_{\mathtt{x}}^{\mathrm{c}}\boldsymbol{x}_{t-1}) \end{aligned}$$

  - where the gates have the form

$$\begin{aligned} \boldsymbol{r}_t^{\mathrm{c}} &= \mathtt{sigmoid}(\mathbf{W}_{\mathtt{rh}}^{\mathrm{c}}\boldsymbol{h}_{t-1} + \mathbf{W}_{\mathtt{rx}}^{\mathrm{c}}\boldsymbol{x}_{t-1}) \\ \boldsymbol{u}_t^{\mathrm{c}} &= \mathtt{sigmoid}(\mathbf{W}_{\mathtt{uh}}^{\mathrm{c}}\boldsymbol{h}_{t-1} + \mathbf{W}_{\mathtt{ux}}^{\mathrm{c}}\boldsymbol{x}_{t-1}) \end{aligned}$$

  - and the input and the history have the form

$$\boldsymbol{x}_{t-1} = \begin{bmatrix} \boldsymbol{c}_{t-1} \\ \boldsymbol{f}_{t-1} \end{bmatrix}; \quad \boldsymbol{h}_{t-1} = \begin{bmatrix} \boldsymbol{z}_{t-1}^{\mathrm{c}} \\ \boldsymbol{z}_{t-1}^{\mathtt{f}} \end{bmatrix}$$

# WaveRNN Fine Generation

- Initially the coarse elements are generated

$$\boldsymbol{c}_t \sim P(\boldsymbol{c}_t)$$

- Equations can be split into distinct parts

$$\begin{aligned}
P(\boldsymbol{c}_t) &= \texttt{softmax}(\mathbf{O}_4\texttt{relu}(\mathbf{O}_3\mathbf{z}^{\text{f}}_t)) \\
\boldsymbol{z}^{\text{f}}_t &= \boldsymbol{u}^{\text{f}}_t \odot \boldsymbol{h}^{\text{f}}_{t-1} + (\mathbf{1} - \boldsymbol{u}^{\text{f}}_t) \odot \boldsymbol{e}^{\text{f}}_t \\
\boldsymbol{e}^{\text{f}}_t &= \texttt{tanh}(\boldsymbol{r}^{\text{f}}_t \odot (\mathbf{W}^{\text{f}}_{\texttt{e}}\boldsymbol{h}_{t-1}) + \mathbf{W}^{\text{f}}_{\texttt{x}}\boldsymbol{x}_{t-1} + \mathbf{W}_{\texttt{uc}}\boldsymbol{c}_t)
\end{aligned}$$

  - where the "fine" gates have the form

$$\begin{aligned}
\boldsymbol{r}^{\text{f}}_t &= \texttt{sigmoid}(\mathbf{W}^{\text{f}}_{\texttt{rh}}\boldsymbol{h}_{t-1} + \mathbf{W}^{\text{f}}_{\texttt{rx}}\boldsymbol{x}_{t-1} + \mathbf{W}_{\texttt{rc}}\boldsymbol{c}_t) \\
\boldsymbol{u}^{\text{f}}_t &= \texttt{sigmoid}(\mathbf{W}^{\text{f}}_{\texttt{uh}}\boldsymbol{h}_{t-1} + \mathbf{W}^{\text{f}}_{\texttt{ux}}\boldsymbol{x}_{t-1} + \mathbf{W}_{\texttt{uc}}\boldsymbol{c}_t)
\end{aligned}$$

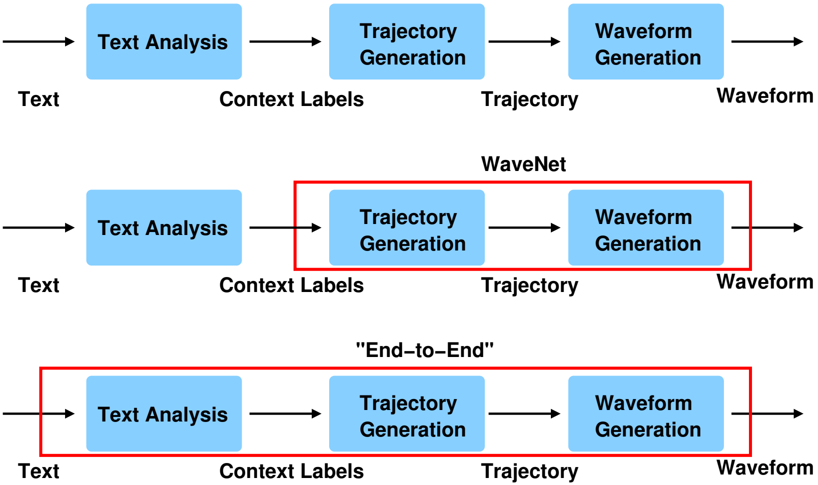
  - input, $\boldsymbol{x}_{t-1}$, and history, $\boldsymbol{h}_{t-1}$, same as coarse

# Conditioning Vectors

# Conditional Synthesis

- To generate speech require conditioning on text:
  - convert text to context features
  - generate durations for each of model states
  - append "position" features to context
- Yields context features at 200Hz (5ms frame rate)
  - up-sample to yield required (16KHz) context features $\boldsymbol{\lambda}_{1:T}^{(q)}$
- Requires linguistic information:
  - text processing and POS tags
  - phonetic lexicon (may introduce errors)
  - phone/state duration models

# Synthesis Pipelines



# "End-to-End" Synthesis

- Use deep-learning to derive $\boldsymbol{\lambda}_{1:T}^{(q)}$
  - map word sequence $\boldsymbol{\omega}_{1:L}$ to character sequence $\mathbf{c}_{1:P}$
  - map character sequence $\mathbf{c}_{1:P}$ to context features $\boldsymbol{\lambda}_{1:T}^{(q)}$
  - optimise mapping for synthesis performance
  - note increase in sample rate $\approx$ 10-20 Hz to 16Hz
- To handle difference in required sample rate use attention
  - use decode state, $\boldsymbol{s}_{\tau-1}$ as key for attention at time $\tau$

$$
\begin{aligned}
\boldsymbol{c}_{1:P} &\rightarrow \boldsymbol{h}_{1:P}(\texttt{character encoding}) \\
\boldsymbol{\alpha}_{\tau} &= \mathcal{F}_{\texttt{att}}(\boldsymbol{s}_{\tau-1}, \boldsymbol{\alpha}_{\tau-1}, \boldsymbol{h}_{1:P}); \quad \boldsymbol{g}_{\tau} = \sum_{i=1}^{P} \alpha_{\tau i} \boldsymbol{h}_i \\
\boldsymbol{y}_{\tau} &= \texttt{generate}(\boldsymbol{s}_{\tau-1}, \boldsymbol{g}_{\tau}); \quad \boldsymbol{s}_{\tau} = \mathcal{F}_{\texttt{rec}}(\boldsymbol{s}_{\tau-1}, \boldsymbol{g}_{\tau}, \boldsymbol{y}_{\tau})
\end{aligned}
$$

  - form of $\mathcal{F}_{\texttt{att}}(.)$ very general

# Content and Location Based Attention [2]

- Content-based attention - seen before
  - operates between the key and elements of the encoding

$$\boldsymbol{\alpha}_\tau = \mathcal{F}_{\texttt{att}}(\boldsymbol{s}_{\tau-1}, \boldsymbol{h}_{1:P}); \quad \alpha_{\tau,i} = \frac{\exp(\mathbf{f}(\boldsymbol{s}_{\tau-1}, \boldsymbol{h}_i))}{\sum_{j=1}^{P} \exp(\mathbf{f}(\boldsymbol{s}_{\tau-1}, \boldsymbol{h}_j))}$$

$$\mathbf{f}(\boldsymbol{s}_{\tau-1}, \boldsymbol{h}_i) = \mathbf{w}^{\mathsf{T}} \texttt{tanh}(\mathbf{W}_{\texttt{s}} \boldsymbol{s}_{\tau-1} + \mathbf{W}_{\texttt{h}} \boldsymbol{h}_i)$$

- Location-based attention
  - operates between key and previous attention vector

$$\boldsymbol{\alpha}_\tau = \mathcal{F}_{\texttt{att}}(\boldsymbol{s}_{\tau-1}, \boldsymbol{\alpha}_{\tau-1});$$
$$\mathbf{f}(\boldsymbol{s}_{\tau-1}, \boldsymbol{\alpha}_{\tau-1}, i) = \mathbf{w}^{\mathsf{T}} \texttt{tanh}(\mathbf{W}_{\texttt{s}} \boldsymbol{s}_{\tau-1} + \mathbf{W}_{\alpha} [\mathbf{F} \star \boldsymbol{\alpha}_{\tau-1})]_i)$$

  - **F** is the matrix for progression (location) of attention
- Hybrid attention combines attributes of both

# Mixture of Gaussian Functions Attention [5]

- For sequence data left-to-right emphasis useful
  - reduces chance of inappropriate attention for long sequences
- Use modified version of location attention mechanism
  - convolve with an $M$-component mixture of Gaussian functions

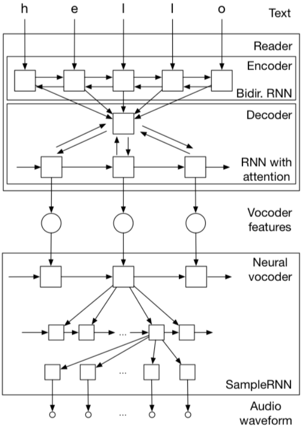
$$\alpha_{\tau i} = \sum_{k=1}^{M} a_t^{(k)} \exp\left(-b_t^{(k)}(\kappa_t^{(k)} - i)^2\right); \quad \boldsymbol{g}_\tau = \sum_{i=1}^{P} \alpha_{\tau i} \boldsymbol{h}_i$$

  - where $\hat{a}_t^{(k)}, \hat{b}_t^{(k)}$ and $\hat{\kappa}_t^{(k)}$ are predicted from the network

$$\begin{aligned} a_t^{(k)} &= \exp(\hat{a}_t^{(k)}); \quad b_t^{(k)} = \exp(\hat{b}_t^{(k)}) \\ \kappa_t^{(k)} &= \kappa_{t-1}^{(k)} + \exp(\hat{\kappa}_t^{(k)}) \end{aligned}$$

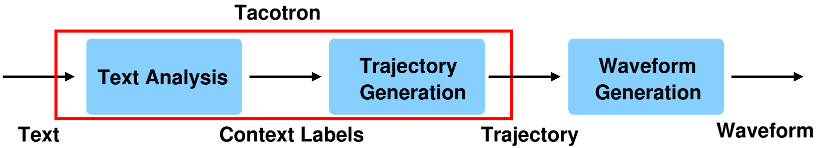
  - has been used for end-to-end synthesis and recognition

# Char2Wav [18]




- Early end-to-end architecture
- Uses location attention for context
  - predicts vocoder features
  - neural vocoder for synthesis
- SampleRNN neural vocoder used

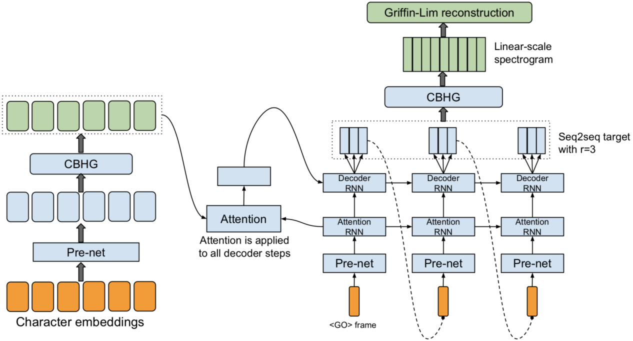
# "End-to-End" Spectrogram Generation




- "End-to-End" systems attractive - just deep-learning
  - requires large quantities of accurately transcribed data
- Alternative approach - predict spectrograms
  - replace text-processing/trajectory models with single block
  - standard sequence-to-sequence mode

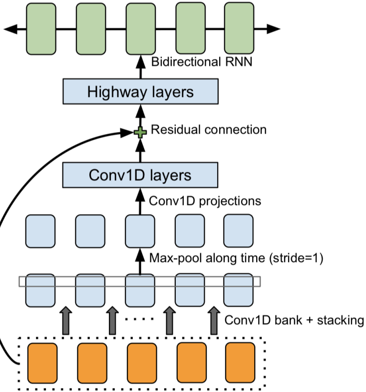
Still needs a vocoder!

# Tacotron [23] (Not Waveform-Level)



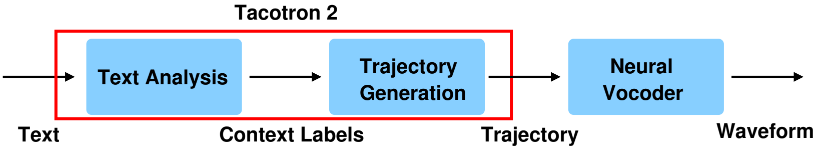

- End-to-end configurations - characters as input
  - content-based attention mechanism
  - CBHG layer added for post-processing
  - predicts linear spectral magnitude (not vocoder parameters)
  - Griffin Lim is used as the synthesiser

# CBHG Layer



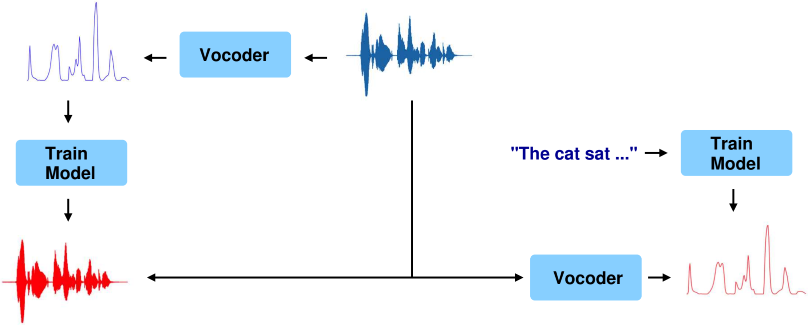
Bidirectional RNN
Highway layers
Residual connection
Conv1D layers
Conv1D projections
Max-pool along time (stride=1)
Conv1D bank + stacking

# "Neural Vocoder"



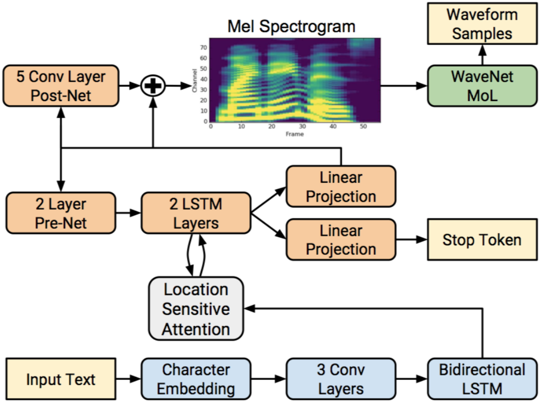

- Split Process into two deep-learning parts
  - text to spectrograms (mel-spectrograms can be used)
  - spectrogram to waveform generation
- (1) has previously been described (e.g. Tacotron)
- (2) can be trained on large amounts of data
  - just needs audio data (waveform)
  - learn a mapping from real spectrogram to real waveform

# Training Neural Vocoders




- Neural vocoder training does not need transcriptions
  - does require high quality trajectories at synthesis time

# Tacotron 2 [17, 23]




- Integrates (modified) Tacotron with (modified) WaveNet

# Tacotron 2 Modifications

- Changes to the original Tacotron paper:
  - predict Mel-spectrogram not linear
  - simplified network configuration for encoder/decoder
  - location-based attention mechanism

- Changes to the original WaveNet paper:
  - condition on Mel-spectrogram (not linguistic features)
  - uses parallel WaveNet for speed

# Speaker Representations

# Variable Length Mapping

- Range of applications make use of speaker representations
  - speaker clustering
  - speaker recognition/verification
  - speaker adaptation
- Simplest form is multi-speaker (1-of-K coding)
- More generally require a fixed-length representation
  - variable length sequence $\boldsymbol{x}_{1:T}^{(s)} \rightarrow$ speaker representation $\boldsymbol{\lambda}^{(s)}$

$$\boldsymbol{\lambda}^{(s)} = \phi(\boldsymbol{x}_{1:T}^{(s)})$$

  - in 4F10 already seen application using SVMs
  - makes use of Fisher Kernel
- Can make use of a UBM ($\boldsymbol{\theta}_{\texttt{ubm}}$)
  - large GMM used to represent all speakers
  - MAP adapt model to target speaker $\boldsymbol{\theta}_{\texttt{ubm}}^{(s)}$

# Fisher Kernel [14]

- From 4F10 lectures

$$\phi(\boldsymbol{x}_{1:T}) = \left[ \begin{array}{c} \log(p(\boldsymbol{x}_{1:T}|\boldsymbol{\theta}^{(s)}_{\texttt{ubm}})) - \log(p(\boldsymbol{x}_{1:T}|\boldsymbol{\theta}_{\texttt{ubm}})) \\ \nabla_{\boldsymbol{\theta}} \log\left(p\left(\boldsymbol{x}_{1:T}|\boldsymbol{\theta}\right)\right)\big|_{\boldsymbol{\theta}^{(s)}_{\texttt{ubm}}} \end{array} \right]$$

  - the first term is the standard GMM-based score
  - the second term is Fisher score for the speaker model
  - only derivatives wrt the mean parameters used
- If only the derivative part is used then

$$\phi(\boldsymbol{x}_{1:T}) = \left[ \begin{array}{c} \sum_{t=1}^{T} P(1|\boldsymbol{x}_t, \boldsymbol{\theta}^{(s)}_{\texttt{ubm}}) \boldsymbol{\Sigma}^{(s1)-1}_{\texttt{ubm}} (\boldsymbol{x}_t - \boldsymbol{\mu}^{(s1)}_{\texttt{ubm}}) \\ \vdots \\ \sum_{t=1}^{T} P(\texttt{M}|\boldsymbol{x}_t, \boldsymbol{\theta}^{(s)}_{\texttt{ubm}}) \boldsymbol{\Sigma}^{(sM)-1}_{\texttt{ubm}} (\boldsymbol{x}_t - \boldsymbol{\mu}^{(sM)}_{\texttt{ubm}}) \end{array} \right]$$

- Fisher Information Matrix is sometimes used as a metric

# Mean Super-Vector Kernel [1]

- Rather than taking derivative, it is possible to use parameters
  - consider the means of the speaker adapted UBM

$$\boldsymbol{\lambda}^{(s)} = \phi(\boldsymbol{x}_{1:T}^{(s)}) = \begin{bmatrix} \boldsymbol{\mu}_{\texttt{ubm}}^{(s1)} \\ \vdots \\ \boldsymbol{\mu}_{\texttt{ubm}}^{(sm)} \\ \vdots \\ \boldsymbol{\mu}_{\texttt{ubm}}^{(sM)} \end{bmatrix}$$

- Both this form and Fisher Kernel yield large spaces
  - if only means used $M \times d$ elements
  - originally used for SVM-based systems (see 4F10)
- Can we make the speaker information more compact?

# Joint Factor Analysis (JFA) [8]

- The actual observed data is impacted by multiple factors
  - speaker (desired variability to model)
  - channel/session attributes (not desired)
- Decomposing the mean supervector yields

$$\boldsymbol{\lambda}^{(s)} = \boldsymbol{\mu}_{\mathtt{si}} + \mathbf{V}\boldsymbol{\lambda}^{(s)}_{\mathtt{sp}} + \mathbf{U}\boldsymbol{\lambda}^{(s)}_{\mathtt{ch}} + \mathbf{D}\boldsymbol{z}$$

  - $\mathbf{V}$ and $\mathbf{U}$ and loading matrices
  - $\boldsymbol{\mu}_{\mathtt{si}}$ is the speaker-independent mean
  - $\boldsymbol{\lambda}^{(s)}_{\mathtt{sp}}$ point in speaker-space (prior $\mathcal{N}(\mathbf{0}, \mathbf{I})$)
  - $\boldsymbol{\lambda}^{(s)}_{\mathtt{ch}}$ point in channel/session-space (prior $\mathcal{N}(\mathbf{0}, \mathbf{I})$)
  - $\mathbf{D}$ the noise matrix, $\boldsymbol{z}$ noise term (prior $\mathcal{N}(\mathbf{0}, \mathbf{I})$)
- Effectively a large Gaussian distribution: typical dimensions
  - $\boldsymbol{\lambda}^{(s)}$: 20000; $\boldsymbol{\lambda}^{(s)}_{\mathtt{sp}}$: 300; $\boldsymbol{\lambda}^{(s)}_{\mathtt{ch}}$: 100
  - iterative training process - see paper

# iVector Model Training [3]

- Identity Vector (iVector): simplify JFA merge speaker/channel

$$\boldsymbol{\lambda}^{(s)} = \boldsymbol{\mu}_{\texttt{si}} + \mathbf{T}\boldsymbol{\lambda}_{\texttt{sp}}^{(s)}$$

  - $\mathbf{T}$ is the total variability matrix
  - $\boldsymbol{\lambda}_{\texttt{sp}}^{(s)}$ point in speaker-space (prior $\mathcal{N}(\mathbf{0},\mathbf{I})$)
- This is similar to Factor Analysis: use EM
  - unobserved: speaker $\boldsymbol{\lambda}_{\texttt{sp}}$, component at $t$ $P(m|\boldsymbol{\lambda}_{\texttt{sp}}, \boldsymbol{x}_t^{(s)}\boldsymbol{\theta})$

$$\begin{aligned}\mathcal{Q}(\boldsymbol{\theta},\hat{\boldsymbol{\theta}}) &= \sum_{s=1}^{S}\int p(\boldsymbol{\lambda}_{\texttt{sp}}|\boldsymbol{\theta},\boldsymbol{x}_{1:T}^{(s)})\sum_{t=1}^{T}\sum_{m=1}^{M}P(m|\boldsymbol{\lambda}_{\texttt{sp}},\boldsymbol{x}_t^{(s)},\boldsymbol{\theta}) \\ &\qquad \log\left(\mathcal{N}(\boldsymbol{x}_t^{(s)};\hat{\boldsymbol{\mu}}_{\texttt{si}}^{(m)}+\hat{\mathbf{T}}^{(m)}\boldsymbol{\lambda}_{\texttt{sp}},\hat{\boldsymbol{\Sigma}}^{(m)})\right)d\boldsymbol{\lambda}_{\texttt{sp}}\end{aligned}$$

  - new model parameters $\hat{\boldsymbol{\theta}} = \left\{\ldots,\hat{\mathbf{T}}^{(m)},\hat{\boldsymbol{\mu}}_{\texttt{si}}^{(m)},\hat{\boldsymbol{\Sigma}}^{(m)},\ldots\right\}$
  - for simplicity $P(m|\boldsymbol{\lambda}_{\texttt{sp}},\boldsymbol{x}_t^{(s)},\boldsymbol{\theta})$ often fixed for training

# iVector Extraction [7, 11, 4]

- At test-time iVector extracted using

$$\hat{\boldsymbol{\lambda}}_{\text{sp}}^{(s)} = \arg\max_{\boldsymbol{\lambda}_{\text{sp}}} \left\{ p(\boldsymbol{\lambda}_{\text{sp}} | \boldsymbol{x}_{1:T}^{(s)}, \boldsymbol{\theta}) \right\}$$

  - again EM is used to find iVector
- Model related to CAT and EigenVoices
  - point estimate of $\boldsymbol{\lambda}_{\text{sp}}^{(s)}$ used, rather than distribution
  - treated as part of the parameter estimation stage

$$\begin{aligned} \mathcal{Q}(\boldsymbol{\theta}, \hat{\boldsymbol{\theta}}) &= \sum_{s=1}^{S} \sum_{m=1}^{M} \sum_{t=1}^{T} P(m | \boldsymbol{\lambda}_{\text{sp}}^{(s)}, \boldsymbol{x}_t^{(s)} \boldsymbol{\theta}) \Big[ \log(P(\hat{\boldsymbol{\lambda}}_{\text{sp}}^{(s)})) \\ &\quad + \log\left( \mathcal{N}(\boldsymbol{x}_t^{(s)}; \hat{\boldsymbol{\mu}}_{\text{si}}^{(m)} + \hat{\mathbf{T}}^{(m)} \hat{\boldsymbol{\lambda}}_{\text{sp}}^{(s)}, \hat{\boldsymbol{\Sigma}}^{(m)}) \right) \Big] \end{aligned}$$

  - possible to factorise $\boldsymbol{\lambda}_{\text{sp}}^{(s)}$ (JFA) include orthogonality constraint

# iVectors for Speaker Recognition

- Extract iVectors for all enrolled speakers, $\boldsymbol{\lambda}_{\text{sp}}^{(1)}, \ldots, \boldsymbol{\lambda}_{\text{sp}}^{(S)}$
  - extract for test speaker $\boldsymbol{\lambda}_{\text{sp}}$
  - need to select "closest" enrolled speaker
- For speed look at distances between iVectors

$$\hat{s} = \arg\min_{s} \left\{ d(\boldsymbol{\lambda}_{\text{sp}}, \boldsymbol{\lambda}_{\text{sp}}^{(s)}) \right\}$$

  - euclidean distance:

$$d(\boldsymbol{\lambda}_{\text{sp}}, \boldsymbol{\lambda}_{\text{sp}}^{(s)}) = ||\boldsymbol{\lambda}_{\text{sp}} - \boldsymbol{\lambda}_{\text{sp}}^{(s)}||^2$$

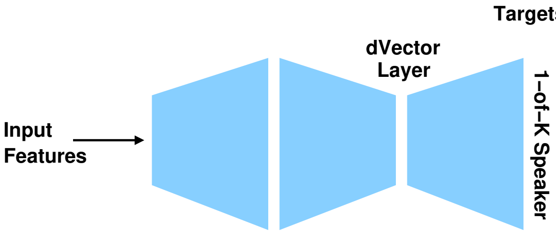
  - (-) cosine distance:

$$d(\boldsymbol{\lambda}_{\text{sp}}, \boldsymbol{\lambda}_{\text{sp}}^{(s)}) = -\frac{\boldsymbol{\lambda}_{\text{sp}}^{\mathsf{T}} \boldsymbol{\lambda}_{\text{sp}}^{(s)}}{\sqrt{\boldsymbol{\lambda}_{\text{sp}}^{\mathsf{T}} \boldsymbol{\lambda}_{\text{sp}} \boldsymbol{\lambda}_{\text{sp}}^{(s)\mathsf{T}} \boldsymbol{\lambda}_{\text{sp}}^{(s)}}}$$

  popular choice (empirically good!)

# dVector Representation [21]

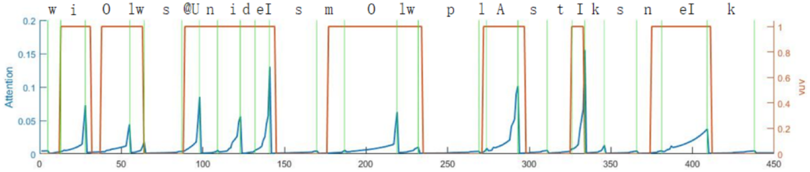
- Train vector to discriminate between speakers
  - related to bottleneck features for ASR




- Targets are a 1-of-K coding of speaker
  - wide window of features to yield good performance
- Simple approach used to handle temporal aspect of signal
  - $\boldsymbol{\lambda}_t^{(s)}$ is the vector for frames centered at time $t$

$$\boldsymbol{\lambda}^{(s)} = \frac{1}{T}\sum_{t=1}^{T}\boldsymbol{\lambda}_t^{(s)}$$

# Attention-based dVector Representation [22]

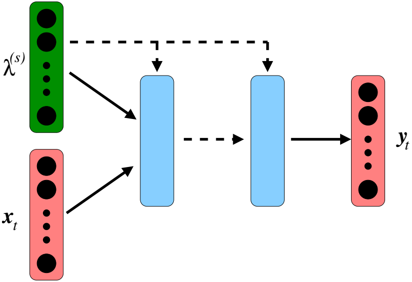



- Rather than using simple averaging of d-Vectors, use attention

$$\boldsymbol{\lambda}^{(s)} = \sum_{t=1}^{T} \alpha_t \boldsymbol{\lambda}_t^{(s)}$$

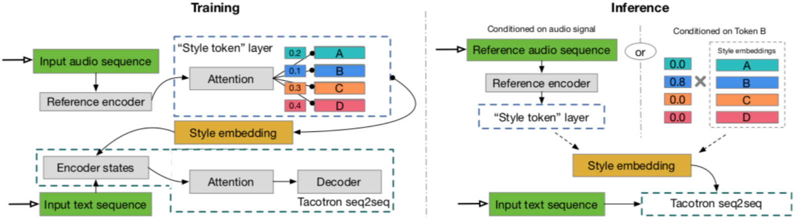
  - self-attention mechanism used based on context features
  - model trained in an integrated fashion (including attention)
- Attention focuses on voiced regions

# Speaker Representations for Adaptation




- Speaker representation can be used as auxiliary information
  - simple for of speaker adaptation
  - no initial hypothesis required
  - can be optionally be applied to other layers of network

# General Style Tokens [24]




- In addition to speaker, also interested in style
  - speakers prosody varies with context
  - narrative speech, emotions, audiobooks
- It is hard to consistently label "style"
  - unsupervised approaches increasingly popular
  - general style tokens for Tacotron one example

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