

Speech

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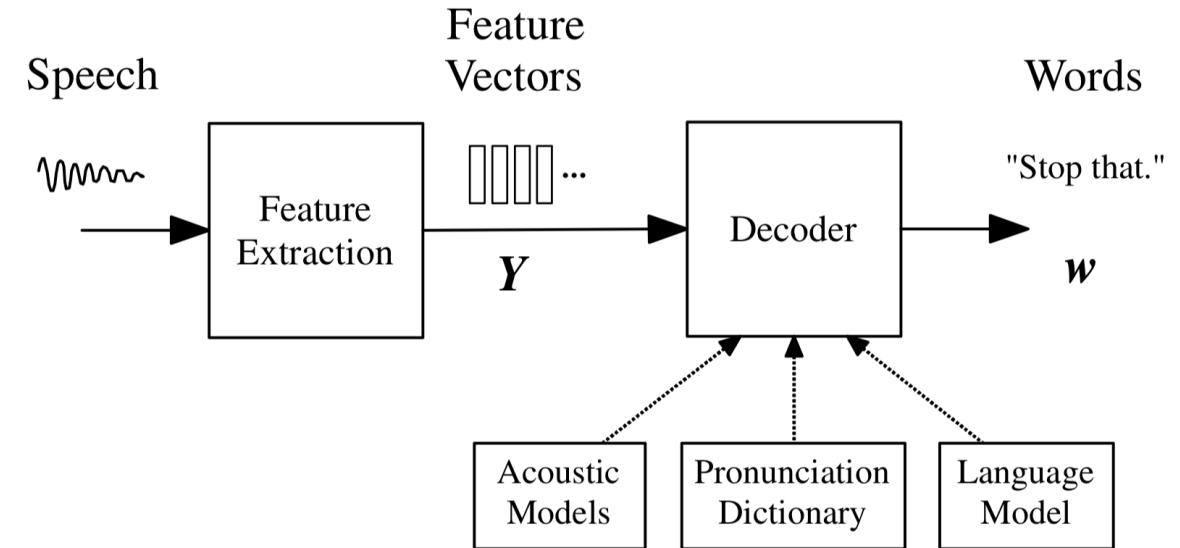
Outline

- Motivation
- Speech and audio
- Pre processing
- Network structures
- Speaker identification
- Keyword spotting and command recognition
- Conditional modeling
- Speech to text
- Text to speech
- References

Motivation

Classical Speech To Text

- Speech or audio waveform
 - $x(n), n = 0, \dots, N - 1$
- Feature vectors
 - $\mathbf{Y} = [\mathbf{y}_0 \dots \mathbf{y}_{T-1}]$
 - MFCC, Δ , $\Delta\Delta$ with ~ 40 total features are common
- Word sequence \mathbf{w}
 - $\hat{\mathbf{w}} = \arg \max_{\mathbf{w}} (P(\mathbf{w} | \mathbf{Y}))$
 - The acoustic model uses ~ 44 phonemes for the English language (24 consonants, 20 vowels)
 - Phonemes are concatenated via a pronunciation dictionary to make words \mathbf{w}
 - The language model determines $P(\mathbf{w})$; N gram language models that estimate the probability of a word given the previous $N - 1$ words are commonly used



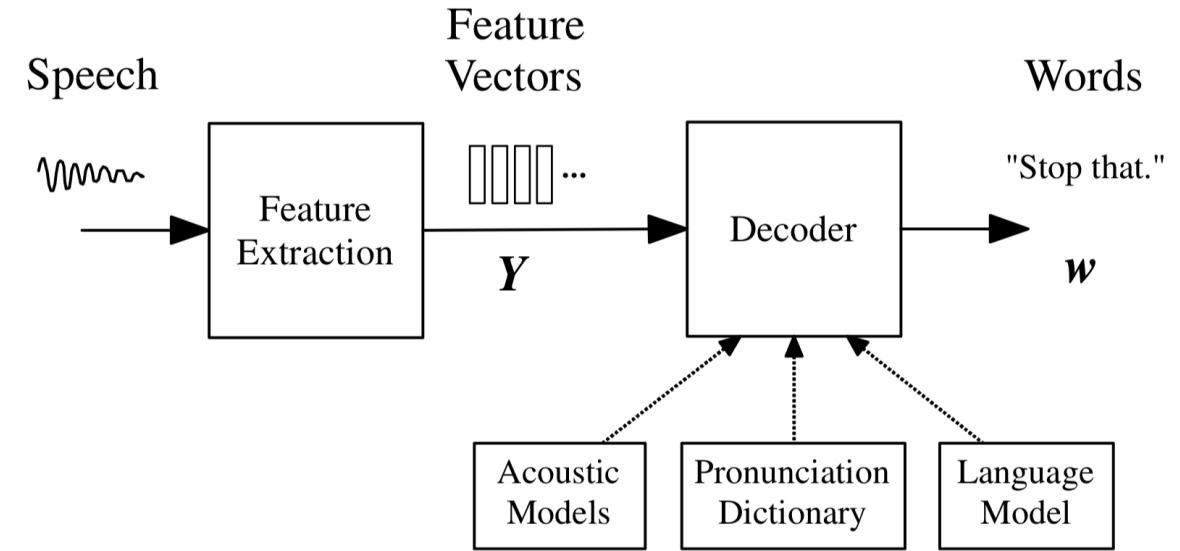
For a nice overview see

- Speech recognition
<https://github.com/oxford-cs-deepnlp-2017/lectures/blob/master/Lecture%209%20-%20Speech%20Recognition.pdf>
- Deep audio
http://slazebni.cs.illinois.edu/spring17/lec26_audio.pdf

Classification Problems

- Motivation
- Speech and audio
- Pre processing
- Network structures
- Speaker identification
- Keyword spotting
- Speech to text
- Text to speech
- References

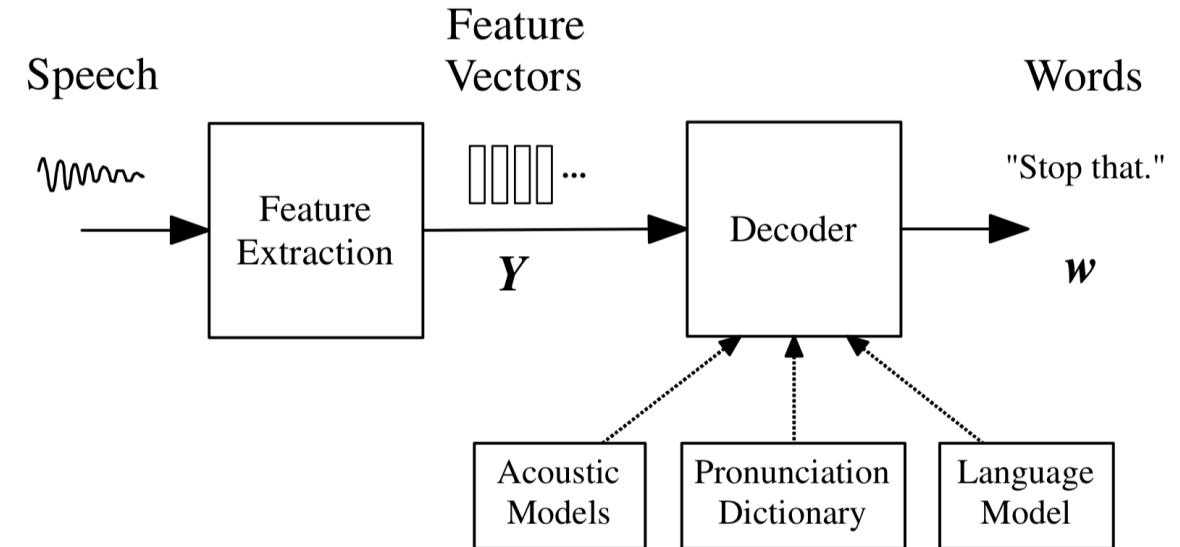
Common speech problems are classification problems at their core: map a sound waveform to a finite number of classes



Generation Problems

- Motivation
- Speech and audio
- Pre processing
- Network structures
- Speaker identification
- Keyword spotting
- Speech to text
- Text to speech
- References

Speech also includes common generation problems



The Strategy Described Here

- Pre processing divides a speech waveform into an input sequence of vectors
- A CNN, RNN or attention based model is trained end to end in an encoder decoder style configuration to map the input sequence of vectors to classes appropriate for the problem
- Example classes include
 - Speakers
 - Keywords
 - Phonemes / graphemes / word pieces / words
 - ...
- Side information (frequently language) is applied to improve the accuracy

Disclaimer

- There's a lot of speech related stuff not included here
 - Different methods within the categories of problems included here
 - Problems that are not included here
- Possibly some of this will be addressed in future versions of the slides
- Regardless of whether it is or not, hopefully these slides provide enough of a base from which to branch off and learn more on your own

Speech And Audio

The Human Speech And Audio Chain

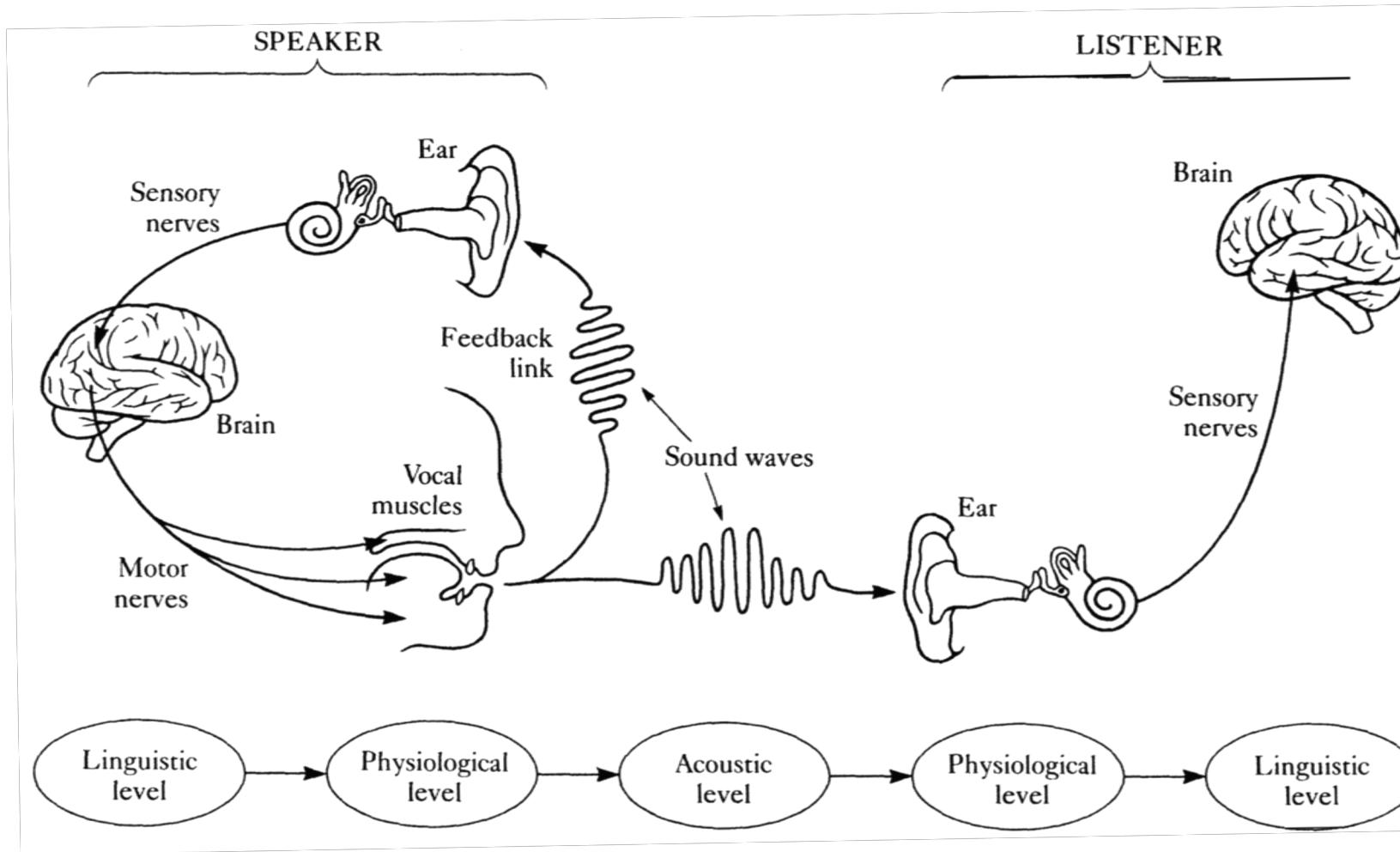
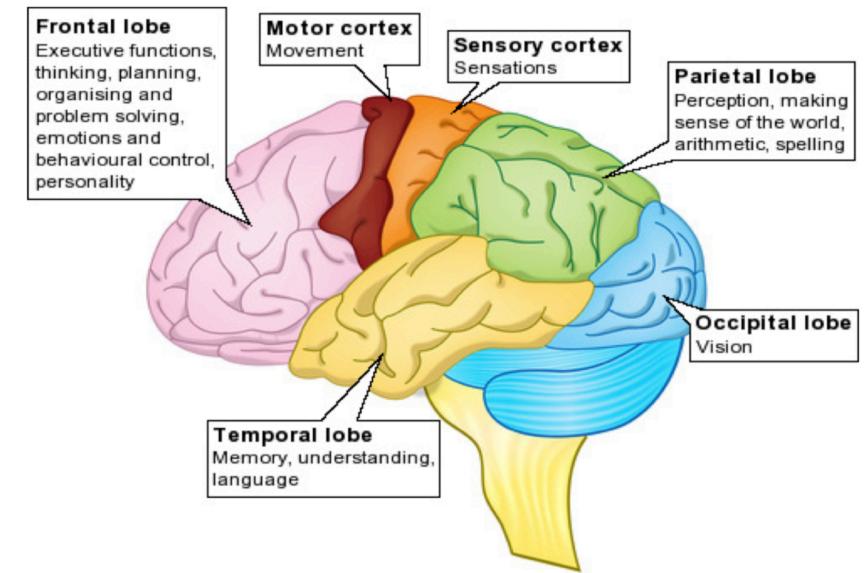
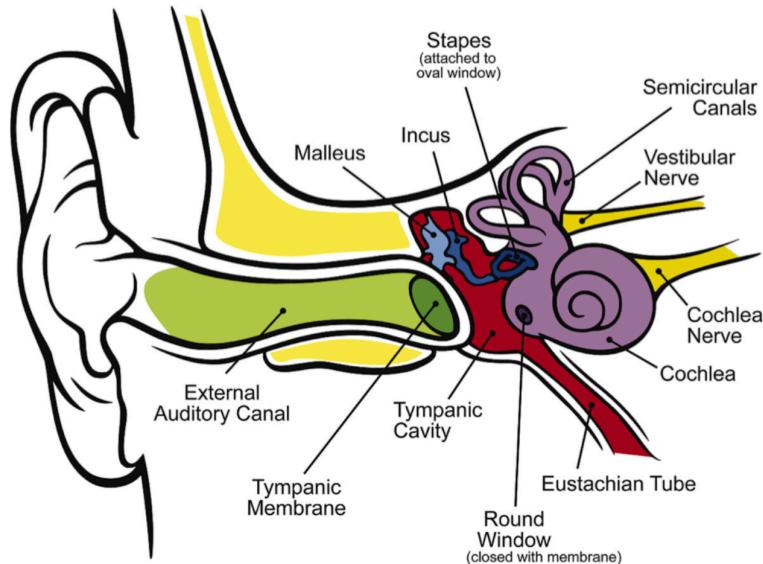
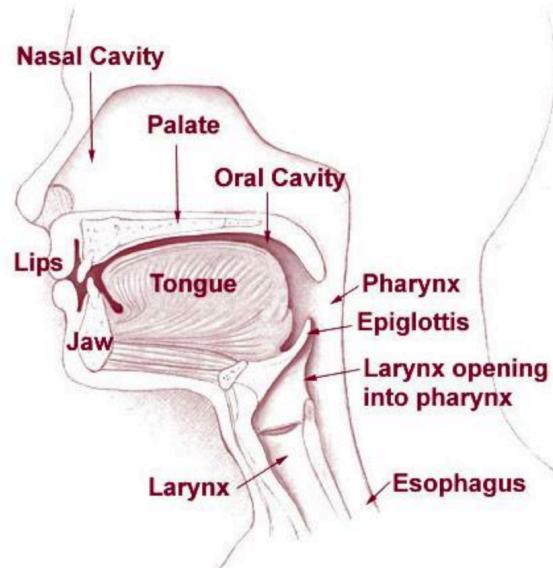


Figure from http://www.columbia.edu/~rmk7/HC/HC_Readings/Denes_Pinson1-2.PDF

Generation, Perception And Understanding



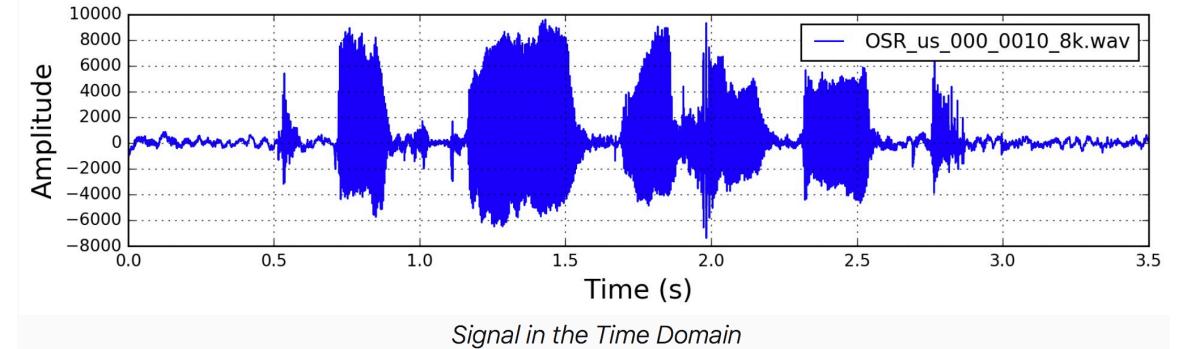
The Machine Speech And Audio Chain

- Synthesis
 - Information
 - Text to digital speech waveform
 - DAC and amplifier
 - Speaker
- Sound waveform
- Analysis
 - Microphone
 - Amplifier and ADC
 - Digital speech waveform to text
 - Information

Pre Processing

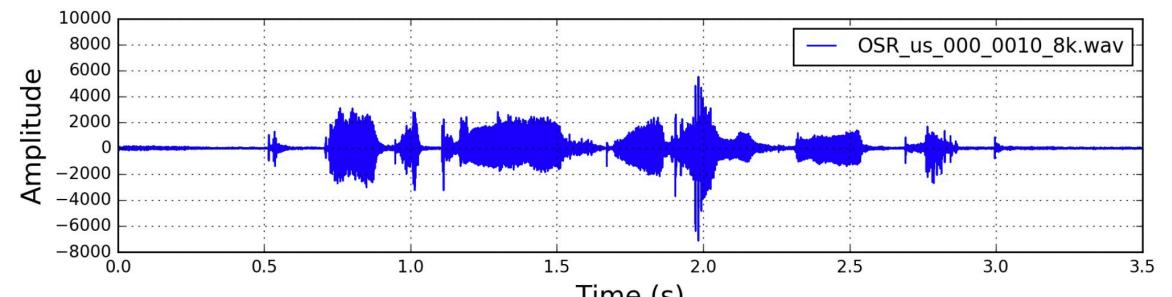
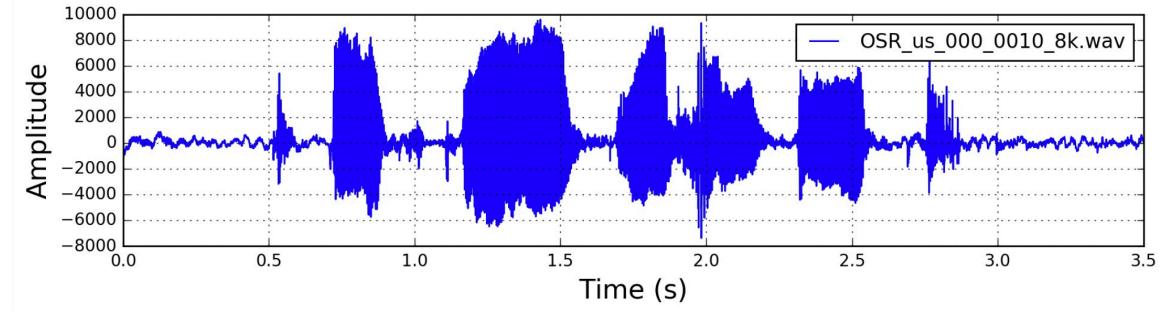
Time Domain Waveform

- The microphone is a transducer that converts sound waves to continuous time voltages
- Continuous time voltages are sampled by an ADC to create discrete time domain samples
 - Typically the ADC produces a specific number of bits per sample at a particular rate
 - A continuous real baseband signal bandlimited to B Hz can be reproduced exactly via samples at $2B$ Hz
 - This would imply no loss of information
- Humans can hear sounds from $\sim 20 - 20$ kHz so sampling frequencies would need to be > 40 kHz to prevent a loss of information for humans
 - For reference CDs are sampled at 44.1 kHz at 16 bits
 - Speech datasets for machine learning are frequently sampled at 4, 8 or 16 kHz



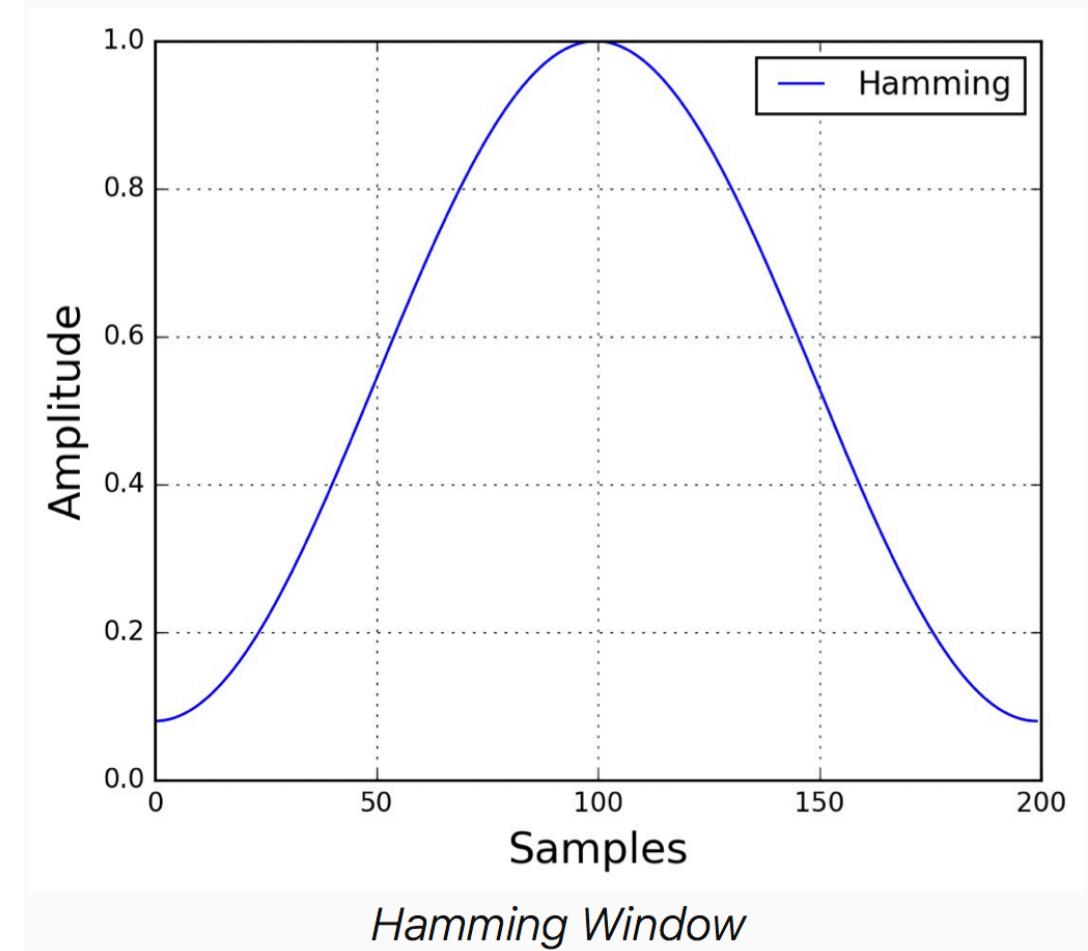
Pre Emphasis

- To help with later processing a pre emphasis filter is sometimes applied at this point to increase high frequency components
 - High frequency components tend to be smaller than low frequency components for human created sounds
- Not all systems include pre emphasis



Windowing And Spectrogram

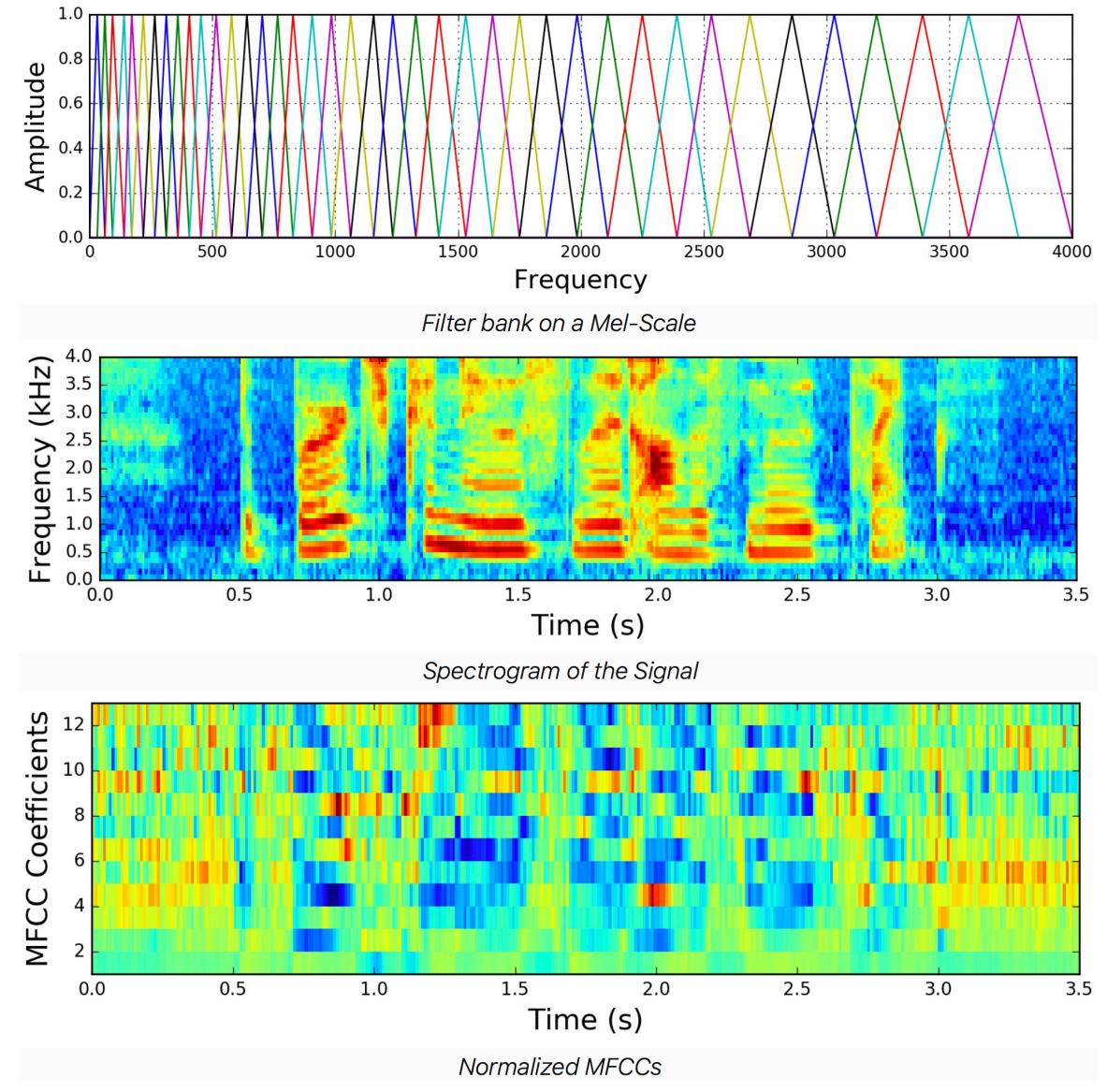
- To better understand the speech or audio signal it's useful to look at it in the frequency domain
 - But taking a DFT of the whole waveform would lose all temporal information
- So the input waveform is blocked into frames of $\sim 20 - 25$ ms with ~ 10 ms of overlap
 - Blocking is equivalent to windowing by a rectangular function which has a sinc() for a transform and results in spectral leakage (multiplication in the time domain == convolution in the frequency domain)
 - To reduce the spectral leakage a Hamming window is typically applied (lower side lobes in the freq domain)
- The DFT of each frame is taken and the magnitude is used to create the spectrogram



MFCC

Mel frequency cepstral coefficients; note that there are variations of this

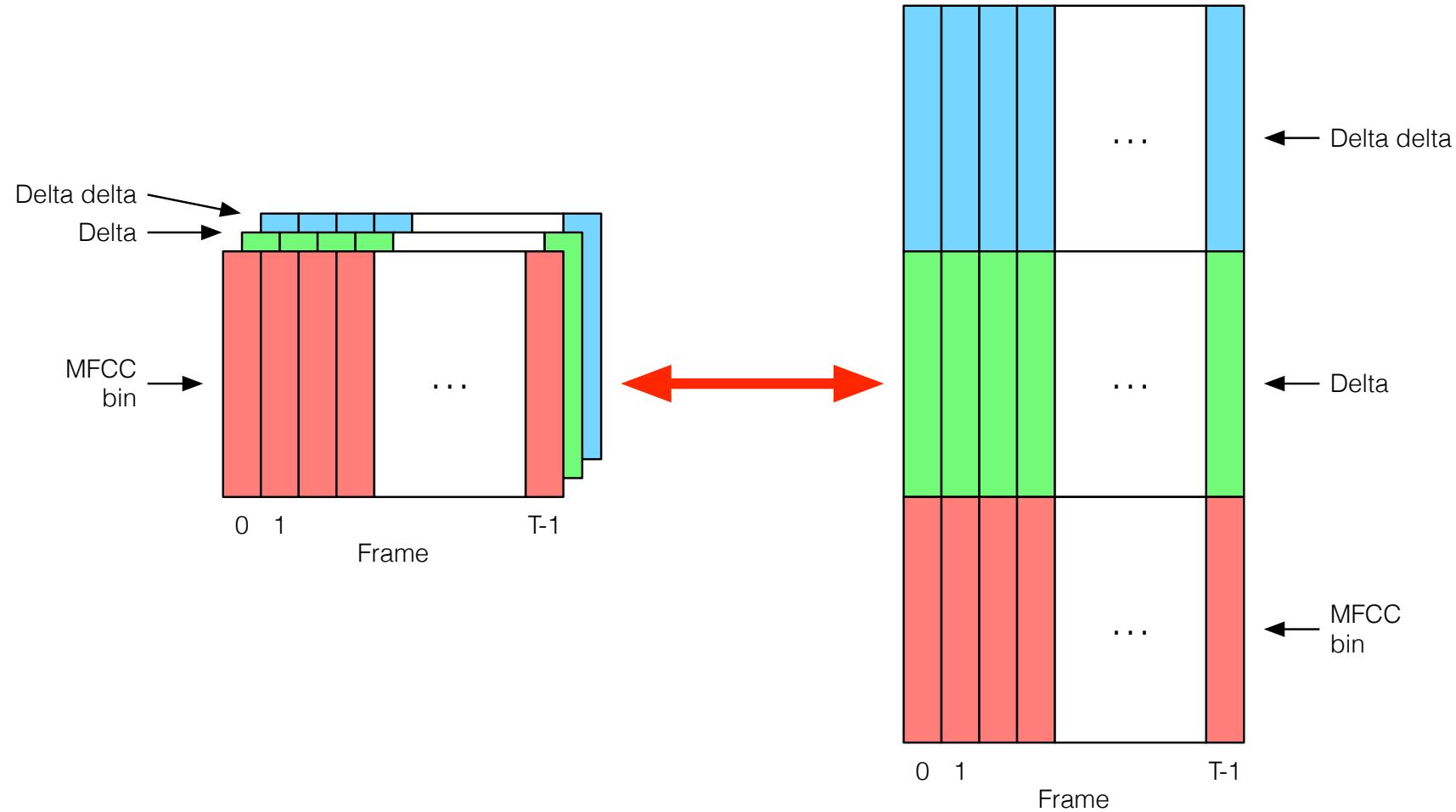
- Humans don't respond to all frequencies equally
 - The mel frequency spacing mimics the greater sensitivity of the ear to lower frequencies
 - A mel filter bank with ~ 40 filters can be applied to the spectrogram output to create a mel filter bank output
 - For log mel take the log of the mel spectrogram
- Next steps
 - Take the DCT of this to concentrate energy
 - Keep coefficients 2 – 13 (replace coefficient 1 with the log energy, throw away coefficients 14+ as most information is in lower frequencies)
 - Create additional features with Δ values representing 1st order differences in coefficients 1 – 13 (\sim 1st order derivative, provides shape info)
 - Create additional features with $\Delta\Delta$ values representing 1st order differences in Δ values (\sim 2nd order derivative, provides shape info)
 - Normalize coefficients to 0 mean and 1 variance



Network Structures

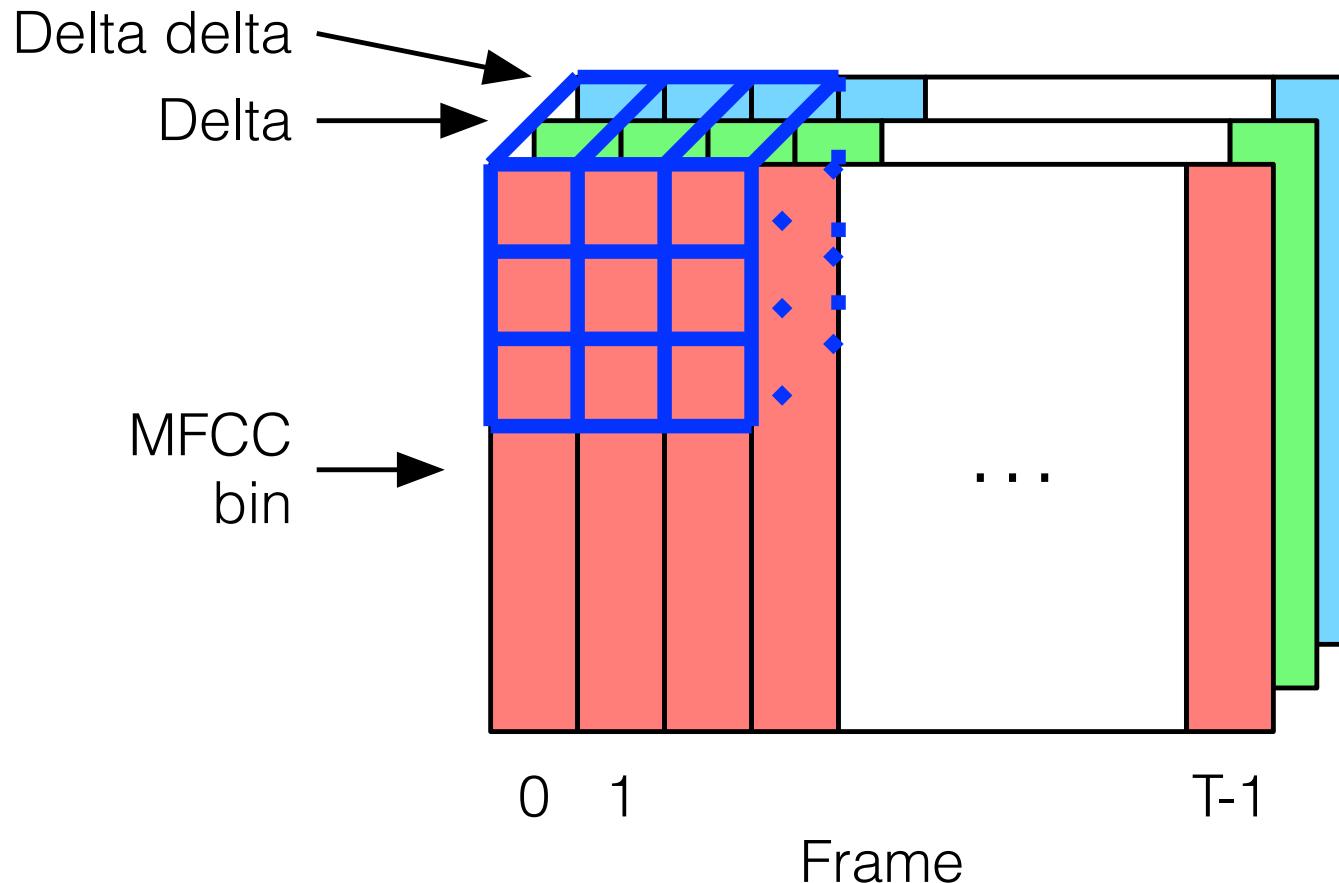
Different Views Of Pre Processed Speech

A 2D image of derivatives x bins x frames or a sequence of 1D vectors of stacked derivatives and bins



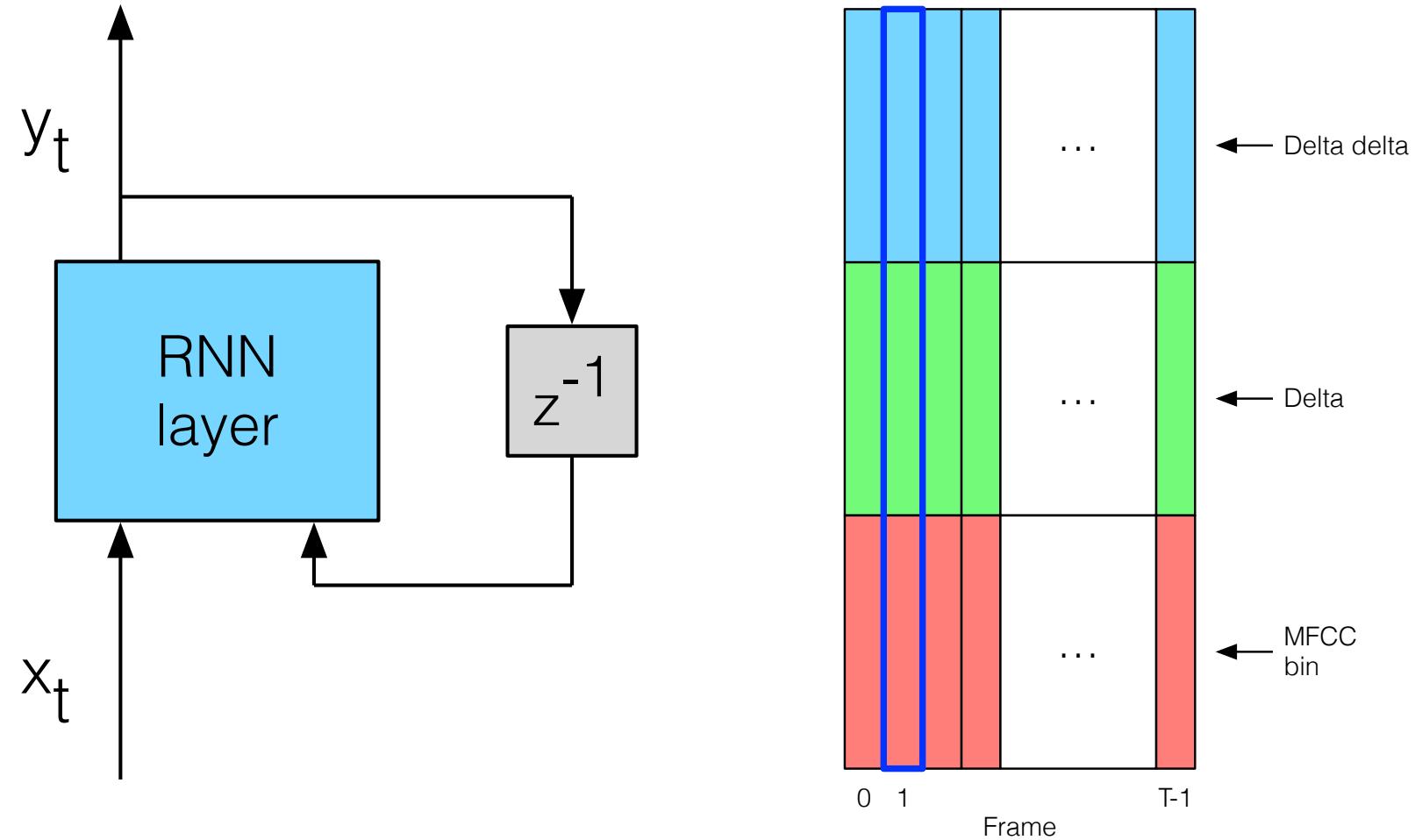
CNNs

CNNs exploit translation invariance in space (in this case time and bin) for efficiency to combine info across time and bin to create stronger features



RNNs

RNNs exploit sequential structure in time (frame) to map from weaker features to stronger features



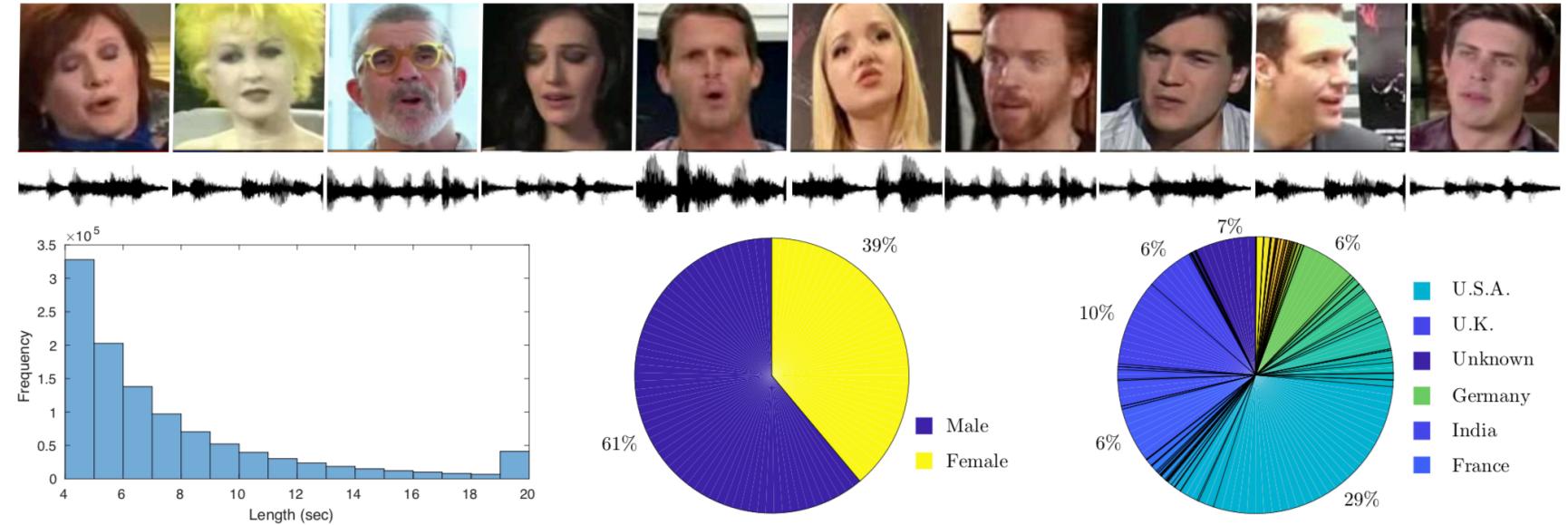
Should You Use A CNN, RNN Or Self Attention?

- For the problem of interest
 - Which is better for mapping from weak features to strong features with respect to accuracy?
 - Which is better for mapping from weak features to strong features with respect to efficiency of implementation?
 - What matters?
- The traditional split has been CNNs for vision and RNN / variants for speech and language
 - But there are blurring lines and CNNs are finding more uses in problems with sequential data
 - An argument can be made that RNNs / LSTMs are not the most efficient structure for propagating longer range information and are also inefficient to implement as they're memory bound
 - Attention based models are also starting to see more applications in speech
 - For more commentary see: The fall of RNN / LSTM (<https://towardsdatascience.com/the-fall-of-rnn-lstm-2d1594c74ce0>)
 - Also see: When recurrent models don't need to be recurrent (<https://bair.berkeley.edu/blog/2018/08/06/recurrent/>)
- It will be interesting to see how this evolves

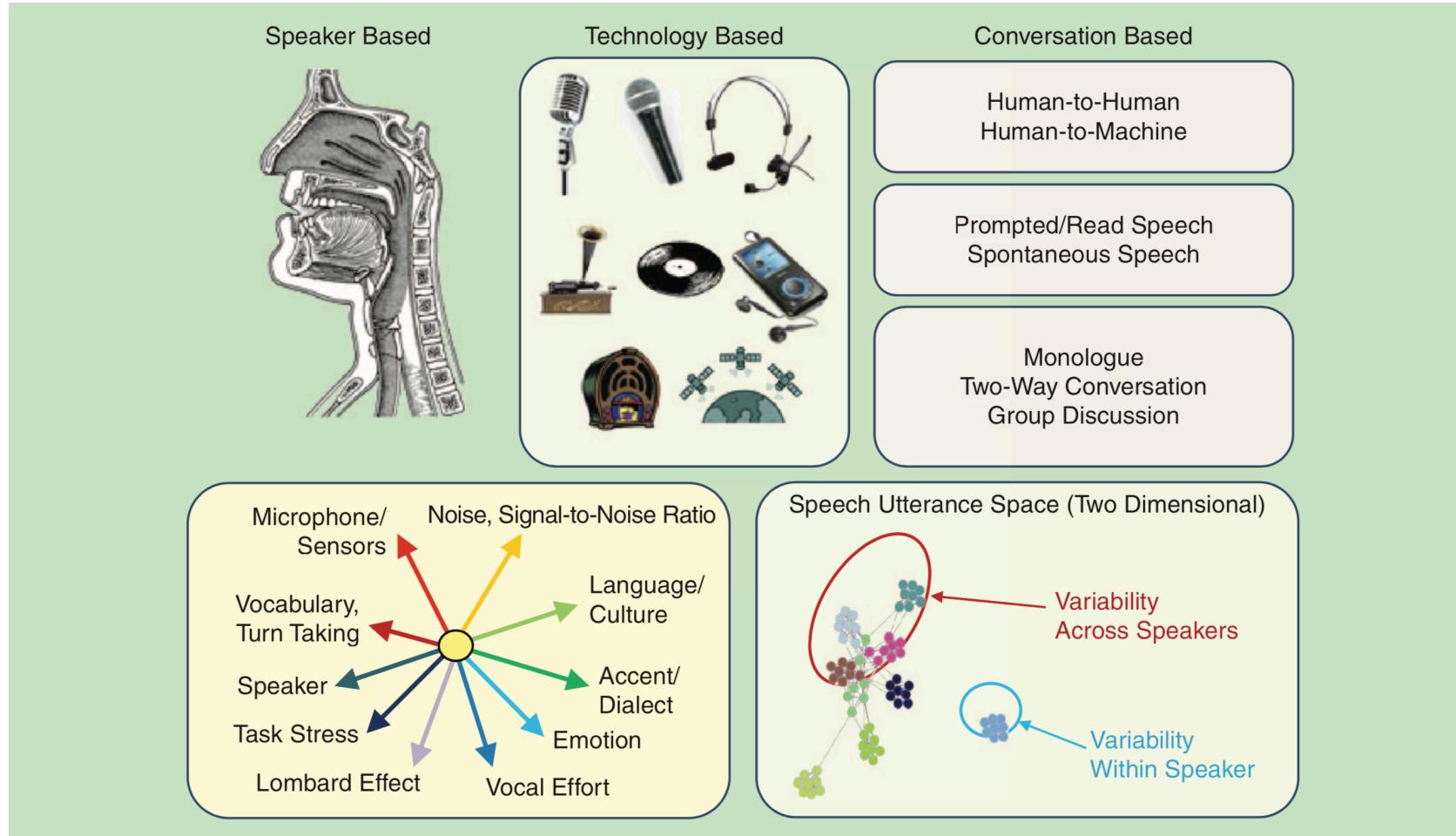
Speaker Identification

Recognition And Verification

- Recognition
 - Identify which of (potentially) many speakers is speaking
- Verification
 - Identify if a person is who they say they are or not
- Data
 - VoxCeleb1
 - VoxCeleb2
 - Speakers in the wild



Sources Of Variability



More Challenges

- Text independent (vs text dependent)
- Different lengths of text
 - Can probably handle with pooling in the time dimension
- Scaling to a large number of people
 - Straightforward method is a 1 hot classification problem
 - But there's a point when this vector becomes too big
 - So need to think of a good strategy to handle
 - Possibly at this point better to project a speaker to a vector, then find the closest reference vector
 - Or use a hierarchical network head

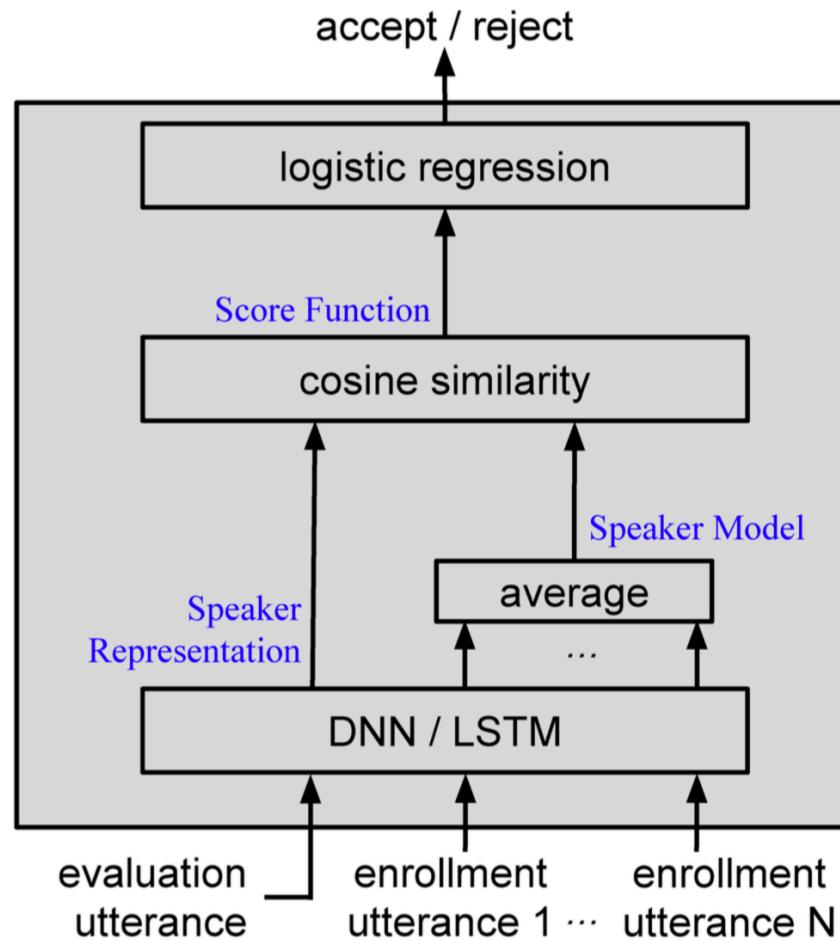
For a comprehensive review see:

- Machine learning for speaker recognition
<http://www.eie.polyu.edu.hk/~mwmak/papers/IS2016-tutorial.pdf>

Imprinting Strategy

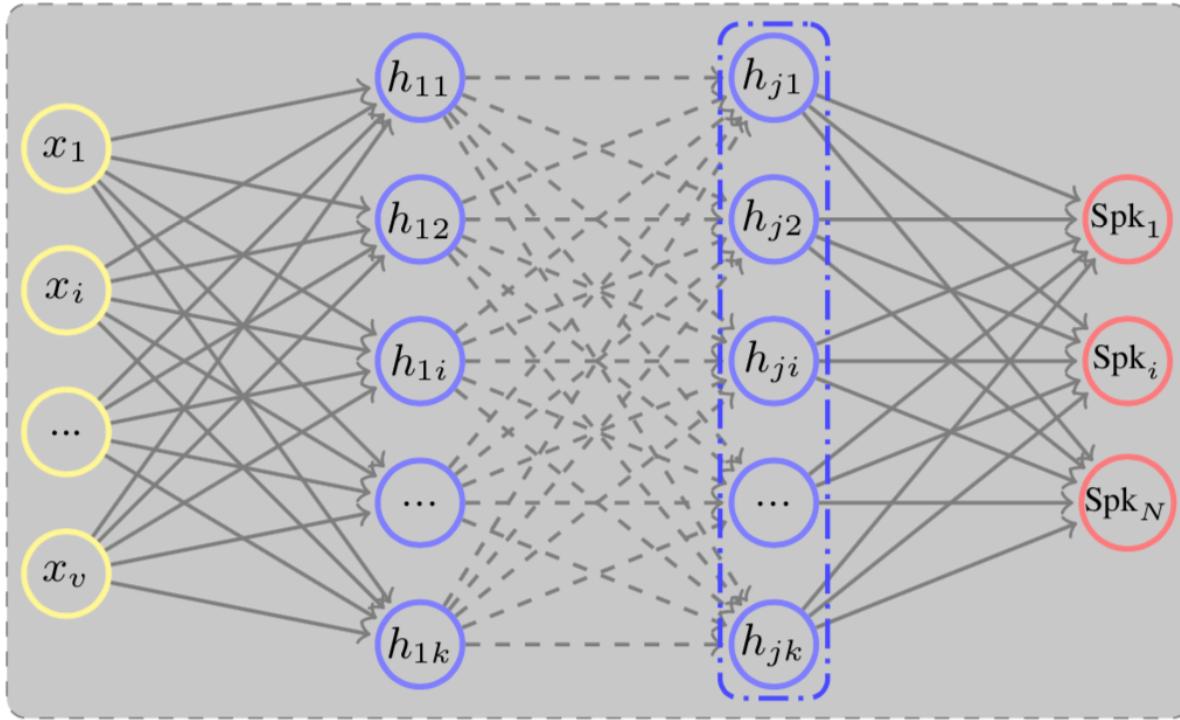
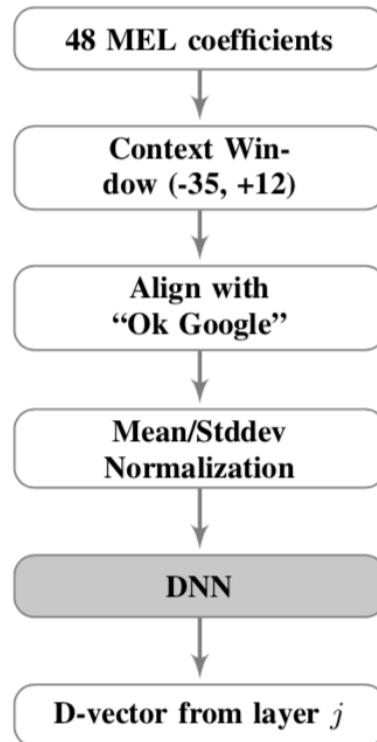
- Example problem: quickly train a system to accurately recognize a few users or other
 - Have each user provide a small amount of speech
 - Minimal training time, all local processing to add a user (no large cloud compute or processing)
- Training: pre train a model on a large database then use imprinting to add new users
 - Using a large speech / speaker database pre train a model that maps from speech to speakers
 - Speech → [CNN / RNN / attention model] → final features → [col normalized linear mapping with no bias] → speakers
 - Normalizing columns in the linear mapping makes all speakers equally likely
 - To add each user
 - Using the pre trained model map training speech samples to final features
 - Average all the final features together and normalize to get a feature vector for the user
 - Ideally want the final feature for the user to be relatively stable across speech samples
 - Add the user feature vector as a column to the linear mapping also creating a new speaker class
 - Ideally want a large distance of this user to existing users as represented by the cosine of the angle between columns in the normalized linear mapping (otherwise it will be difficult to distinguish this user from others)
- Use: distinguish users via classification
 - Can bias the results to make new users more likely via changing weightings of the columns in the linear mapping

Example: A Basic Framework For Verification



Example: Small Footprint Speaker Recognition

Verification is based on cos distance of d vectors between enrolled and evaluation; $d_i = \max_t (h_{ji}^t)$



Note that this NN could be replaced with other xNN designs

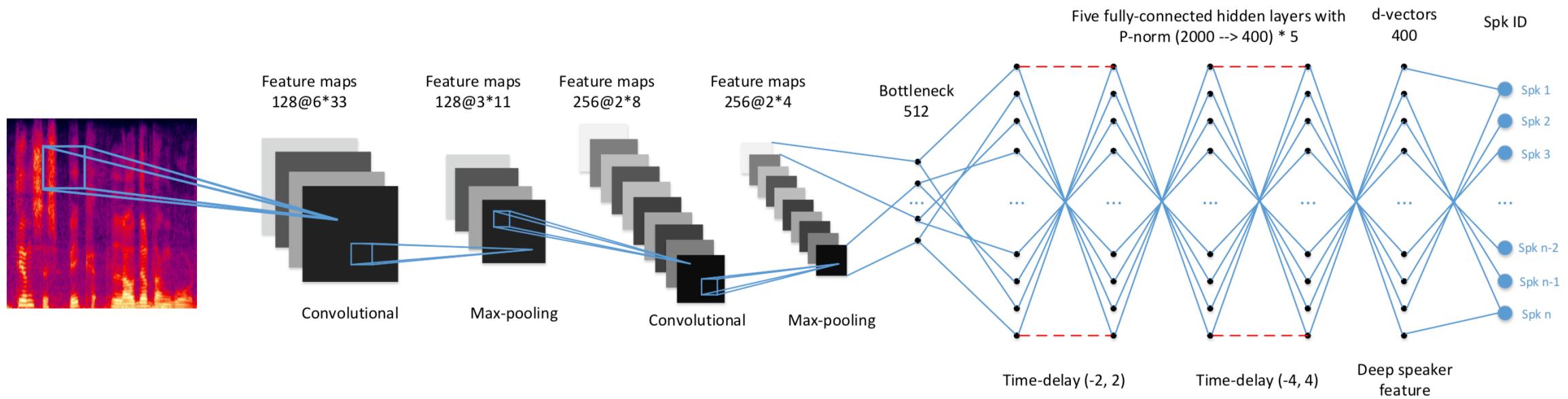
Topology

- $c = 48$ mel-filterbanks.
- $l = 35, r = 12$ context frames.
- $v = 2304$ visible units.
- $M = 4$ hidden layers.
- $k = 256$ hidden units.
- $N = 3200$ output speakers.
- $w = 787k$ model weights (excluding output layer).
- Rectified Linear Units.
- Softmax output Layer.

Training

- Stochastic Gradient Descent.

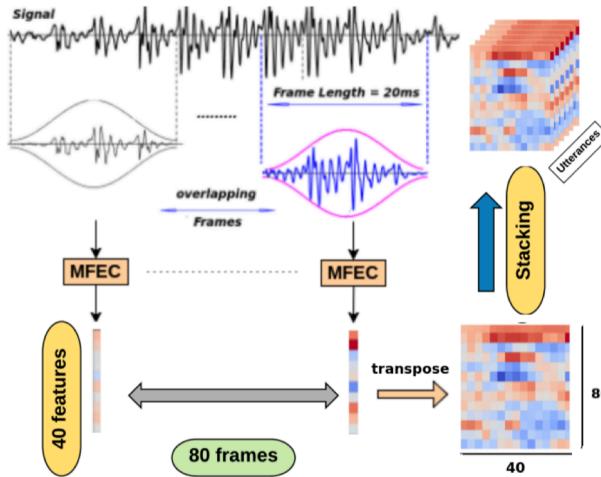
Example: CT-DNN



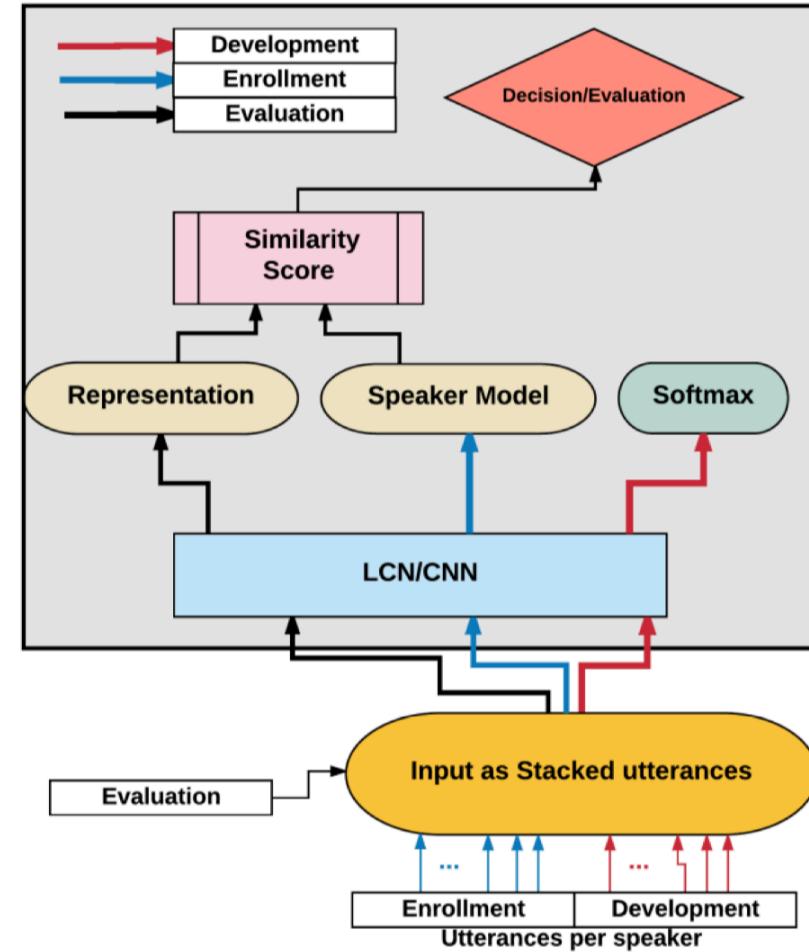
Example: VGGVox

layer name	res-34	res-50
conv1	$7 \times 7, 64$, stride 2	$7 \times 7, 64$, stride 2
pool1	3×3 , max pool, stride 2	3×3 , max pool, stride 2
conv2_x	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
conv3_x	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$
conv4_x	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$
conv5_x	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$
fc1	$9 \times 1, 512$, stride 1	$9 \times 1, 2048$, stride 1
pool_time	$1 \times N$, avg pool, stride 1	$1 \times N$, avg pool, stride 1
fc2	$1 \times 1, 5994$	$1 \times 1, 5994$

Example: 3D-CNN



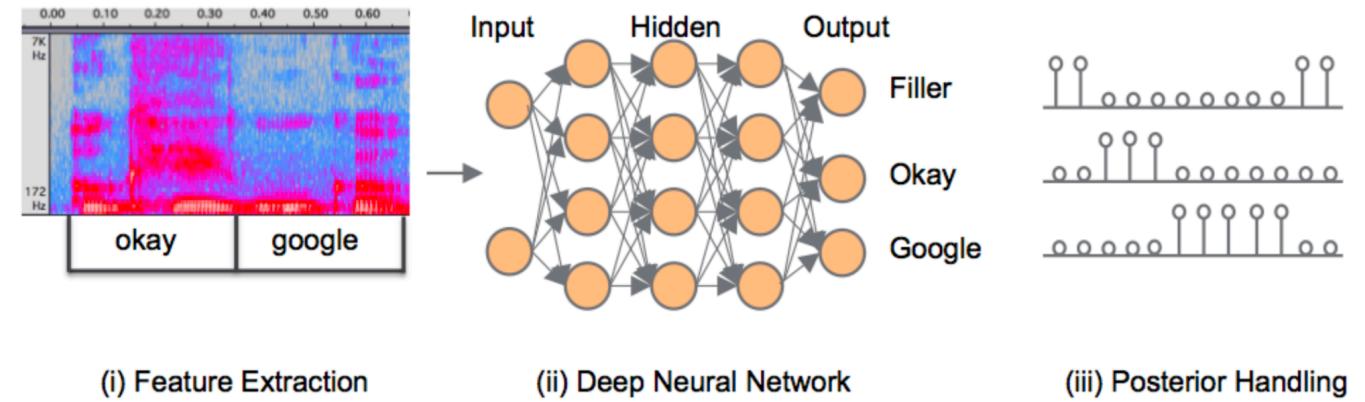
layer	input-size	output-size	kernel	stride
Conv1-1	$\zeta \times 80 \times 40$	$80 \times 36 \times 16$	$3 \times 1 \times 5$	$1 \times 1 \times 1$
Conv1-2	$80 \times 36 \times 16$	$36 \times 36 \times 16$	$3 \times 9 \times 1$	$1 \times 2 \times 1$
Pool1	$36 \times 36 \times 16$	$36 \times 18 \times 16$	$1 \times 1 \times 2$	$1 \times 1 \times 2$
Conv2-1	$36 \times 18 \times 16$	$36 \times 15 \times 32$	$3 \times 1 \times 4$	$1 \times 1 \times 1$
Conv2-2	$36 \times 15 \times 32$	$15 \times 15 \times 32$	$3 \times 8 \times 1$	$1 \times 2 \times 1$
Pool2	$15 \times 15 \times 32$	$15 \times 7 \times 32$	$1 \times 1 \times 2$	$1 \times 1 \times 2$
Conv3-1	$15 \times 7 \times 32$	$15 \times 5 \times 64$	$3 \times 1 \times 3$	$1 \times 1 \times 1$
Conv3-2	$15 \times 5 \times 64$	$9 \times 5 \times 64$	$3 \times 7 \times 1$	$1 \times 1 \times 1$
Conv4-1	$9 \times 5 \times 64$	$9 \times 3 \times 128$	$3 \times 1 \times 3$	$1 \times 1 \times 1$
Conv4-2	$9 \times 3 \times 128$	$3 \times 3 \times 128$	$3 \times 7 \times 1$	$1 \times 1 \times 1$
FC5	$4 \times 3 \times 3 \times 128$	128	-	-



Keyword Spotting And Command Recognition

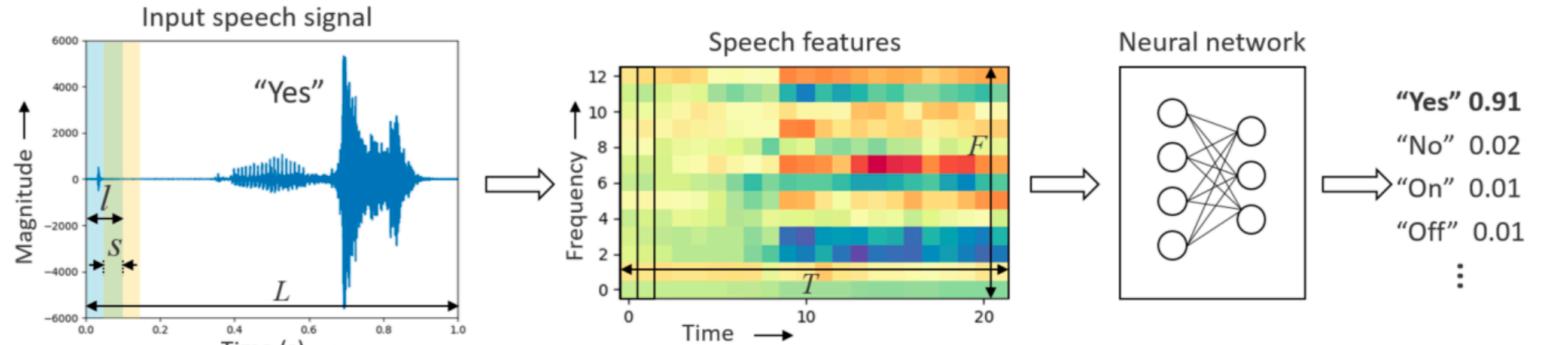
Wake Up

- In a power constrained environment the wakeup process can be staged with less reliable lower power / complexity operations gating more reliable higher power / complexity operations
- Example flow
 - Sound detection
 - Voice activity detection
 - Wake word or phrase detection
 - Key word spotting or speech recognition
- These are all classification problems



Limited Vocabulary Speech Recognition

- Also referred to as keyword spotting or command recognition
- Like wake up but
 - A few more positive classes
 - Typically a little extra system power to work with
- Examples
 - Free spoken digit dataset (FSDD)
 - Google command data set
- This is also a classification problem

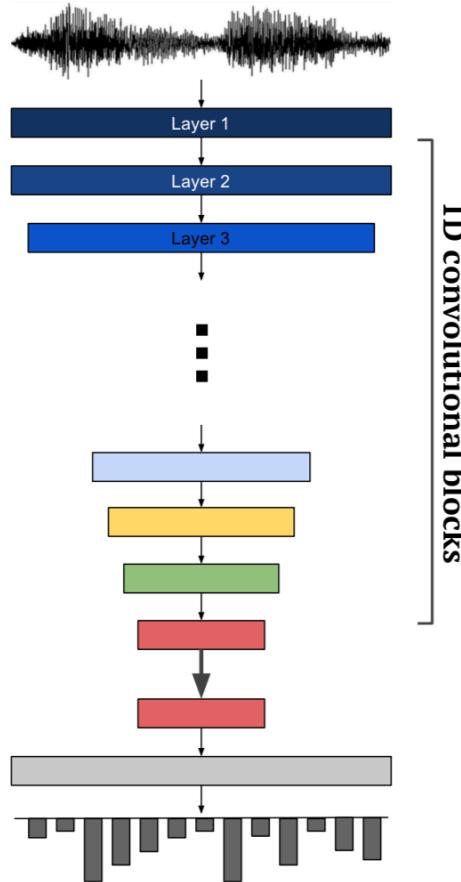


Strategy

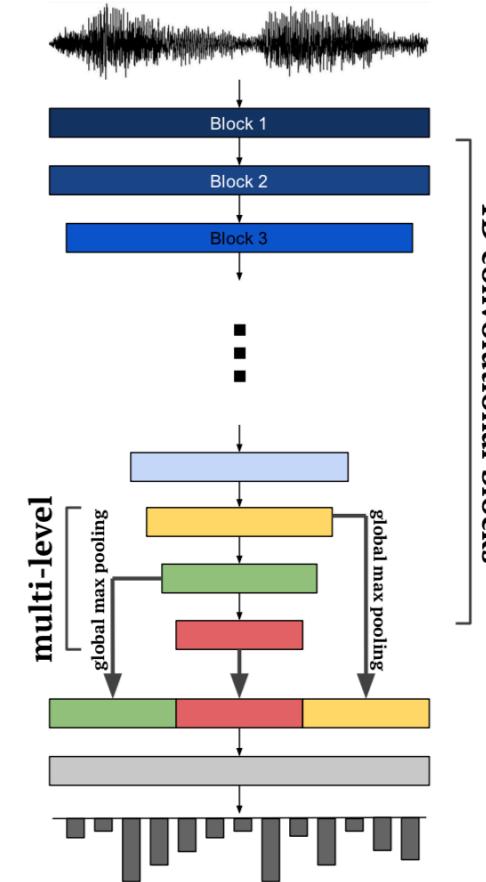
- Build a xNN based classifier
 - The input is raw audio (ok if short) or pre processed vectors
 - The network maps the input to classes
 - Classes are {key word, not key word} or {class 0, ..., class C, not in limited vocabulary}
 - The whole thing is trained end to end as always
- Network considerations
 - How to appropriately combine input data across time and frequency to achieve a high accuracy for the given problem
 - Training and use with imbalanced class probabilities ("not" is much more common)
 - Low latency for a positive user experience
 - Low complexity to minimize resource usage

Example: Raw Waveform Audio Classification

Residual network with squeeze and excite and multi level feature concatenation



(a) SampleCNN



(b) ReSE-2-Multi

Evaluation Via A Confusion Matrix

A convenient way to visualize classification network performance; sometimes probabilities are intensity or color coded to make the visualization easier

		Word spoken				
		w1	w2	wN		
Word recognized		w1	P(w1 w1)	P(w1 w2)	-----	P(w1 wN)
		w2	P(w2 w1)	P(w2 w2)	-----	P(w2 wN)
		⋮	⋮	⋮	⋮	
		wN	P(wN w1)	P(wN w2)	-----	P(wN wN)

Some Recent References

- A neural attention model for speech command recognition
 - <https://arxiv.org/abs/1808.08929>
- Stochastic adaptive neural architecture search for keyword spotting
 - <https://arxiv.org/abs/1811.06753>
- End-to-end streaming keyword spotting
 - <https://arxiv.org/abs/1812.02802>

Conditional Modeling

Model → Conditional Model

A single framework for thinking about speech to text, text to speech, language translation and other problems with an input and feedback in the prediction

- Model
 - Assigns probabilities to a sequence of elements y_i (words, audio samples, ...)
 - $P(y_{n-1}, y_{n-2}, \dots, y_1, y_0) = P(y_{n-1} | y_{n-2}, \dots, y_1, y_0) \dots P(y_1 | y_0) P(y_0)$
 - The key to creating a model is next element prediction (next word, next audio sample, ...) given previous elements
 - $P(y_{n-1} | y_{n-2}, \dots, y_1, y_0) = P(y_{n-1}, y_{n-2}, \dots, y_1, y_0) / P(y_{n-2}, \dots, y_1, y_0)$
- It's possible to cast a large number of problems as leaning a model using output data (next element prediction) then focusing / biasing the prediction by conditioning the model on input data x
 - $P(y_{n-1} | y_{n-2}, \dots, y_1, y_0, x)$
 - Effectively, conditioning on the input data makes the next element prediction less uniform / more spiky (ideally 1 hot like)
 - Reduces the entropy of the conditional pmf
 - Needs input output data pairs for training
- During testing previous true outputs y_{n-2}, \dots, y_1, y_0 are replaced with previous predicted outputs
 - $P(y_{n-1} | y_{n-2}^{\text{hat}}, \dots, y_1^{\text{hat}}, y_0^{\text{hat}}, x)$
 - Use beam search or some similar variant to reduce error feedback
 - Even better if x contributes strongly to the prediction as that helps prevent error feedback effects

Conditional Model For Language Translation

This is covered in the language lecture

- Learn a model for language 2 that can predict the next word in language 2 given previous words in language 2
 - This model can be optimized for specific or general text from language 2 by training on that type of text from language 2
- Then focus / bias the language 2 predictions via conditioning on features generated from specific text of language 1
 - This creates a conditional model that produces text of language 2 corresponding to the given text of language 1
- In equations (the network approximates this pmf)
 - Notation:
 - y_i are the words in language 2
 - x are the text features in language 1
 - Language 2 model:
$$P(y_{n-1} | y_{n-2}, \dots, y_1, y_0)$$
 - Conditioned on features from language 1:
$$P(y_{n-1} | y_{n-2}, \dots, y_1, y_0, x)$$
 - Using previous predicted outputs:
$$P(y_{n-1} | y_{n-2}^{\text{hat}}, \dots, y_1^{\text{hat}}, y_0^{\text{hat}}, x)$$

Conditional Model For Speech To Text

This is covered in the next section

- Learn a model for text that can predict the next phoneme, grapheme / character, word piece or word given previous phonemes, graphemes / characters, word pieces or words
 - This model can be optimized for specific or general types of text by training on that type of text
- Then focus / bias the text predictions via conditioning on features generated from a specific speech signal
 - This creates a conditional model that produces text corresponding to the given speech signal
- In equations (the network approximates this pmf)
 - Notation:
 - y_i is the text
 - x is the speech signal
 - Text model: $P(y_{n-1} | y_{n-2}, \dots, y_1, y_0)$
 - Conditioned on features from speech: $P(y_{n-1} | y_{n-2}, \dots, y_1, y_0, x)$
 - Using previous predicted outputs: $P(y_{n-1} | \hat{y}_{n-2}, \dots, \hat{y}_1, \hat{y}_0, x)$

Conditional Model For Text To Audio

This is covered in the section after the next section

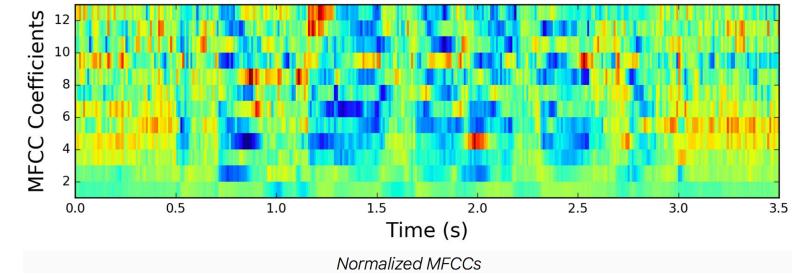
- Learn a model for audio that can predict the next audio sample given previous audio samples
 - This model can be optimized for specific or general types of audio by training on that type of audio
 - Ex: human speech, 1980s hairspray metal, ...
- Then focus / bias the audio sample predictions via conditioning on features generated from a specific text
 - This creates a conditional model that produces audio (speech, music) corresponding to the given text (words, instruments)
 - Note that it's possible to condition on more than 1 thing (e.g., words + voice characteristics from a specific speaker to create a conditional model that produces speech corresponding to the specific words in the voice of the specific speaker)
- In equations (the network approximates this pmf)
 - Notation:
 - y_i is the audio samples
 - x is the text signal
 - Audio model:
$$P(y_{n-1} | y_{n-2}, \dots, y_1, y_0)$$
 - Conditioned on features from text:
$$P(y_{n-1} | y_{n-2}, \dots, y_1, y_0, x)$$
 - Using previous predicted outputs:
$$P(y_{n-1} | \hat{y}_{n-2}, \dots, \hat{y}_1, \hat{y}_0, x)$$

Speech To Text

Goal And Challenges

Also called speech recognition or automatic speech recognition

- Map audio inputs to linguistic outputs
 - This is a mapping from 1 sequence (e.g., sound) to another sequence (e.g., text); converting from 1 form to another is called transduction (in general)
- Challenge 1: alignment
 - Training data is typically in the form of an audio clip and a text transcription
 - What's not included is the alignment between the input audio and the associated text
 - What parts of the audio signal are useful for predicting the next output?
- Challenge 2: language
 - Want to ultimately predict words or sentences
 - But that space is too large to directly predict
 - To keep the size of the prediction space manageable it's common to predict phonemes, graphemes / characters or word pieces
 - These need to be composed into appropriate words and sentences
 - There's an underlying sequential structure that matters
 - Is it possible to exploit the structure of language?



The quick brown fox jumps
over the lazy dog

Data

- DeepSpeech
- Google Voice Search
- LibriSpeech
- The LJ speech dataset
- MGB
- Switchboard
- TED-LIUM
- Timit
- Wall Street Journal
- YouTube

An Abbreviated History

- Classical (-ish): HMM–GMM
 - Predict phonemes (sounds) from speech via an acoustic model
 - Concatenate phonemes to words via a pronunciation model
 - Rescore sequences of words via a language model
- An intermediate hybrid step: HMM–xNN
 - Replace the GMM used for acoustic modeling with an xNN
- Present (or more precisely what's described here): xNN
 - The methods described here can still predict phonemes
 - But the focus will typically be on predicting graphemes (~ characters) from speech
 - Sometimes there's a 1 to 1 correspondence between phonemes and graphemes, sometimes a phoneme corresponds to multiple graphemes, sometimes a grapheme is unvoiced
 - Nice because a separate pronunciation model is no longer needed and a network can learn a basic pronunciation and a language model
 - Sometimes word pieces are predicted including graphemes as a subset such that there are no out of model words

Geoffrey Hinton, Li Deng, Dong Yu, George E. Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N. Sainath, and Brian Kingsbury

Deep Neural Networks for Acoustic Modeling in Speech Recognition

The shared views of four research groups



Most current speech recognition systems use hidden Markov models (HMMs) to deal with the temporal variability of speech and Gaussian mixture models (GMMs) to determine how well each state of each HMM fits a frame or a short window of frames of coefficients. An alternative way to evaluate the fit is to use a feed-forward neural network that takes several frames of coefficients as input and produces posterior proba-

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Date of publication: 15 October 2012

bilities over HMM states as output. Deep neural networks (DNNs) that have many hidden layers and are trained using new methods have been shown to outperform GMMs on a variety of speech recognition benchmarks, sometimes by a large margin. This article provides an overview of this progress and represents the shared views of four research groups that have had recent successes in using DNNs for acoustic modeling in speech recognition.

INTRODUCTION
New machine learning algorithms can lead to significant advances in automatic speech recognition (ASR). The biggest

Acoustic Model

The acoustic model maps sound to phonemes, graphemes or word pieces

- Pre processing to generate MFCCs or a variant is common
 - Other options are also possible
 - May 0 pad the input to a constant length
- Encoder generates strong features from MFCCs
 - RNN, LSTM, bi directional, pyramidal, CNN, self attention, ...
 - Possibly uses transfer learning for low resource languages
- Decoder does alignment and phoneme, grapheme (character) or word piece pmf prediction and assembly
 - If doing phoneme prediction then a separate pronunciation model is required to generate words
 - If doing word piece prediction then typically include graphemes as a subset such that there are no out of vocabulary words
 - Possible to keep most likely predictions or a N best list of predictions which enables an external language model
- Post processing
 - Incorporation of an external language model to go from N best list to transcription

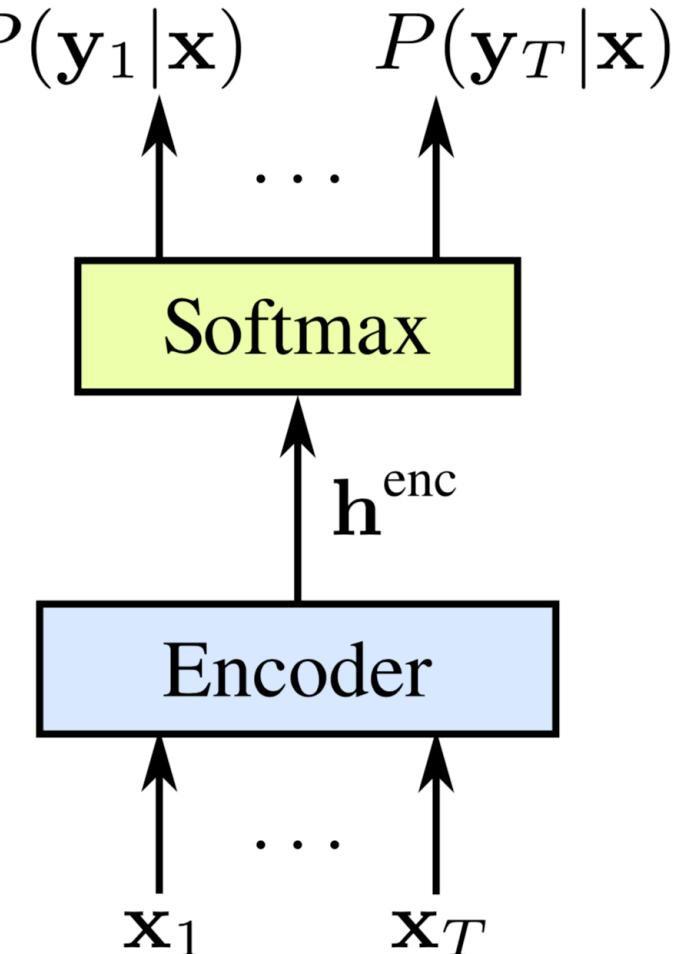
Think about the mapping required from the encoder (e.g., MFCCs to features corresponding to graphemes) – what is the optimal network structure for this?

Acoustic Model Output

The CTC Loss Function

Connectionist temporal classification makes it possible to train xNNs based acoustic models with unknown input / output alignments

- Note
 - CTC is described here in the context of grapheme prediction
 - Phoneme, word piece, ... are also possible
- Challenge 1: alignment
 - A xNN is a classifier that wants to map an input frame to a class
 - But the correct frame to class mapping is not known until the classifier is trained (because sound to text alignment is typically not given in training data)
 - This results in a circular dependency
- Solution: CTC loss function
 - The basic idea is for each frame for the xNN to predict a pmf over all graphemes plus a blank symbol
 - Repeated graphemes and the blank symbol are removed to create labels
 - The likelihood of each label is computed which allows the definition of a loss



CTC Decoding

For an input,
like speech



Predict a
sequence of
tokens

h e e ε | ε | | o o !

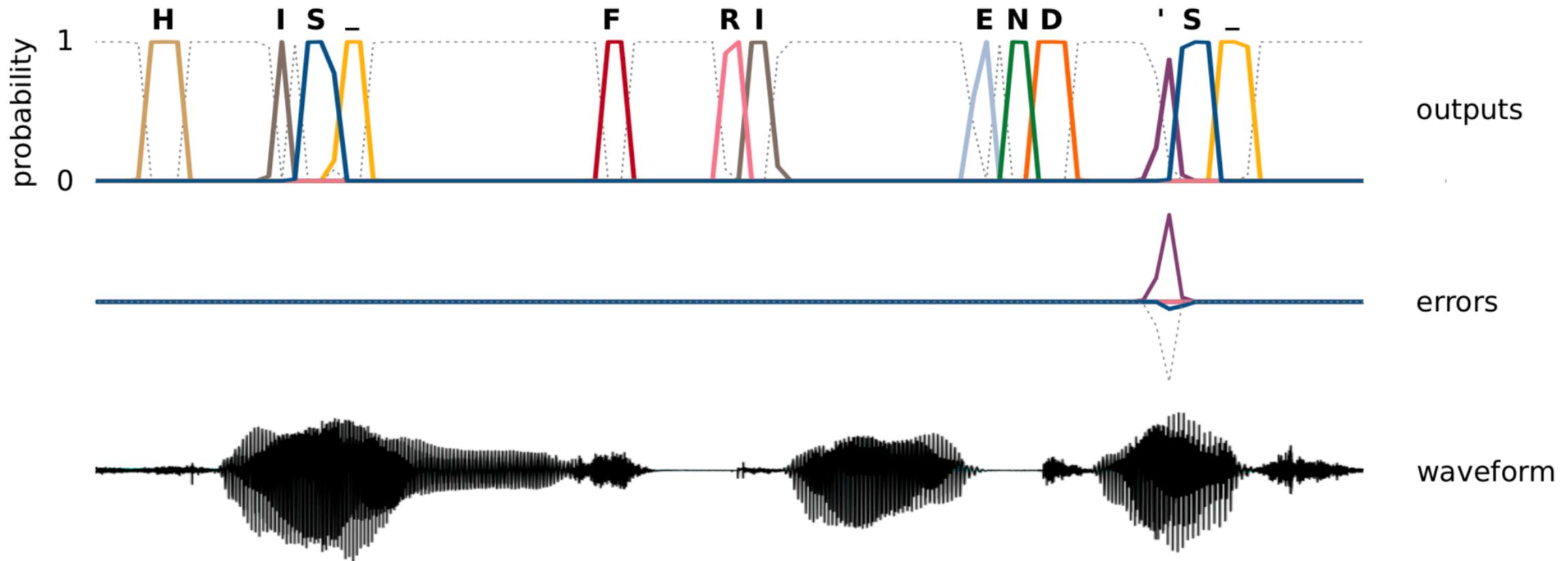
Merge repeats,
drop ϵ

h e | | o !

Final output

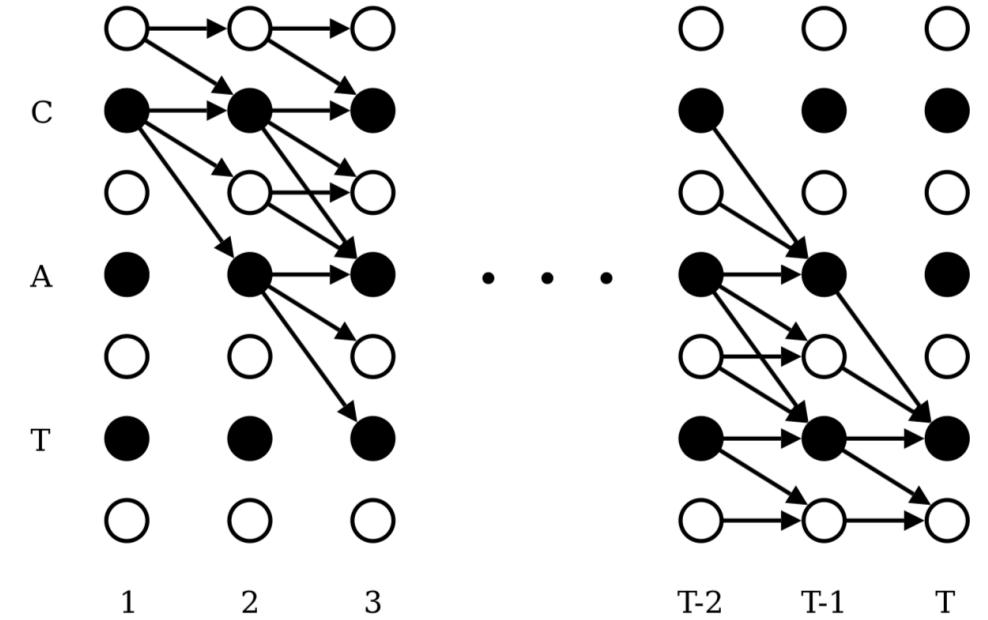
h e | | o !

CTC Decoding



CTC Definitions

- X is the network input (e.g., bins $\times T'$)
- Y is the network output (e.g., classes $\times T$)
 - Let classes == $\{a, \dots, z, -\}$
 - So for each time frame the network is predicting a pmf over all the letters + blank (the ' $-$ ') for the corresponding input frame
 - Note that other options are possible for the classes (e.g., phonemes for smaller, word pieces for larger)
 - Note that the T' can be the same size as T or different (frequently T is smaller than T')
 - The key is the inclusion of the blank class for alignment purposes
- π is a path that corresponds to selecting 1 class at each of the T times
 - Ex: $\pi = (a, a, a, -, r, -, -, t, t, t, t, t, -)$



CTC Definitions

- B is a many to 1 mapping that takes a path π and 1st removes repeated classes then 2nd removes blanks to produce a label ℓ
 - Ex: $\ell = B(\pi) = B(a, a, a, -, r, -, -, t, t, t, t, -) = (a, r, t)$
 - Note that this ordering of what is removed allows repeated letters to potentially be produced such as the ‘tt’ in ‘letter’

- ℓ is a label that corresponds to (potentially exponentially) many paths
 - Ex: The set of all path corresponding to a label

$$\begin{aligned}\{\pi\} &= B^{-1}(\ell) \\ &= B^{-1}(a, r, t) \\ &= \{(a, r, t, -, -, -, -, -, -, -, -), \\ &\quad (a, a, r, t, -, -, -, -, -, -, -, -), \\ &\quad (a, a, -, r, t, -, -, -, -, -, -, -), \\ &\quad \dots, \\ &\quad (-, -, -, -, -, -, -, -, a, r, t)\}\end{aligned}$$

CTC Path

- The probability of a path π given input X
 - $P(\pi | X) = \prod_t Y(\pi(t), t)$
 - The product of the pmf values of the class elements for the path
- The probability of a label ℓ given input X
 - $P(\ell | X) = \sum P(\pi_i | X) \forall \pi_i \in B^{-1}(\ell)$
 - This is a sum over all paths that can possibly generate the label
 - But in practice only a small number of paths will contribute meaningfully to the probability (multiplying multiple small numbers corresponding to unlikely classes results in a very small value)
 - This observation can be used to simplify the probability calculation via dynamic programming
- Training vs testing
 - During training, parameters are optimized to minimize the negative log likelihood of $P(\ell | X)$
 - During testing, greedy / arg max decoding is used or an N best list is saved for subsequent use with an external language model via beam search

CTC Properties

- The specific network used to map from input features to output classes used in the original paper was a bidirectional LSTM
 - A nice part of this is the forwards and backwards sequential combination of information to map from weak features (MFCC) to classes
 - However, the use of this network is not a requirement and other networks can be used
- Network output predictions are independent
 - This does not take advantage of the structure of language (challenge 2)
 - This can be addressed in multiple ways, the most common being using beam search decoding on a N best list to include an external language model(s)
 - This makes adaptation to new domains easier as only the external language model changes

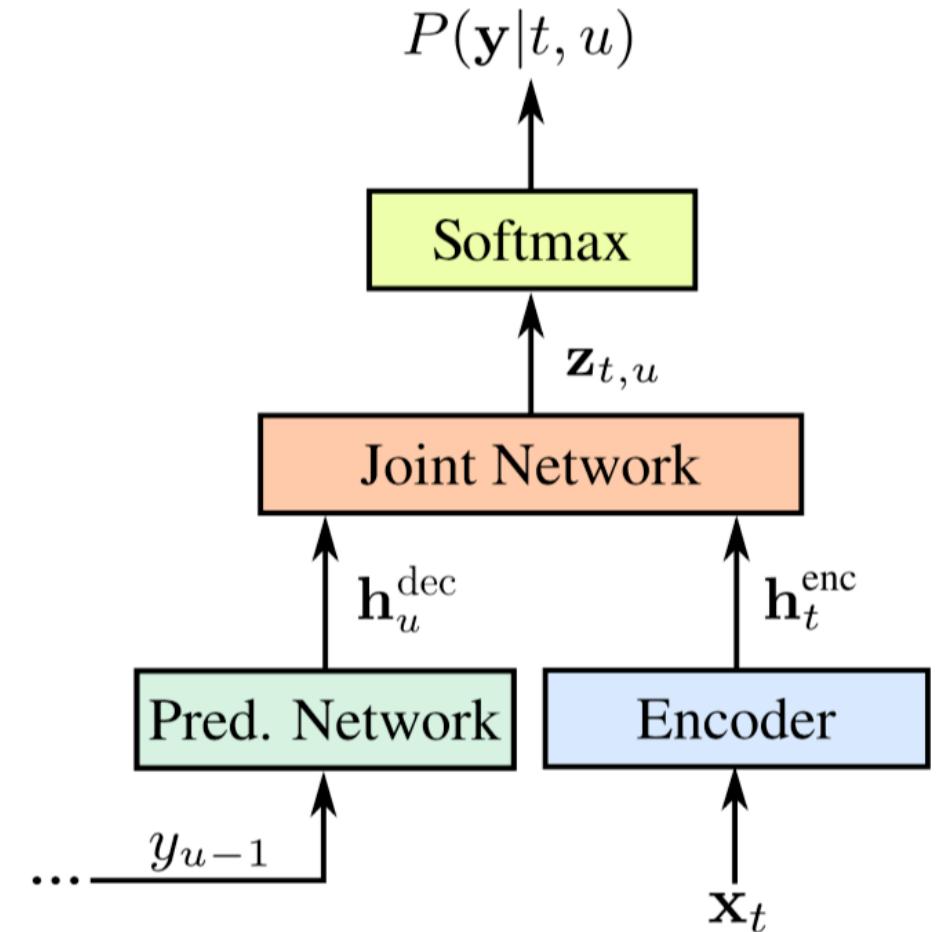
CTC Properties

- The output sequence length cannot be longer than the input sequence length
 - This is not a big deal for speech to text as the number of speech frames is typically \gg the number of output graphemes
 - But it will be an issue for using CTC in text to speech systems
- Alignments are monotonic from output classes to labels
 - This is reasonable for speech
 - But not valid for other sequence to sequence models like language translation

Adding A Language Model To The Acoustic Model

RNN transducer adds a data dependent language model that predicts the present letter given previous letters

- The RNN transducer adds conditional dependence in the predicted graphemes by feeding back previous outputs to a prediction network for an implicit language model
 - True value during training
 - Most likely prediction during testing
- Various xNN based architectures are possible for the encoder and prediction network
 - Note that the prediction network needs to be optimized for the target usage
 - The encoder can be an encoder used by the CTC



Adding A Language Model To The Acoustic Model

RNN transducer adds a data dependent language model that predicts the present letter given previous letters

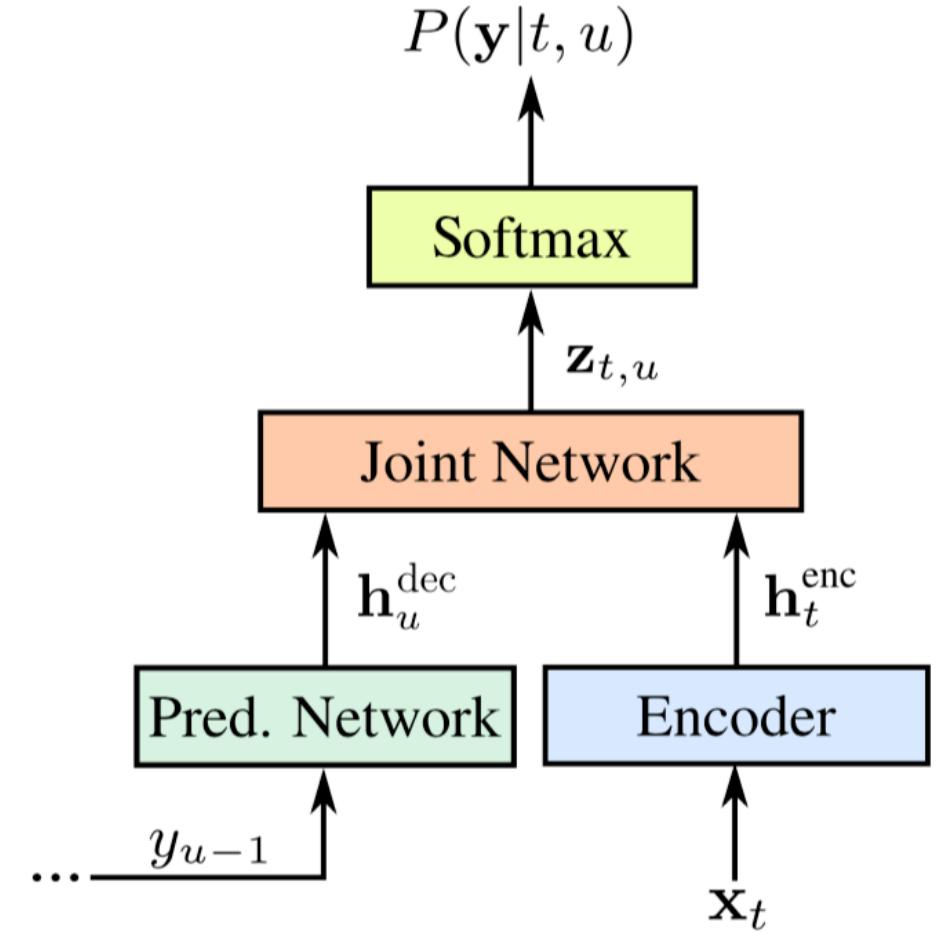
- Equations

- $h_{t,u}^{\text{joint}} = \tanh(A h_t^{\text{enc}} + B h_u^{\text{dec}} + c)$
- $z_{t,u} = D h_{t,u}^{\text{joint}} + e$
- $P(Y | t, u) = \text{softmax}(z_{t,u})$

- Output is a probability cube

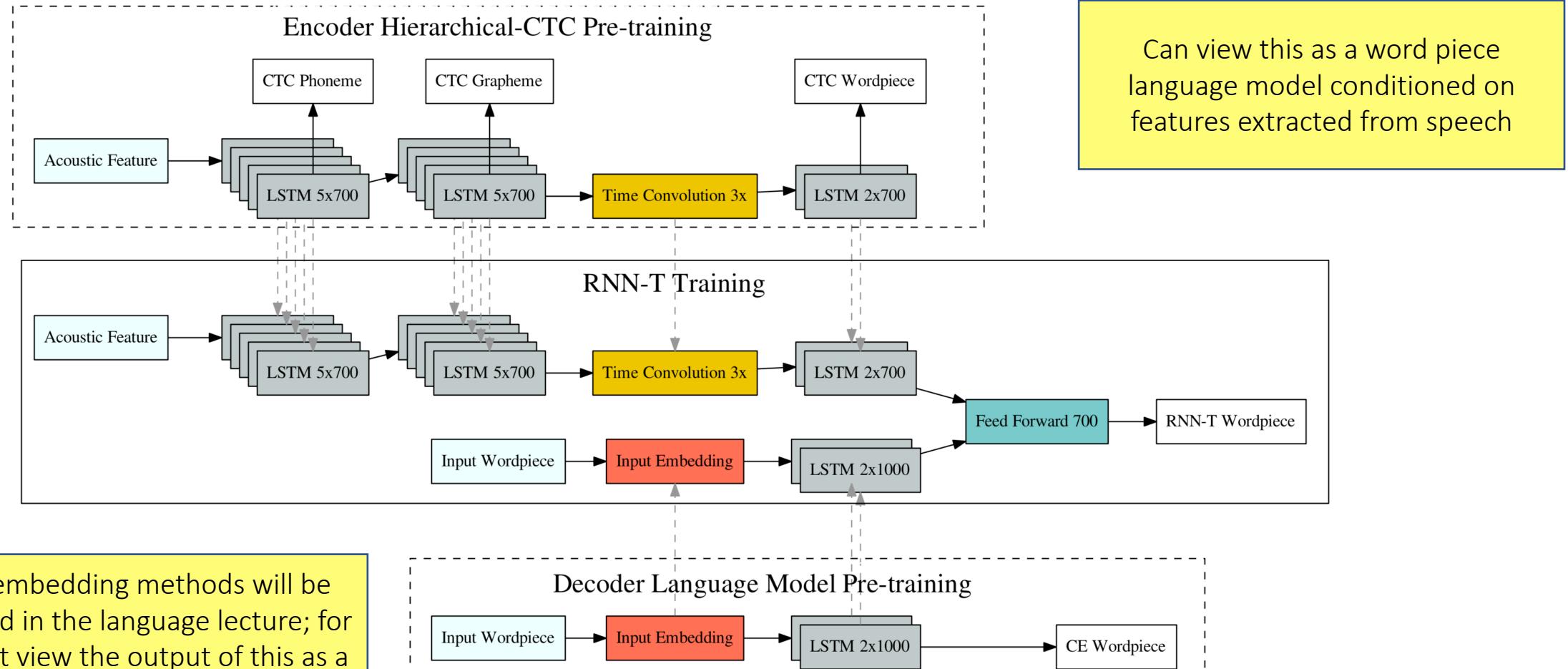
- (Graphemes + blank) x (T frames) x (U outputs)
- Beam search decoding to convert to a sequence
- Output sequence can be longer than the input sequence based on the traversal method through the cube

- An external language model can be used to augment the implicit internal language model
 - Needs to be trained on a large separate text for maximum effectiveness



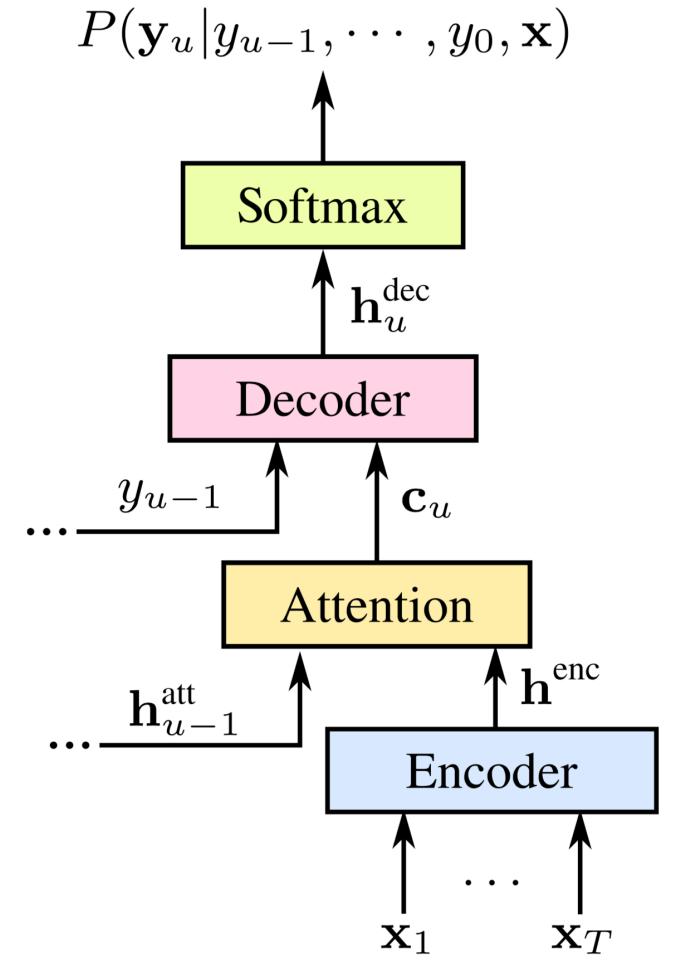
Adding A Language Model To The Acoustic Model

RNN transducer adds a data dependent language model that predicts the present letter given previous letters (or in this case word piece)



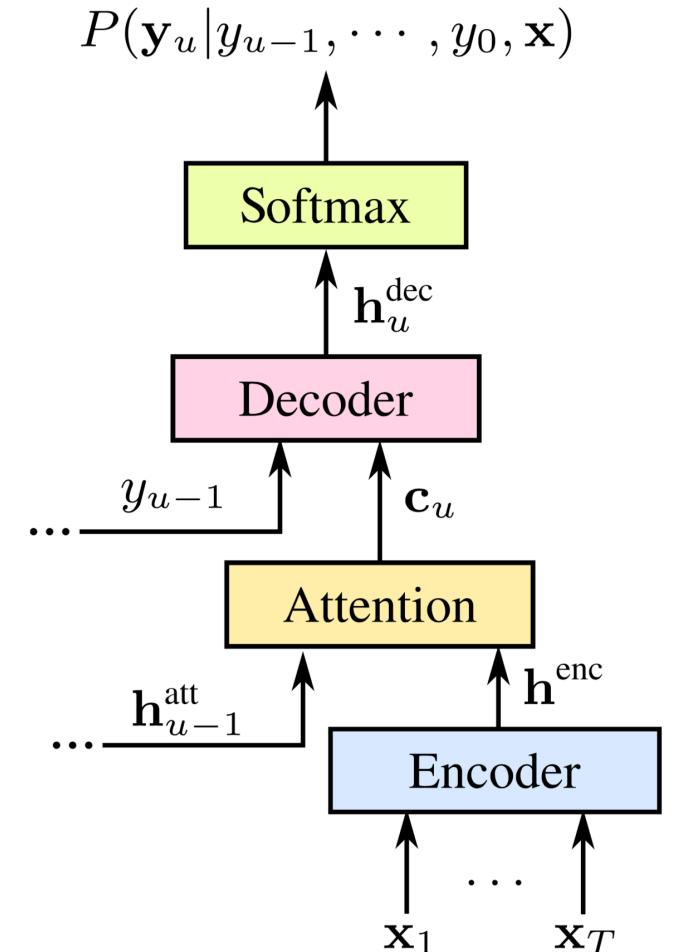
Adding Attention To The Transduction Model

- Attention
 - Sequence to sequence models encode a variable length input into hidden states
 - Attention allows a decoder to adaptively select hidden states to generate the output
- Attention is a general strategy that applies to more than just speech
 - Encoder – attention – decoder structure
 - Different combinations of inputs are used to create each output (i.e., the network learns what part of the input to pay attention to to generate each output)
 - Monotonic alignments are not required; this is especially beneficial for translation
- Example speech to text system: listen attend spell
 - Listen - encoder generates features
 - Attend - attention creates a context vector from all the features appropriate for the specific decoder state
 - Spell - decoder outputs graphemes; the conditional dependence in graphemes creates an implicit internal language model



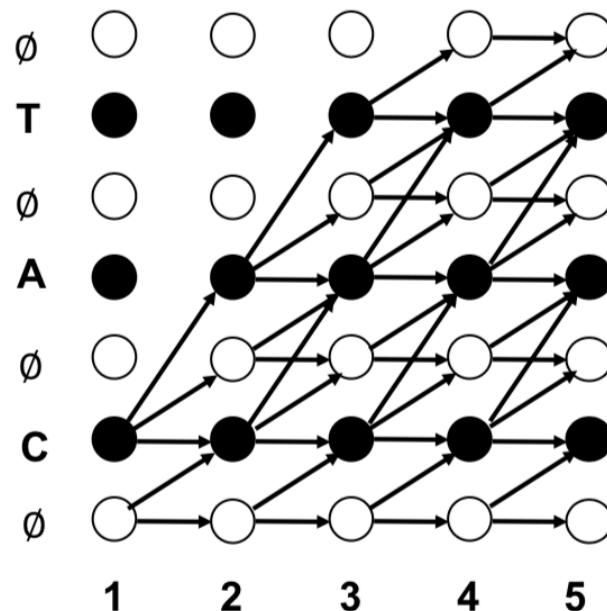
Adding Attention To The Transduction Model

- An example attention mechanism to create a context vector
 - h_{u-1}^{att} is the state of the lowest layer of the decoder after predicting the previous symbol
 - $\beta_{t,u} = \langle \phi(h_t^{enc}), \psi(h_{u-1}^{att}) \rangle$, ϕ and ψ are learnable linear embeddings
 - $\alpha_{:,u} = \text{softmax}(\beta_{:,u})$
 - $c_u = \text{diag}(\alpha_{:,u}) h_t^{enc}$
- Similar decoding options are available

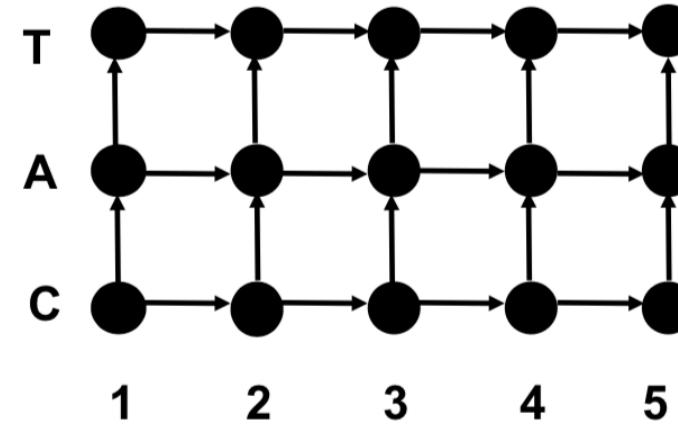


Comparing Transducer Transition Possibilities

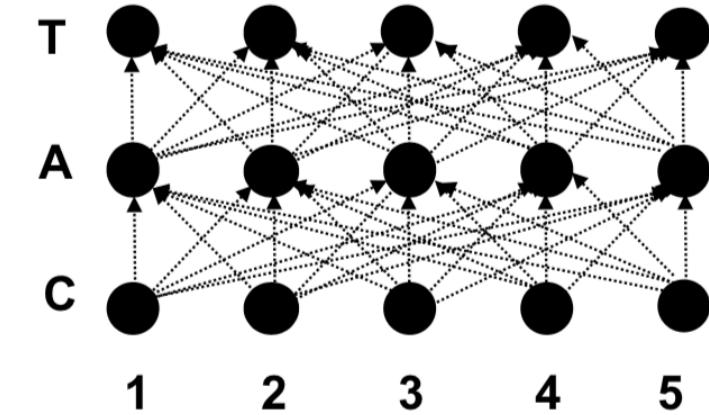
Output symbol vs input frame transition possibilities for the word 'cat'



(a) CTC



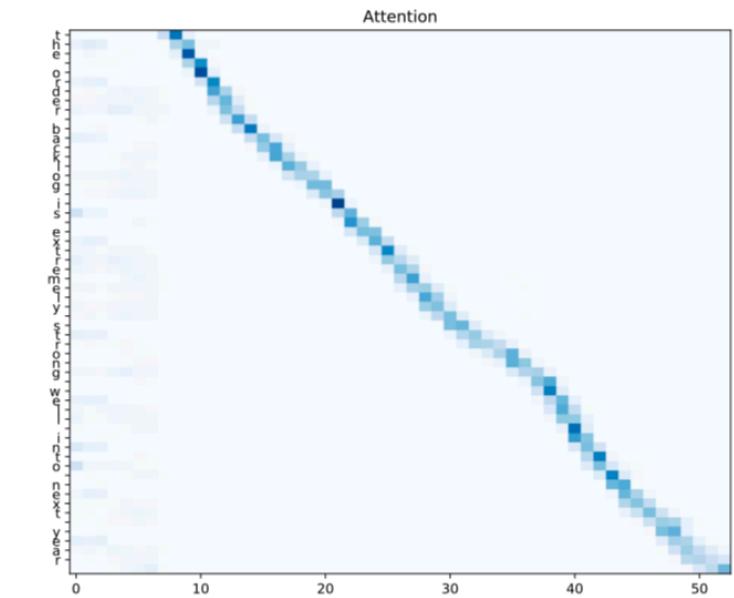
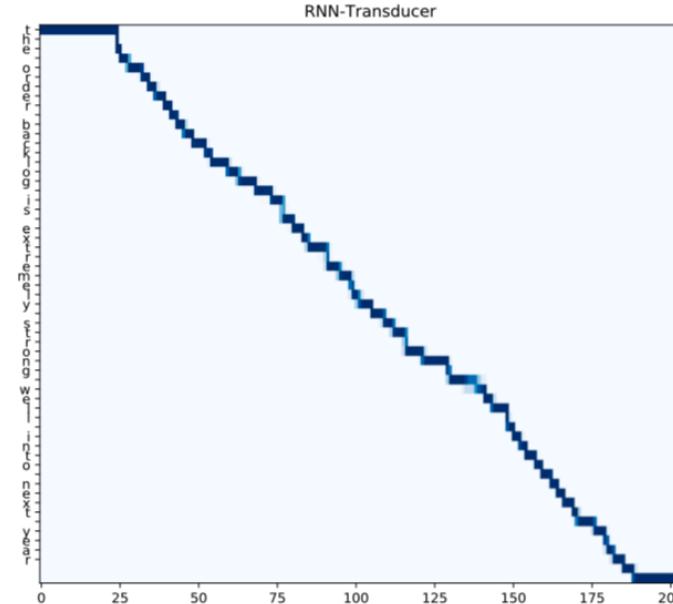
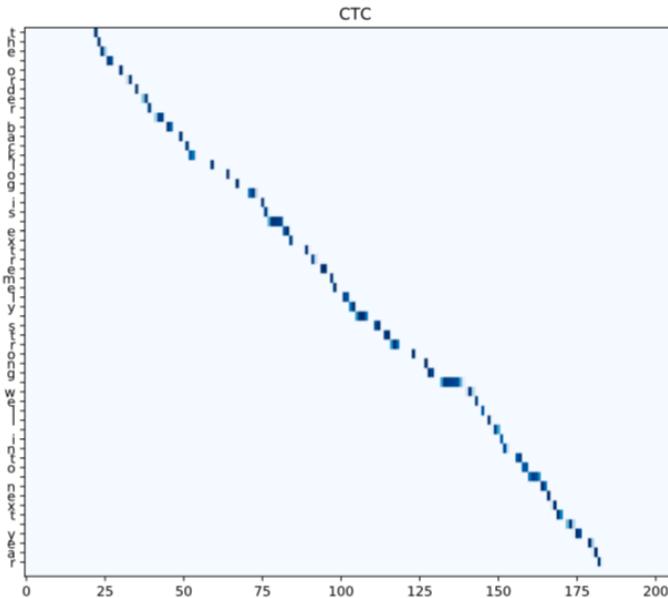
(b) RNN-Transducer



(c) Attention

Comparing Transducers Alignments

Output symbol vs input frame alignment for the phrase ‘the order backlog is extremely strong well into next year’; for additional discussion on differences in transducers see: https://www.isca-speech.org/archive/Interspeech_2017/pdfs/0233.PDF



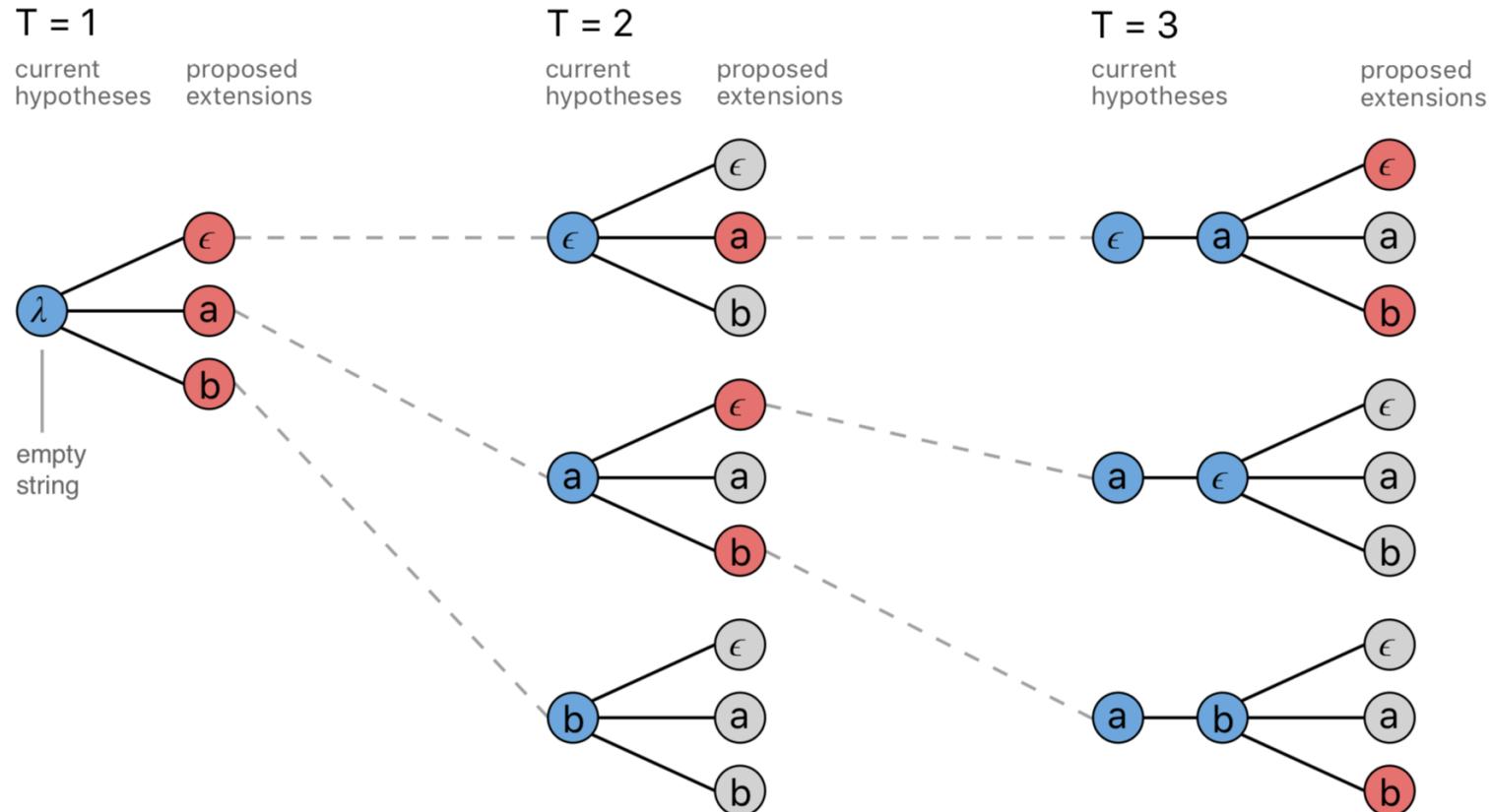
External Language Model

The language lecture looked at this in more detail

- A language model assigns a probability to a sequence of words
 - $P(w_{n-1}, w_{n-2}, \dots, w_1, w_0) = P(w_{n-1} | w_{n-2}, \dots, w_1, w_0) \dots P(w_1 | w_0) P(w_0)$
 - So it's possible to create a language model from learning to predict the next word for all different length sequences $P(w_{n-1} | w_{n-2}, \dots, w_1, w_0)$
 - The nice part about this is that the language model can be learned offline using very large sources of text (e.g., Wikipedia)
 - A few different options for this will be discussed in the language lecture
- N gram language model
 - Given $N - 1$ words, predict the pmf of the N th word
- How can a language model be used for speech recognition?
 - Incorporate the language model into beam search by complementing the pmf of letters / words produced by the network with a pmf of letters / words based on language in the form of a conditional language model
 - Example uses in linear and log form
 - $\ell^* = \arg \max_\ell (P(\ell | X) P_{LM}(\ell)^\alpha \text{length}(\ell)^\beta)$
 - $\ell^* = \arg \max_\ell (\log(P(\ell | X)) + \alpha \log(P_{LM}(\ell)) + \beta \log(\text{length}(\ell)))$

Beam Search

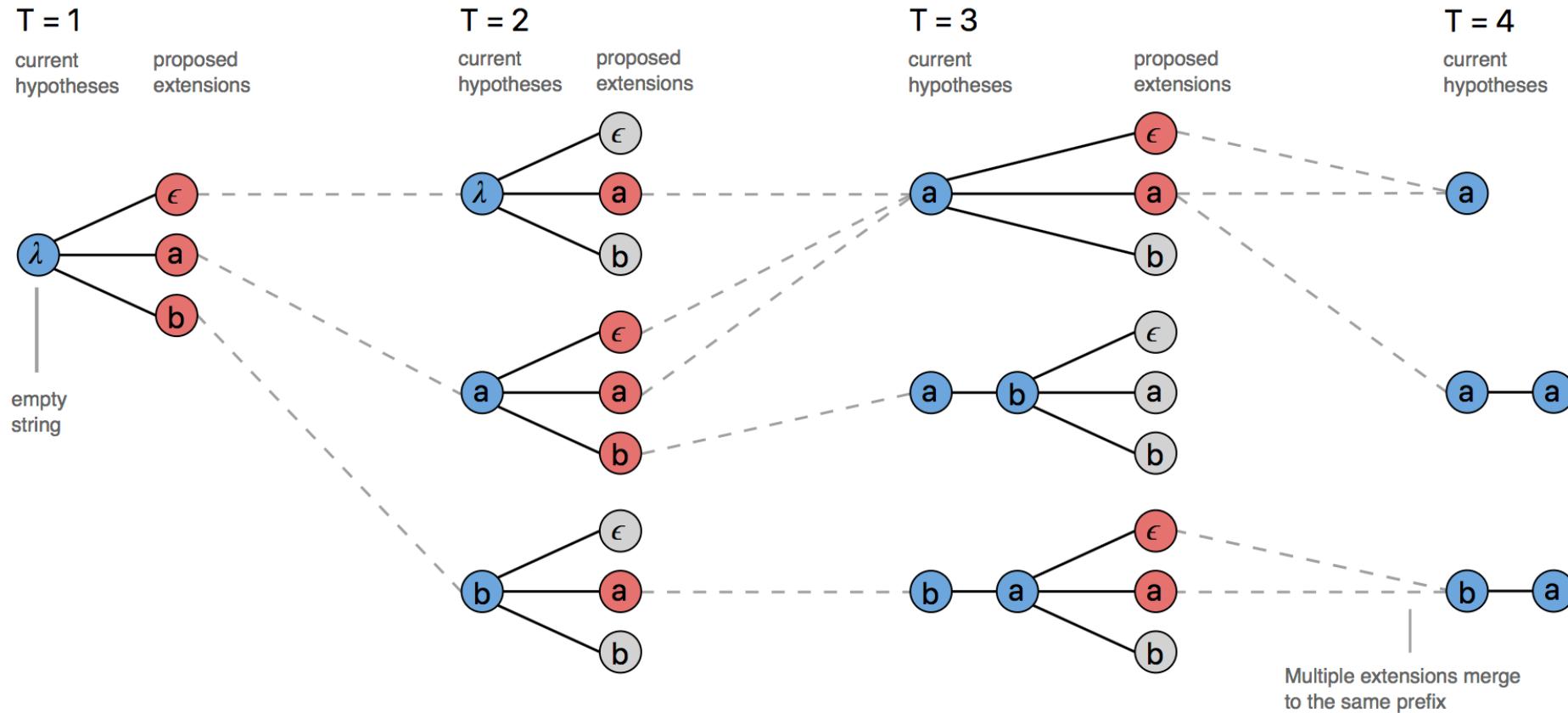
A common method for going for a sequence of phoneme, grapheme or word piece probabilities, based on the CTC, RNN Transducer or Attention based network output and the language model, to a sequence of letters or words; beam size = 1 is greedy decoding; see <https://arxiv.org/abs/1408.2873>



A standard beam search algorithm with an alphabet of $\{\epsilon, a, b\}$ and a beam size of three.

Beam Search

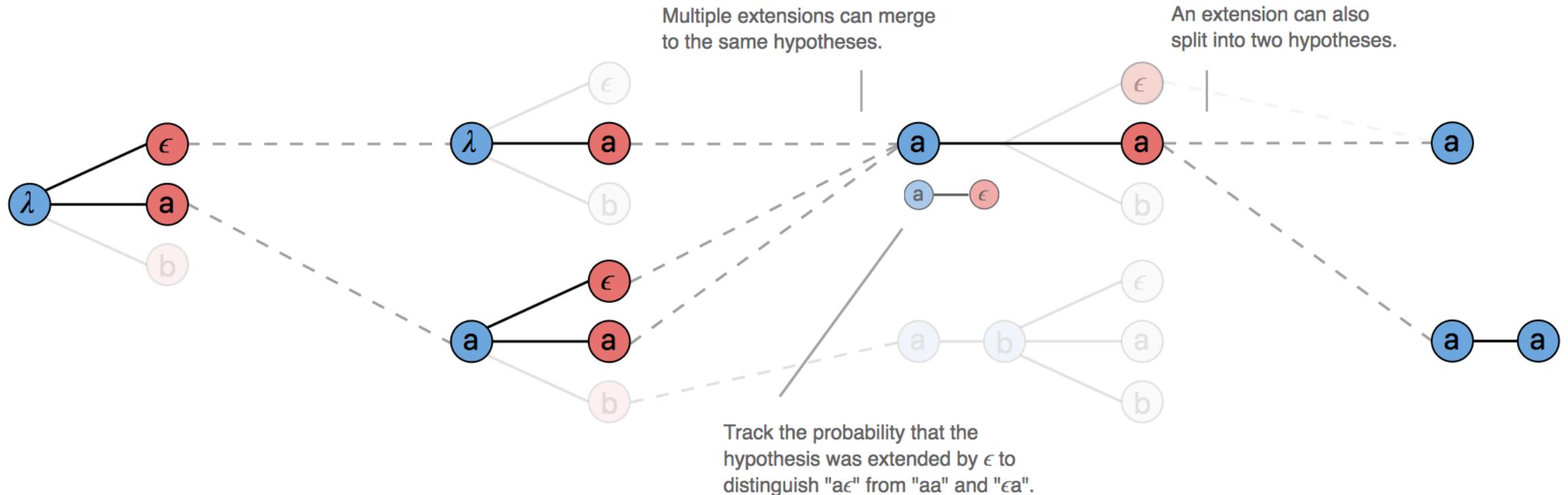
The CTC blank symbol introduces a few challenges into the standard beam search algorithm; see <https://medium.com/corti-ai/ctc-networks-and-language-models-prefix-beam-search-explained-c11d1ee23306>



The CTC beam search algorithm with an output alphabet $\{\epsilon, a, b\}$ and a beam size of three.

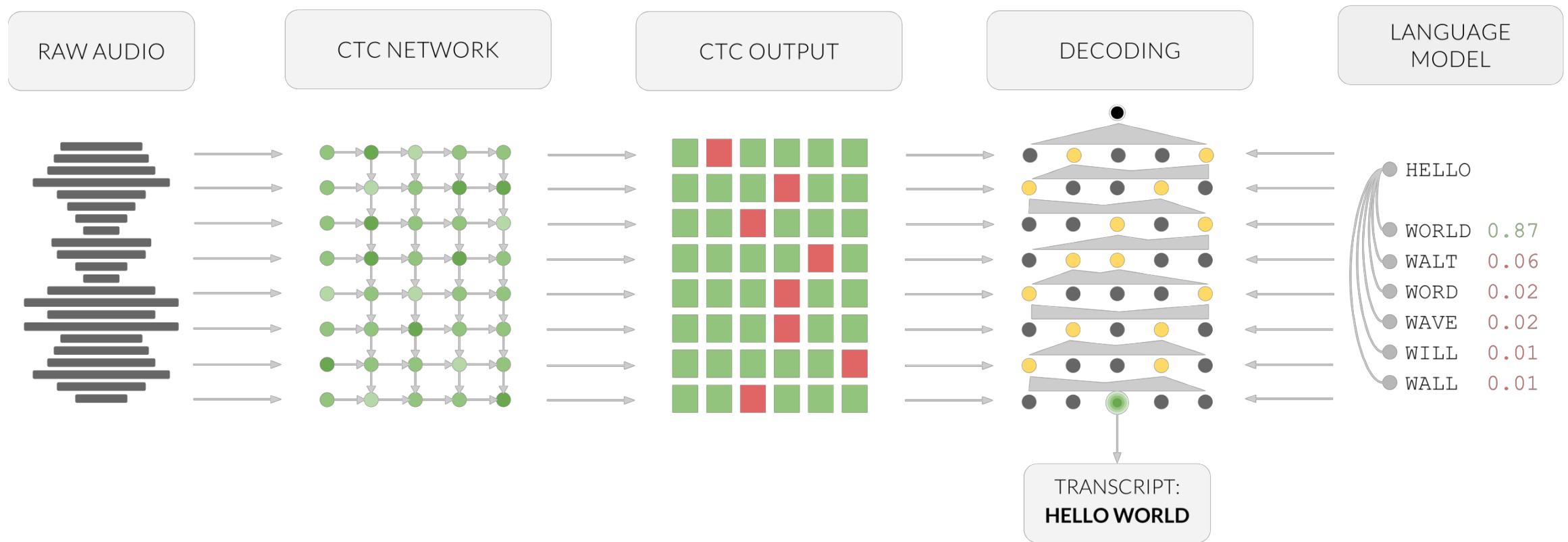
Beam Search

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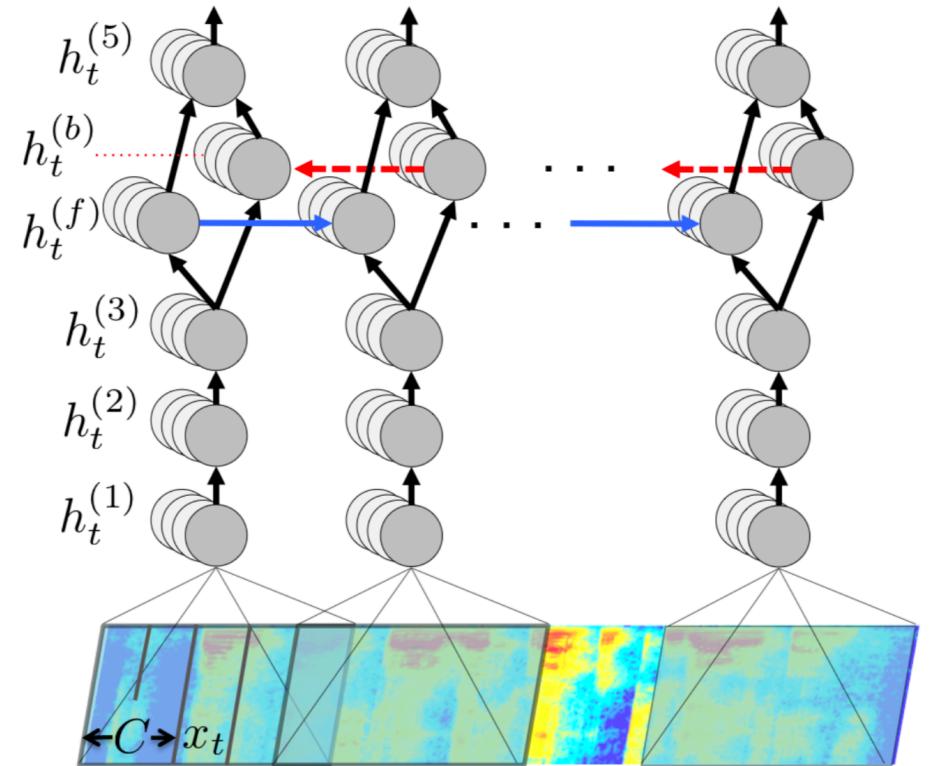
Beam Search

CTC networks and language models: prefix beam search explained (<https://medium.com/corti-ai/ctc-networks-and-language-models-prefix-beam-search-explained-c11d1ee23306>)



Example: Baidu's DeepSpeech

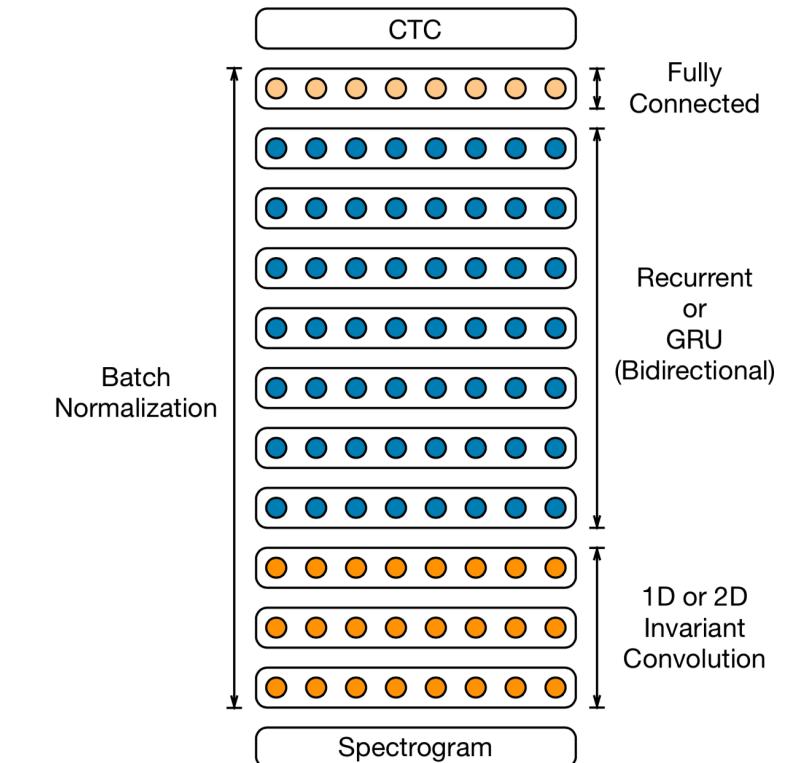
- DeepSpeech 1 (2014)
 - 7000 hours of labeled English speech + augmentation
 - A simple model is competitive with state of the art
 - Multilayer RNN encoder with a CTC loss function
- DeepSpeech 2 (2015)
 - Generalized to multiple languages
 - 11000+ hours of labeled English and 9000+ hours of labeled Mandarin + augmentation
 - 10s of exaflops for training
 - Multilayer convolution + RNN encoder with a CTC loss function
- DeepSpeech 3 (2017)
 - Switched from CTC to RNN transducer with an external pre trained language model used during training (see the blog post and ColdFusion paper)



Note the equal focus on algorithms and software / hardware implementation

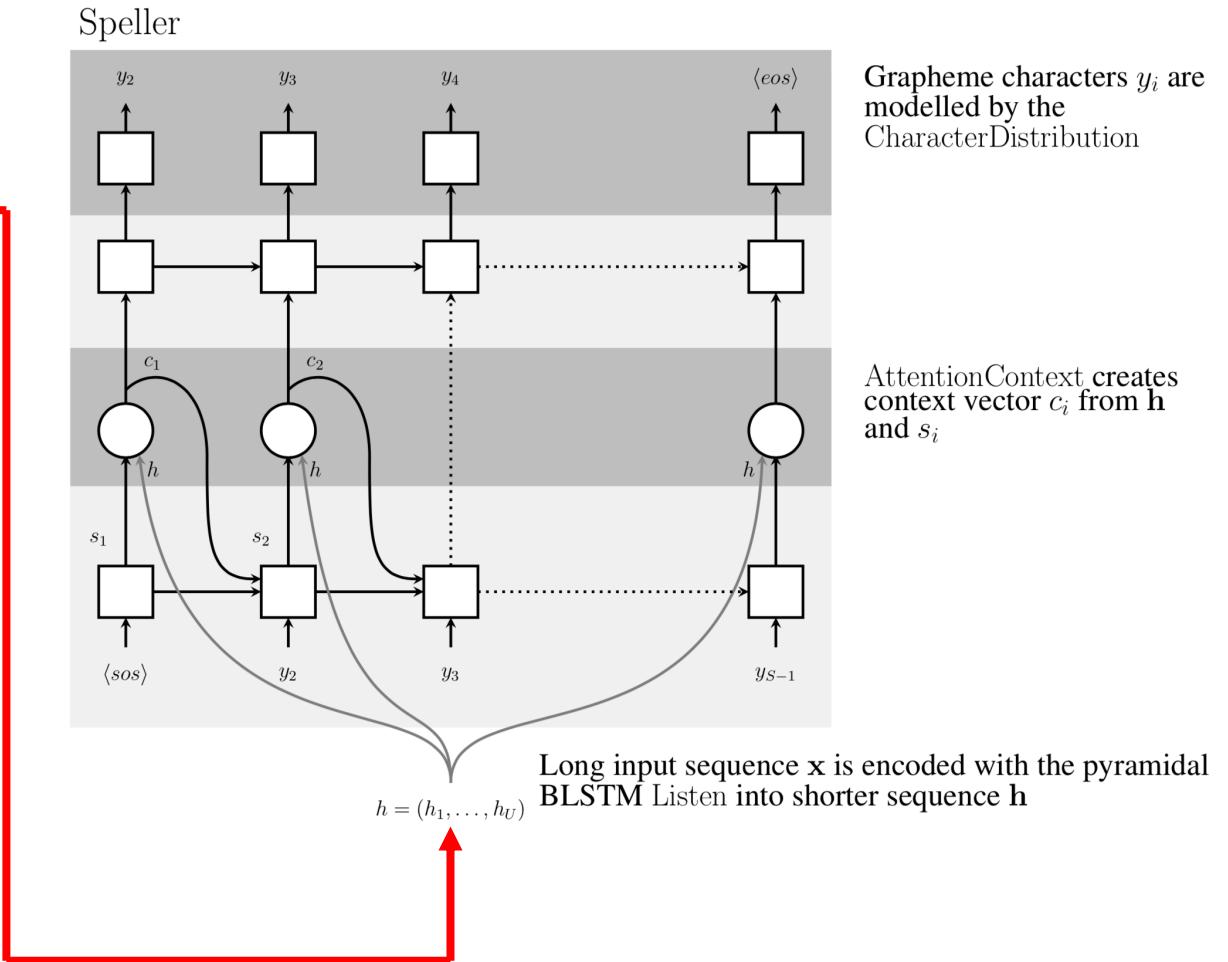
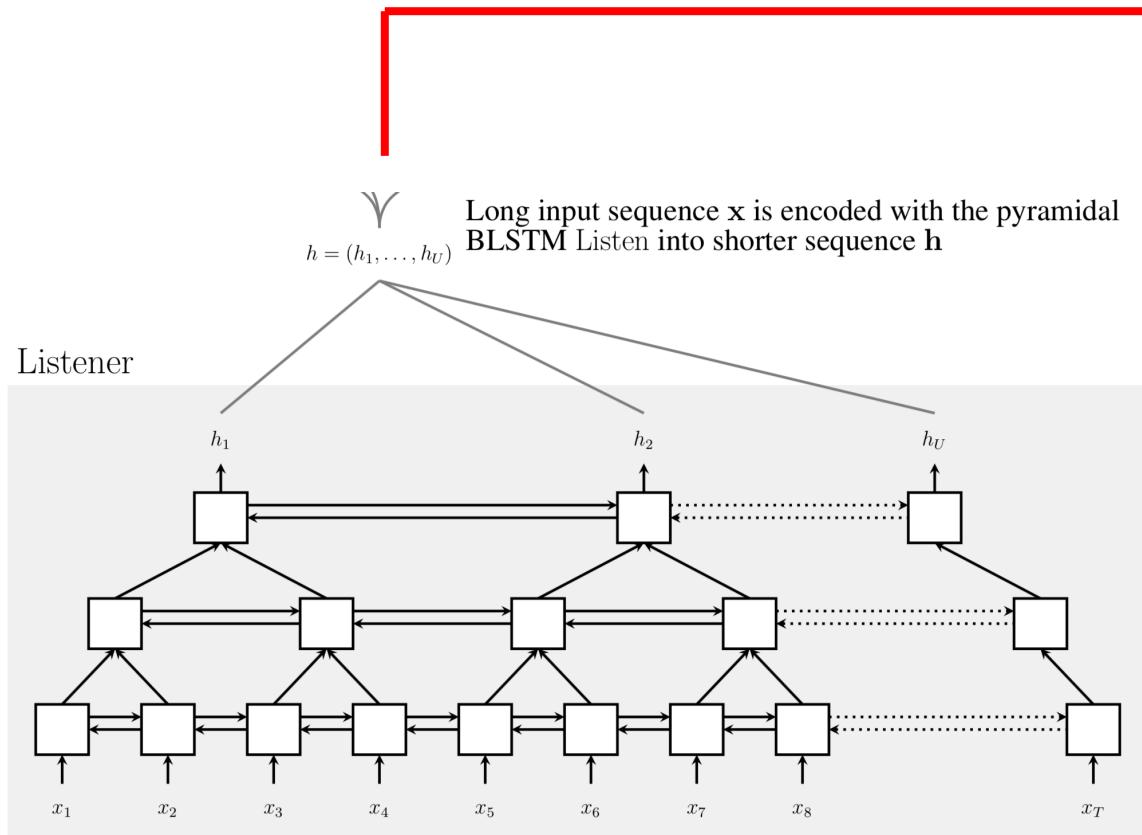
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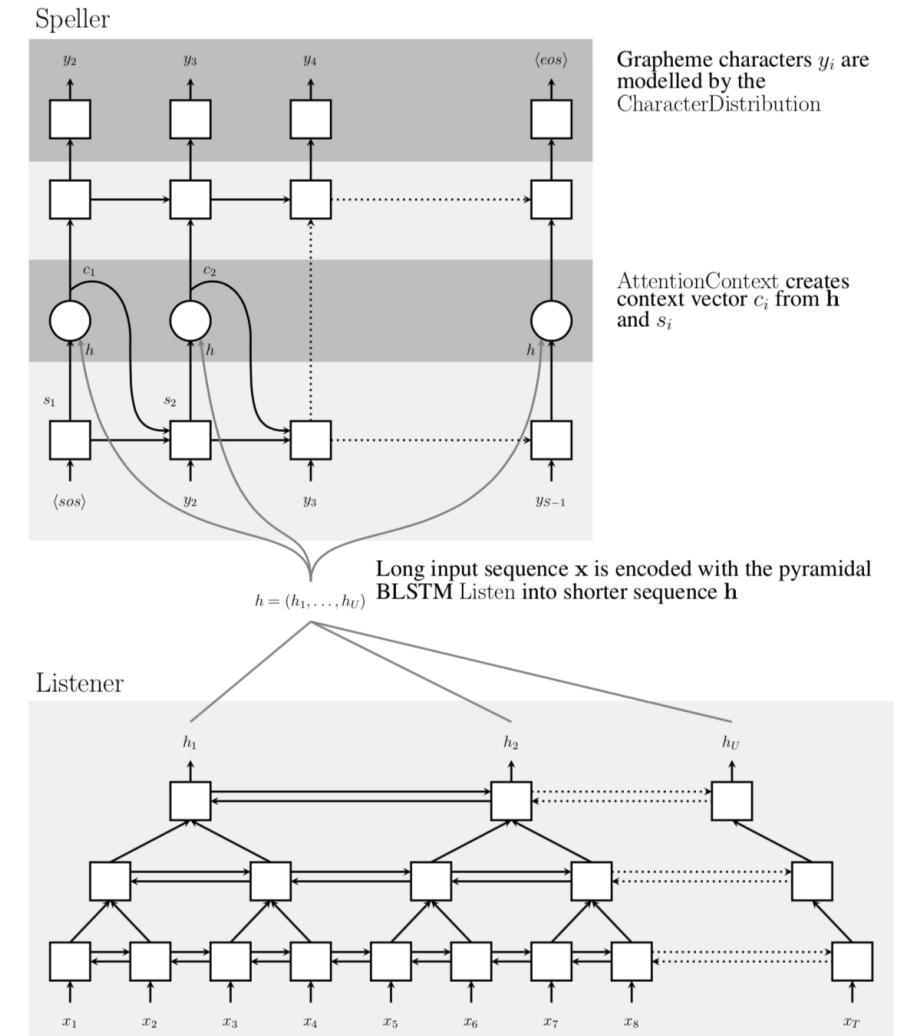
Note the equal focus on algorithms and software / hardware implementation

Example: Google's Listen Attend Spell



Example: Google's Listen Attend Spell

- Output: $P(y | x) = \prod_i P(y_i | x, y_{<i})$
- Listen: $h = \text{Listen}(x)$
 - Let i be the time step and j be the layer
 - 1x: $h_i^j = \text{BLSTM}(h_{i-1}^j, h_{i-1}^{j-1})$
 - 3x: $h_i^j = \text{pBLSTM}(h_{i-1}^j, [h_{2i}^{j-1}, h_{2i+1}^{j-1}])$
- Attend and spell: $P(y | x) = \text{AttendAndSpell}(h, y)$
 - $c_i = \text{AttentionContext}(s_i, h)$
 - See attention slide
 - $s_i = \text{RNN}(s_{i-1}, y_{i-1}, c_{i-1})$
 - RNN is a 2 layer LSTM
 - $P(y_i | x, y_{<i}) = \text{CharacterDistribution}(s_i, c_i)$
 - CharacterDistribution is a MLP with softmax output over characters



Evaluation

- Metrics
 - Word error rate
 - Substitutions
 - Insertions
 - Deletions
- Leaderboard (also a really good GitHub repository name)
 - https://github.com/syhw/wer_are_we

Some Recent References

- Wav2Letter: an end-to-end convnet-based speech recognition system
 - <https://arxiv.org/abs/1609.03193>
- Joint CTC-attention based end-to-end speech recognition using multi-task learning
 - <https://arxiv.org/abs/1609.06773>
- ESPnet: end-to-end speech processing toolkit
 - <https://arxiv.org/abs/1804.00015>
 - <https://github.com/espnet/espnet>
- Streaming end-to-end speech recognition for mobile devices
 - <https://arxiv.org/abs/1811.06621>
 - <https://ai.googleblog.com/2019/03/an-all-neural-on-device-speech.html>
- Bytes are all you need: end-to-end multilingual speech recognition and synthesis with bytes
 - <https://arxiv.org/abs/1811.09021>
- Fully convolutional speech recognition
 - <https://arxiv.org/abs/1812.06864>

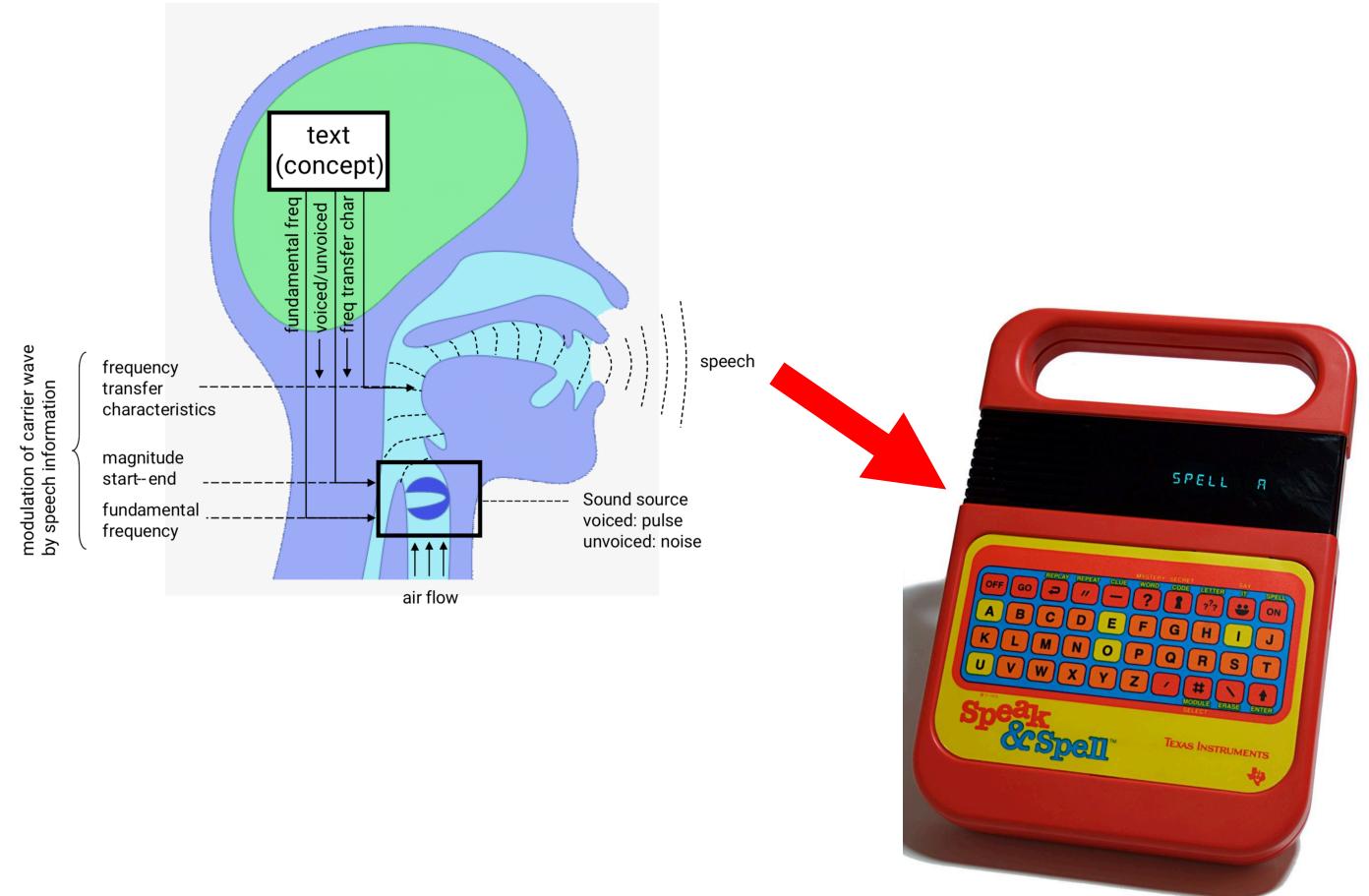
Some Recent References

- A spelling correction model for end-to-end speech recognition
 - <https://arxiv.org/abs/1902.07178>
- SpecAugment: a simple data augmentation method for automatic speech recognition
 - <https://arxiv.org/abs/1904.08779>
- A comparative study on transformer vs RNN in speech applications
 - <https://arxiv.org/abs/1909.06317>
- Improving RNN transducer modeling for end-to-end speech recognition
 - <https://arxiv.org/abs/1909.12415>
- Hybrid CTC/attention architecture for end-to-end speech recognition
 - <https://www.merl.com/publications/docs/TR2017-190.pdf>

Text To Speech

Goal

- Generate speech from text
 - Also called speech synthesis
- This is a sequence to sequence transduction problem just like speech to text (but now with a many to 1 mapping)
- History
 - Rule based formant synthesis
 - Sample based concatenative synthesis
 - Model based generative synthesis
- Here we'll mainly look at model based generative synthesis including sequence to sequence based methods



Basics

- Given
 - Training speech waveforms
 - Training text
 - Testing text
- Generate
 - Testing speech waveforms
- In a model based system
 - The training speech waveforms and training text are used to create a model
 - The model is used with the testing text to generate testing speech waveforms

For a nice introduction to text to speech methods with much more information than is included here, the following links are a good starting point:

- Generative model-based text-to-speech synthesis
<https://github.com/oxford-cs-deepnlp-2017/lectures/blob/master/Lecture%2010%20-%20Text%20to%20Speech.pdf>
- Text normalization, letter to sound, prosody
<http://web.stanford.edu/class/cs224s/lectures/224s.17.lec14.pdf>
- Waveform synthesis in TTS
<http://web.stanford.edu/class/cs224s/lectures/224s.17.lec15.pdf>
- Parametric TTS, intoxication, depression, trauma, personality
<http://web.stanford.edu/class/cs224s/lectures/224s.17.lec16.pdf>

Basics

- 2 parts
 - Part 1: convert text into an intermediate representation; traditional steps include
 - Text normalization
 - Grapheme to phoneme conversion
 - Prosodic features generation
 - Part 2: convert the intermediate representation into audio
- Traditional part 1 is linguistic, duration and F_0 features
- Traditional part 2 is Griffin-Lim algorithm (if the output of part 1 is a spectrogram)

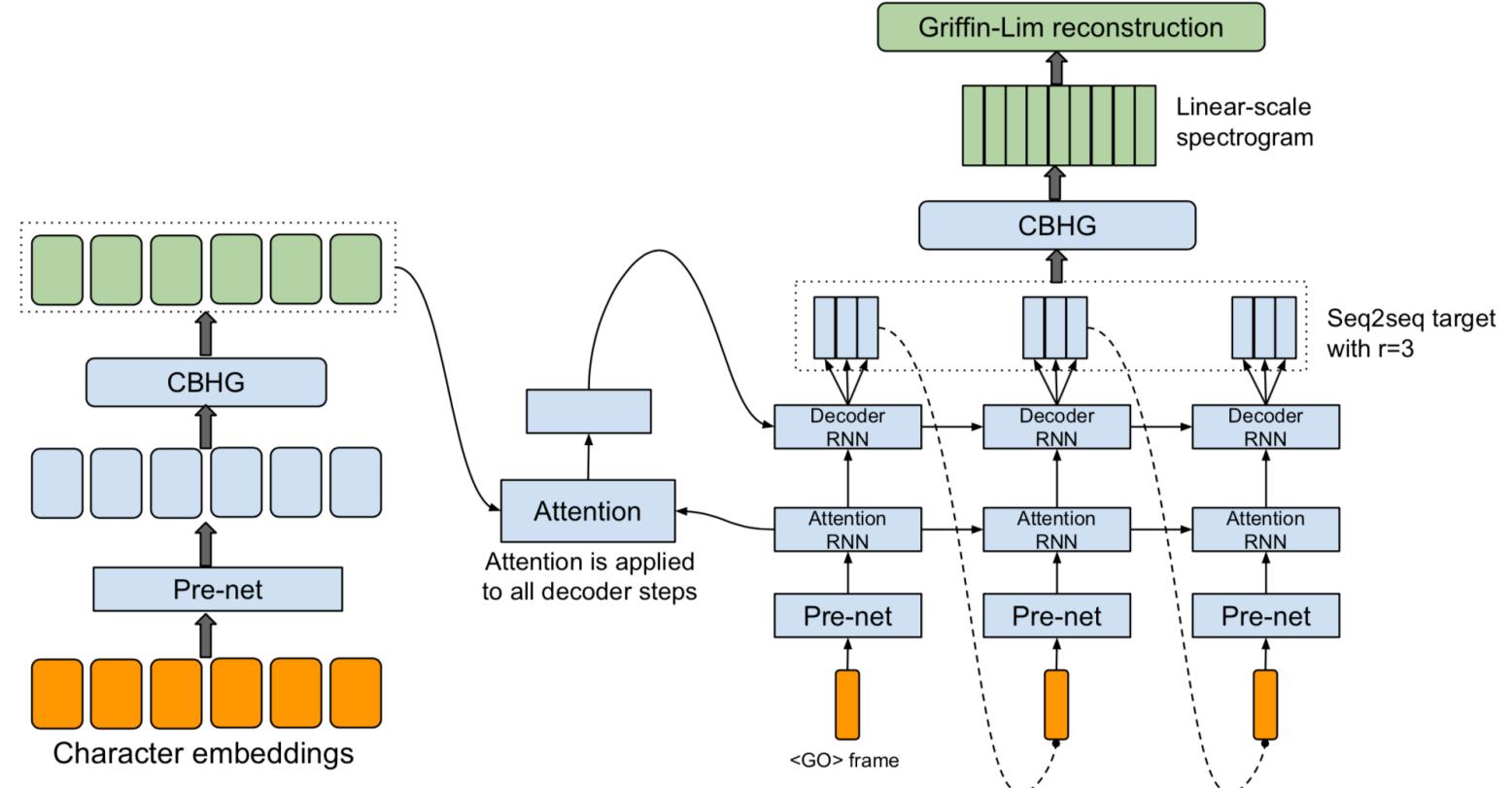
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- Parametric TTS, intoxication, depression, trauma, personality
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Example: Tacotron 1

An incomplete list of things I never expected in life: to present a slide with the title Tacotron at the top

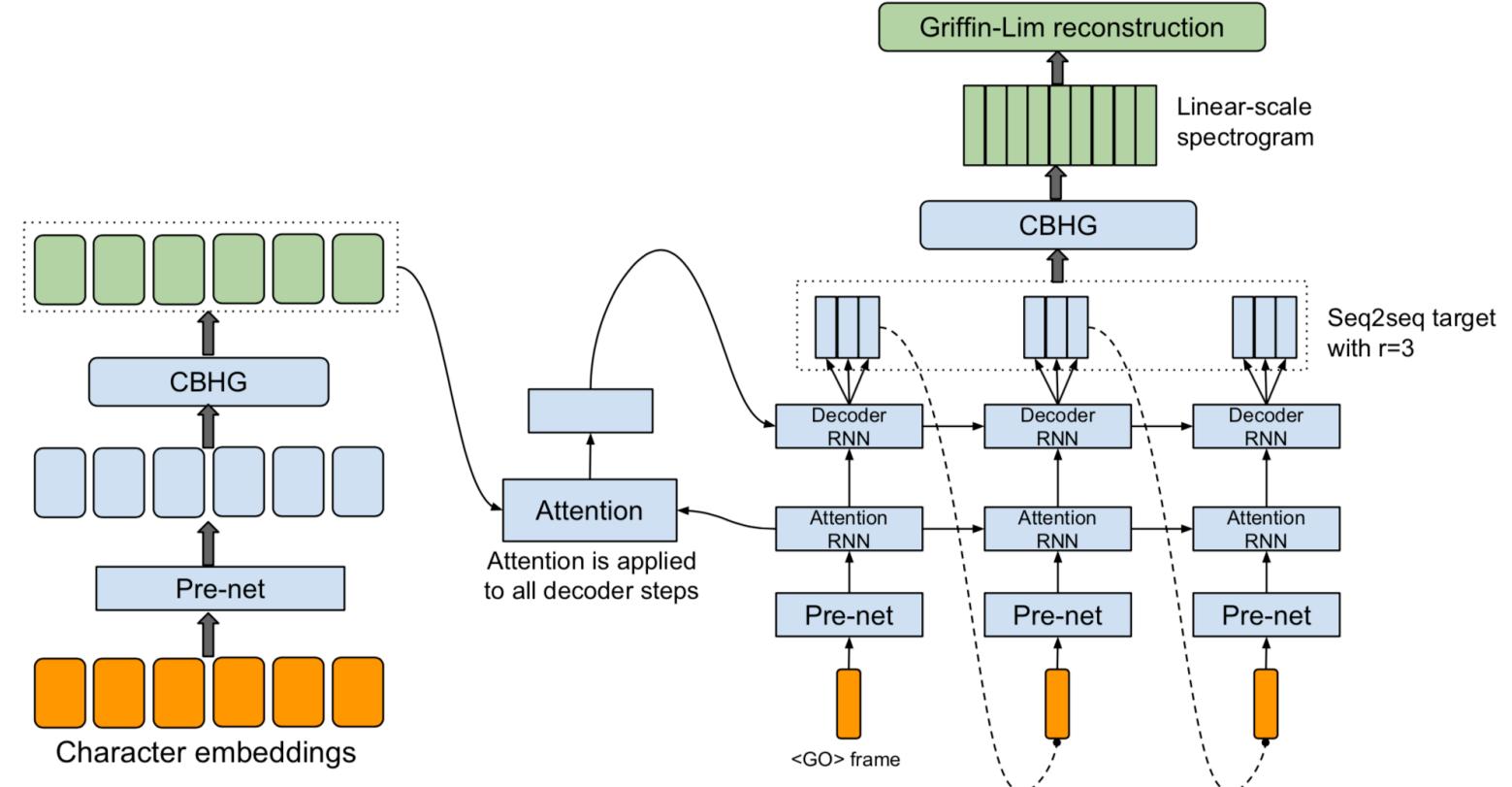
- A neural network based method for part 1
- A neural attention based sequence to sequence model that predicts linear spectrograms from characters
 - Linear spectrograms are used as an intermediate representation
- Training input is text and audio pairs



Example: Tacotron 1

An incomplete list of things I never expected in life: to present a slide with the title Tacotron at the top

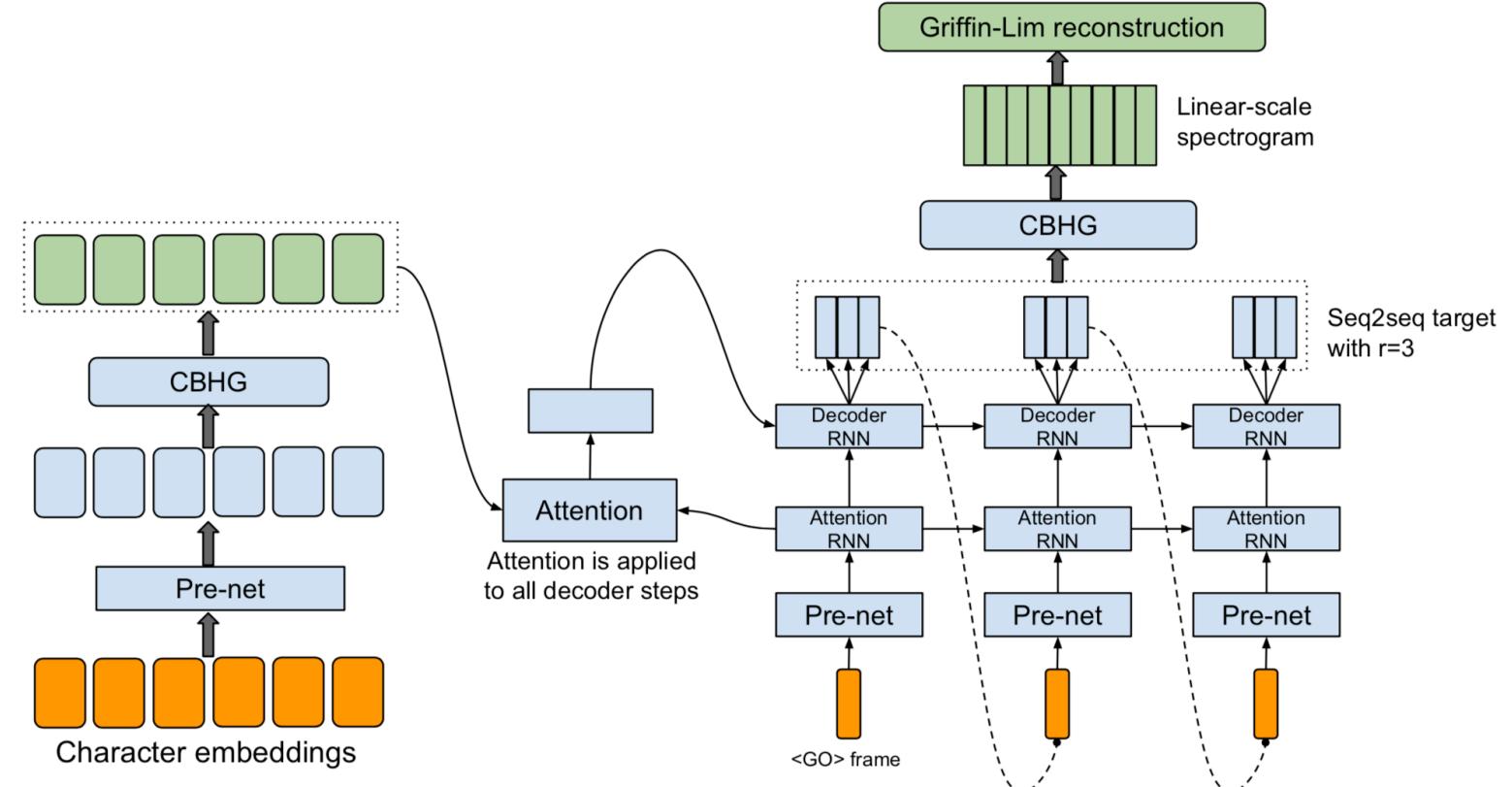
- 1 hot encoded characters are embedded into a vector
- The pre net is a bottleneck layer with dropout
- A CBHG network creates the encoder output features
 - 1D convolution
 - Highway network
 - Bi directional GRU



Example: Tacotron 1

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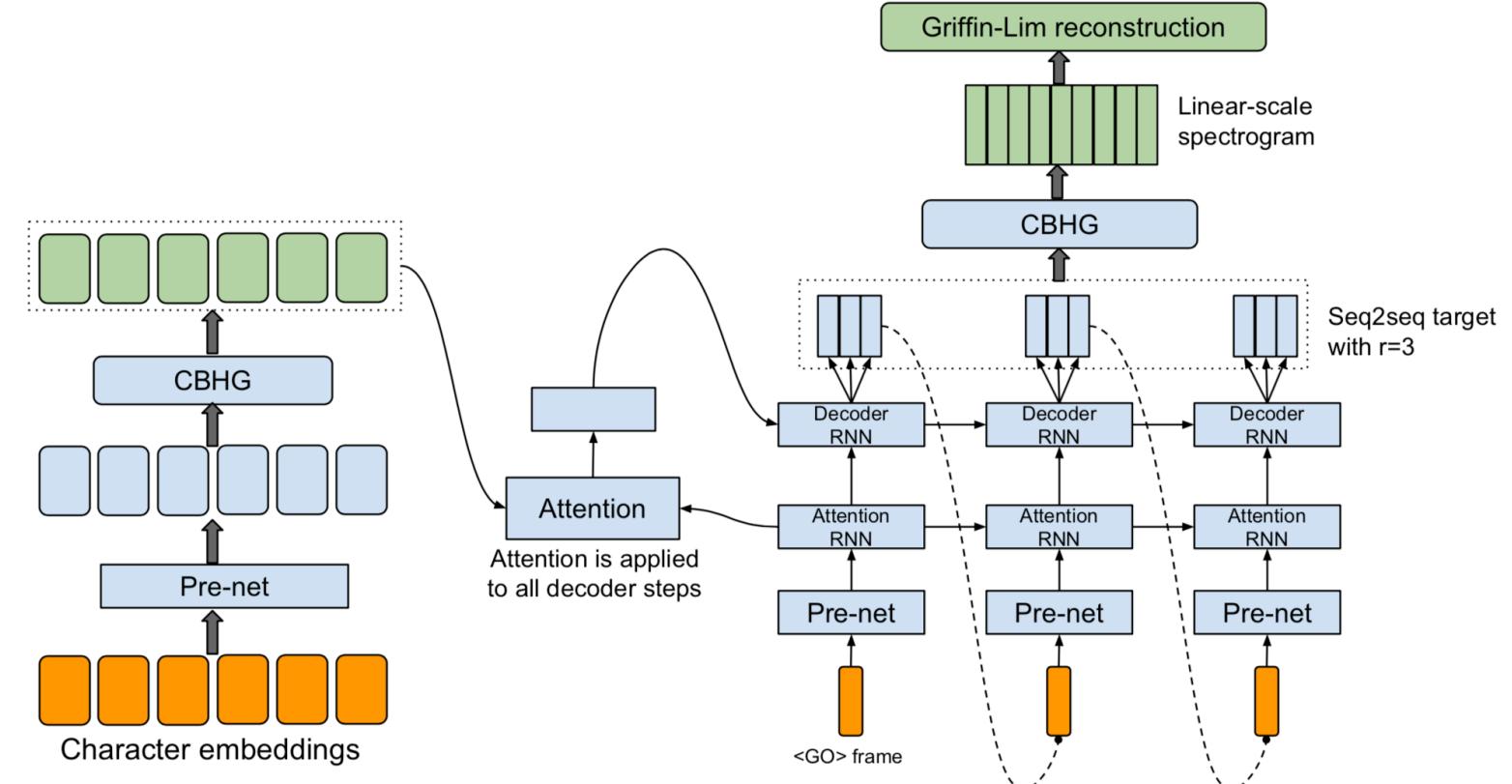
- Attention RNN produces an attention query and the resulting context vector is concatenated with the attention RNN output
- The decoder RNN is a stack of GRUs with vertical residual connections
 - The decoder target is a 80 band mel spectrogram
 - Multiple non overlapping frames are predicted at each stage
 - The last predicted frame is fed back as the next input to the decoder



Example: Tacotron 1

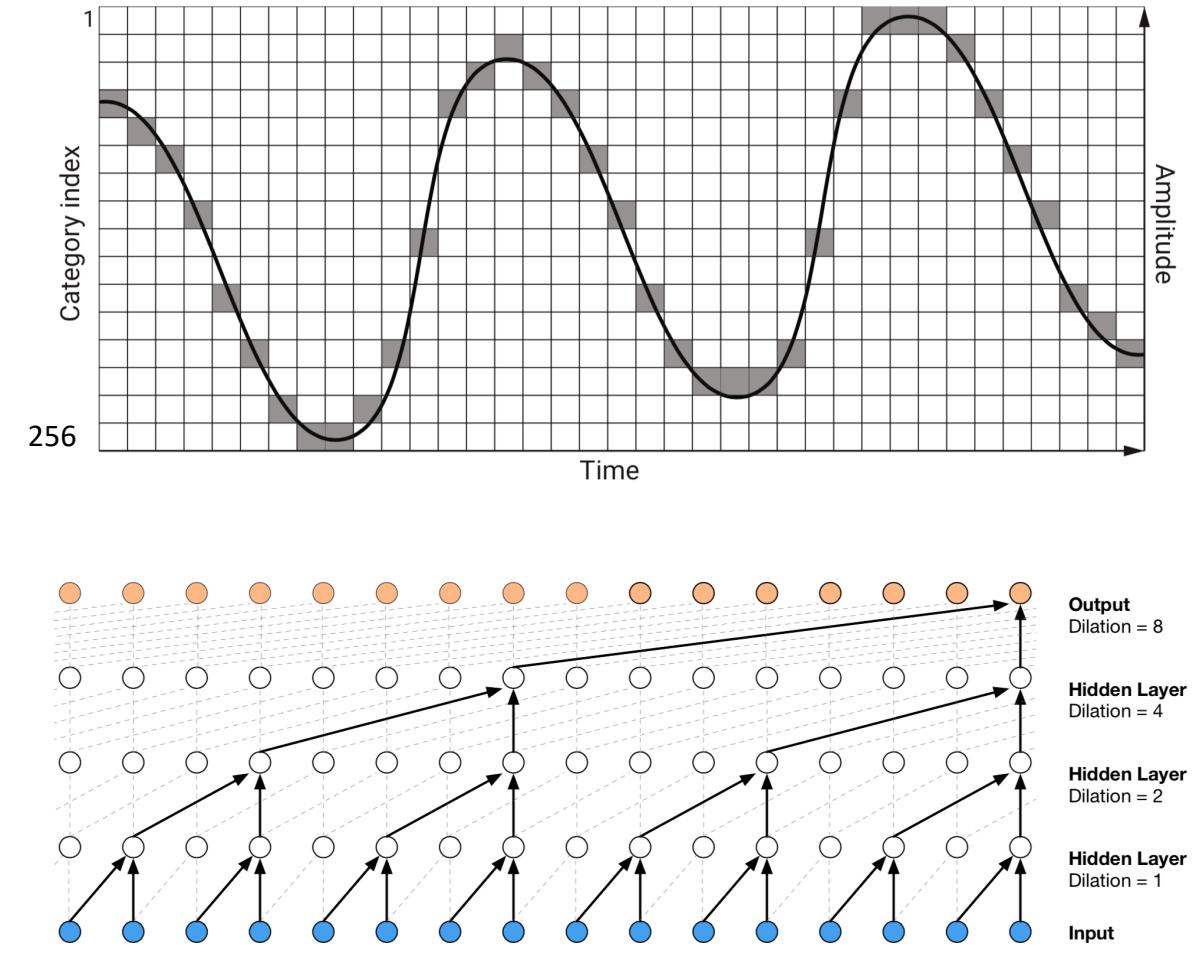
An incomplete list of things I never expected in life: to present a slide with the title Tacotron at the top

- The final CBHG network predicts linear scale spectrograms from the 80 band mel spectrogram
- Traditional Griffin-Lim reconstruction is used to go from linear spectrograms to time domain audio samples



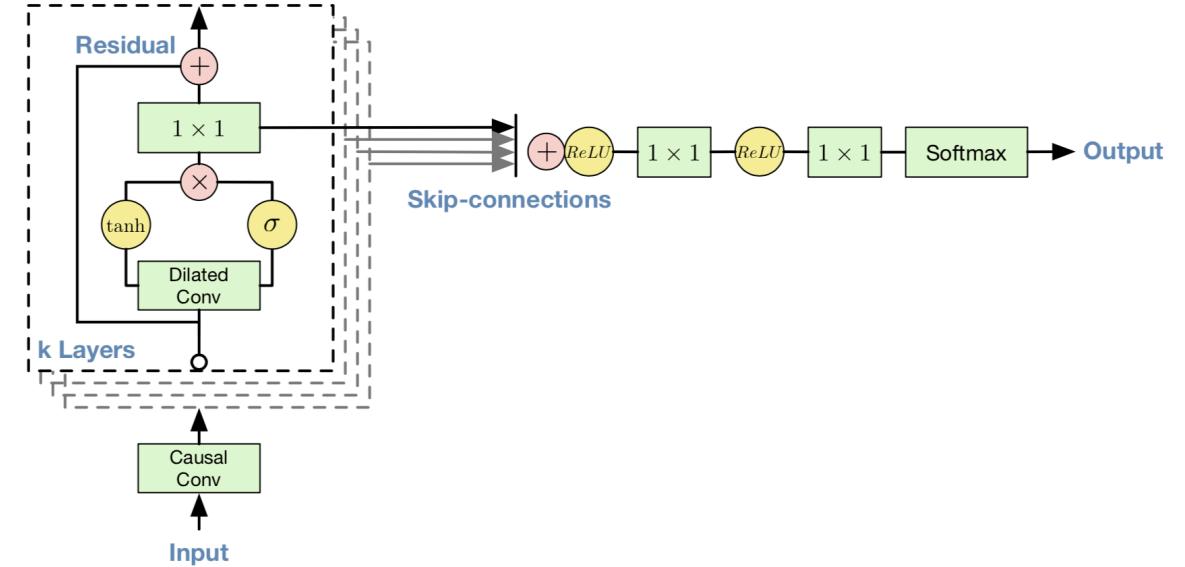
Example: WaveNet

- A neural network based method for part 2
- Sample by sample classification to an output level that is conditioned on previous outputs, speaker and linguistic features of the text
- Output waveform $x = \{x_1, \dots, x_T\}$ factored as
 - $p(x) = \prod_t p(x_t | x_{t-1}, \dots, x_1)$
 - Each sample x_t is conditioned on all previous samples
 - During testing the previous output sample is fed back into the network to produce the next sample such that generation is sequential
- Causal (non bi directional convolution)
 - Dilated convolution to increase receptive field size
 - The dilation factor is doubled after every layer up to a limit of 512 then the process is repeated



Example: WaveNet

- Gated activation units
 - $z = \tanh(W_{f,k} \odot x) \odot \sigma(W_{g,k} \odot x)$
 - k is the layer index
 - $W_{f,k}$ is a learnable filter, $W_{g,k}$ is a learnable gate
 - Chosen because it worked better than ReLU in experiments
- Residual connections in the encoder with summed skip connections in the decoder
- μ law quantization x_t of to 256 levels
 - $f(x_t) = \text{sign}(x_t) \ln(1 + \mu |x_t|) / \ln(1 + \mu)$
 - $\mu = 256, -1 < x_t < 1$
 - Note that this is a non uniform quantization method that is well matched to human speech



Example: WaveNet

- It's common to condition WaveNet on an additional global or local input to generate
 - Speech with the characteristics of a particular speaker
 - Speech from text
 - Music
- The output conditioned on an additional input h
 - $p(x) = \prod_t p(x_t | x_1, \dots, x_{t-1}, h)$
- Resulting global and local gated activation units
 - Global: $z = \tanh(W_{f,k} \odot x + V_{f,k}^T h) \odot \sigma(W_{g,k} \odot x + V_{g,k}^T h)$
 - Ex: A particular speaker
 - As h is fixed globally this results in a fixed offset
 - Local: $z = \tanh(W_{f,k} \odot x + V_{f,k} \odot h) \odot \sigma(W_{g,k} \odot x + V_{g,k} \odot h)$
 - Ex: linguistic features, log F_0 and phoneme durations
 - As h varies locally this changes locally
 - V is a 1×1 convolution

For audio samples see (hear?):
<https://deepmind.com/blog/wavenet-generative-model-raw-audio/>

Issues

- 8 bit output resolution (ideally would like 16 bit)
- Slow speed as samples are generated 1 at a time and $\sim 16k$ are needed per second

These have been addressed in subsequent variations and extensions

Example: Tacotron 2 \approx Tacotron 1 + WaveNet

- Thought chain
 - Tacotron 1 is a model for generating spectrograms from text (that was used with a classical model for generating speech from spectrograms)
 - WaveNet is a model for generating audio samples that can be conditioned on different inputs
- Idea
 - Couple a modified version of Tacotron 1 spectrogram prediction with a modified version of Wavenet audio sample generation
- 2 parts to Tacotron 2
 - Part 1: recurrent sequence to sequence feature prediction network that maps characters to mel scale spectrograms
 - Part 2: modified WaveNet that maps mel scale spectrograms to audio samples

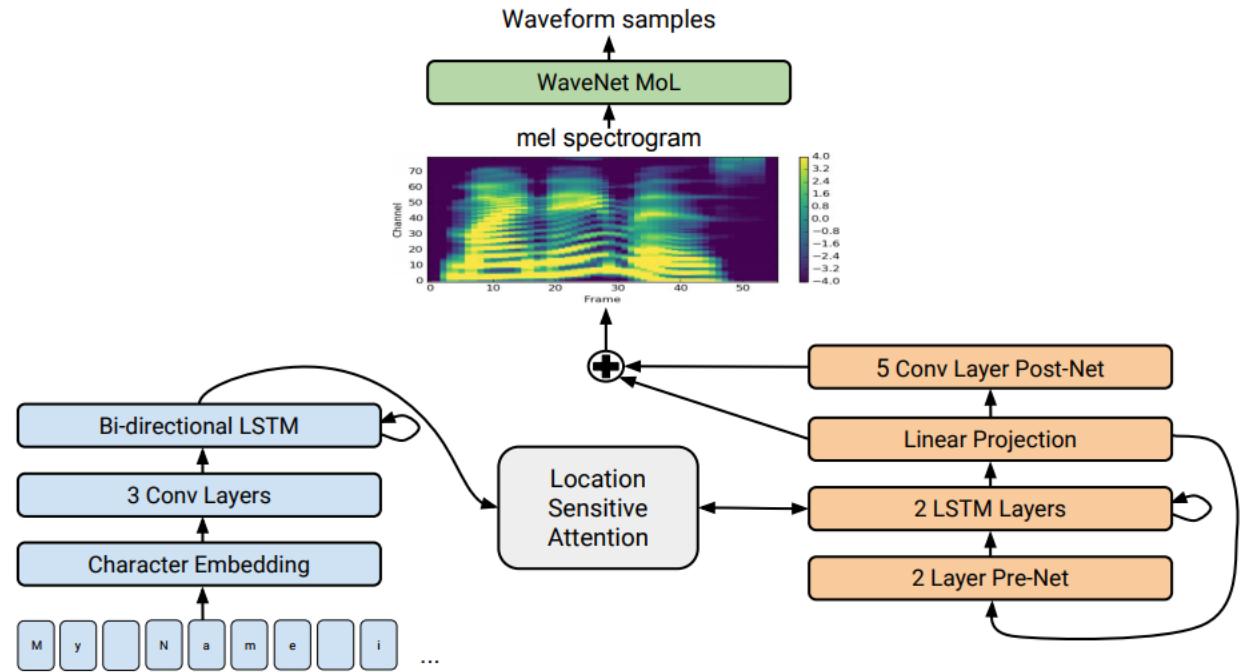
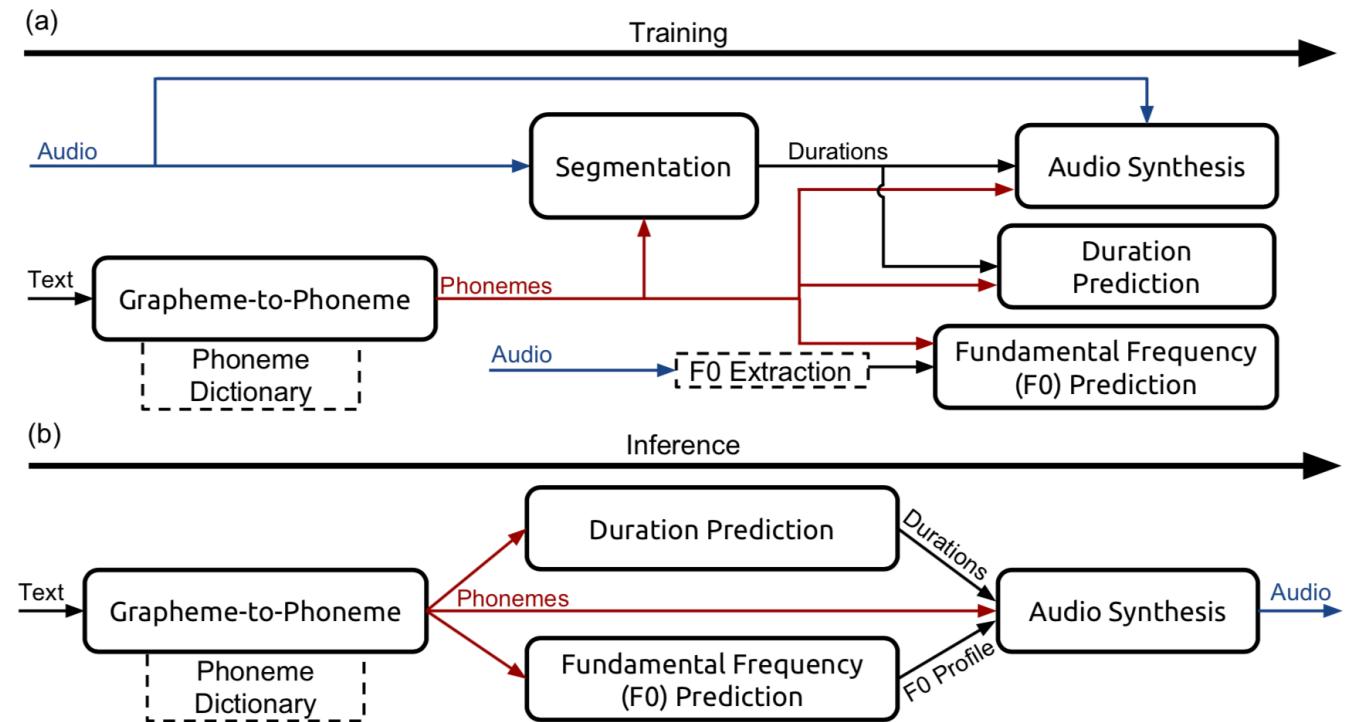


Figure from <https://ai.googleblog.com/2017/12/tacotron-2-generating-human-like-speech.html> 89

Example: DeepVoice 1

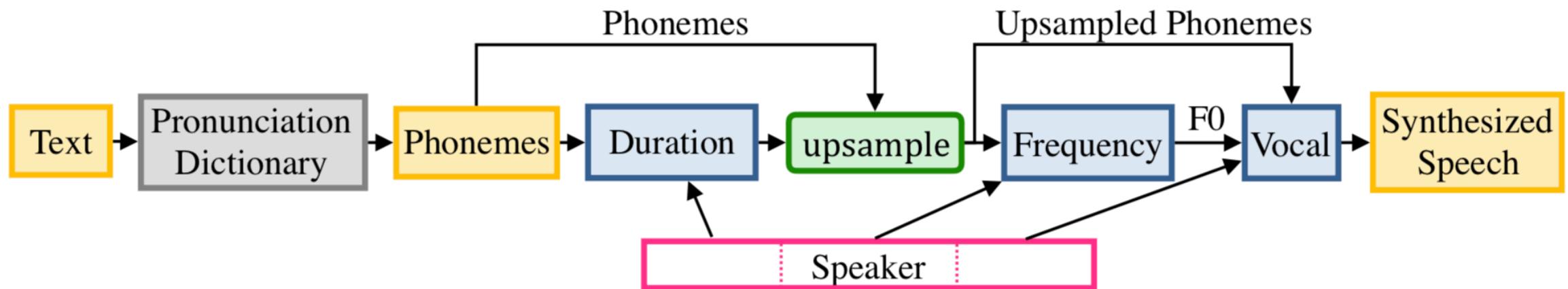
DeepVoice 1 and 2 replaced components in a traditional text to speech pipeline with xNN variants

- Uses 5 neural network based components to generate speech from text
 - A grapheme to phoneme conversion model that converts from text to phonemes for text that is not in the phoneme directory
 - A segmentation model for locating phoneme boundaries based on a deep neural network with a CTC loss based on predicting the location of pairs of phonemes (thus finding their boundary)
 - A phoneme duration prediction model to predict the temporal duration of all of the phonemes
 - A fundamental frequency prediction model predicts if the phoneme is voiced and if so what is the fundamental frequency
 - An audio synthesis model based on a smaller version of WaveNet



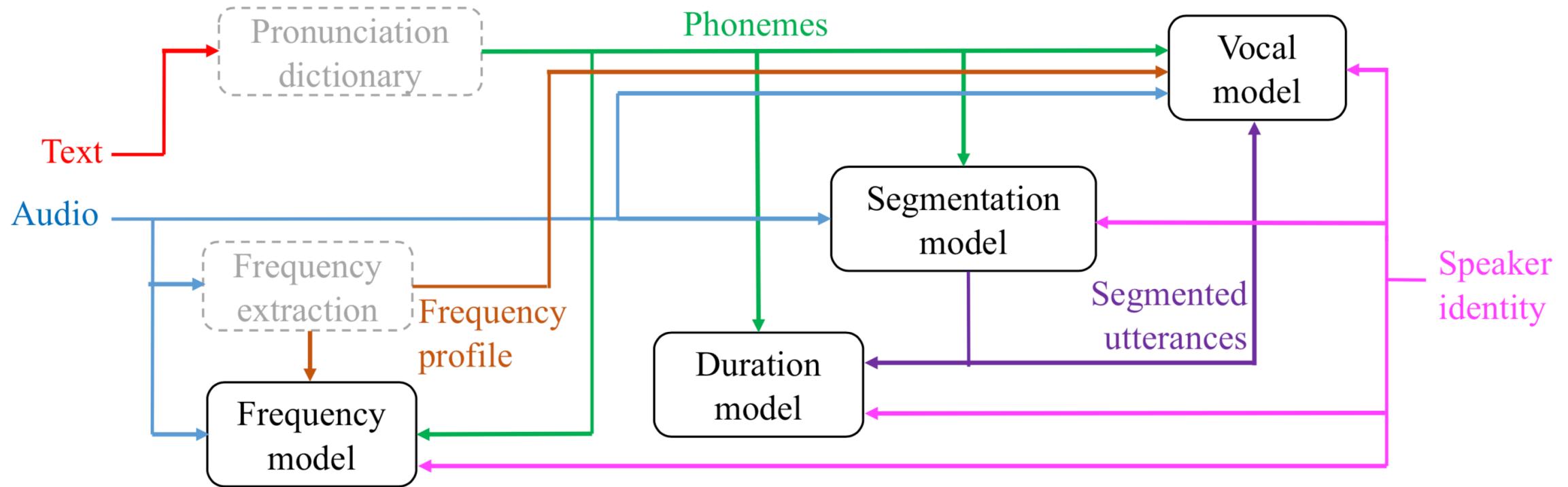
Example: DeepVoice 2

Testing diagram



Example: DeepVoice 2

Training diagram for the frequency, segmentation, duration and vocal model



Example: DeepVoice 2

Segmentation, duration and frequency model details

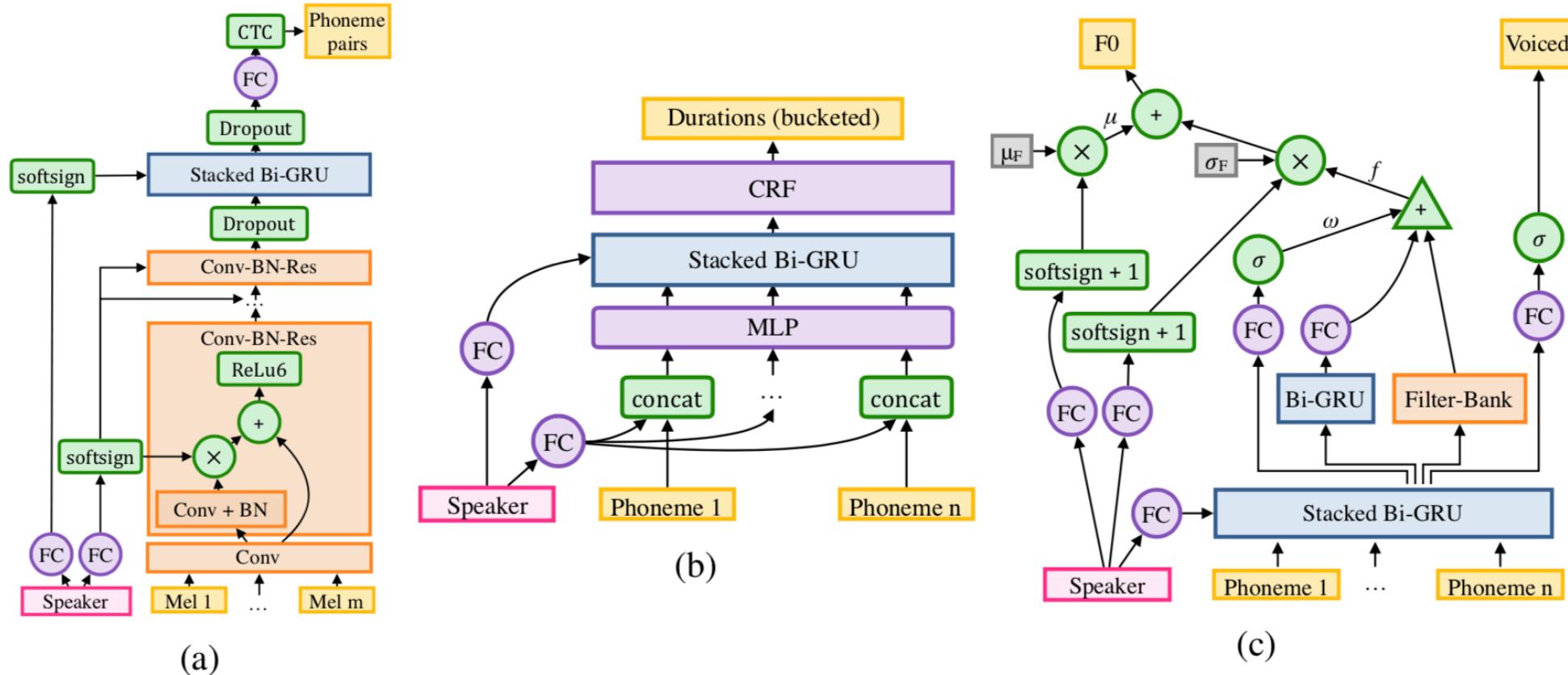
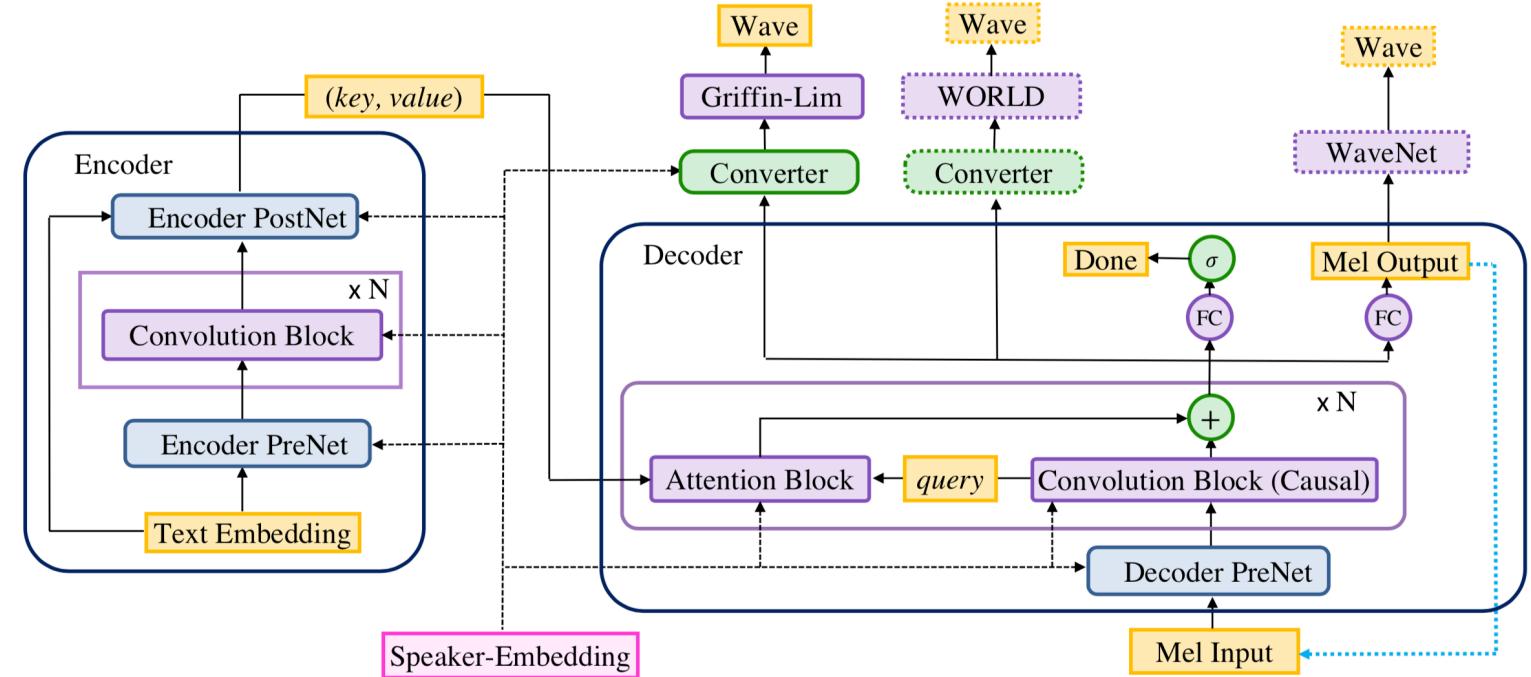


Figure 2: Architecture for the multi-speaker (a) segmentation, (b) duration, and (c) frequency model.

Example: DeepVoice 3

DeepVoice 3 uses an attention based sequence to sequence architecture based on convolutional building blocks for efficiency.

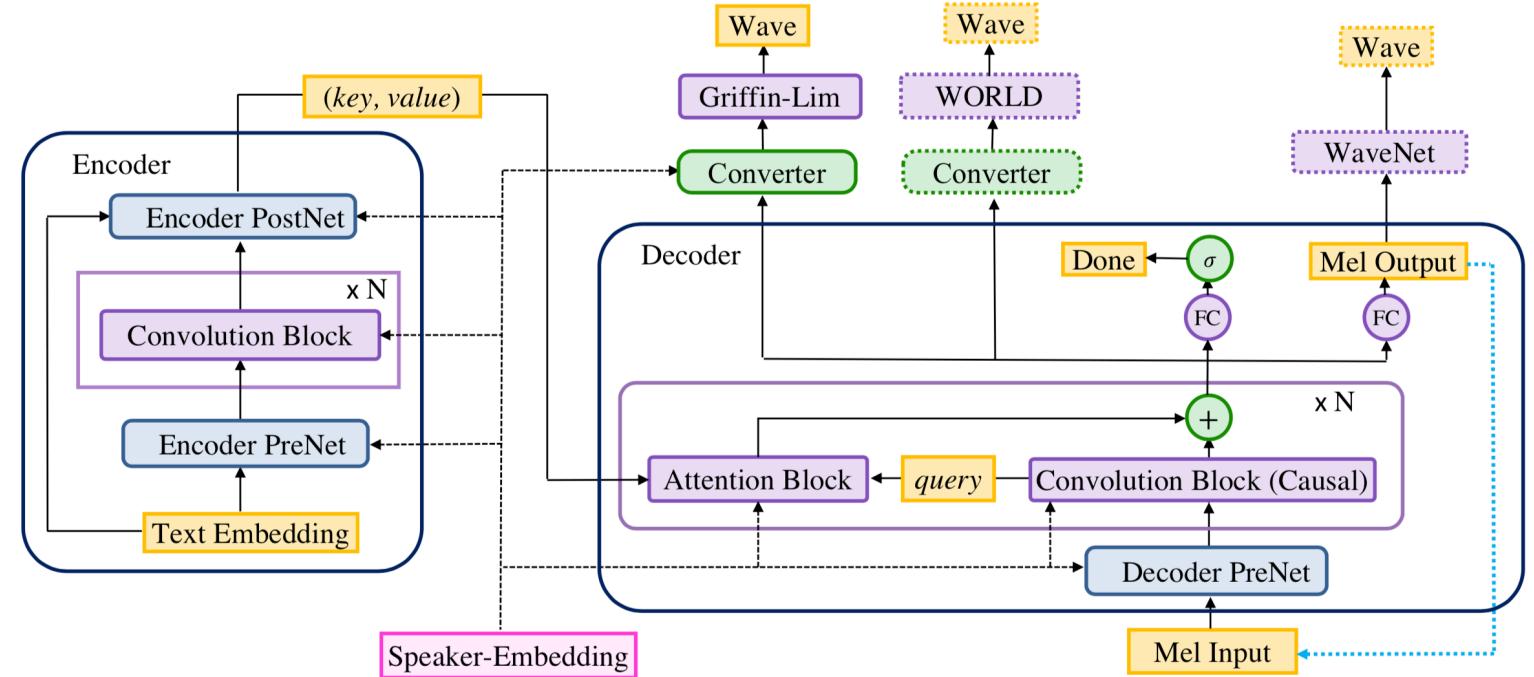
- Fully convolutional character to spectrogram model
 - Optimized for efficient inference on modern hardware
 - Can be integrated with different audio synthesis models
 - Griffin-Lim
 - WORLD
 - WaveNet



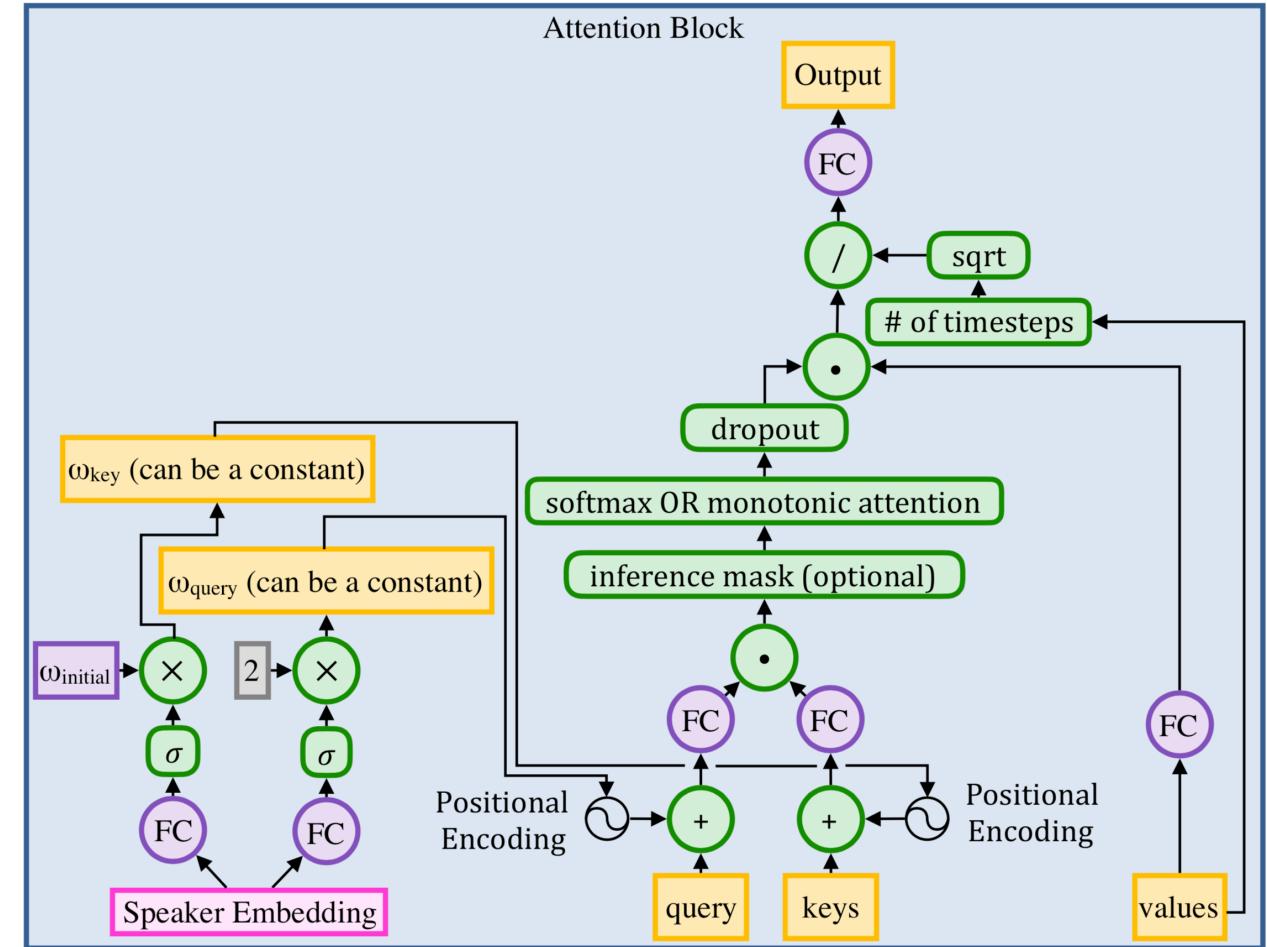
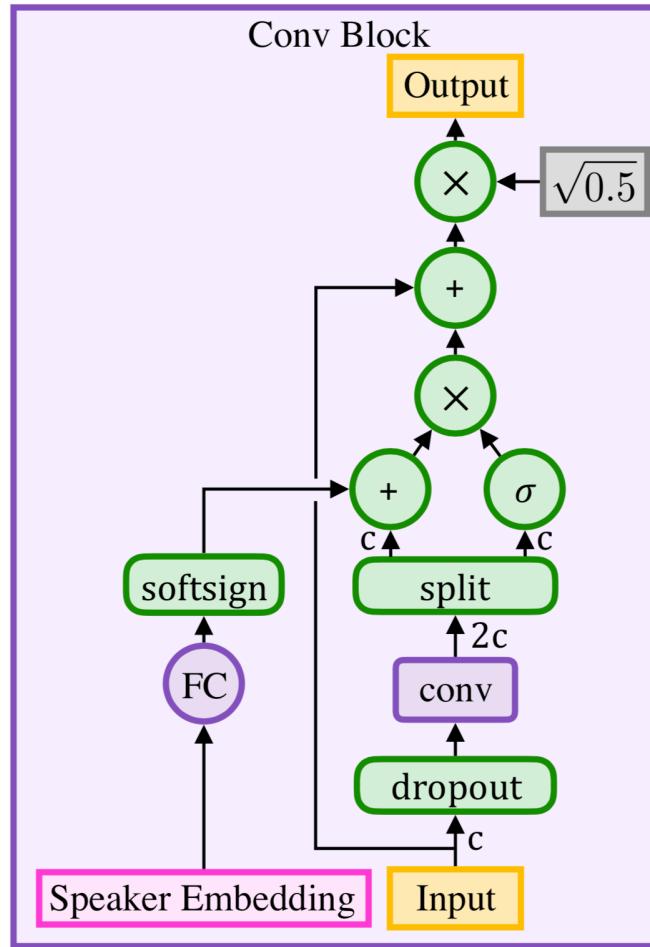
Example: DeepVoice 3

DeepVoice 3 uses an attention based sequence to sequence architecture based on convolutional building blocks for efficiency

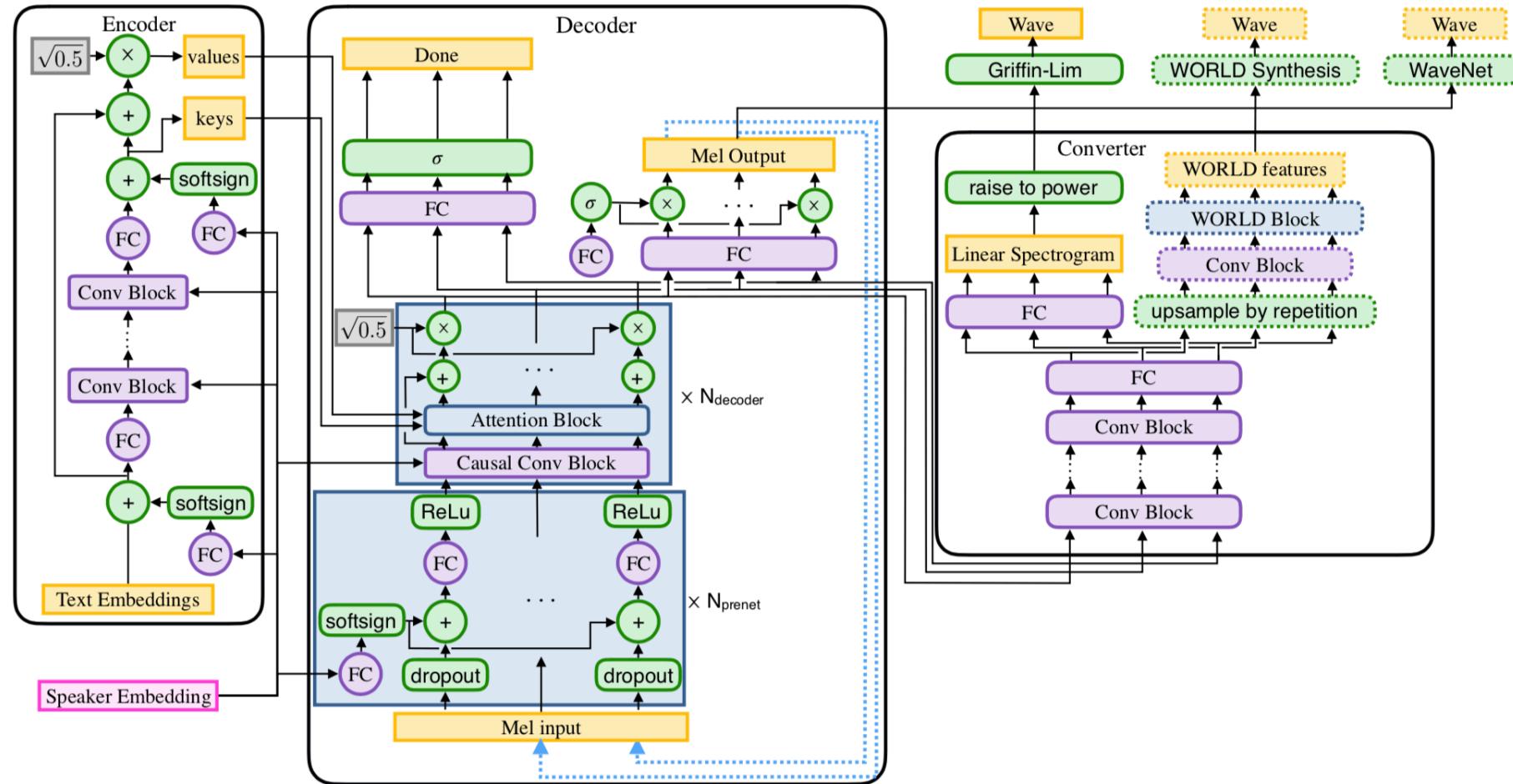
- Encoder
 - Fully convolutional encoder converts text into an internal representation
- Decoder
 - Auto regressive conversion of the internal representation with a fully convolutional causal decoder using a multi hop attention mechanism into a low dimensional audio representation (mel spectrogram)
- Converter
 - (All) vocoder parameter prediction with a fully convolutional non causal network



Example: DeepVoice 3



Example: DeepVoice 3



Pointers To Some Recent Results

- This is an evolving field, a few interesting recent papers are listed below
 - A lot of the focus is on improving the performance and making synthesized voices more life like
- Neural voice cloning with a few samples
 - <https://arxiv.org/abs/1802.06006>
- Transfer learning from speaker verification to multispeaker text-to-speech synthesis
 - <https://arxiv.org/abs/1806.04558>
 - <https://github.com/CorentinJ/Real-Time-Voice-Cloning>
- Glow: Generative flow with invertible 1x1 convolutions
 - <https://arxiv.org/abs/1807.03039>
- WaveGlow: a flow-based generative network for speech synthesis
 - <https://arxiv.org/abs/1811.00002>
 - <https://github.com/NVIDIA/WaveGlow>
- ESPnet-TTS: unified, reproducible, and integratable open source end-to-end text-to-speech toolkit
 - <https://arxiv.org/abs/1910.10909>

Question

- Combining the material in the speech lecture with the material in the language lecture we have the following capabilities
 - Speech in language 1 to text in language 1
 - CTC, RNN transducer, attention, ...
 - Translation from text in language 1 to text in language 2
 - Sequence to sequence, attention, ...
 - Text language 2 to speech in language 2
 - Text to spectrogram to generative model, ...
- Applying these 3 networks sequentially allows us to translate from speech in language 1 to speech in language 2
- A question: why not design a network to directly map from speech in language 1 to speech in language 2?
 - A partial answer: remember back to the design lecture and the suggestion to keep your problems simple
 - However, it's interesting to think more about this

A quick survey for students that can speak more than 1 language

How do you translate from 1 language to another?
Directly from speech 1 to speech 2? Or from speech 1 to a mental text translation to speech 2?

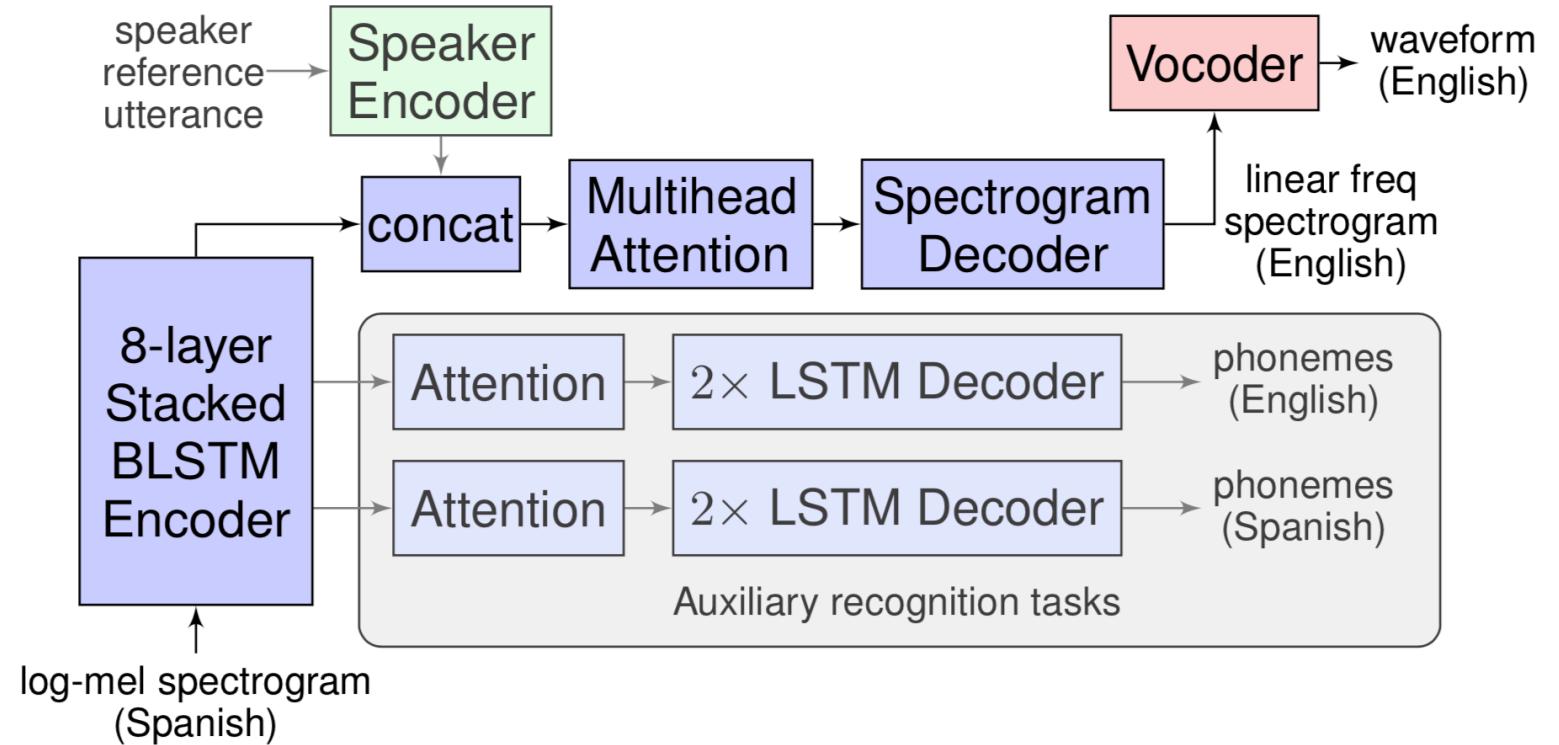
How do you converse with someone in the 2nd language you learned? Do you think and reply all in the 2nd language? Or do you make a round trip through the 1st language for thinking?

Is your deepest thinking language independent or language dependent?

Do the answers to these questions evolve as you become more familiar with the 2nd language?

Question

- So I had the previous slide in the deck when I initially taught the class, then I see the following paper ...
- Direct speech-to-speech translation with a sequence-to-sequence model
 - <https://arxiv.org/abs/1904.06037>



A Related Idea

- Replace text input to text to speech transduction with brain wave ...
- Intelligible speech synthesis from neural decoding of spoken sentences
 - <https://www.biorxiv.org/content/10.1101/481267v1.full>

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- Introduction to speech recognition
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 - <http://www.openslr.org/12/>
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- TED-LIUM 3: twice as much data and corpus repartition for experiments on speaker adaptation
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Data

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- AudioSet
 - <https://github.com/tensorflow/models/tree/master/research/audioset>
- FMA: a dataset for music analysis
 - <https://github.com/mdeff/fma>
- Million song dataset
 - <https://labrosa.ee.columbia.edu/millionsong/>
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 - http://recherche.ircam.fr/pub/dafx11/Papers/27_e.pdf
- Generative model-based text-to-speech synthesis
 - <https://github.com/oxford-cs-deepnlp-2017/lectures/blob/master/Lecture%2010%20-%20Text%20to%20Speech.pdf>
- Text normalization, letter to sound, prosody
 - <http://web.stanford.edu/class/cs224s/lectures/224s.17.lec14.pdf>
- Waveform synthesis in TTS
 - <http://web.stanford.edu/class/cs224s/lectures/224s.17.lec15.pdf>
- Parametric TTS, intoxication, depression, trauma, personality
 - <http://web.stanford.edu/class/cs224s/lectures/224s.17.lec16.pdf>

Text To Speech

- WaveNet: a generative model for raw audio
 - <https://deepmind.com/blog/wavenet-generative-model-raw-audio/>
 - <https://arxiv.org/abs/1609.03499>
- Speaker-dependent WaveNet vocoder
 - <https://pdfs.semanticscholar.org/487a/a8076bf3c0edb4134759e1ddf09d64f21476.pdf>
- Fast Wavenet generation algorithm
 - <https://arxiv.org/abs/1611.09482>
- Parallel WaveNet: fast high-fidelity speech synthesis
 - <https://arxiv.org/abs/1711.10433>
- WaveGlow: a flow-based generative network for speech synthesis
 - <https://arxiv.org/abs/1811.00002>
 - <https://github.com/NVIDIA/WaveGlow>
- Tacotron: towards end-to-end speech synthesis
 - <https://arxiv.org/abs/1703.10135>
- Natural TTS synthesis by conditioning WaveNet on mel spectrogram predictions
 - <https://arxiv.org/abs/1712.05884>

Text To Speech

- Deep voice: real-time neural text-to-speech
 - <https://arxiv.org/abs/1702.07825>
- Deep voice 2: multi-speaker neural text-to-speech
 - <https://arxiv.org/abs/1705.08947>
- Deep voice 3: scaling text-to-speech with convolutional sequence learning
 - <https://arxiv.org/abs/1710.07654>
- Deep voice 3: 2000-speaker neural text-to-speech
 - <http://research.baidu.com/Blog/index-view?id=91>

Text To Speech

- Fast, compact, and high quality LSTM-RNN based statistical parametric speech synthesizers for mobile devices
 - <https://arxiv.org/abs/1606.06061>
- Unidirectional long short-term memory recurrent neural network with recurrent output layer for low-latency speech synthesis
 - <https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/43266.pdf>
- VoiceLoop: voice fitting and synthesis via a phonological loop
 - <https://research.fb.com/wp-content/uploads/2018/04/voiceloop-voice-fitting-and-synthesis-via-a-phonological-loop.pdf>