Speech

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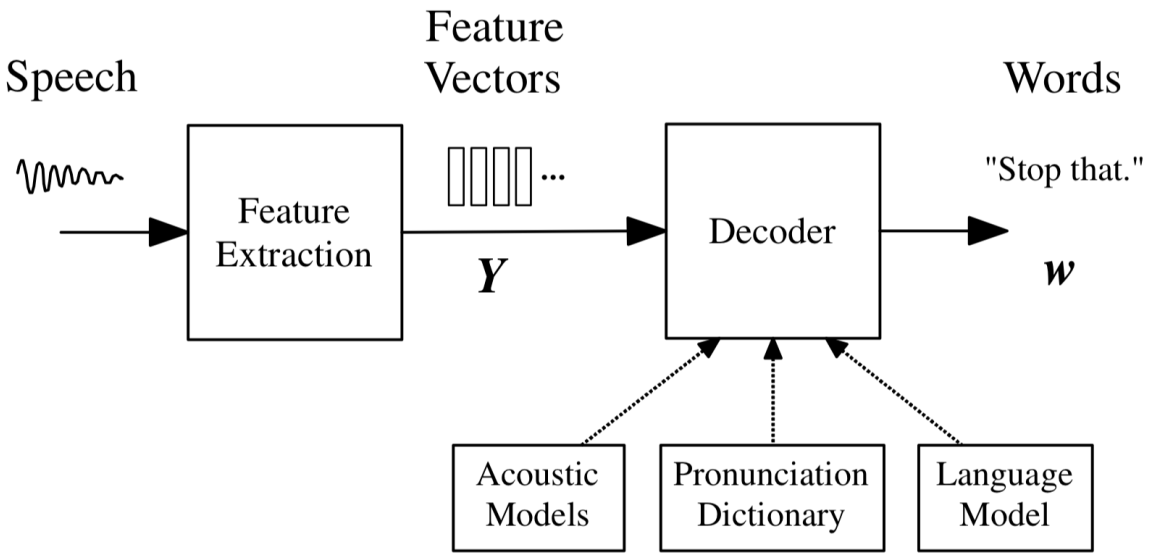
Outline

- Motivation
- Speech and audio
- Pre processing
- Network structures
- Speaker verification and identification
- Wake word detection, keyword spotting and command recognition
- Conditional modeling
- Speech to text
- Text to speech
- References

Motivation

Classical Speech To Text Transduction

- Speech or audio waveform
  - x(n), n = 0, ..., N – 1
- Feature vectors
  - $\mathbf{Y} = [\mathbf{y}_0 \ldots \mathbf{y}_{T-1}]$
  - MFCC, Δ, ΔΔ with ~ 40 total features are common
- Word sequence **w**
  - $\mathbf{w}_{hat} = \arg\max_{\mathbf{w}} (P(\mathbf{w} \mid \mathbf{Y}))$
  - The acoustic model uses ~ 44 phonemes for the English language (24 consonants, 20 vowels)
  - Phonemes are concatenated via a pronunciation dictionary to make words **w**
  - The language model determines P(**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

Figure from https://mi.eng.cam.ac.uk/~mjfg/mjfg_NOW.pdf

Classification Problems

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

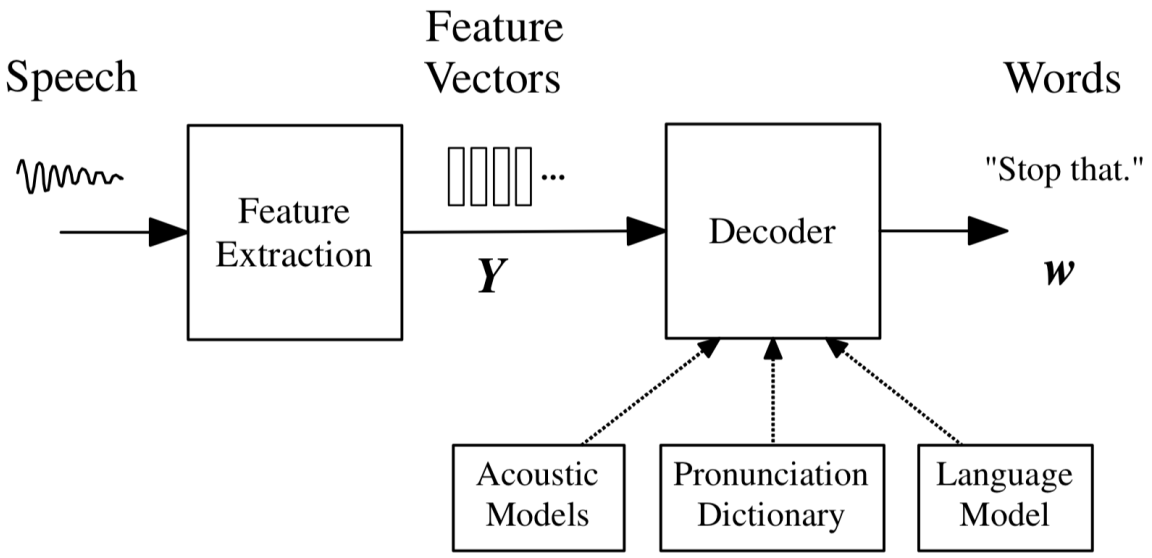

Figure from https://mi.eng.cam.ac.uk/~mjfg/mjfg_NOW.pdf

Generation Problems

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Speech also includes common generation problems

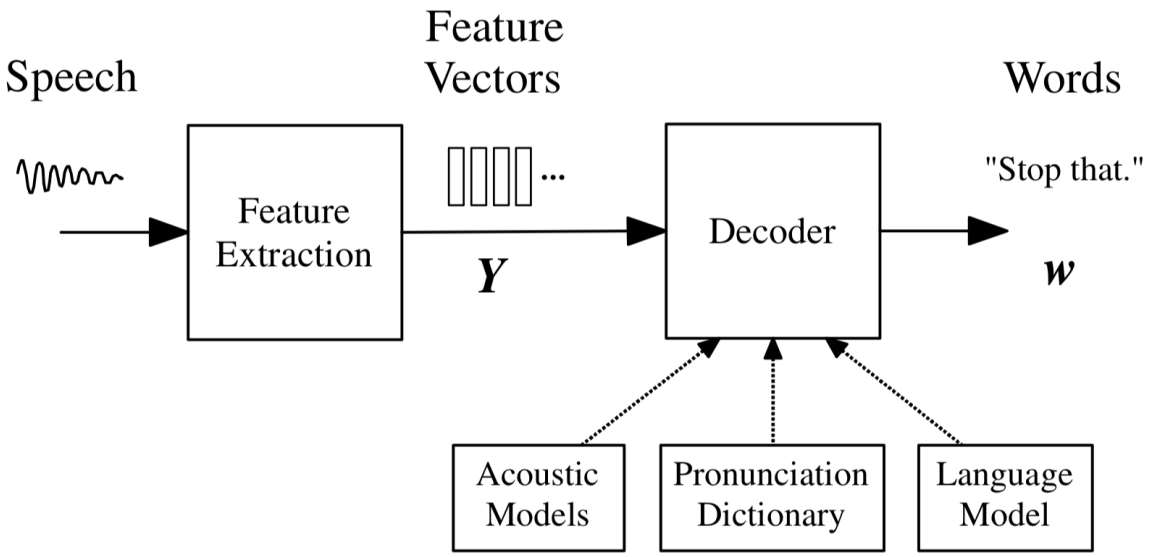


Figure from https://mi.eng.cam.ac.uk/~mjfg/mjfg_NOW.pdf

The Strategy Described Here

- Pre processing divides a speech waveform into an input sequence of vectors
- A CNN, RNN or transformer 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
  - Very similar to language translation

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

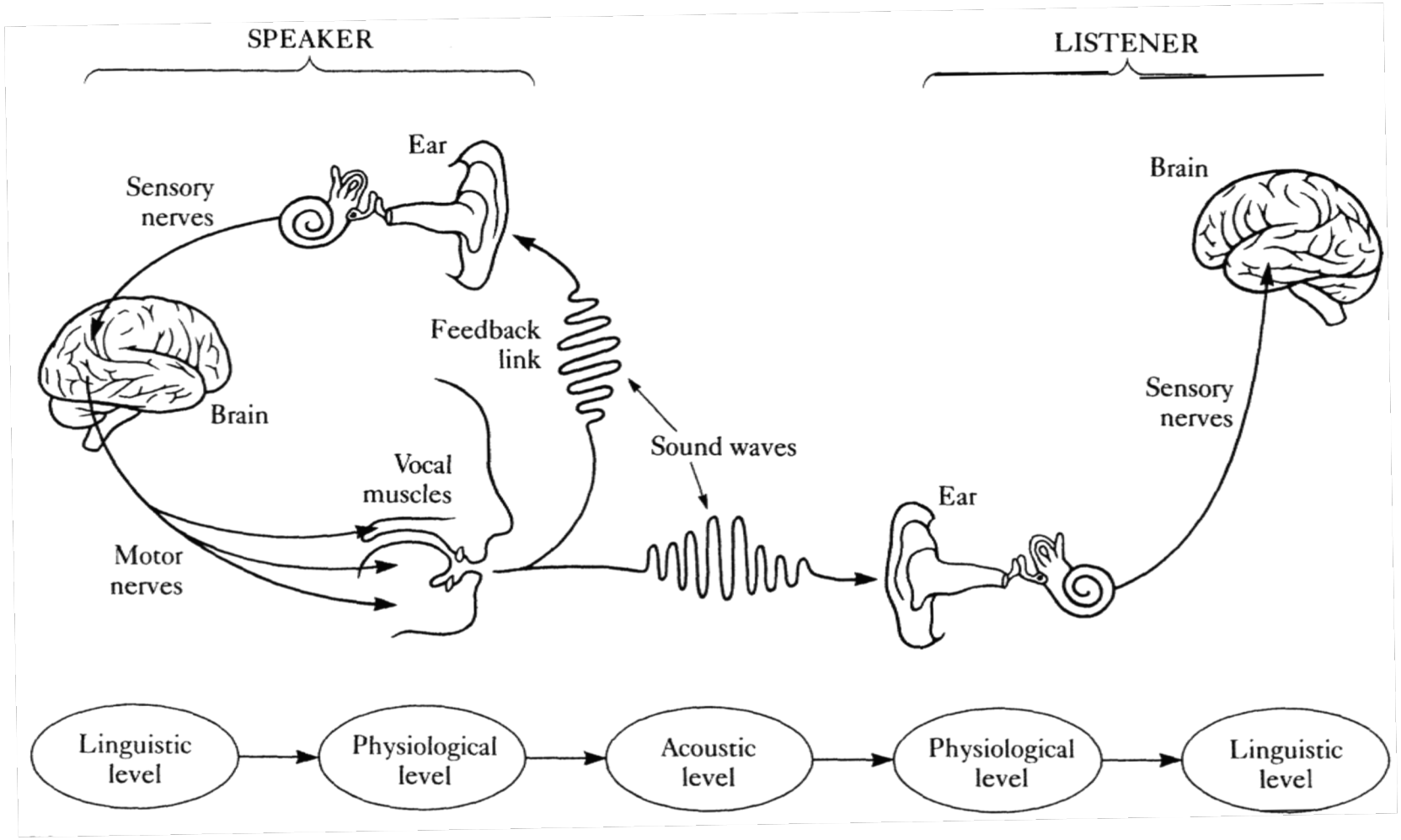
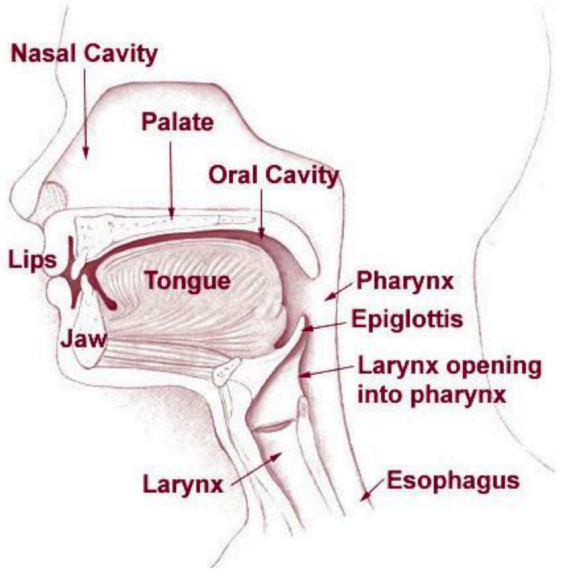
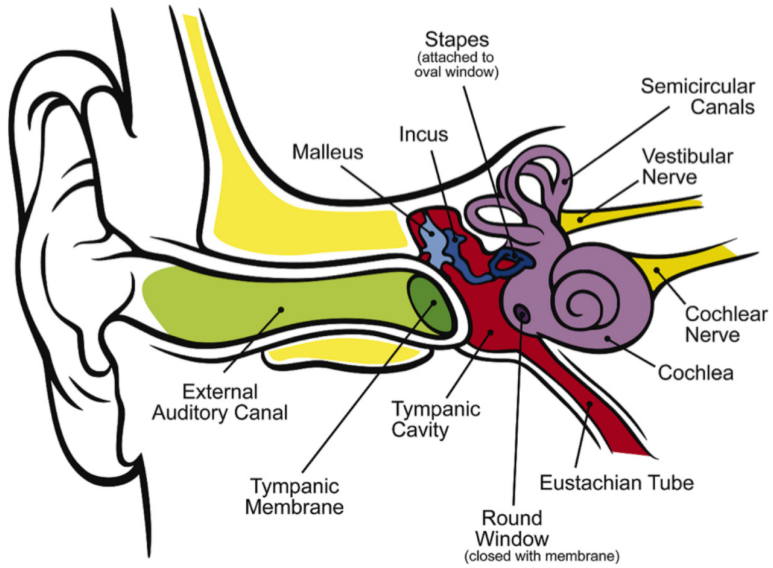
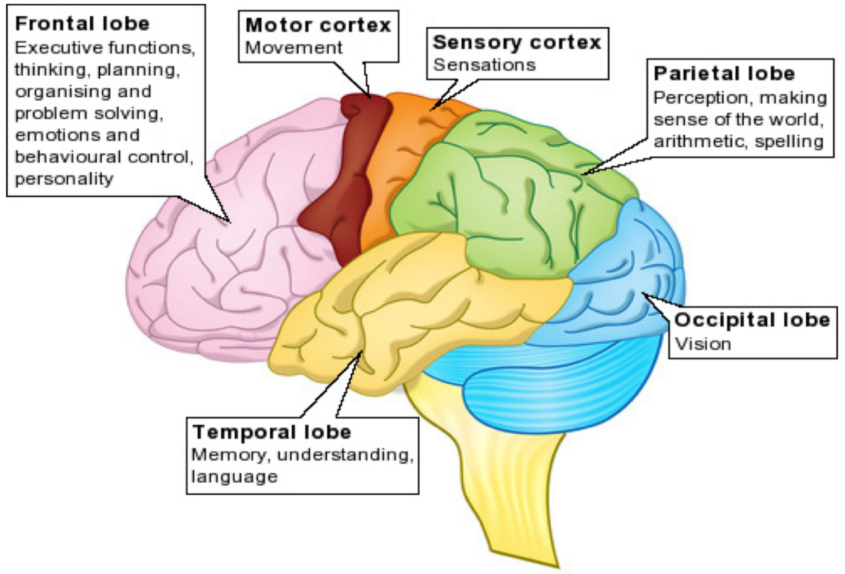


Figure from http://www.columbia.edu/~rmk7/HC/HC_Readings/Denes_Pinson1-2.PDF

Generation, Perception And Understanding







Figures from http://lxmls.it.pt/2017/talk.pdf

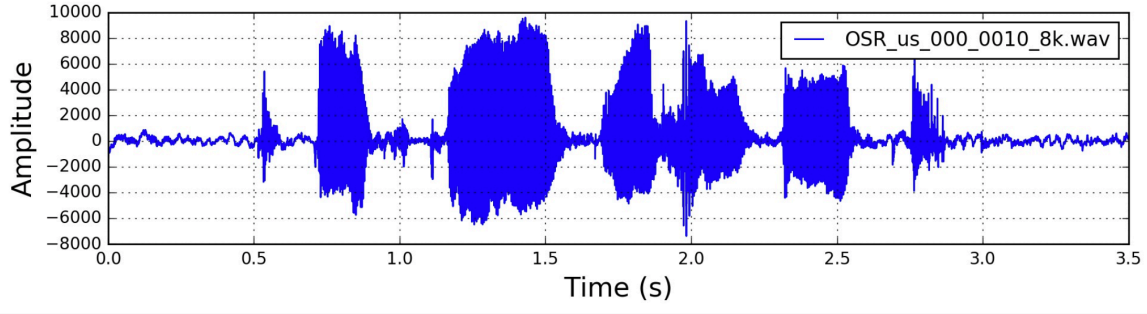
The Machine Speech And Audio Chain

- 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

Start With A 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 ~ 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

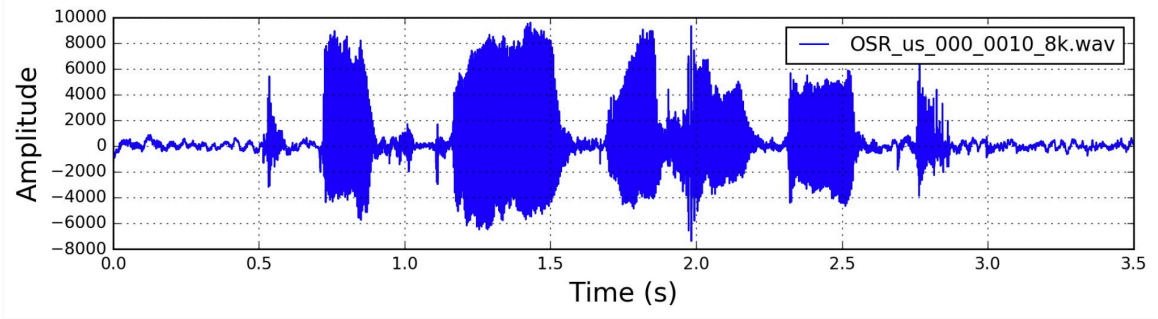


Signal in the Time Domain

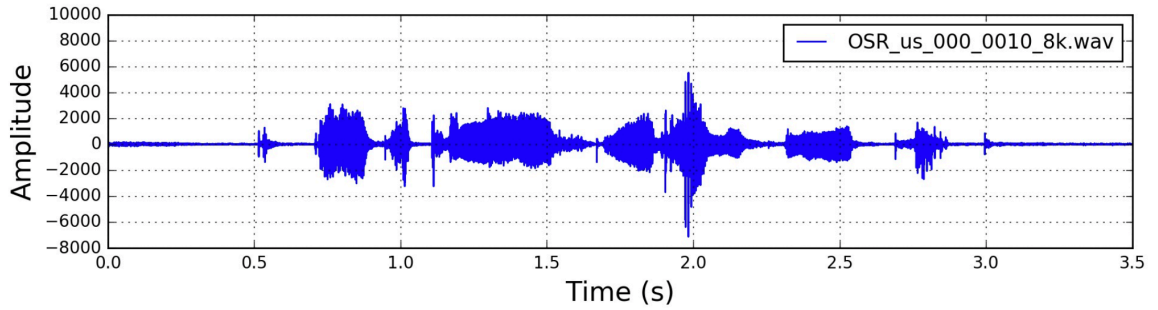
Figure from https://haythamfayek.com/2016/04/21/speech-processing-for-machine-learning.html

Apply 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



Signal in the Time Domain



Signal in the Time Domain after Pre-Emphasis

Figure from https://haythamfayek.com/2016/04/21/speech-processing-for-machine-learning.html

Window And Create A 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 ~ 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

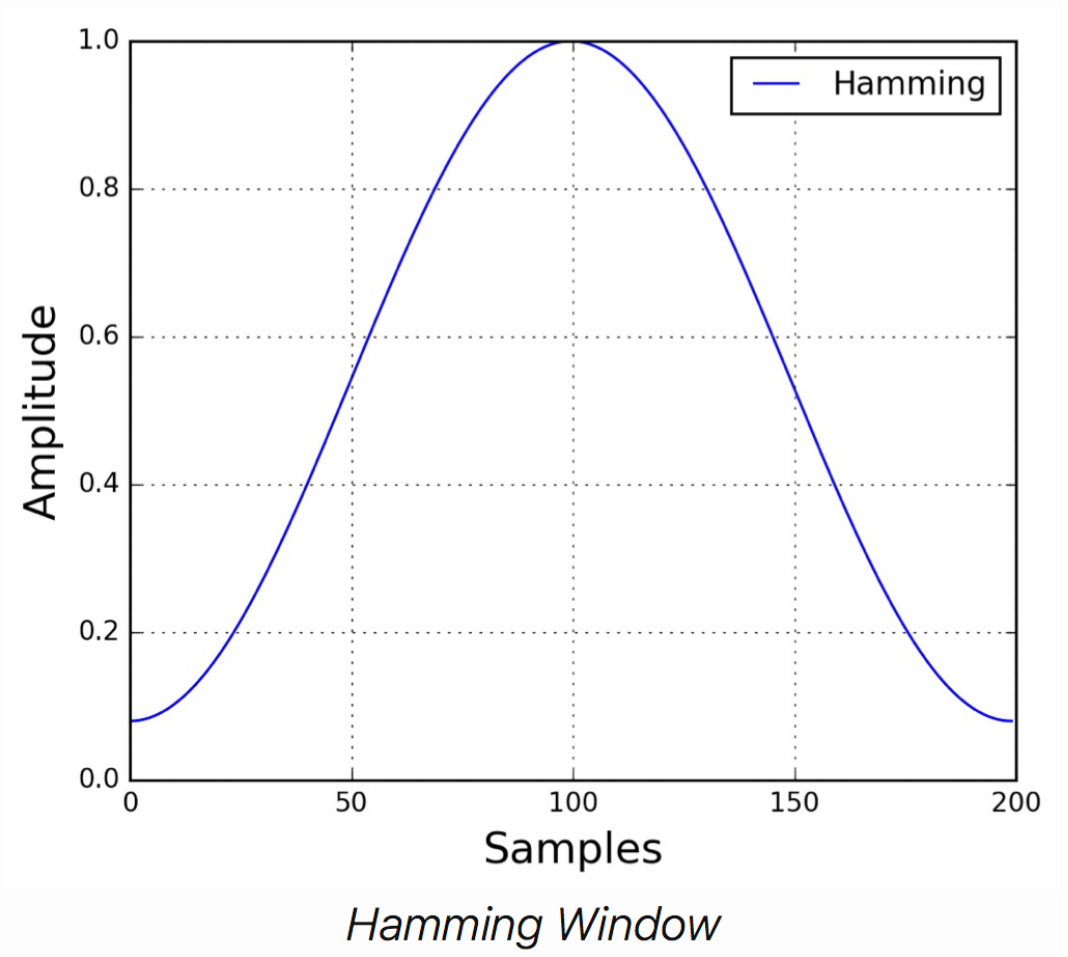
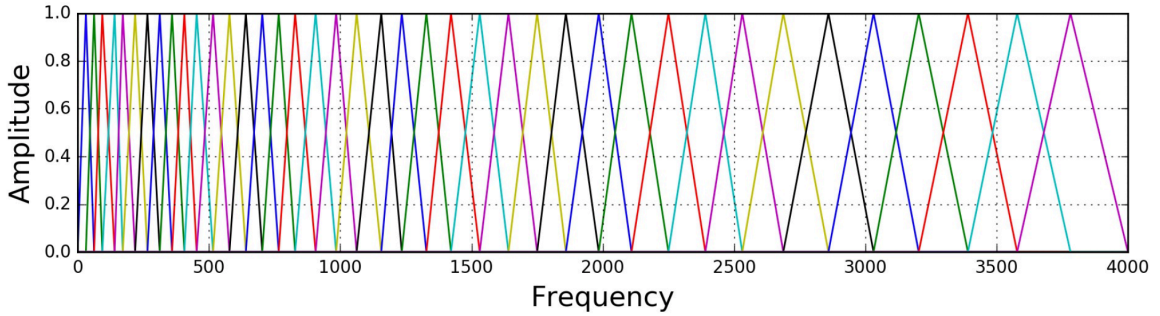


Figure from https://haythamfayek.com/2016/04/21/speech-processing-for-machine-learning.html

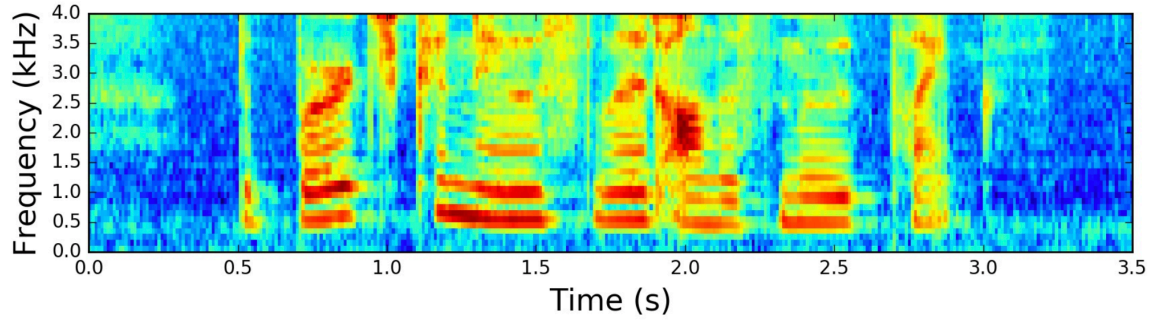
Transform To MFCCs

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

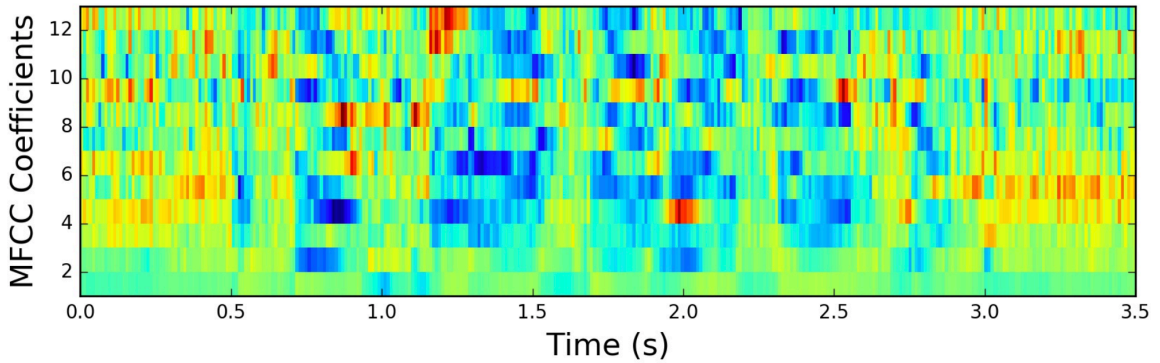
- Humans don't respond to all frequencies equally
  - The mel frequency spacing mimics the greater sensitivity of the ear to lower frequencies
  - A mel filter bank with ~ 40 filters can be applied to the spectrogram output to create a mel filter bank output
  - For log mel take the log of the mel spectrogram
- 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 (~ 1st order derivative, provides shape info)
  - Create additional features with ΔΔ values representing 1st order differences in Δ values (~ 2nd order derivative, provides shape info)
  - Normalize coefficients to 0 mean and 1 variance



Filter bank on a Mel-Scale



Spectrogram of the Signal



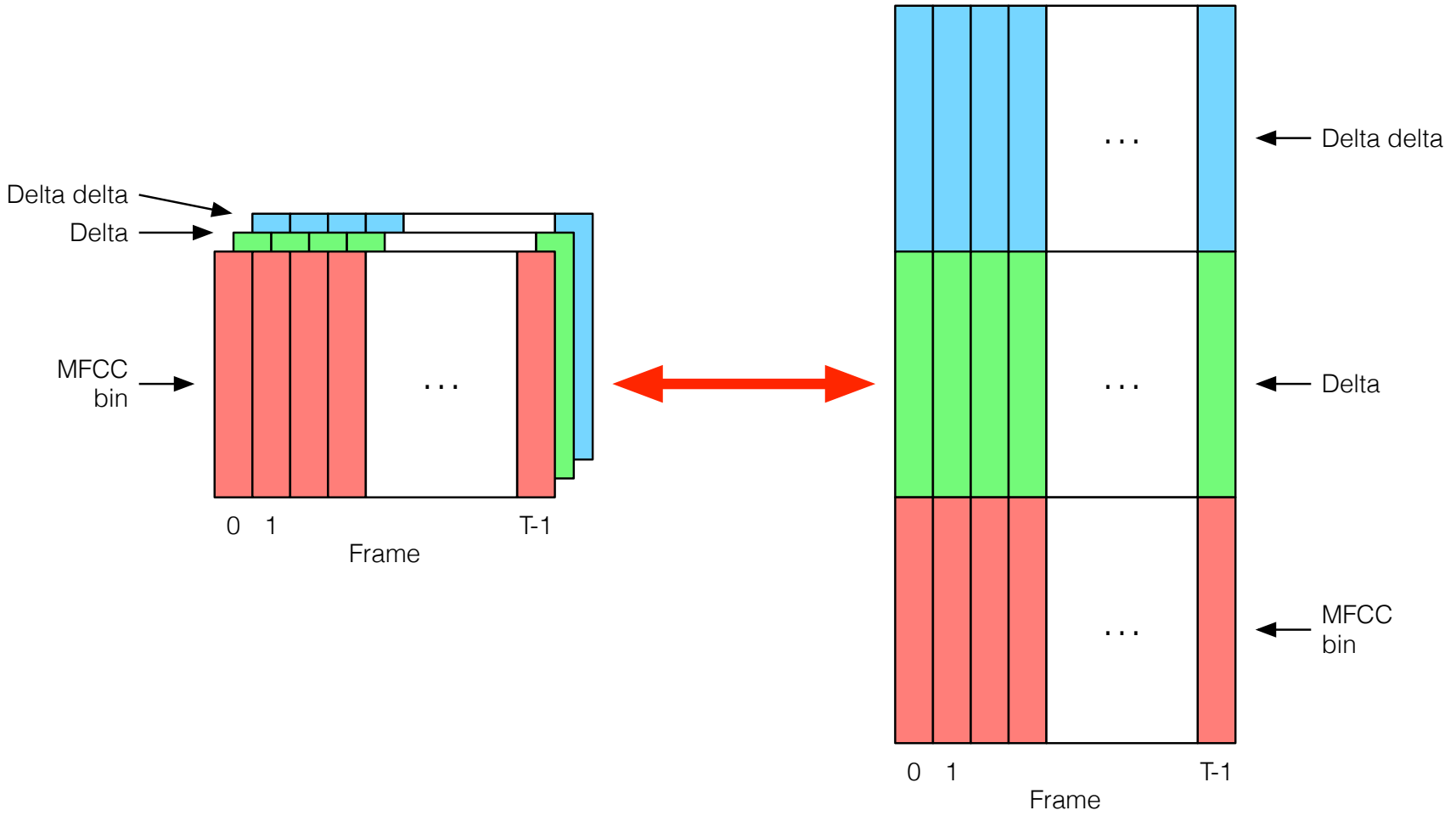
Normalized MFCCs

Figure from https://haythamfayek.com/2016/04/21/speech-processing-for-machine-learning.html

Network Structures

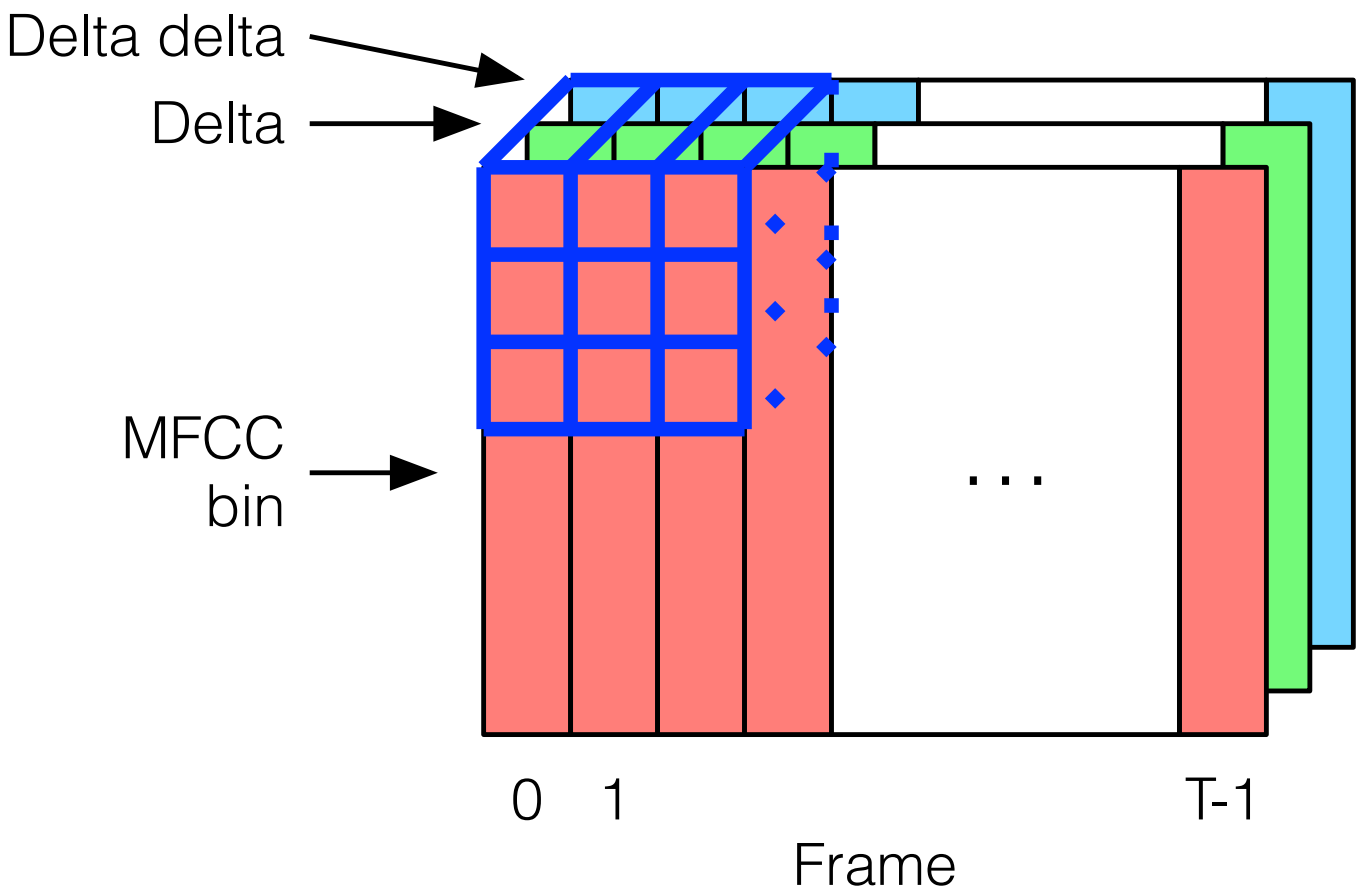
Different Views Of Pre Processed Speech

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



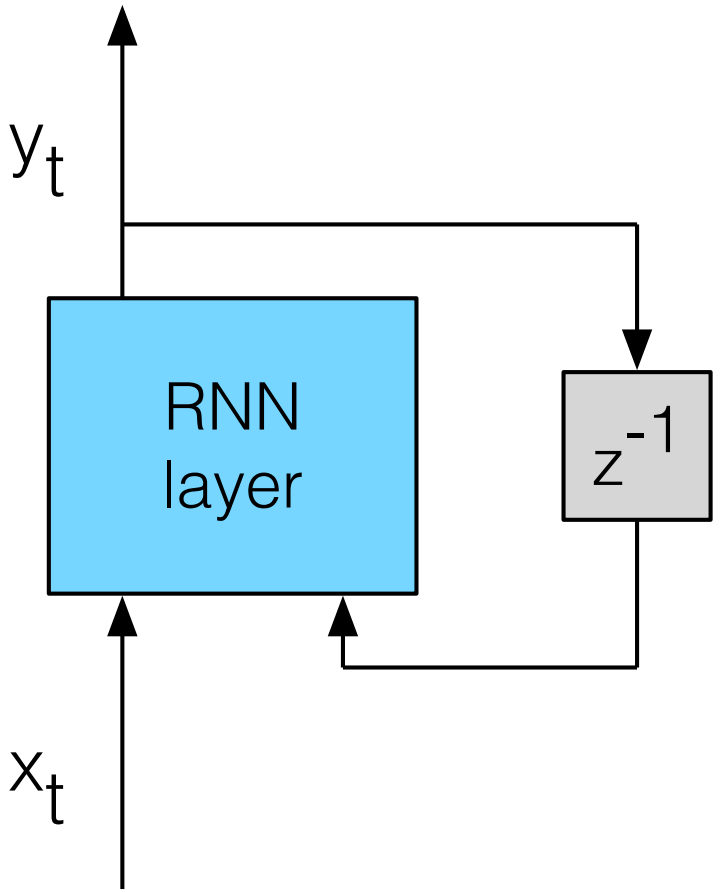
CNNs

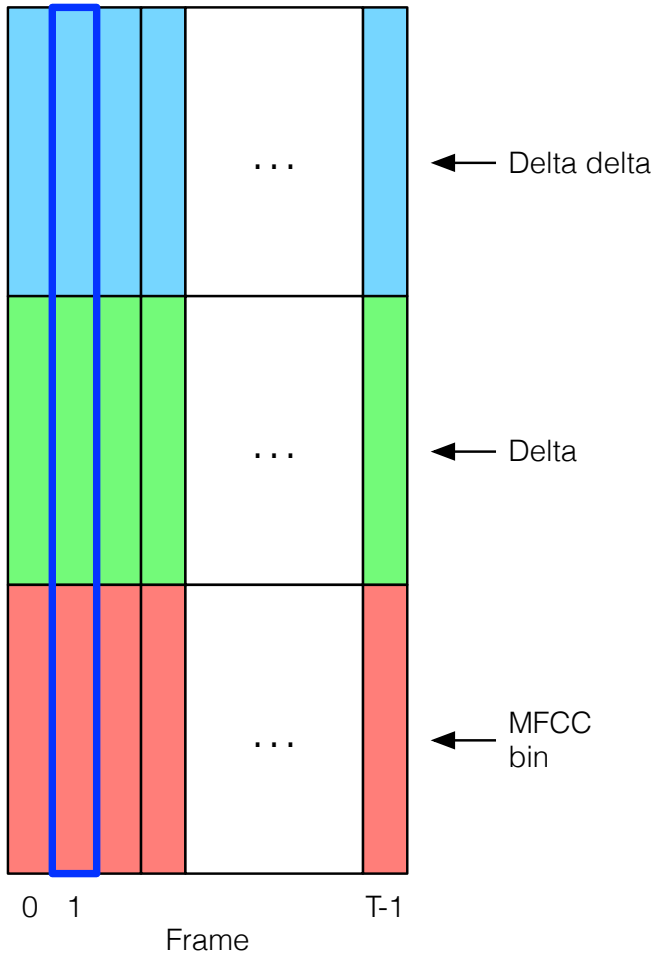
CNNs exploit translation invariance in space (in this case time and bin) for efficiency to combine info across time and bin to create stronger features



RNNs

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





Transformers

Transformers exploit data to mix information across time and bin to map from weaker features to stronger features

Should You Use A CNN, RNN Or Transformer?

- 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?

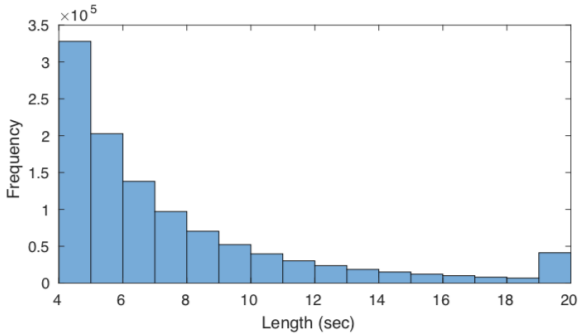
- The historical split was CNNs for vision and RNN / variants for speech and language
  - But there are blurring lines and CNNs are finding more uses in problems with sequential data
  - An argument can be made that RNNs / LSTMs are not the most efficient structure for propagating longer range information and are also inefficient to implement as they're memory bound
  - Transformer 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/)

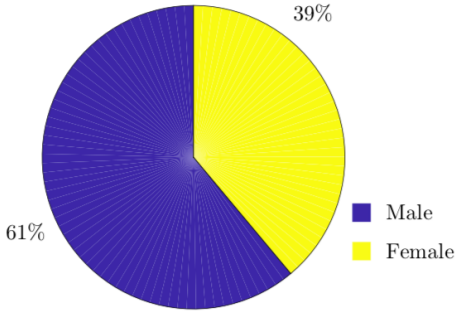
- It will be interesting to see how this evolves

Speaker Verification And Identification

Verification And Identification

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





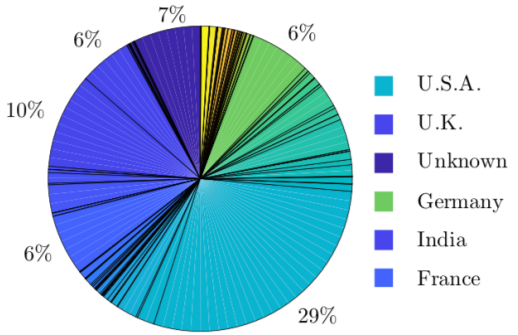


Figure from https://arxiv.org/abs/1806.05622

Sources Of Variability

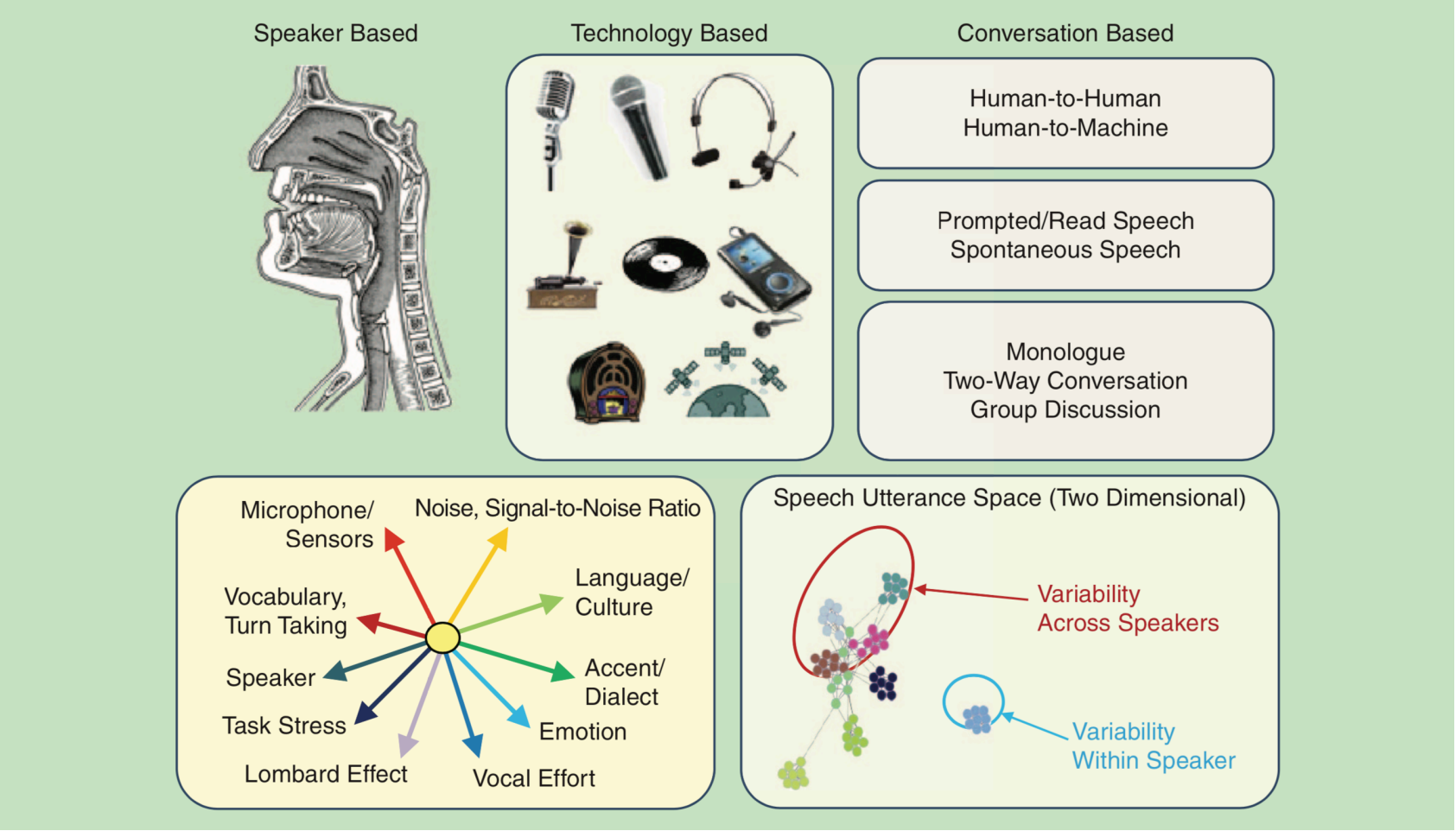


Figure from https://ieeexplore.ieee.org/document/7298570

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
  - Project a speaker to a vector, then find the closest reference vector using something like cosine similarity
  - 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

Example: A Basic Framework For Verification

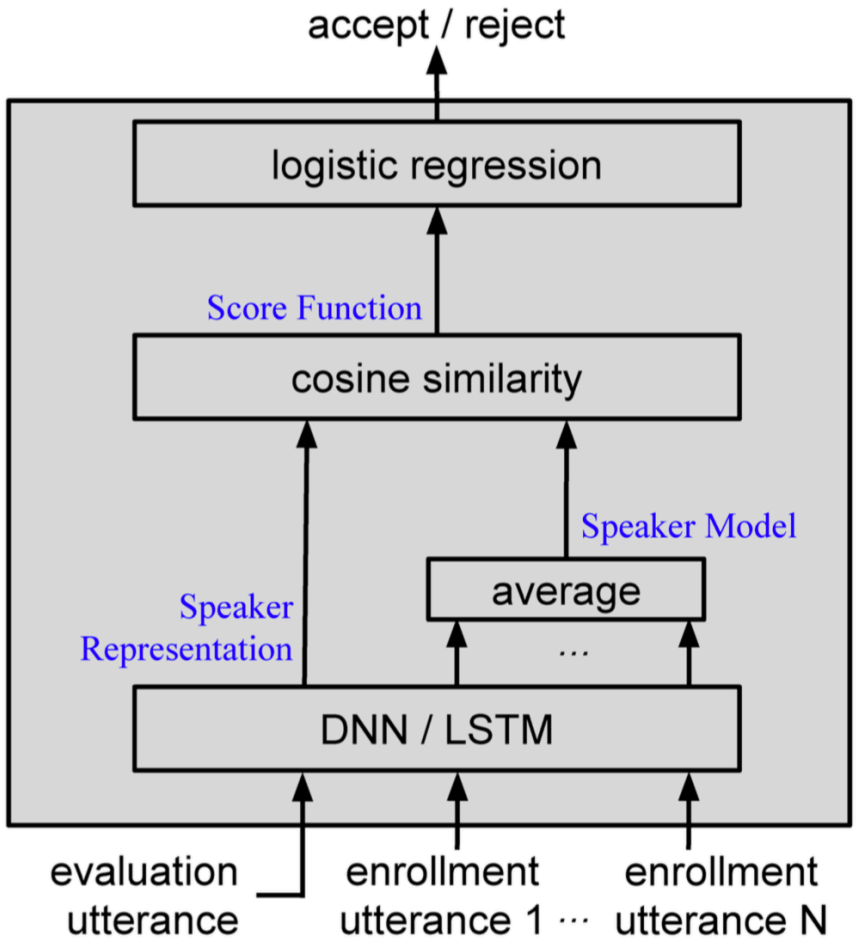
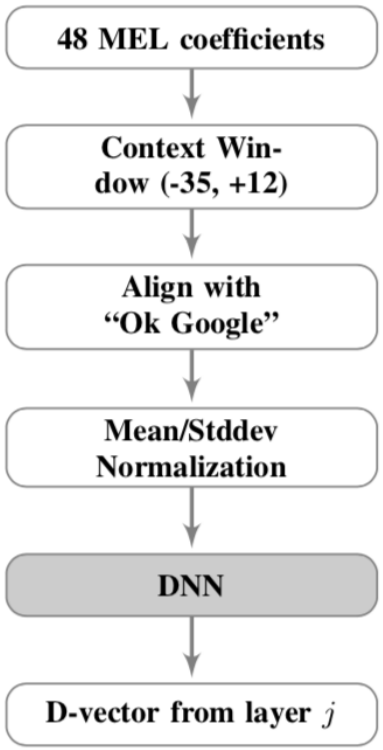
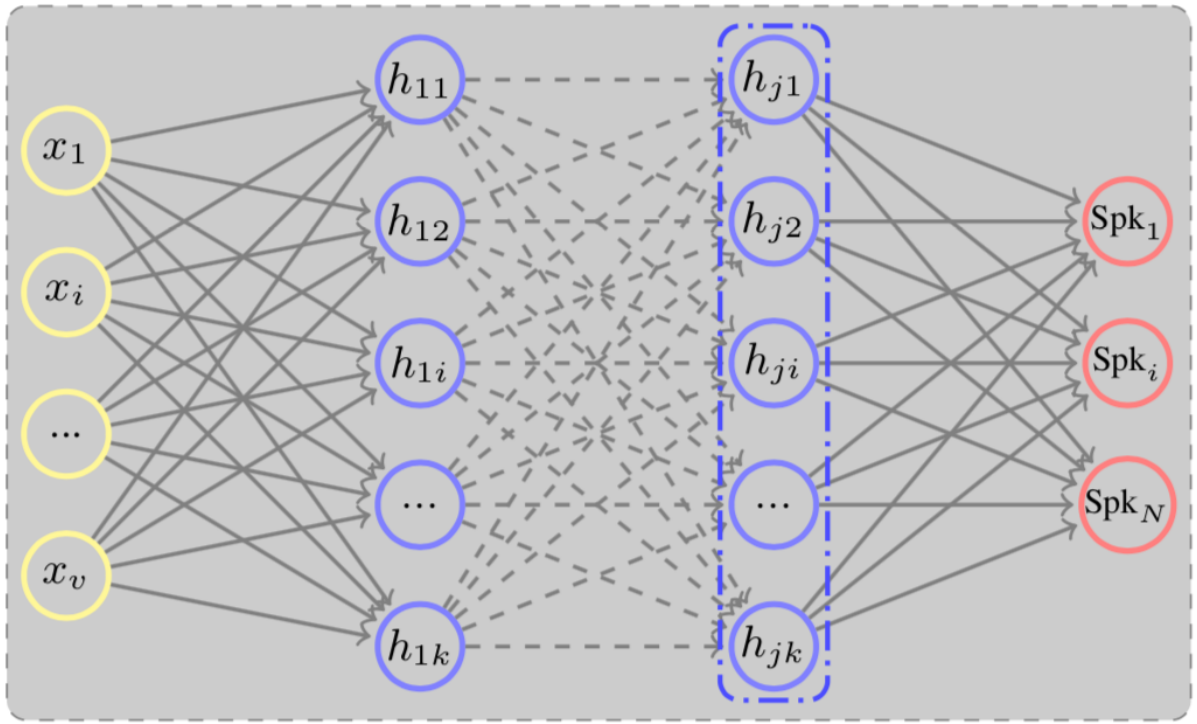


Figure from https://arxiv.org/abs/1509.08062

Example: Small Footprint Speaker Recognition

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





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.
- $w = 787$k model weights (excluding output layer).
- Rectified Linear Units.
- Softmax output Layer.

Training

- Stochastic Gradient Descent.

Note that this NN could be replaced with other xNN designs

Figure from https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/43970.pdf

Example: CT-DNN

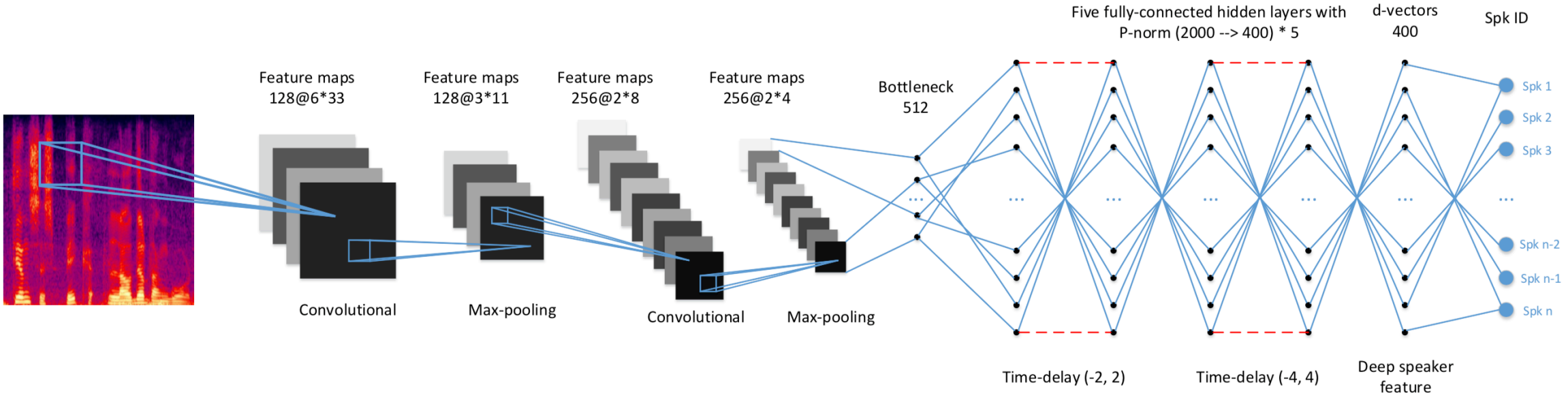


Figure from https://arxiv.org/abs/1705.03670

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	$1 \times 1, 5994$	$1 \times 1, 5994$

Table from https://arxiv.org/abs/1806.05622

Imprinting To Add Additional Speakers

- 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

Recent References

- Speaker identification
  - https://paperswithcode.com/task/speaker-identification
- Deep speaker: an end-to-end neural speaker embedding system
  - https://arxiv.org/abs/1705.02304
- Generalized end-to-end loss for speaker verification
  - https://arxiv.org/abs/1710.10467
- Transfer learning from speaker verification to multispeaker text-to-speech synthesis
  - https://arxiv.org/abs/1806.04558
- Speaker recognition from raw waveform with sincnet
  - https://arxiv.org/abs/1808.00158
- RawNet: advanced end-to-end deep neural network using raw waveforms for text-independent speaker verification
  - https://arxiv.org/abs/1904.08104
- Speech-VGG: a deep feature extractor for speech processing
  - https://arxiv.org/abs/1910.09909

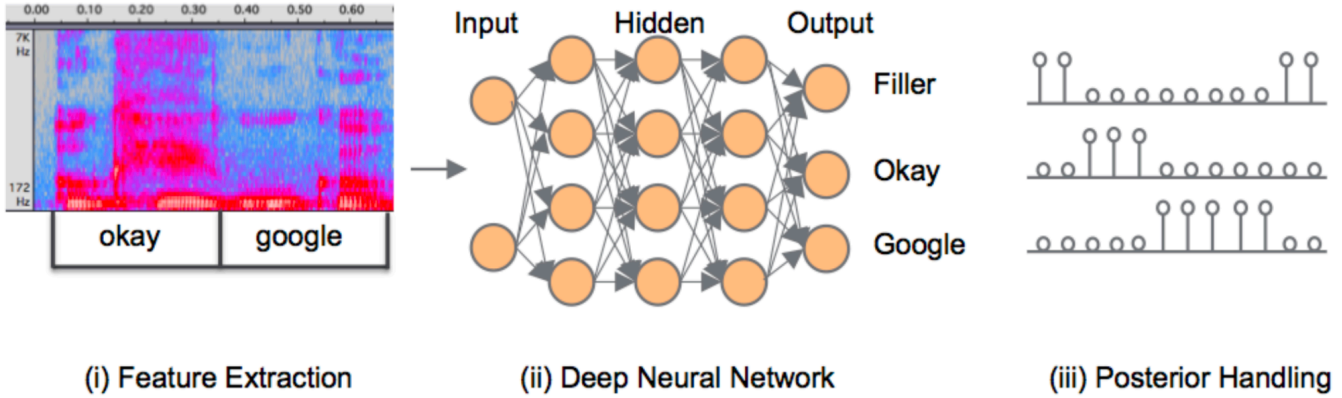
Recent References

- AM-MobileNet1D: a portable model for speaker recognition
  - https://arxiv.org/abs/2004.00132
- Improved RawNet with feature map scaling for text-independent speaker verification using raw waveforms
  - https://arxiv.org/abs/2004.00526
- Meta-learning for short utterance speaker recognition with imbalance length pairs
  - https://arxiv.org/abs/2004.02863
- AutoSpeech: neural architecture search for speaker recognition
  - https://arxiv.org/abs/2005.03215

Wake Word Detection, Keyword Spotting And Command Recognition

Wake Word Detection

- 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 detection
  - Key word spotting, command recognition or speech to text transduction

- These are all classification problems

Figure from https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/42537.pdf

Keyword Spotting

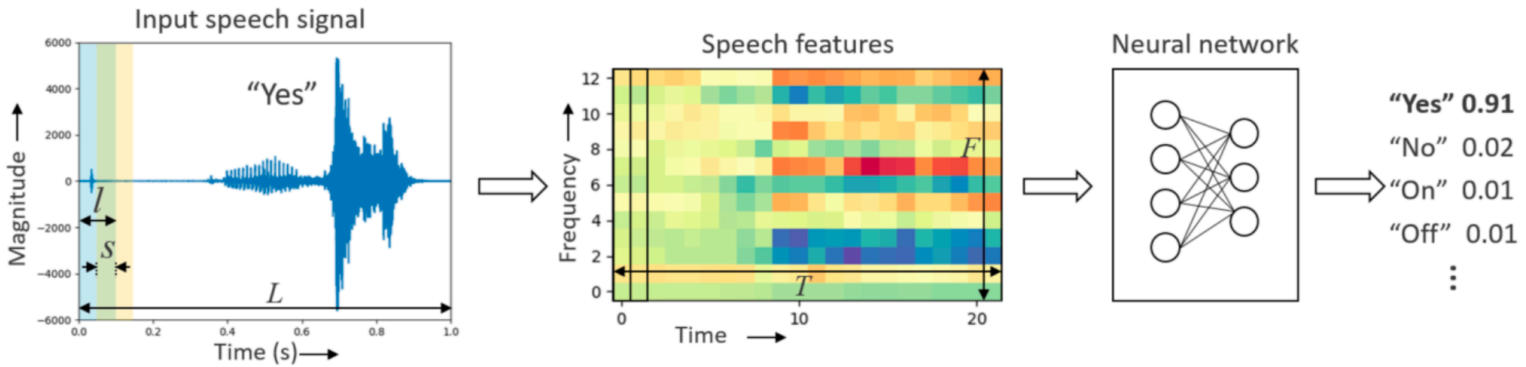
- Like wake word detection, but instead of 2 classes (wake work, no wake word) there can be multiple classes (class 1, class 2, ..., no class)

- As in wake word detection, a challenge is that it's unknown when the key word will occur
  - There can be large periods of time between general speech and keyword speech

- This is a classification problem

Command Recognition

- Like key word spotting but
  - Typically used when the system is in a command entry mode
  - So likely still need to do some alignment, but a higher density of positive vs background classes



- Data
  - Free spoken digit dataset (FSDD)
  - Google command data set

- This is also a classification problem

While wake word detection, key word spotting and command recognition have been listed as 3 separate tasks

- There's a lot of similarity between them
- Don't worry about / get too hung up with distinctions as there's potentially a lot of blurring in a practical system

Figure from https://arxiv.org/abs/1711.07128

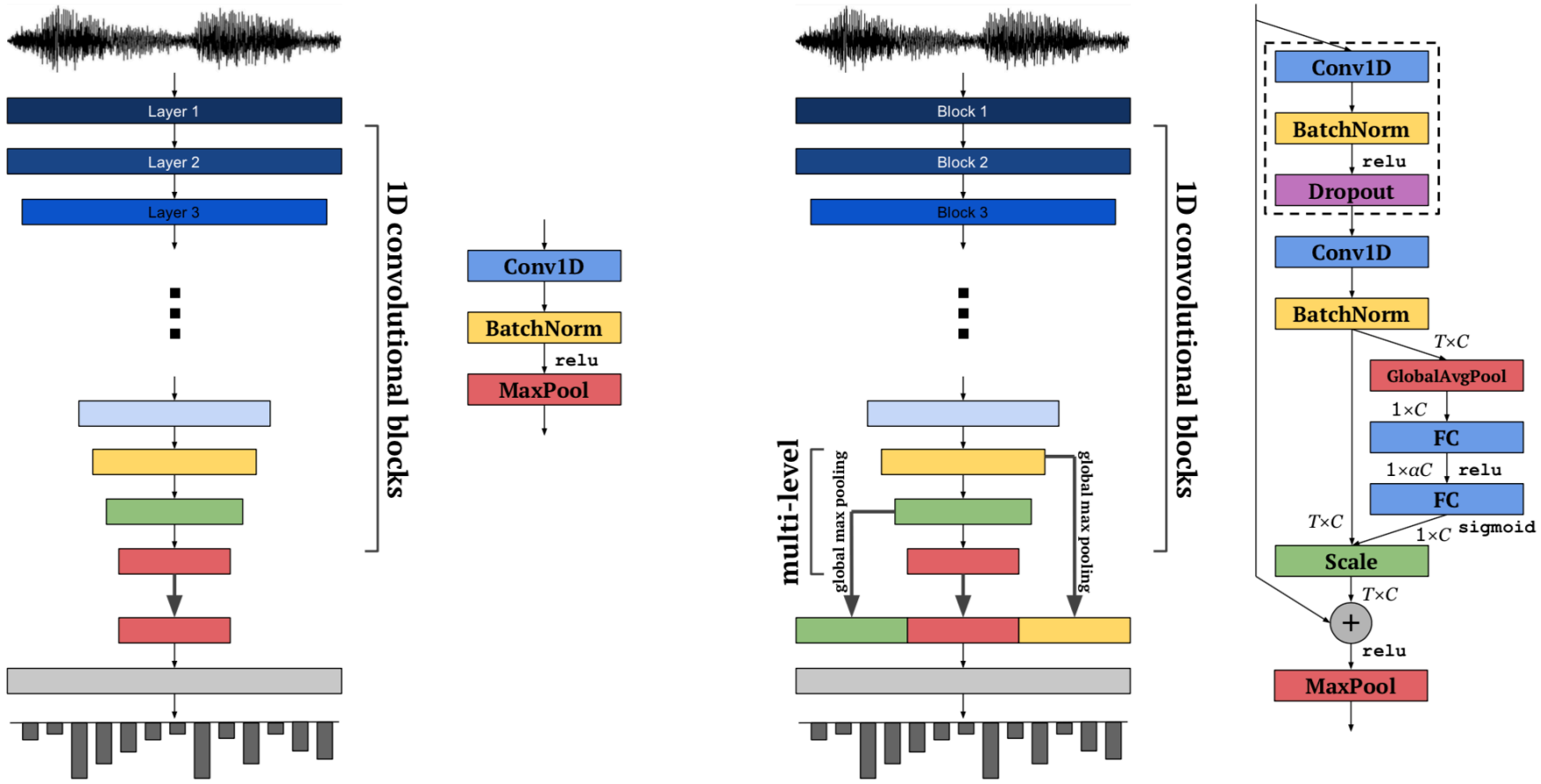
Strategy

- 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 class}
  - 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



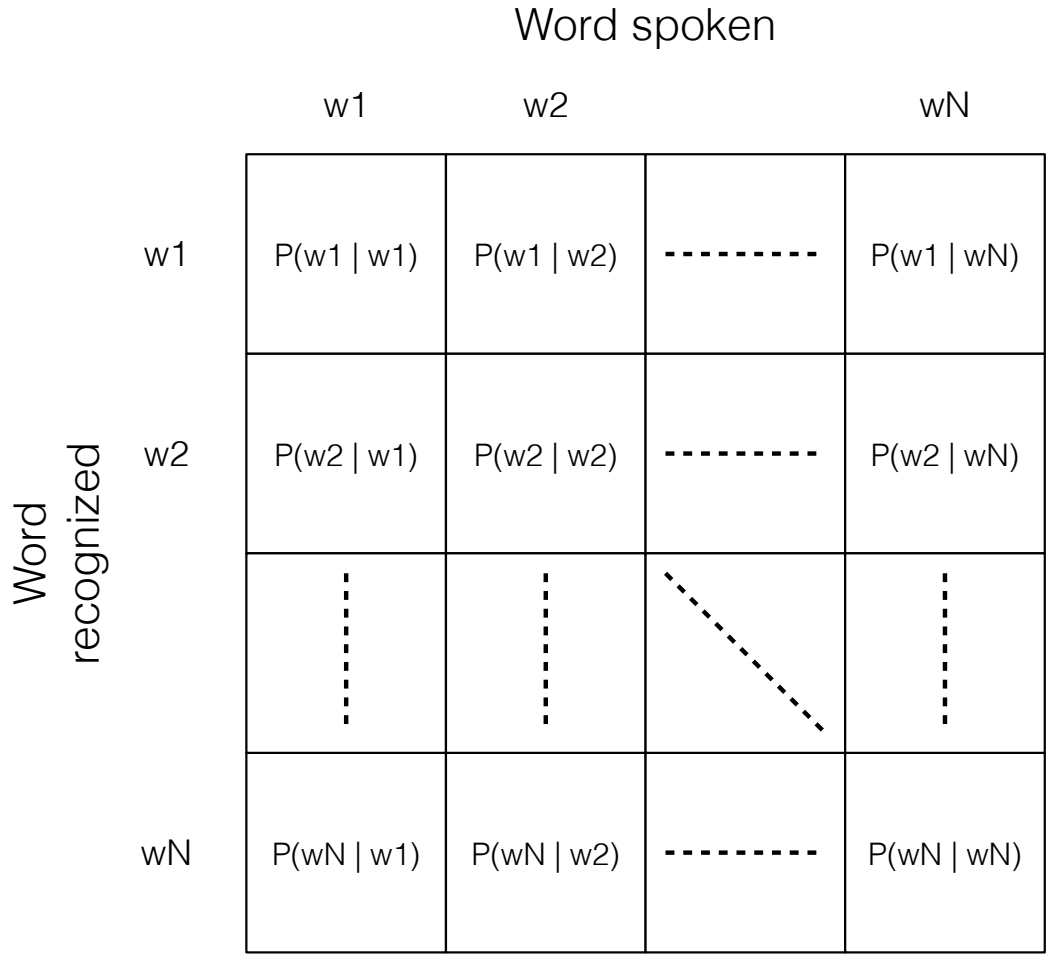
(a) SampleCNN

(b) ReSE-2-Multi

Figure from https://arxiv.org/abs/1712.00866

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



Recent References

- Effective combination of DenseNet and BiLSTM for keyword spotting
  - https://ieeexplore.ieee.org/document/8607038
- Deep residual learning for small-footprint keyword spotting
  - https://arxiv.org/abs/1710.10361
- Hello edge: keyword spotting on microcontrollers
  - https://arxiv.org/abs/1711.07128
- 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
- Efficient keyword spotting using dilated convolutions and gating
  - https://arxiv.org/abs/1811.07684
- End-to-end streaming keyword spotting
  - https://arxiv.org/abs/1812.02802

Recent References

- Multi-layer attention mechanism for speech keyword recognition
  - https://arxiv.org/abs/1907.04536
- Training keyword spotters with limited and synthesized speech data
  - https://arxiv.org/abs/2002.01322
- MatchboxNet: 1d time-channel separable convolutional neural network architecture for speech commands recognition
  - https://arxiv.org/abs/2004.08531
- Streaming keyword spotting on mobile devices
  - https://arxiv.org/abs/2005.06720
- Howl: a deployed, open-source wake word detection system
  - https://arxiv.org/abs/2008.09606
- Neural architecture search for keyword spotting
  - https://arxiv.org/abs/2009.00165

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, ...)
    - $P(y_{n-1}, y_{n-2}, ..., y_1, y_0) = P(y_{n-1} \mid y_{n-2}, ..., y_1, y_0) ... P(y_1 \mid y_0) P(y_0)$
  - The key to creating a model is next element prediction (next word, next audio sample, ...) given previous elements
    - $P(y_{n-1} \mid y_{n-2}, ..., y_1, y_0) = P(y_{n-1}, y_{n-2}, ..., y_1, y_0) / P(y_{n-2}, ..., y_1, y_0)$

- 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**
  - $P(y_{n-1} \mid y_{n-2}, ..., y_1, y_0, \mathbf{x})$
  - Effectively, conditioning on the input data makes the next element prediction less uniform / more spikey (ideally 1 hot like)
  - Reduces the entropy of the conditional pmf
  - Needs input output data pairs for training

- During testing previous true outputs $y_{n-2}, ..., y_1, y_0$ are replaced with previous predicted outputs
  - $P(y_{n-1} \mid y_{n-2}^{hat}, ..., y_1^{hat}, y_0^{hat}, \mathbf{x})$
  - 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 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; $\mathbf{x}$ is the speech signal
  - Text model: $P(y_{n-1} \mid y_{n-2}, \ldots, y_1, y_0)$
  - Conditioned on features from speech: $P(y_{n-1} \mid y_{n-2}, \ldots, y_1, y_0, \mathbf{x})$
  - Using previous predicted outputs: $P(y_{n-1} \mid y_{n-2}^{hat}, \ldots, y_1^{hat}, y_0^{hat}, \mathbf{x})$

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
$\mathbf{x}$ is the text signal
  - Audio model: $P(y_{n-1} \mid y_{n-2}, \ldots, y_1, y_0)$
  - Conditioned on features from text: $P(y_{n-1} \mid y_{n-2}, \ldots, y_1, y_0, \mathbf{x})$
  - Using previous predicted outputs: $P(y_{n-1} \mid y_{n-2}^{hat}, \ldots, y_1^{hat}, y_0^{hat}, \mathbf{x})$

Conditional Model For Language Translation

This was covered in the language slides

- Learn a model for language 1 (French) that can predict the next word in language 1 (French) given previous words in language 1 (French)
  - This model can be optimized for specific or general text from language 1 (French) by training on that type of text from language 1 (French)

- Then focus / bias the language 1 (French) predictions via conditioning on features generated from specific text of language 0 (English)
  - This creates a conditional model that produces text of language 1 (French) corresponding to the given text of language 0 (English)

- In equations (the network approximates this pmf)
  - Notation: y_i are the words in language 1 (French)
$\mathbf{x}$ are the text features in language 0 (English)
  - Language 1 model: $P(y_{n-1} \mid y_{n-2}, \ldots, y_1, y_0)$
  - Conditioned on features from language 0: $P(y_{n-1} \mid y_{n-2}, \ldots, y_1, y_0, \mathbf{x})$
  - Using previous predicted outputs: $P(y_{n-1} \mid y_{n-2}^{hat}, \ldots, y_1^{hat}, y_0^{hat}, \mathbf{x})$

Speech To Text

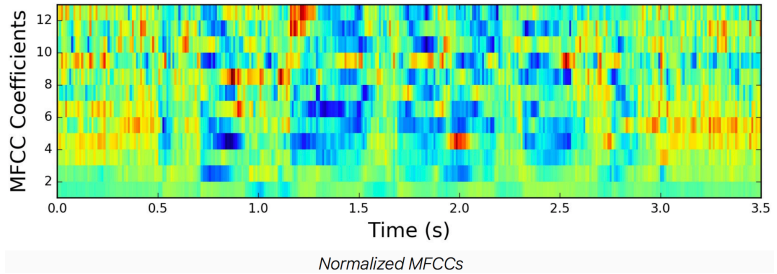
Goal And Challenges

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

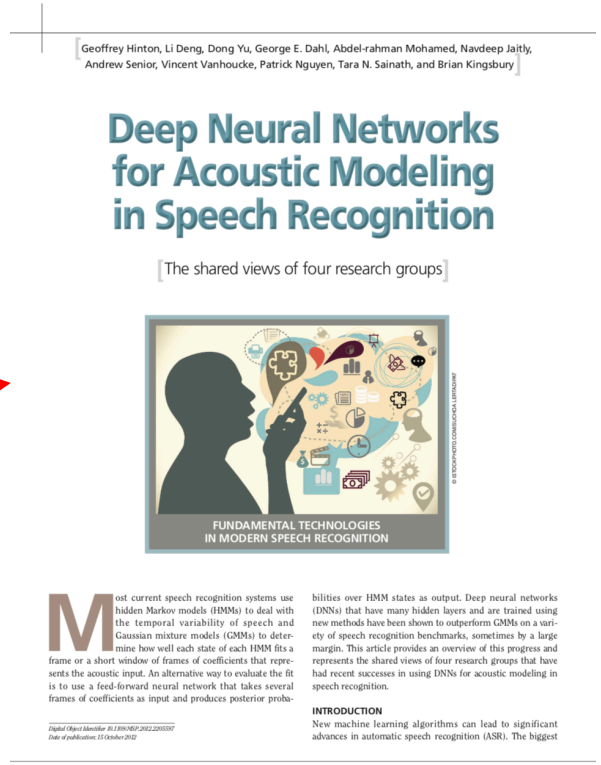
Figure from https://haythamfayek.com/2016/04/21/speech-processing-for-machine-learning.html

Data

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

An Abbreviated History

- Classical (–ish): GMM–HMM
  - 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: xNN–HMM
  - 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 that represents the acoustic input. 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 probabilities 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

Figure from https://ieeexplore.ieee.org/document/6296526

Speech To Text Methods Described Here

- Pre processing
  - Optionally use MFCC or other transformation to pre process speech and make the speech to text transduction problem easier
- 3 different xNN based speech to text transduction strategies
  - Method 1: connectionist temporal classification (CTC)
    - Create a xNN based acoustic model that maps (classifies) pre processed speech vectors to graphemes
    - Use the CTC loss function to handle the unknown alignment between the speech waveform and text
  - Method 2: RNN transducer
    - Pre train a xNN based acoustic model using the CTC loss function (as above, so monotonic alignment) then remove the classification head (so features only)
    - Also pre train a data dependent xNN based language model (see language slides)
    - Combine the outputs of the 2 networks using a shallow joint network to add conditional dependence in the outputs that are decoded via search
  - Method 3: encoder – attention – decoder
    - Pre train a xNN based acoustic model using the CTC loss function (as above, so monotonic alignment) then remove the classification head (so features only)
    - Add xNN based attention and decoder networks to access all needed features and handle the unknown alignment between the speech waveform and text
- Post processing
  - Optionally improve the speech to text transduction output via an external language model

Method 1: Connectionist Temporal Classification (CTC)

- 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

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

- 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

Acoustic Model Output

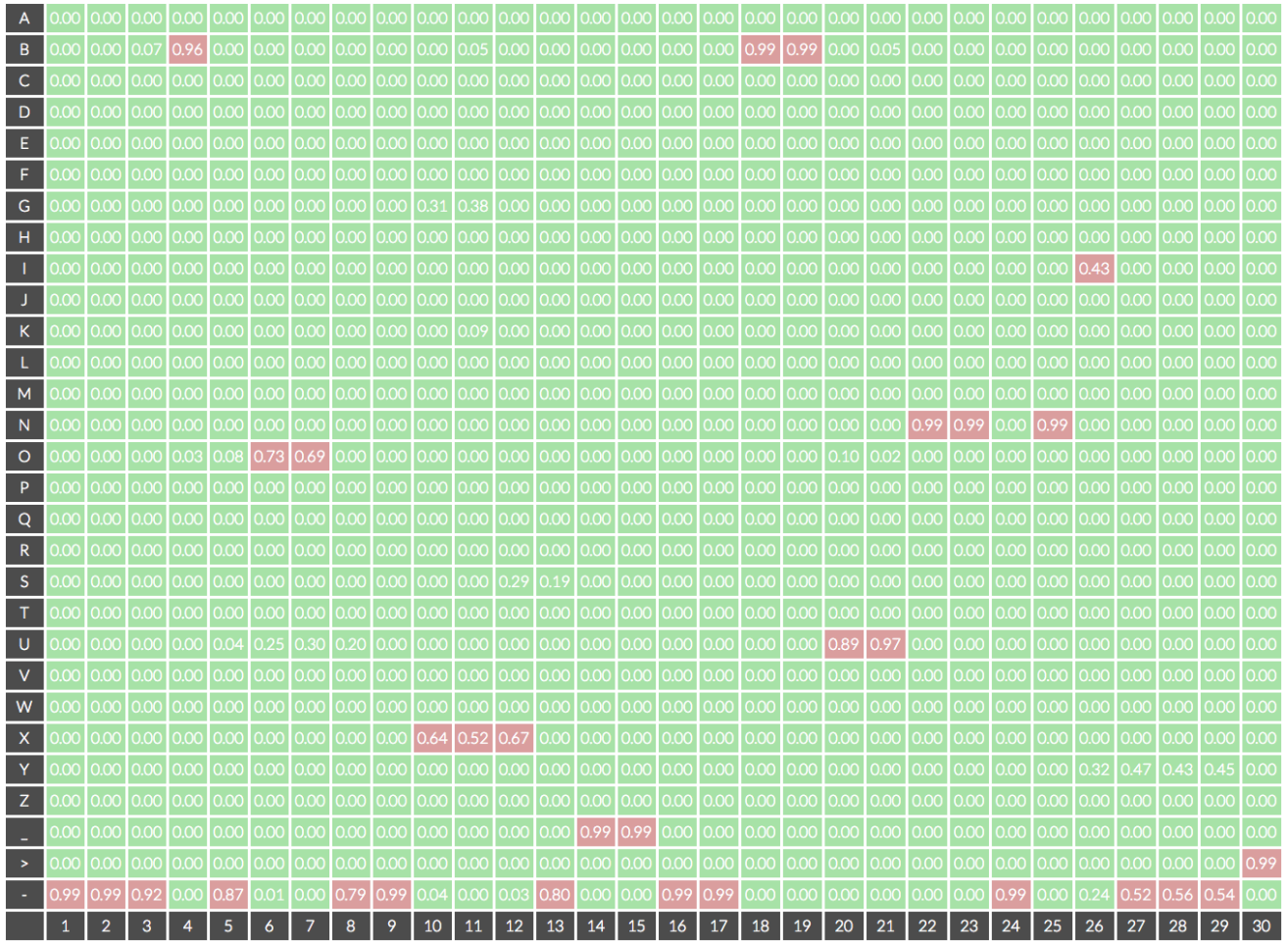


Figure from https://medium.com/corti-ai/ctc-networks-and-language-models-prefix-beam-search-explained-c11d1ee23306

Loss Function

- 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

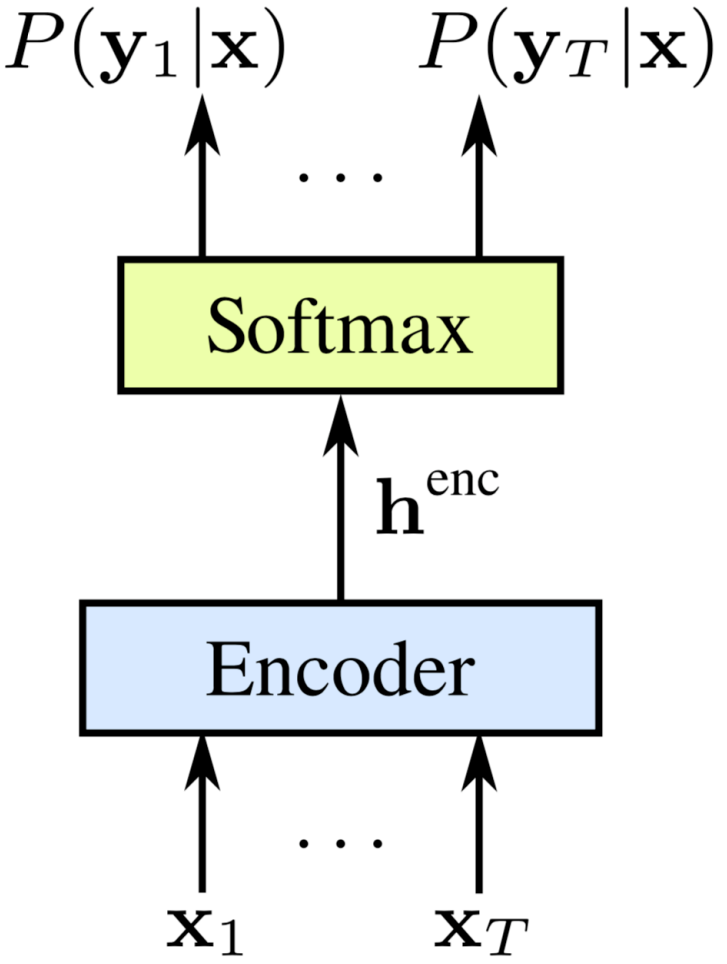


Figure from https://www.isca-speech.org/archive/Interspeech_2017/pdfs/0233.PDF

Decoding

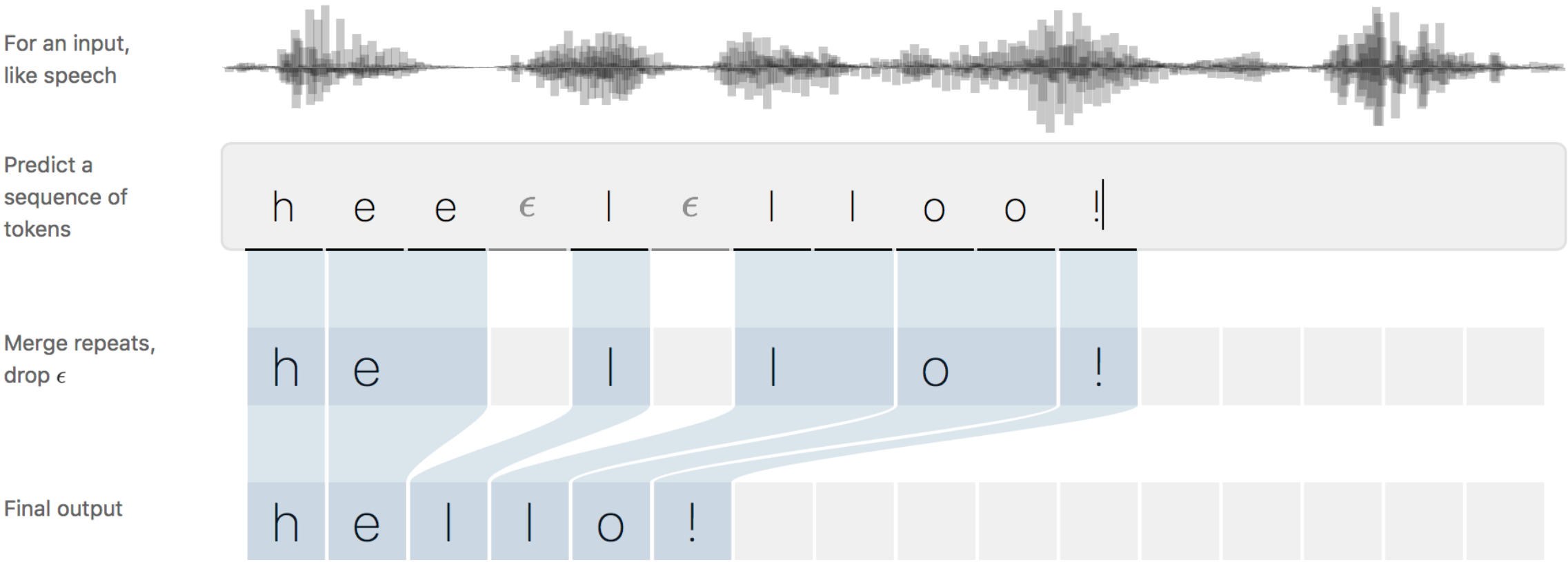


Figure from https://distill.pub/2017/ctc/

Definitions

- X is the network input (e.g., bins x T')
- Y is the network output (e.g., classes x T)
  - Let classes == {a, ..., 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: π = (a, a, a, –, r, –, –, t, t, t, t, –)

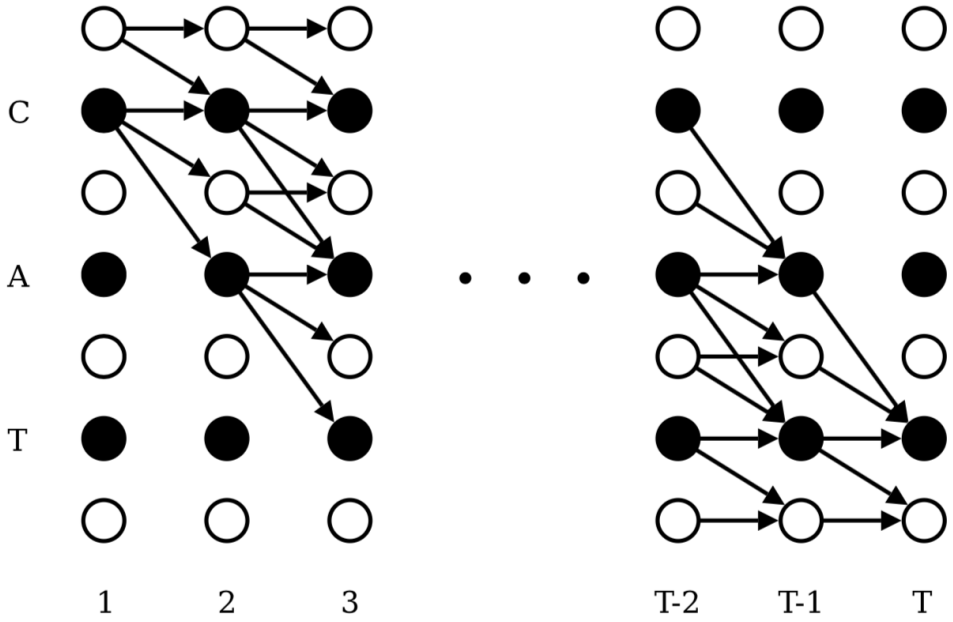


Figure from https://www.cs.toronto.edu/~graves/icml_2006.pdf

More 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

$$\{\pi\} = B^{-1}(\ell)$$
$$= B^{-1}(a, r, t)$$
$$= \{(a, r, t, –, –, –, –, –, –, –, –, –, –),$$
$$(a, a, r, t, –, –, –, –, –, –, –, –, –),$$
$$(a, a, –, r, t, –, –, –, –, –, –, –, –),$$
$$\ldots,$$
$$(–, –, –, –, –, –, –, –, –, –, a, r, t)\}$$

Probability Of Paths And Labels

- The probability of a path π given input X
  - $P(\pi \mid X) = \prod_t Y(\pi(t), t)$
  - The product of the pmf values of the class elements for the path
- The probability of a label ℓ given input X
  - $P(\ell \mid X) = \Sigma P(\pi_i \mid X) \; \forall \; \pi_i \in B^{-1}(\ell)$
  - 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 $P(\ell \mid X)$
  - 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

Network 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

More Network 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 ≫ 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

Method 2: RNN Transducer

- 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

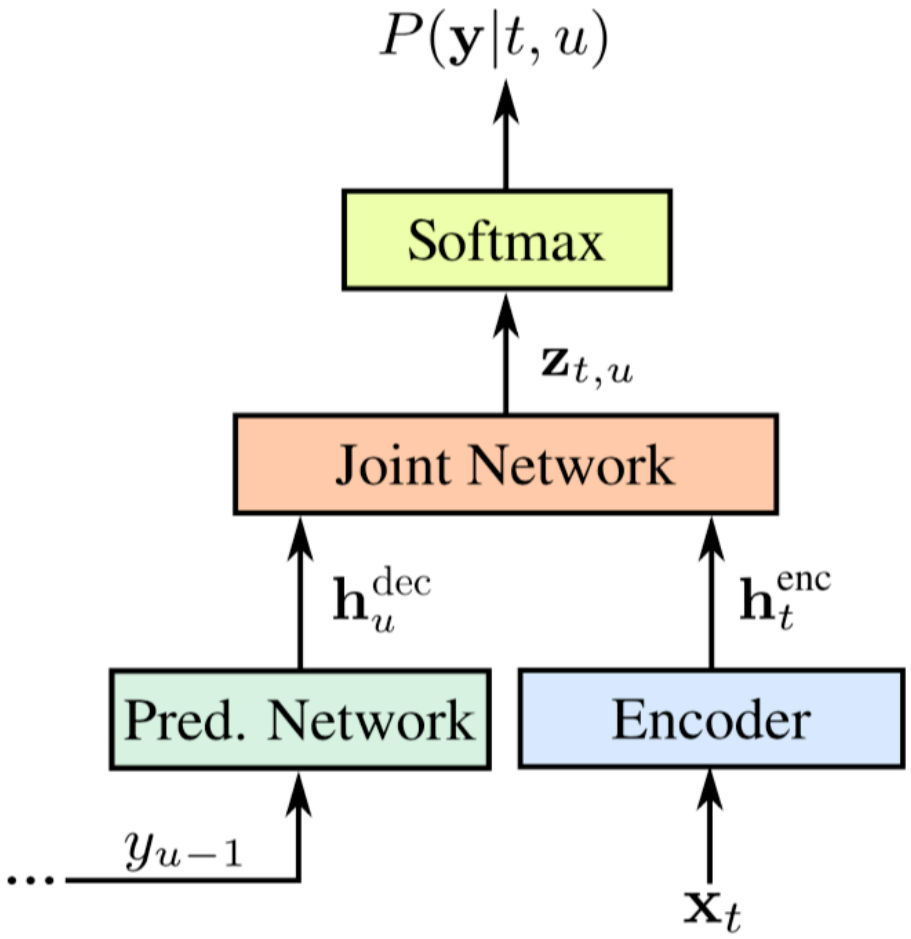


Figure from https://arxiv.org/abs/1801.00841

Joint Network

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

Sequence transduction with recurrent neural networks (https://arxiv.org/abs/1211.3711)

- 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 sequen 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

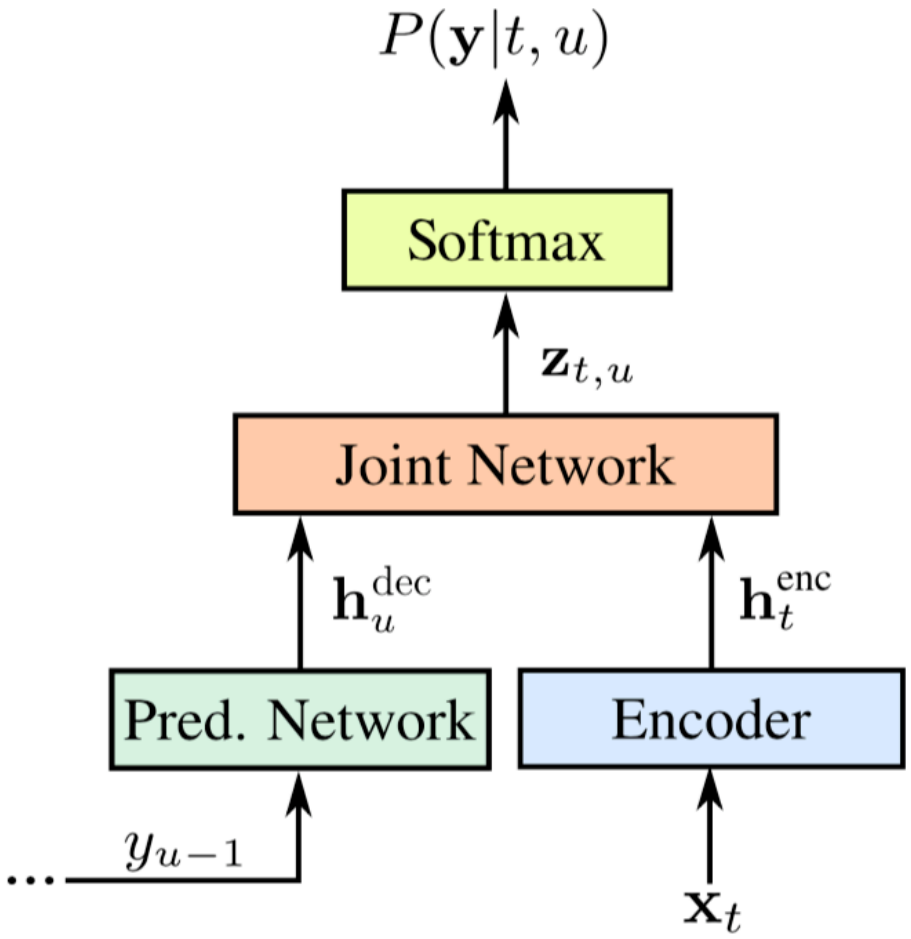
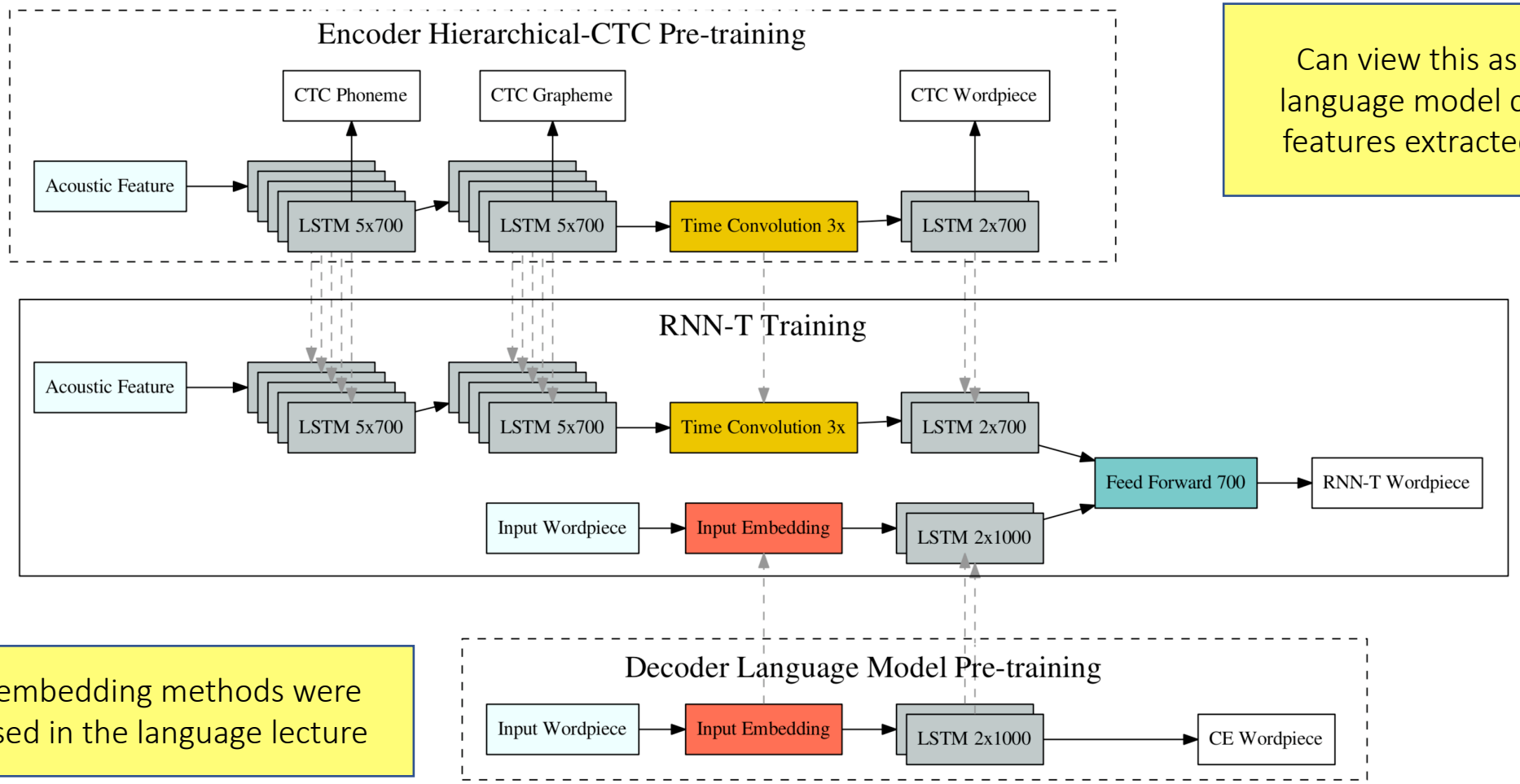


Figure from https://arxiv.org/abs/1801.00841

Network Training



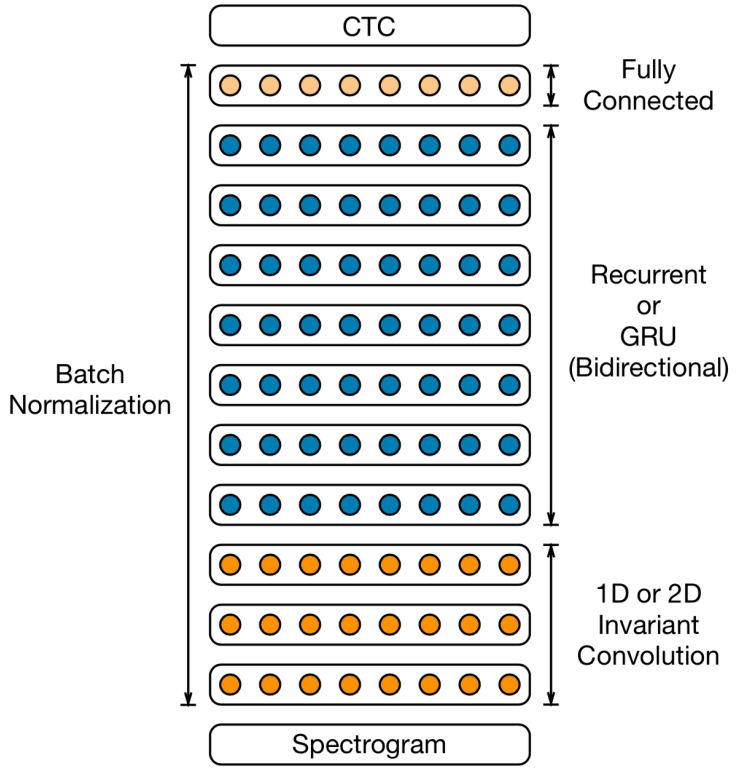
Can view this as a word piece language model conditioned on features extracted from speech

Input embedding methods were discussed in the language lecture

Figure from https://arxiv.org/abs/1801.00841

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

Figure from https://arxiv.org/pdf/1412.5567.pdf

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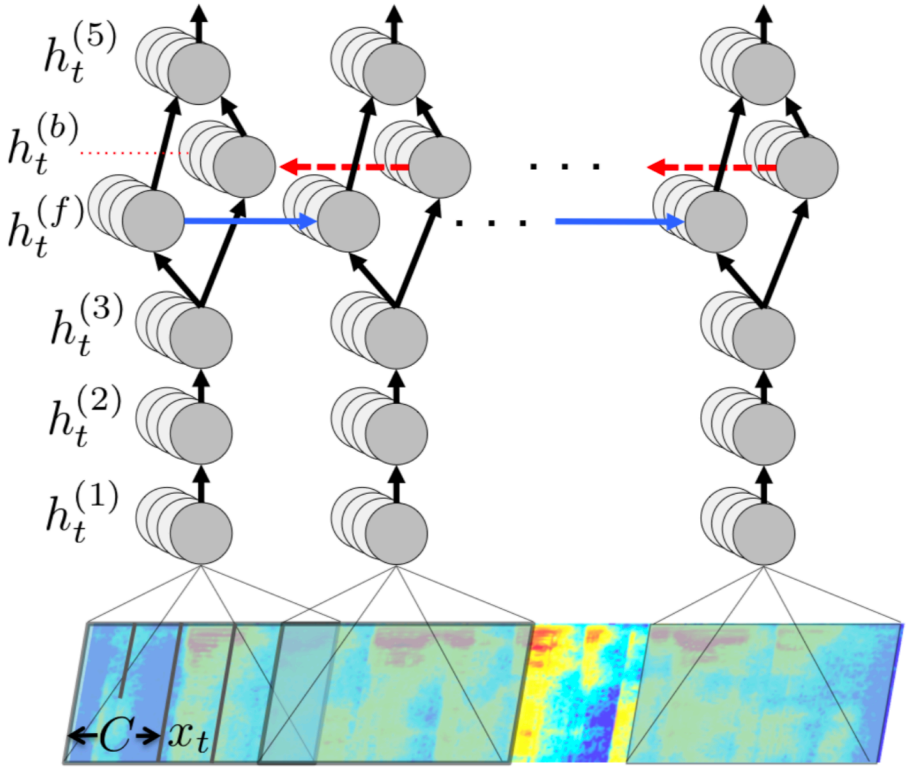


Note the equal focus on algorithms and software / hardware implementation

Figure from https://arxiv.org/pdf/1412.5567.pdf

Method 3: Encoder – Attention – Decoder

- 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

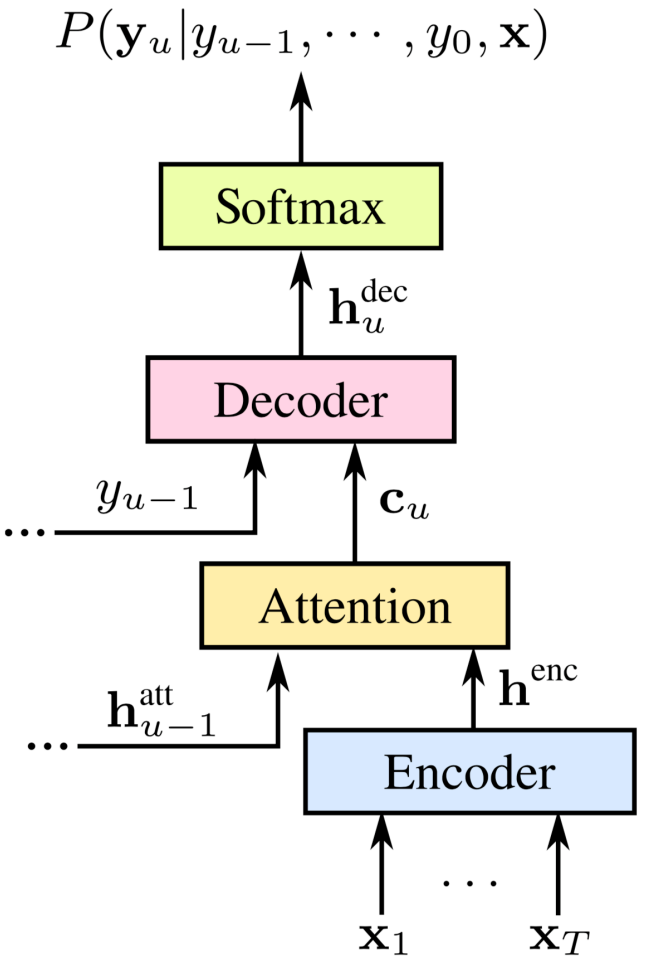
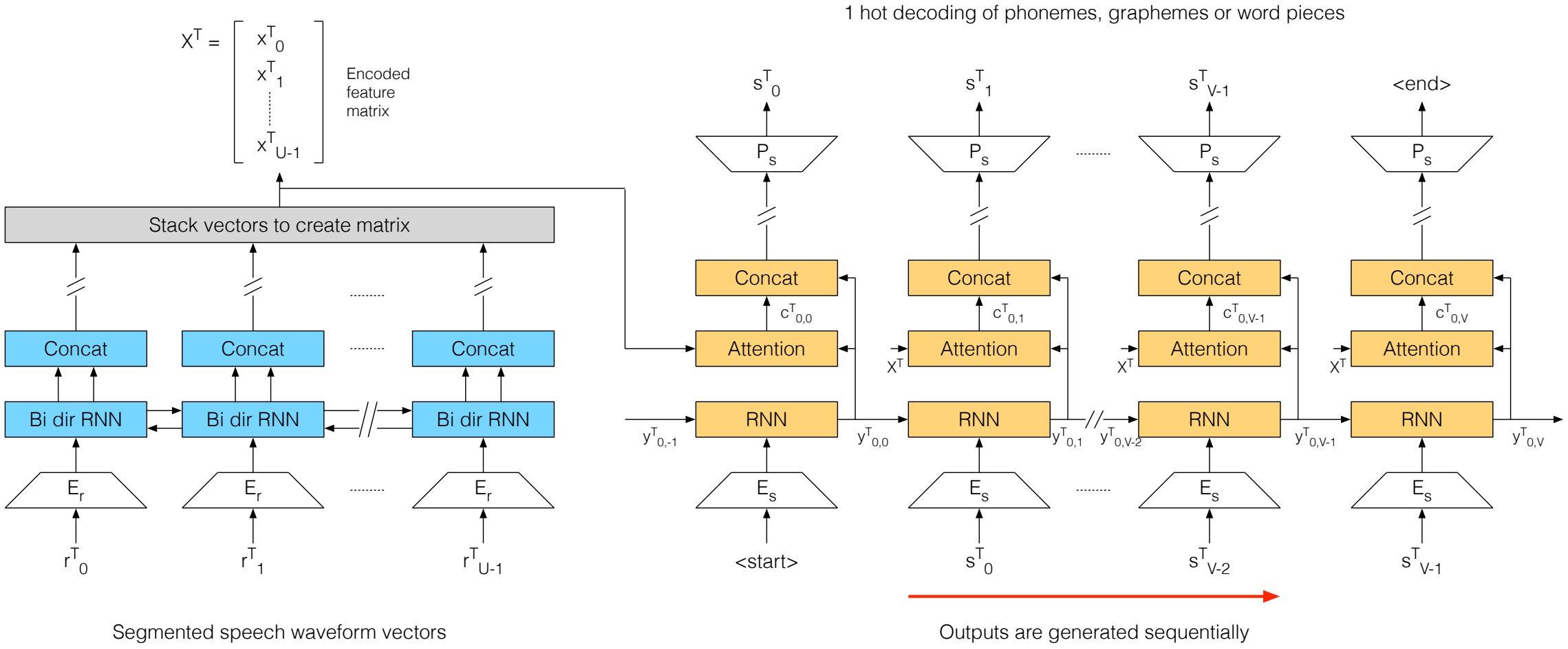


Figure from https://www.isca-speech.org/archive/Interspeech_2017/pdfs/0233.PDF

Example Network

Speech encoder embedding E_r can be MFCC or other pre processing method; decoder embedding E_s / projection P_s can be trivial if the number of graphemes or word pieces is relatively small, otherwise a dense language embedding can be used; an auxiliary CTC loss is frequently added to the encoder to help training via a forced monotonic alignment between speech waveform and output text



Example: Google's Listen Attend Spell

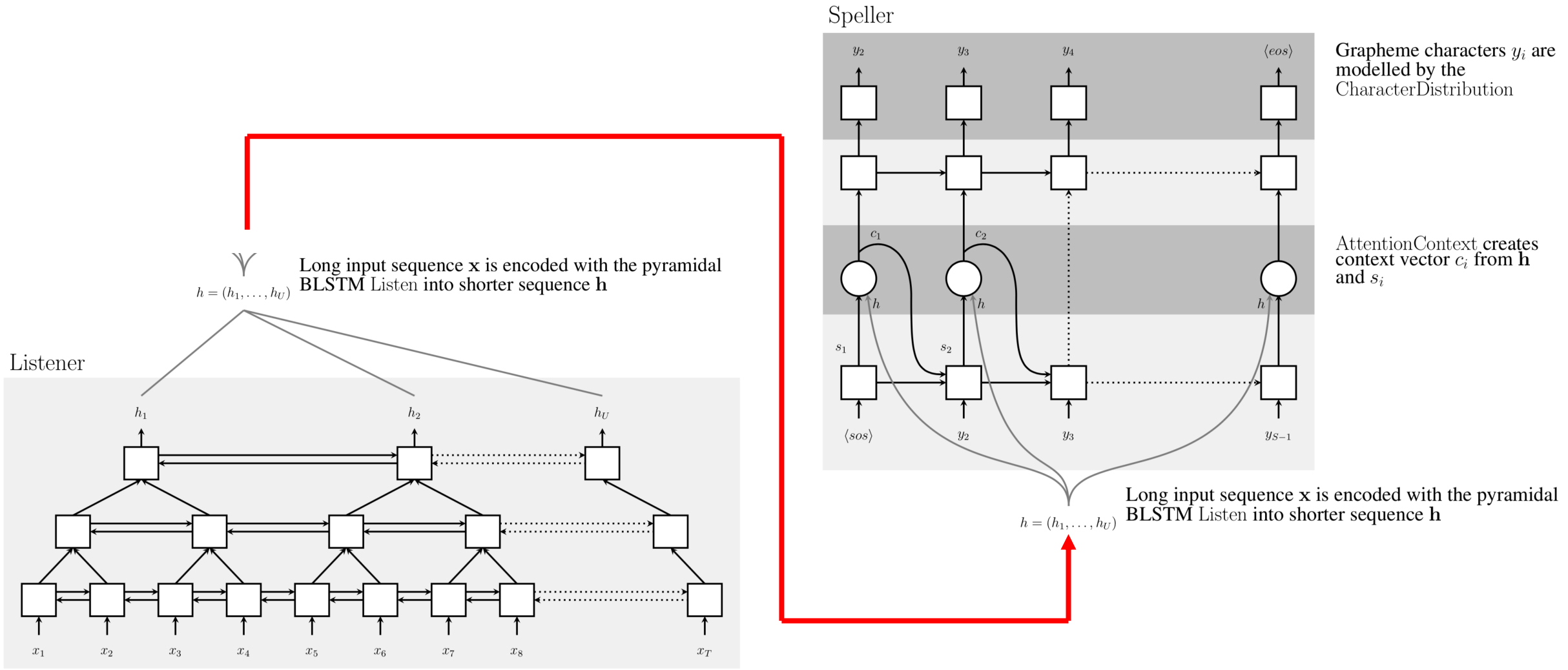


Figure from https://arxiv.org/abs/1508.01211

Example: Google's Listen Attend Spell

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

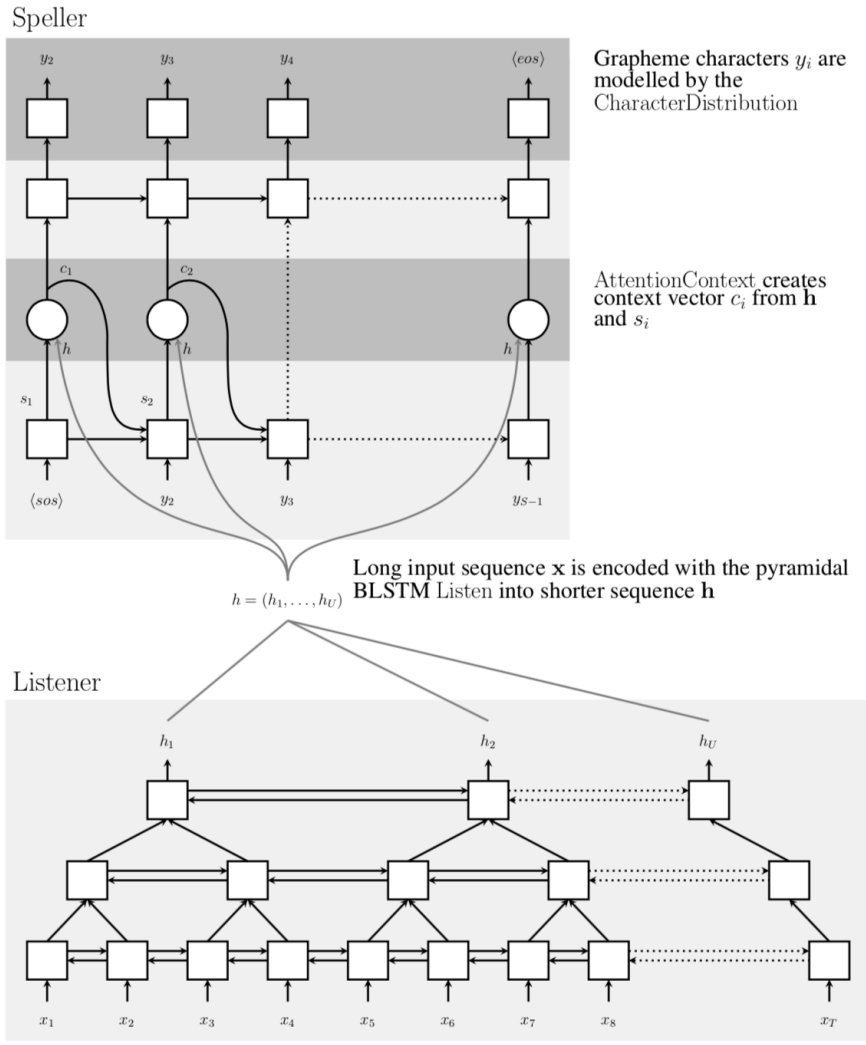


Figure from https://arxiv.org/abs/1508.01211

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

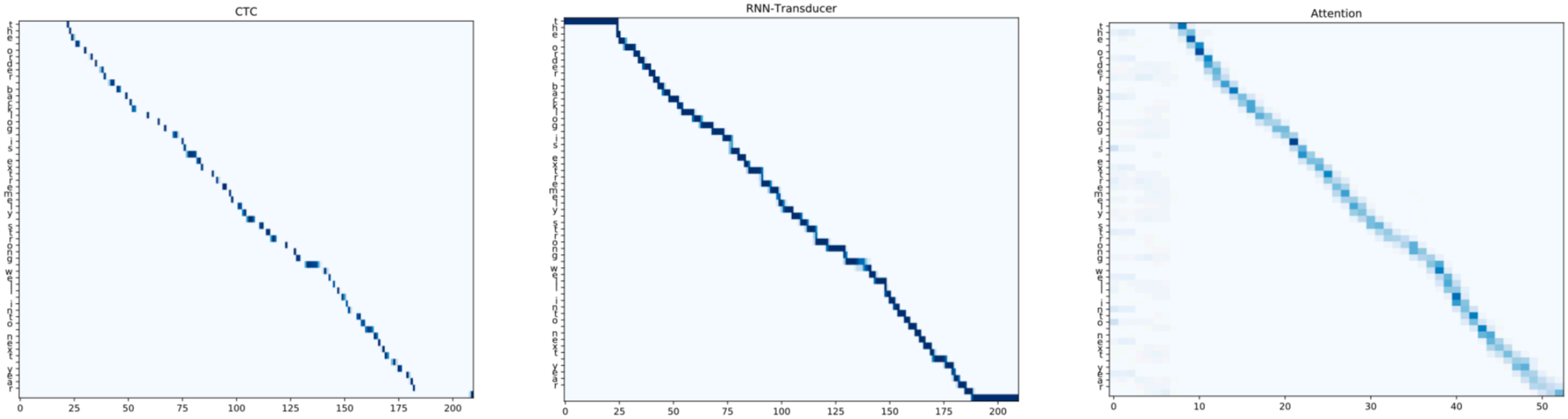


Figure from https://arxiv.org/pdf/1707.07413.pdf

Post Processing With An External Language Model

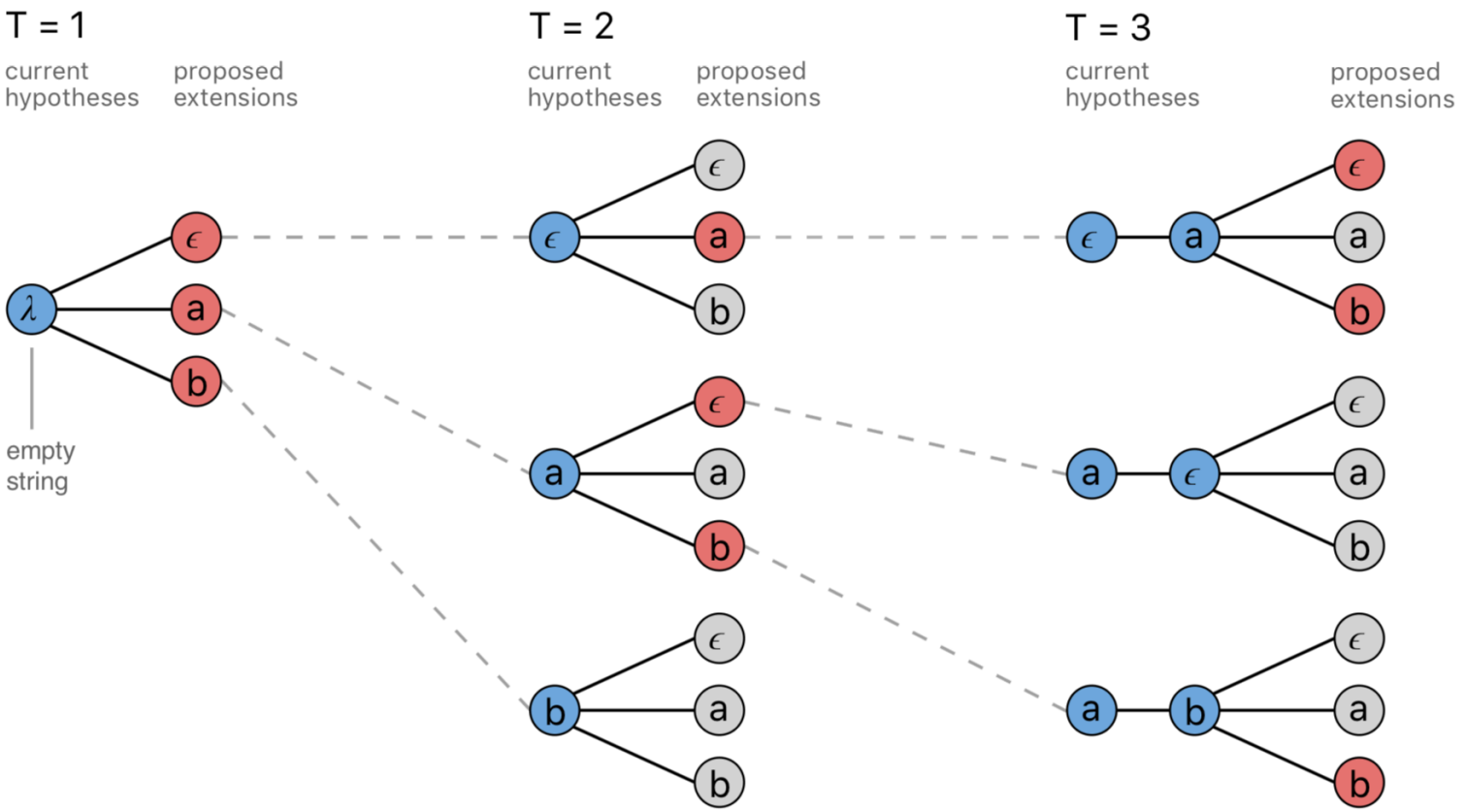
The language lecture looked at this in more detail

- 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
    - $\ell^* = \arg\max_\ell (P(\ell \mid X)\, P_{LM}(\ell)^\alpha\, \text{length}(\ell)^\beta)$
    - $\ell^* = \arg\max_\ell (\log(P(\ell \mid X)) + \alpha \log(P_{LM}(\ell)) + \beta \log(\text{length}(\ell)))$

- How to think about this strategy
  - Speech to text transduction is composed of 2 parts
    - Part 1: a mapping (e.g., xNN structure) from sound to text
    - Part 2: a mapping (e.g., language model) from previous text to next text
  - This is very similar to language translation
    - Part 1: a mapping (e.g., xNN structure) from language 0 to language 1
    - Part 2: a mapping (e.g., language model) from previous text in language 1 to next text in language 1
  - Part 2 is input independent, part 1 is input dependent, they both work together to produce the desired output
    - Beam search is the way we put the 2 parts together

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

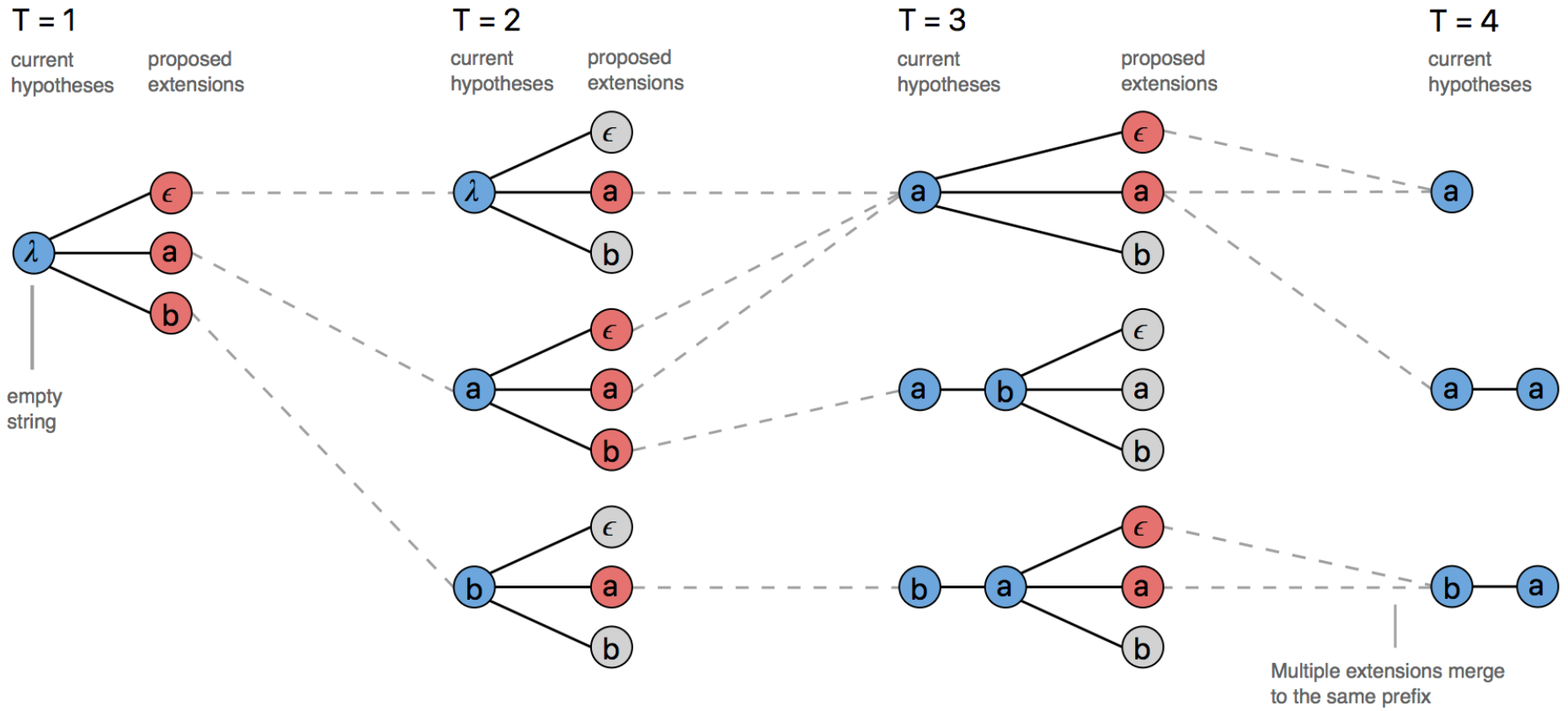


A standard beam search algorithm with an alphabet of $\{\epsilon, a, b\}$ and a beam size of three.

Figure from https://distill.pub/2017/ctc/

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.

Figure from https://distill.pub/2017/ctc/

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

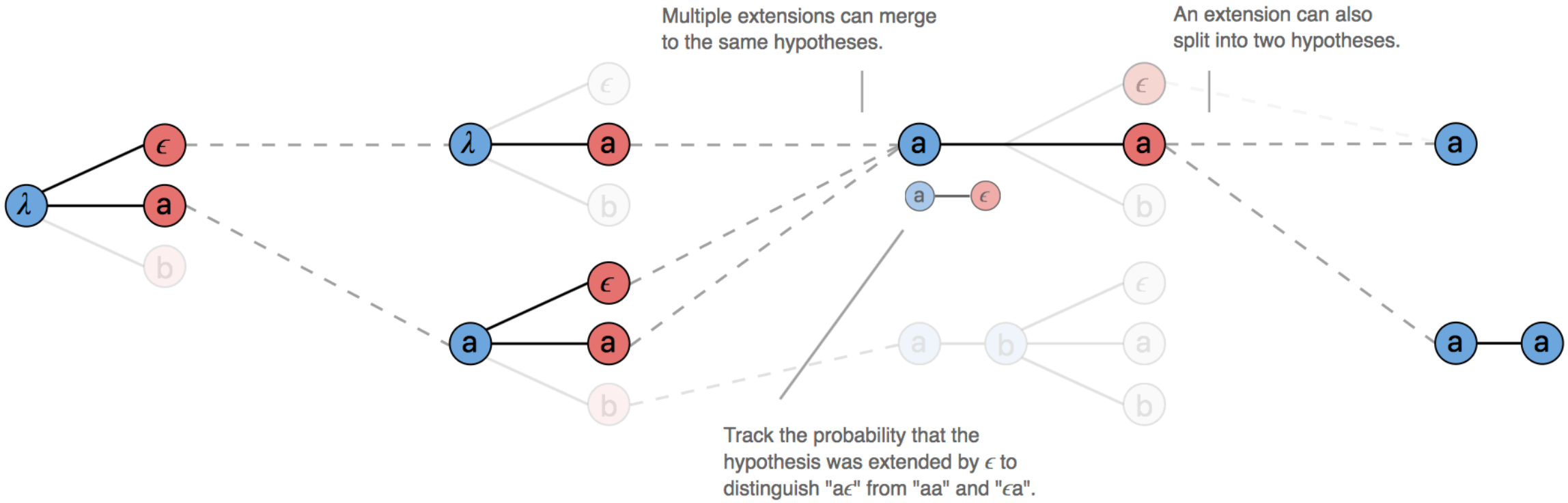


Figure from https://distill.pub/2017/ctc/

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)

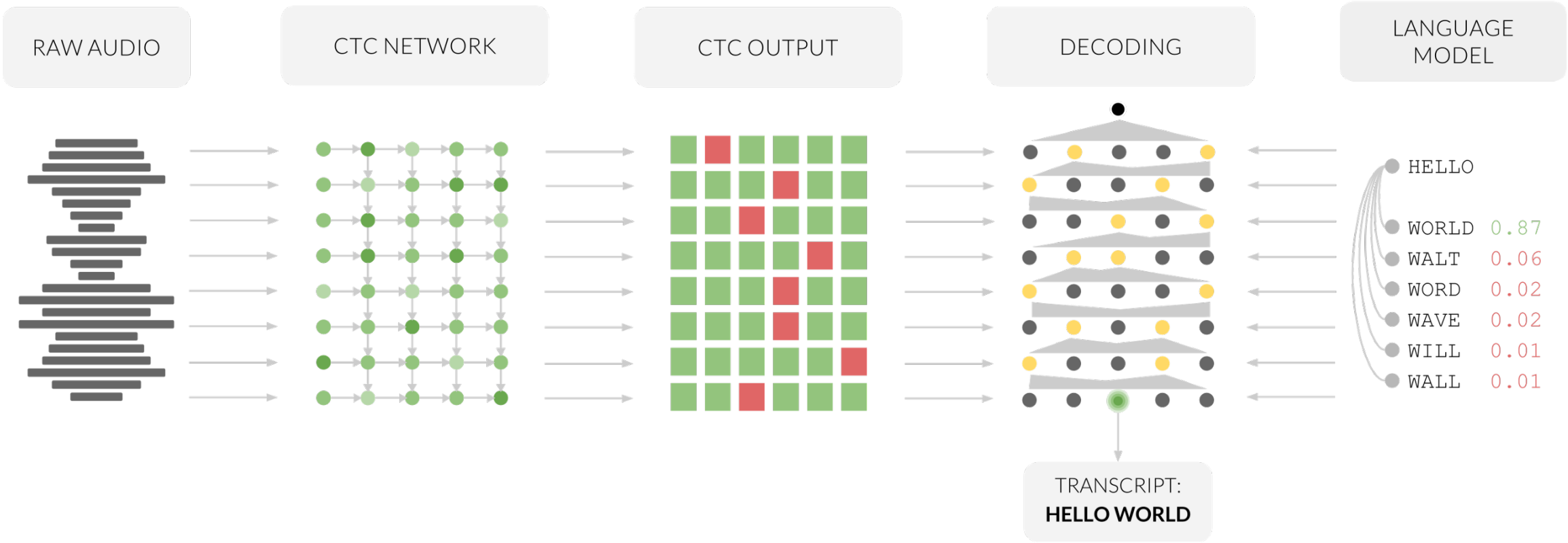


Figure from https://medium.com/corti-ai/ctc-networks-and-language-models-prefix-beam-search-explained-c11d1ee23306

Evaluation

- Metrics
  - Word error rate
  - Substitutions
  - Insertions
  - Deletions

- Papers with code speech recognition
  - https://paperswithcode.com/task/speech-recognition

- Leaderboard (also a really good GitHub repository name)
  - https://github.com/syhw/wer_are_we

Trends

- A few things stand out in top performing systems ...

- Improved training
  - Data augmentation
  - Self supervised learning on unlabeled speech
  - Student teacher iterations
  - Multi task and transfer learning
  - Loss functions more closely matches to evaluation criteria

- Improved architectures
  - Use of CNNs for mixing features optionally with global context and dialation
  - Use transformers for mixing features

- You now should be thinking, wow, there are a lot of similar trends between vision, language and speech
  - This is 1 reason why you're learning about all of them in this class

Recent References

- Efficient implementation of recurrent neural network transducer in TensorFlow
  - https://ieeexplore.ieee.org/document/8639690
- A comparison of sequence-to-sequence models for speech recognition
  - https://www.isca-speech.org/archive/Interspeech_2017/pdfs/0233.PDF
- Hybrid CTC/attention architecture for end-to-end speech recognition
  - https://www.merl.com/publications/docs/TR2017-190.pdf
- Improved vocal tract length perturbation for a state-of-the-art end-to-end speech recognition system
  - https://www.isca-speech.org/archive/Interspeech_2019/abstracts/3227.html

Recent References

- Sequence transduction with recurrent neural networks
  - https://arxiv.org/abs/1211.3711
- Listen, attend and spell
  - https://arxiv.org/abs/1508.01211
- Joint CTC-attention based end-to-end speech recognition using multi-task learning
  - https://arxiv.org/abs/1609.06773
- 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
- Attention-based end-to-end speech recognition on voice search
  - https://arxiv.org/abs/1707.07167
- Exploring neural transducers for end-to-end speech recognition
  - https://arxiv.org/abs/1707.07413

Recent References

- Exploring architectures, data and units for streaming end-to-end speech recognition with RNN-transducer
  - https://arxiv.org/abs/1801.00841
- ESPnet: end-to-end speech processing toolkit
  - https://arxiv.org/abs/1804.00015
  - https://github.com/espnet/espnet
- Hybrid CTC-attention based end-to-end speech recognition using subword units
  - https://arxiv.org/abs/1807.04978
- Streaming end-to-end speech recognition for mobile devices
  - https://arxiv.org/abs/1811.06621
- 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

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- 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
- RWTH ASR systems for LibriSpeech: hybrid vs attention -- w/o data augmentation
  - https://arxiv.org/abs/1905.03072
- 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
- State-of-the-art speech recognition using multi-stream self-attention with dilated 1D convolutions
  - https://arxiv.org/abs/1910.00716
- Transformer-based acoustic modeling for hybrid speech recognition
  - https://arxiv.org/abs/1910.09799
- End-to-end ASR: from supervised to semi-supervised learning with modern architectures
  - https://arxiv.org/abs/1911.08460

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- Streaming automatic speech recognition with the transformer model
  - https://arxiv.org/abs/2001.02674
- ContextNet: improving convolutional neural networks for automatic speech recognition with global context
  - https://arxiv.org/abs/2005.03191
- Improved noisy student training for automatic speech recognition
  - https://arxiv.org/abs/2005.09629
- ASAPP-ASR: multistream CNN and self-attentive SRU for SOTA speech recognition
  - https://arxiv.org/abs/2005.10469
- wav2vec 2.0: a framework for self-supervised learning of speech representations
  - https://arxiv.org/abs/2006.11477
- Efficient minimum word error rate training of RNN-Transducer for end-to-end speech recognition
  - https://arxiv.org/abs/2007.13802

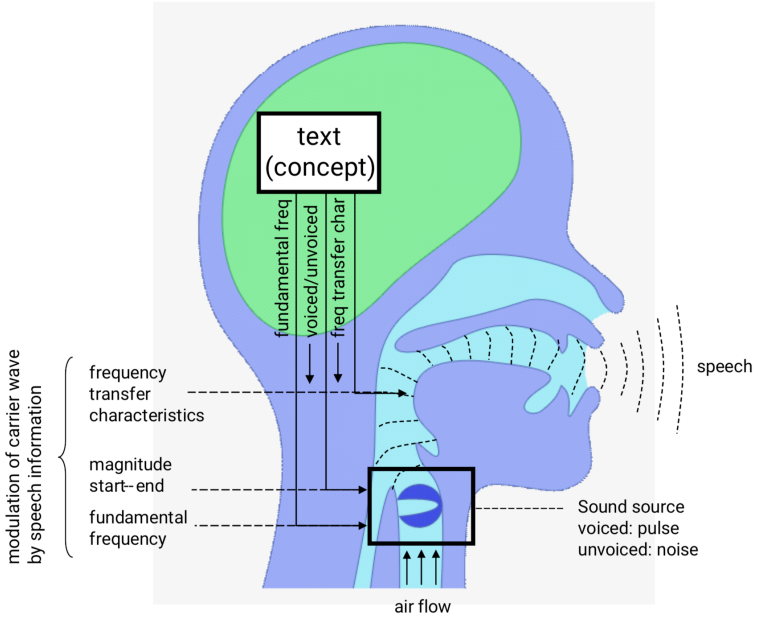
Recent References

- Pushing the limits of semi-supervised learning for automatic speech recognition
  - https://arxiv.org/abs/2010.10504
- Self-training and pre-training are complementary for speech recognition
  - https://arxiv.org/abs/2010.11430
- Improving RNN transducer based ASR with auxiliary tasks
  - https://arxiv.org/abs/2011.03109

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 with a 1 to many 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



Figures from https://www.thoughtco.com/what-is-a-speak-and-spell-1992413 and https://github.com/oxford-cs-deepnlp-2017/lectures/blob/master/Lecture%2010%20-%20Text%20to%20Speech.pdf

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)

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

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

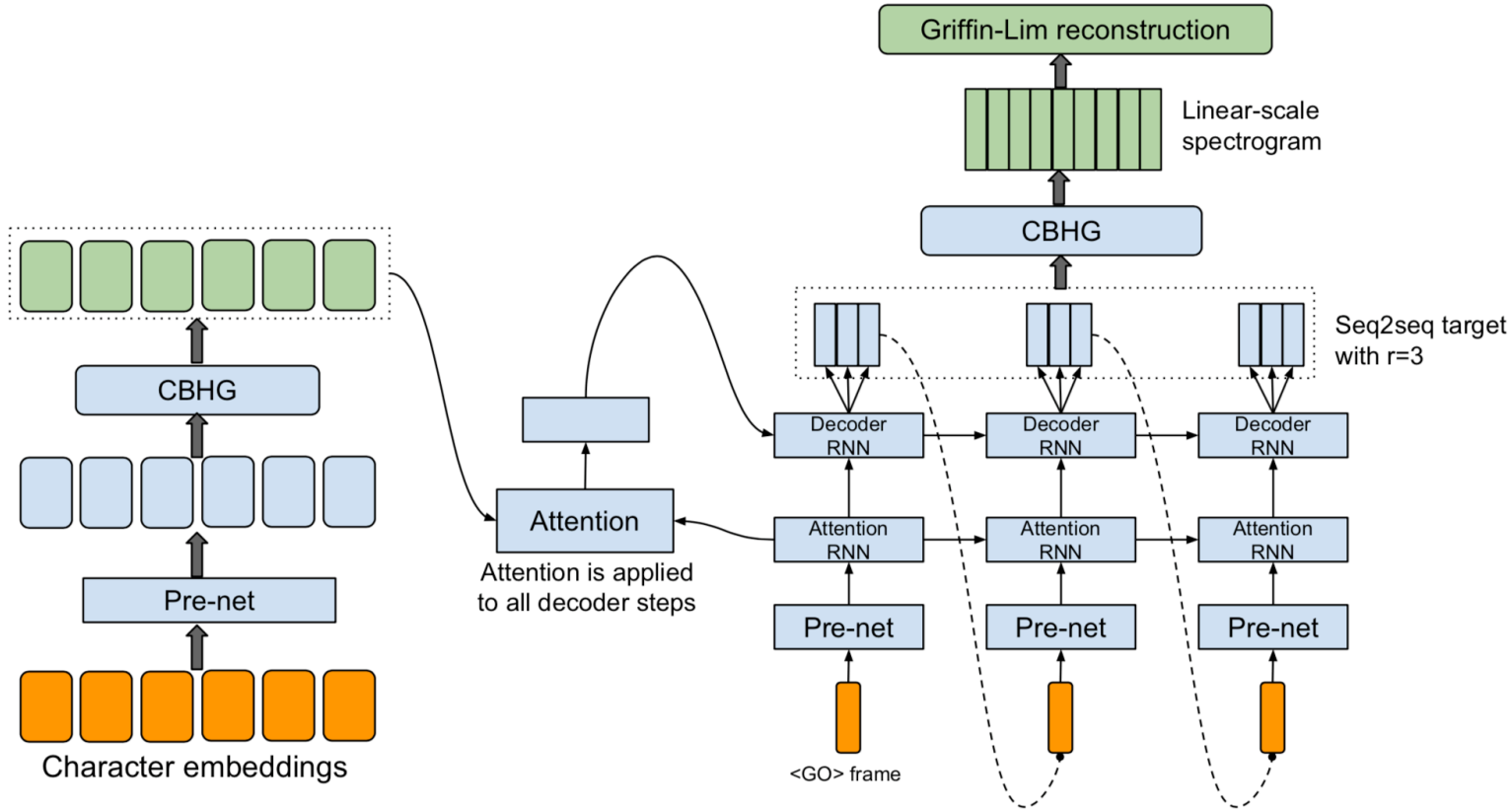


Figure from https://arxiv.org/abs/1703.10135

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

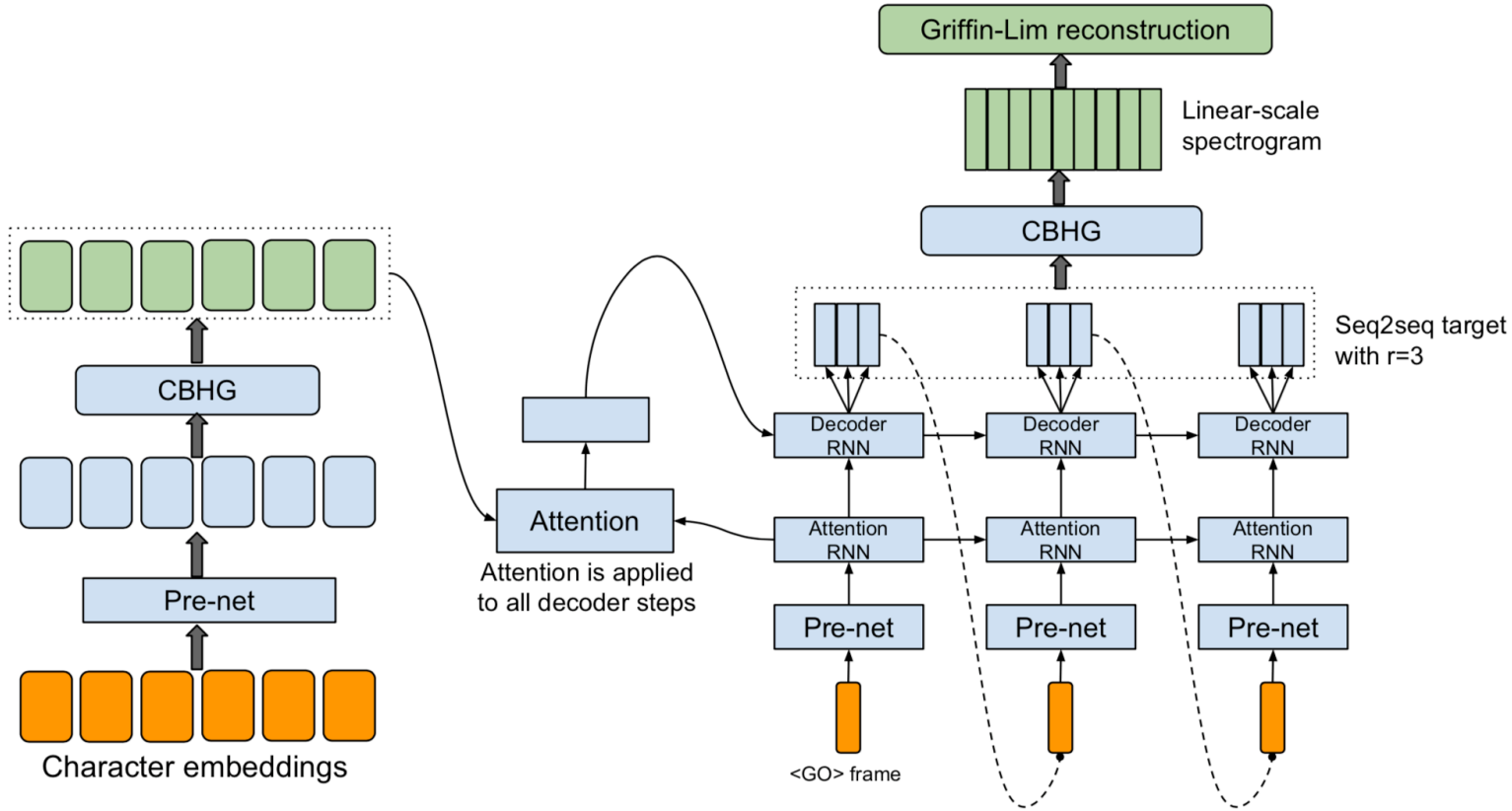


Figure from https://arxiv.org/abs/1703.10135

Example: Tacotron 1

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

- Attention RNN produces an attention query and the resulting context vector is concatenated with 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

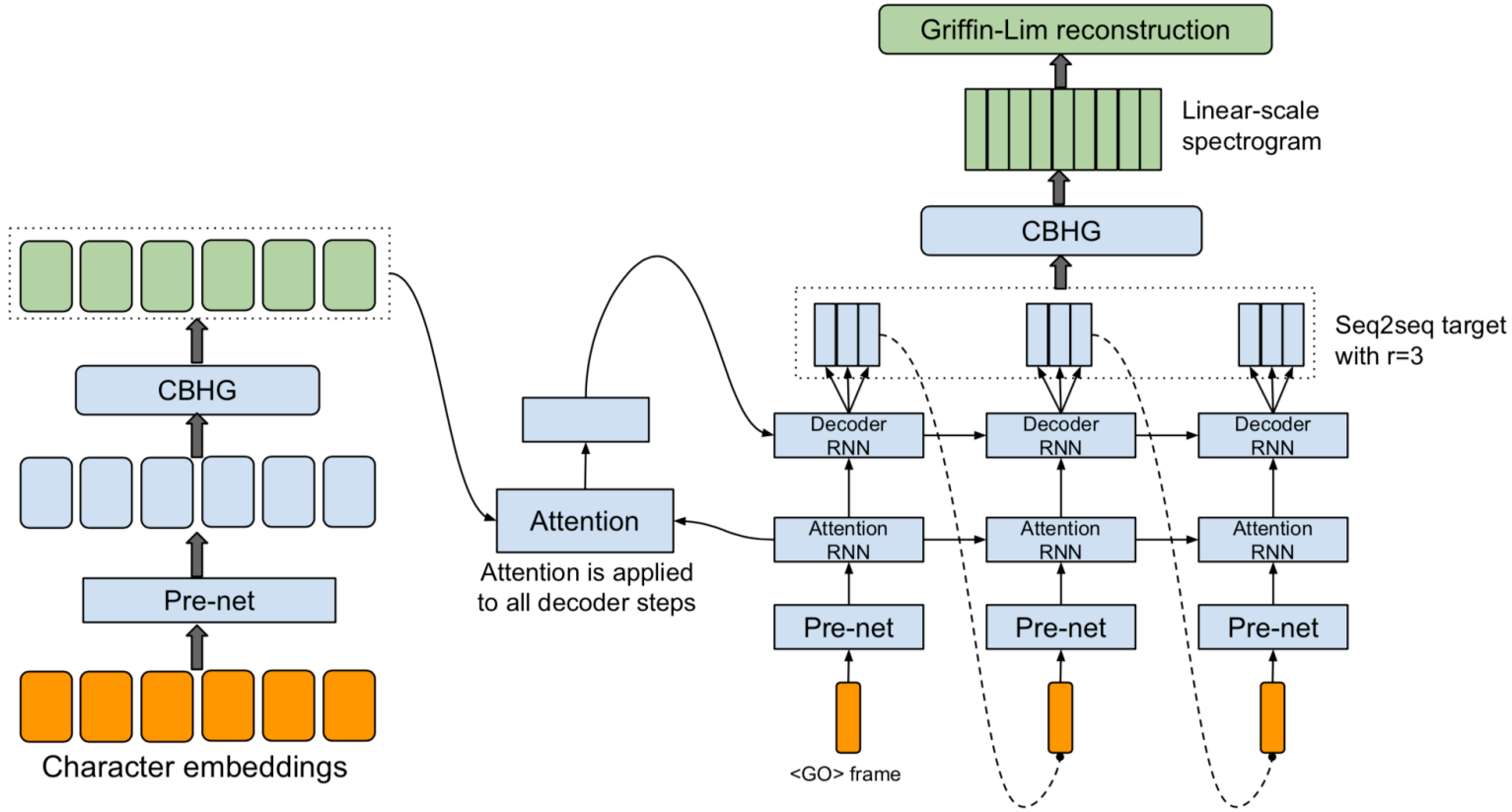


Figure from https://arxiv.org/abs/1703.10135

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

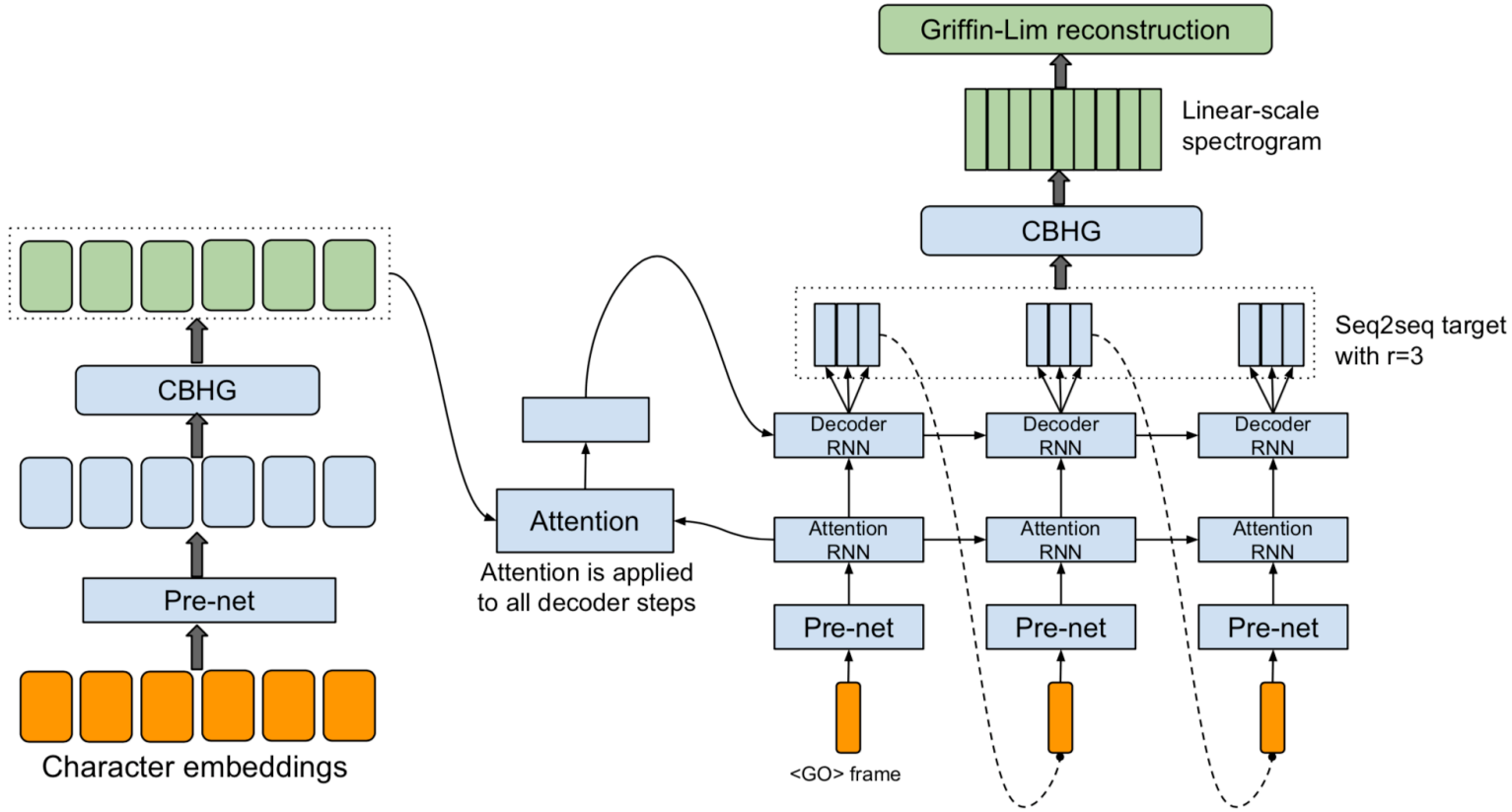
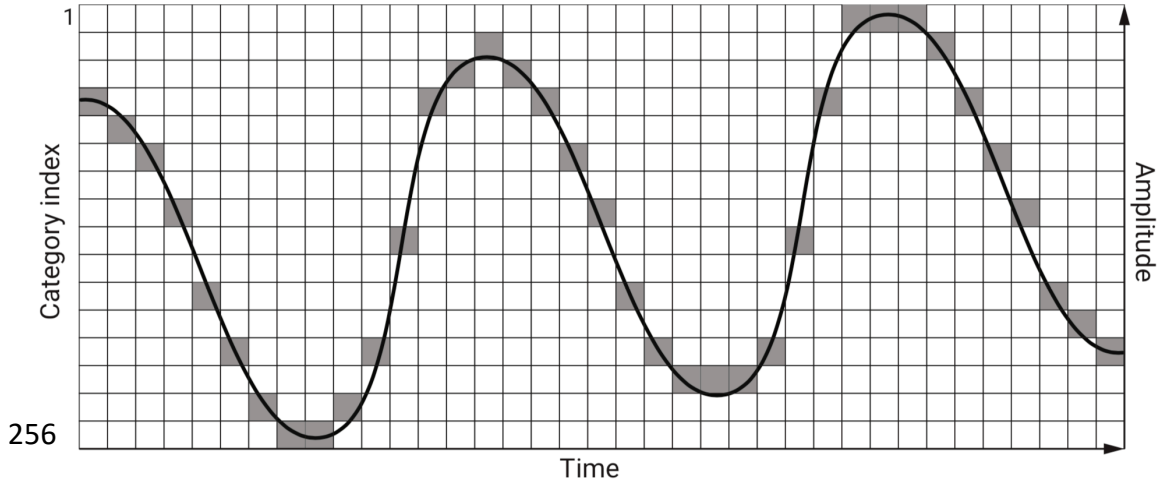
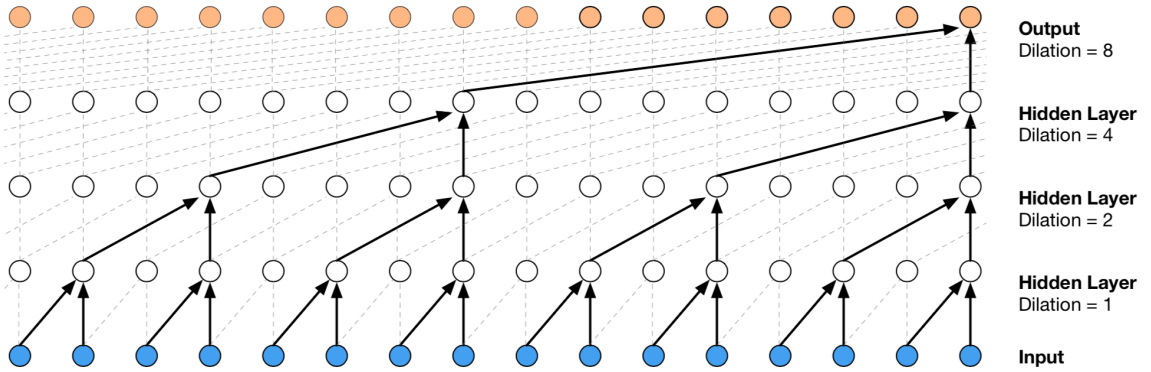


Figure from https://arxiv.org/abs/1703.10135

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 $x = \{x_1, ..., x_T\}$ factored as
  - $p(x) = \prod_t p(x_t \mid x_{t-1}, ..., x_1)$
  - 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





Figures from https://github.com/oxford-cs-deepnlp-2017/lectures/blob/master/Lecture%2010%20-%20Text%20to%20Speech.pdf and https://arxiv.org/abs/1609.03499

Example: WaveNet

- Gated activation units
  - $z = \tanh(W_{f,k} \circledast x) \odot \sigma(W_{g,k} \circledast x)$
  - 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

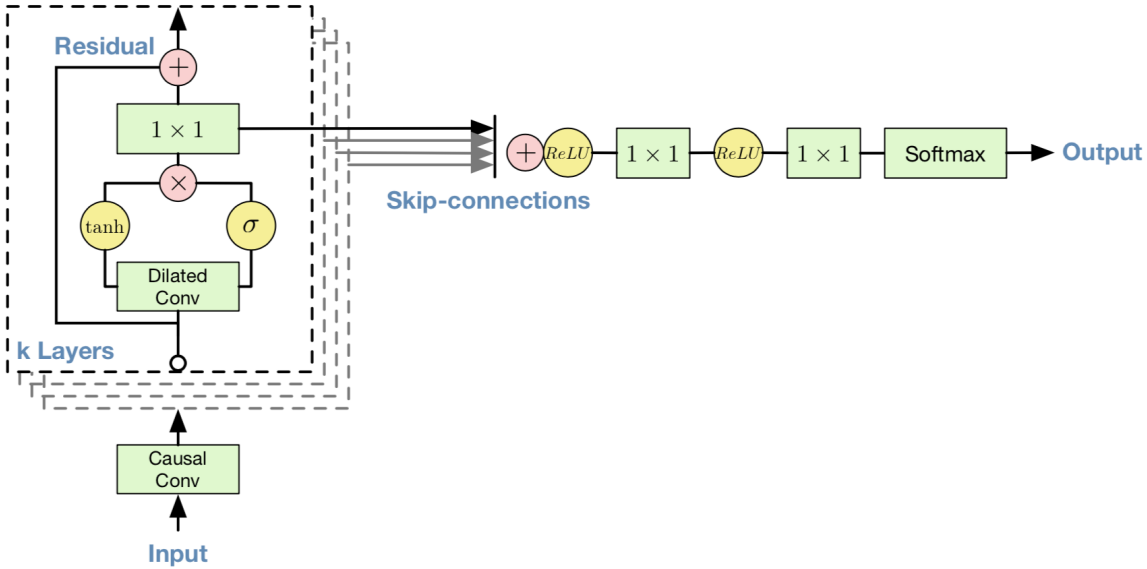


Figure from https://arxiv.org/abs/1609.03499

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
  - $p(x) = \prod_t p(x_t \mid x_1, \ldots, x_{t-1}, h)$

- Resulting global and local gated activation units
  - Global: $z = \tanh(W_{f,k} \circledast x + V_{f,k}^T h) \odot \sigma(W_{g,k} \circledast x + V_{g,k}^T h)$
    - Ex: A particular speaker
    - As h is fixed globally this results in a fixed offset
  - Local: $z = \tanh(W_{f,k} \circledast x + V_{f,k} \circledast h) \odot \sigma(W_{g,k} \circledast x + V_{g,k} \circledast h)$
    - Ex: linguistic features, log F_0 and phoneme durations
    - As h varies locally this changes locally
    - V is a 1x1 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 ~ 16k are needed per second

These have been addressed in subsequent variations and extensions

Example: Tacotron 2 ≈ 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

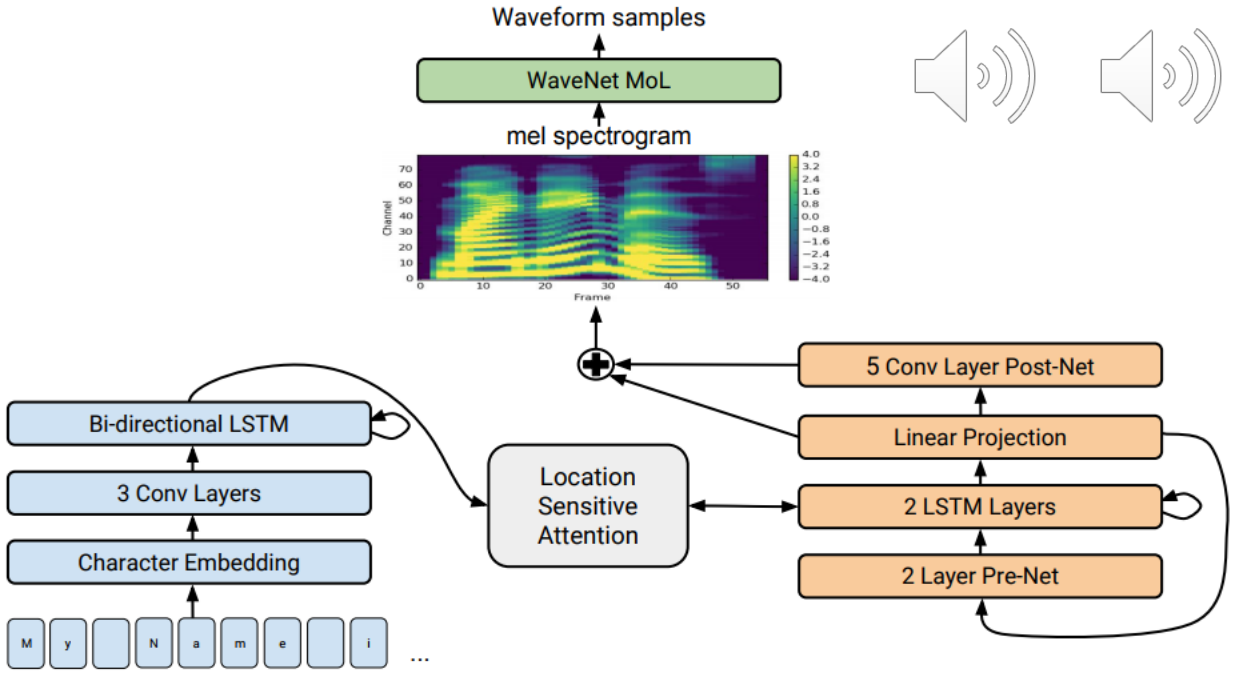


Figure from https://ai.googleblog.com/2017/12/tacotron-2-generating-human-like-speech.html

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- WaveNet: a generative model for raw audio
  - https://arxiv.org/abs/1609.03499
- Tacotron: towards end-to-end speech synthesis
  - https://arxiv.org/abs/1703.10135
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  - https://arxiv.org/abs/1712.05884
- Neural voice cloning with a few samples
  - https://arxiv.org/abs/1802.06006
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- Transfer learning from speaker verification to multispeaker text-to-speech synthesis
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- WaveGlow: a flow-based generative network for speech synthesis
  - https://arxiv.org/abs/1811.00002
  - https://github.com/NVIDIA/WaveGlow
- LibriTTS: a corpus derived from LibriSpeech for text-to-speech
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  - https://arxiv.org/abs/1905.09263
- ESPnet-TTS: unified, reproducible, and integratable open source end-to-end text-to-speech toolkit
  - https://arxiv.org/abs/1910.10909
  - https://github.com/espnet/espnet
- FastSpeech 2: fast and high-quality end-to-end text to speech
  - https://arxiv.org/abs/2006.04558
- A spectral energy distance for parallel speech synthesis
  - https://arxiv.org/abs/2008.01160

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 you 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

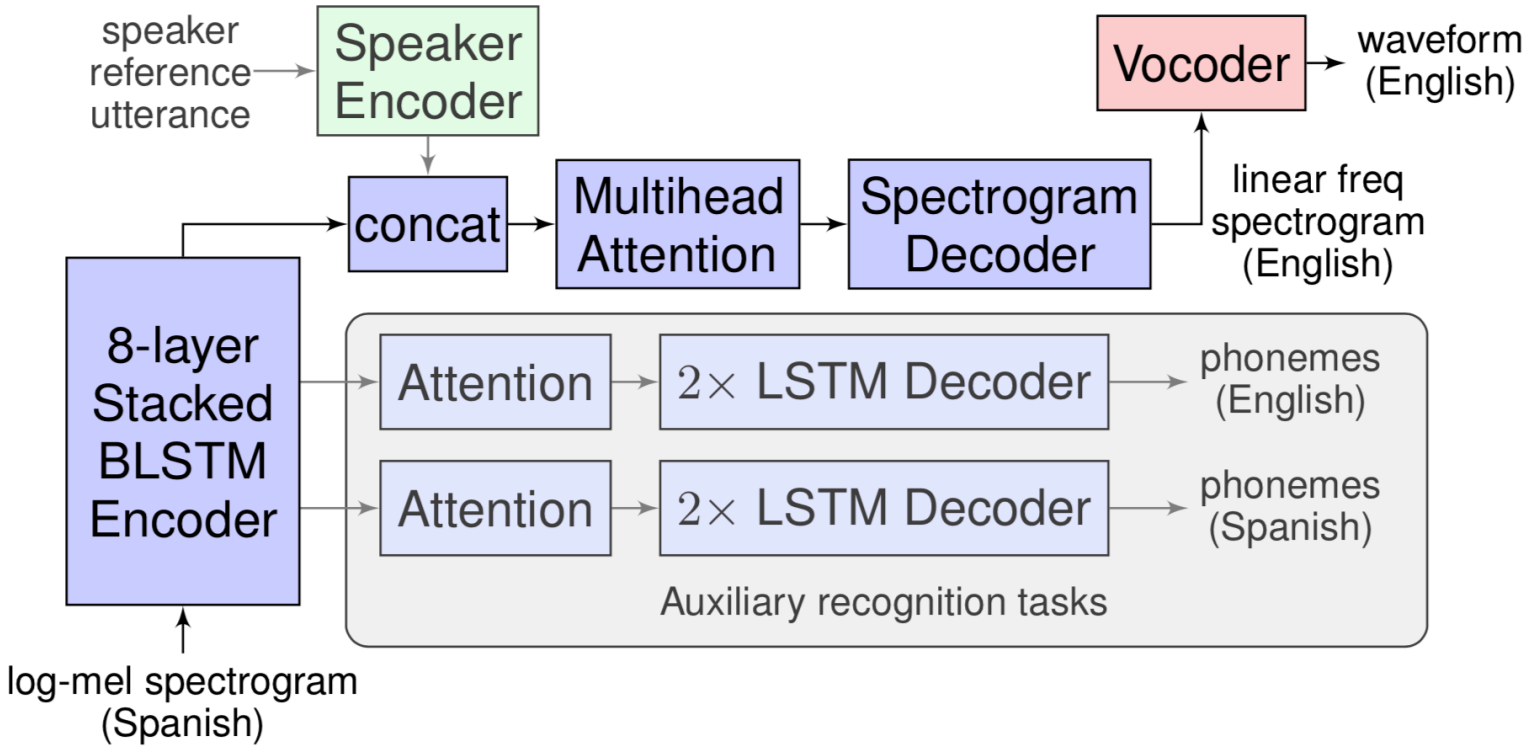


Figure from https://arxiv.org/abs/1904.06037

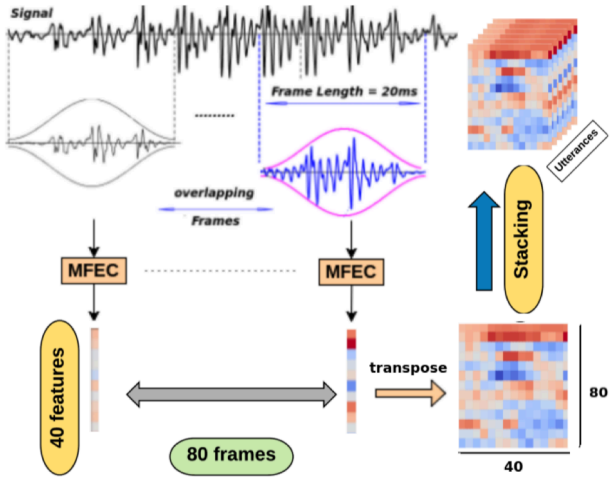
A Related Idea

- Replace text input to text to speech transduction with brain wave ...

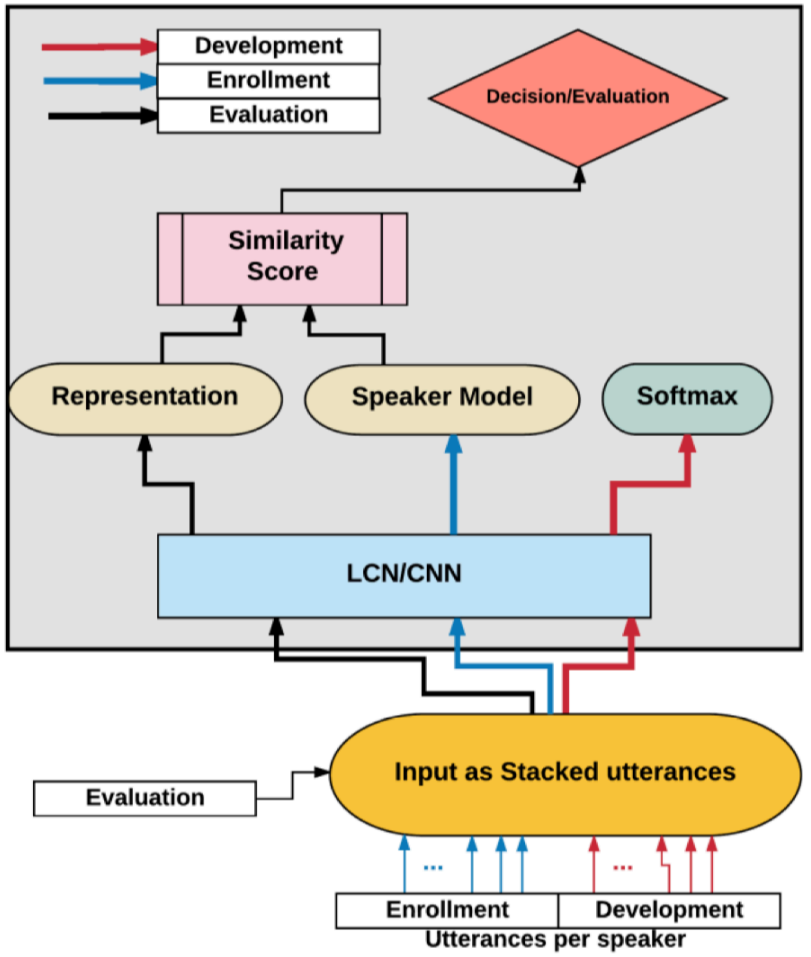
- Intelligible speech synthesis from neural decoding of spoken sentences
  - https://www.biorxiv.org/content/10.1101/481267v1.full

Backup

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	-	-



Figures from https://arxiv.org/abs/1705.09422

Decoding

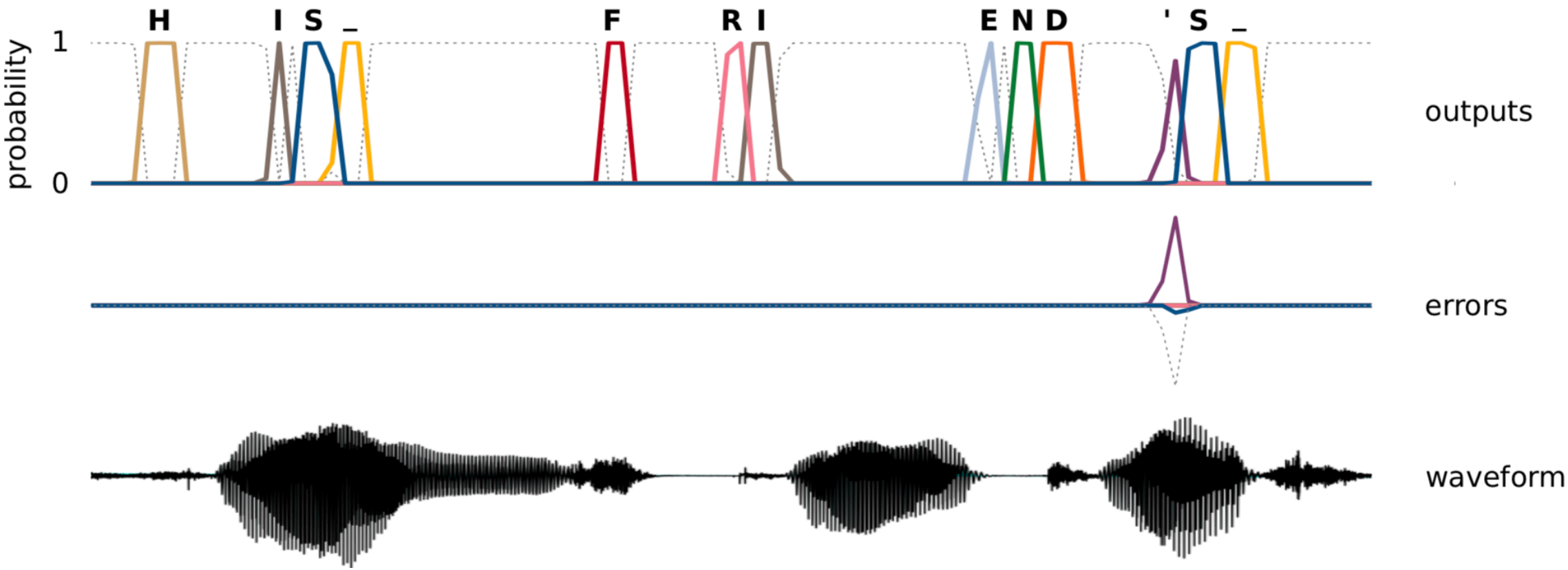
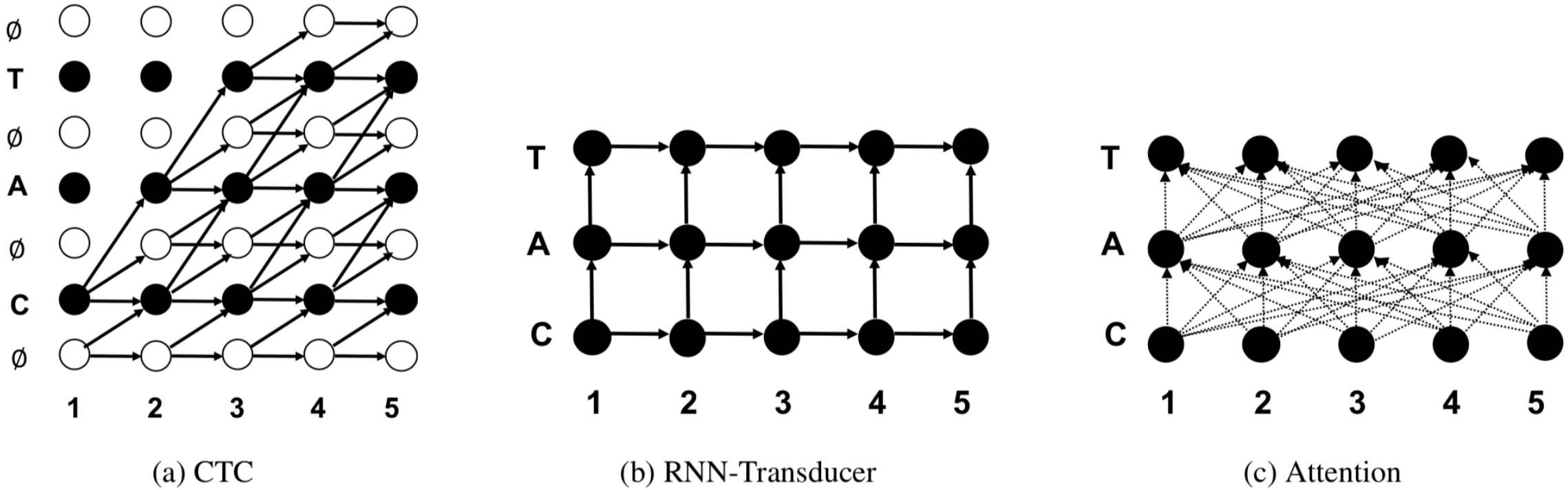


Figure from http://proceedings.mlr.press/v32/graves14.pdf

Comparing Transducer Transition Possibilities

Output symbol vs input frame transition possibilities for the word 'cat'; for additional discussion on differences in transducers see: https://www.isca-speech.org/archive/Interspeech_2017/pdfs/0233.PDF



(a) CTC (b) RNN-Transducer (c) Attention

Figure from https://arxiv.org/pdf/1707.07413.pdf

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

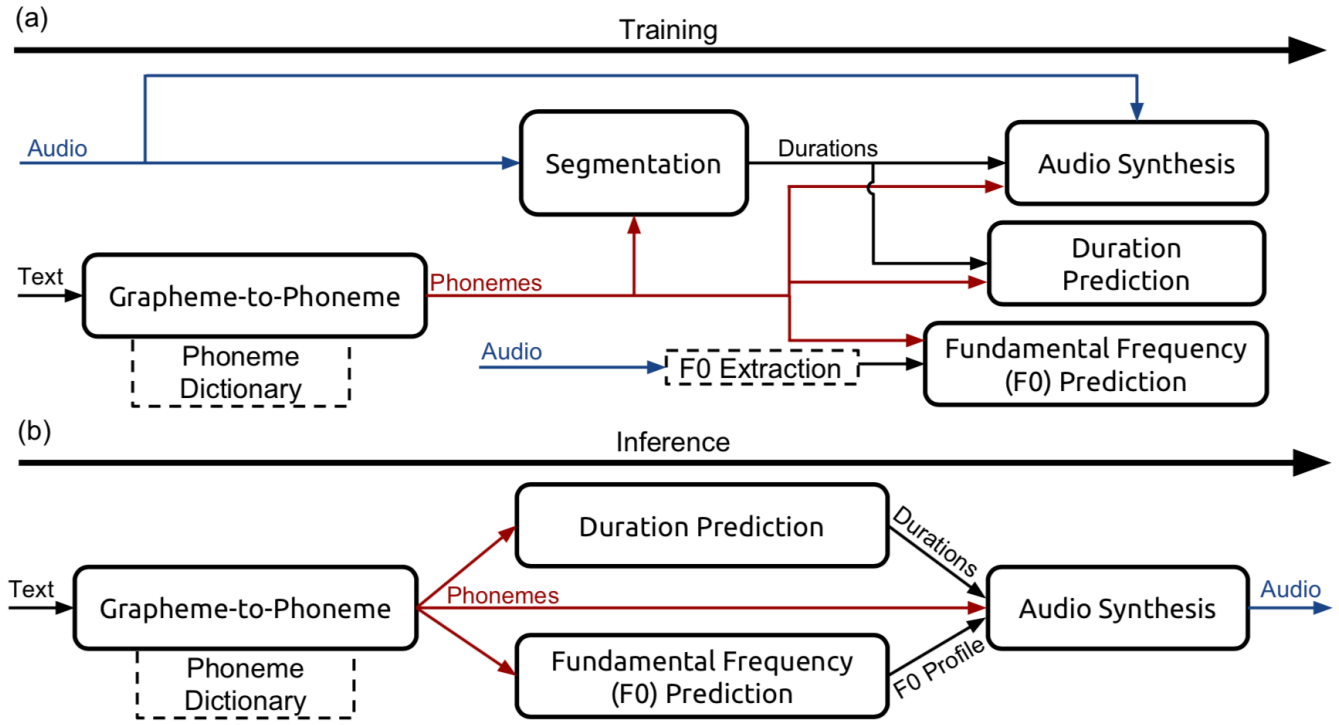


Figure from https://arxiv.org/abs/1702.07825

Example: DeepVoice 2

Testing diagram

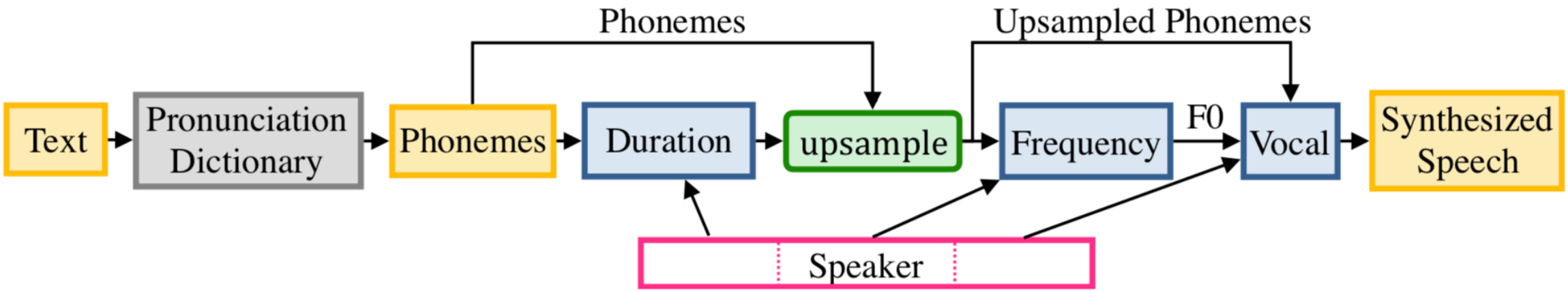


Figure from https://arxiv.org/abs/1705.08947

Example: DeepVoice 2

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

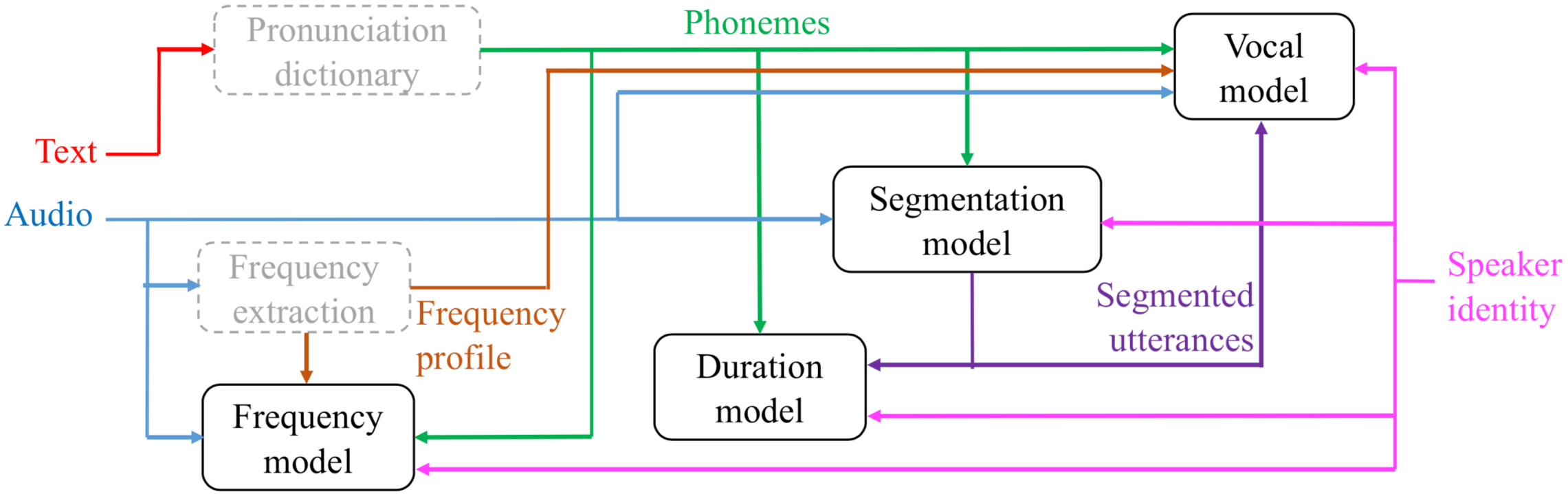


Figure from https://arxiv.org/abs/1705.08947

Example: DeepVoice 2

Segmentation, duration and frequency model details

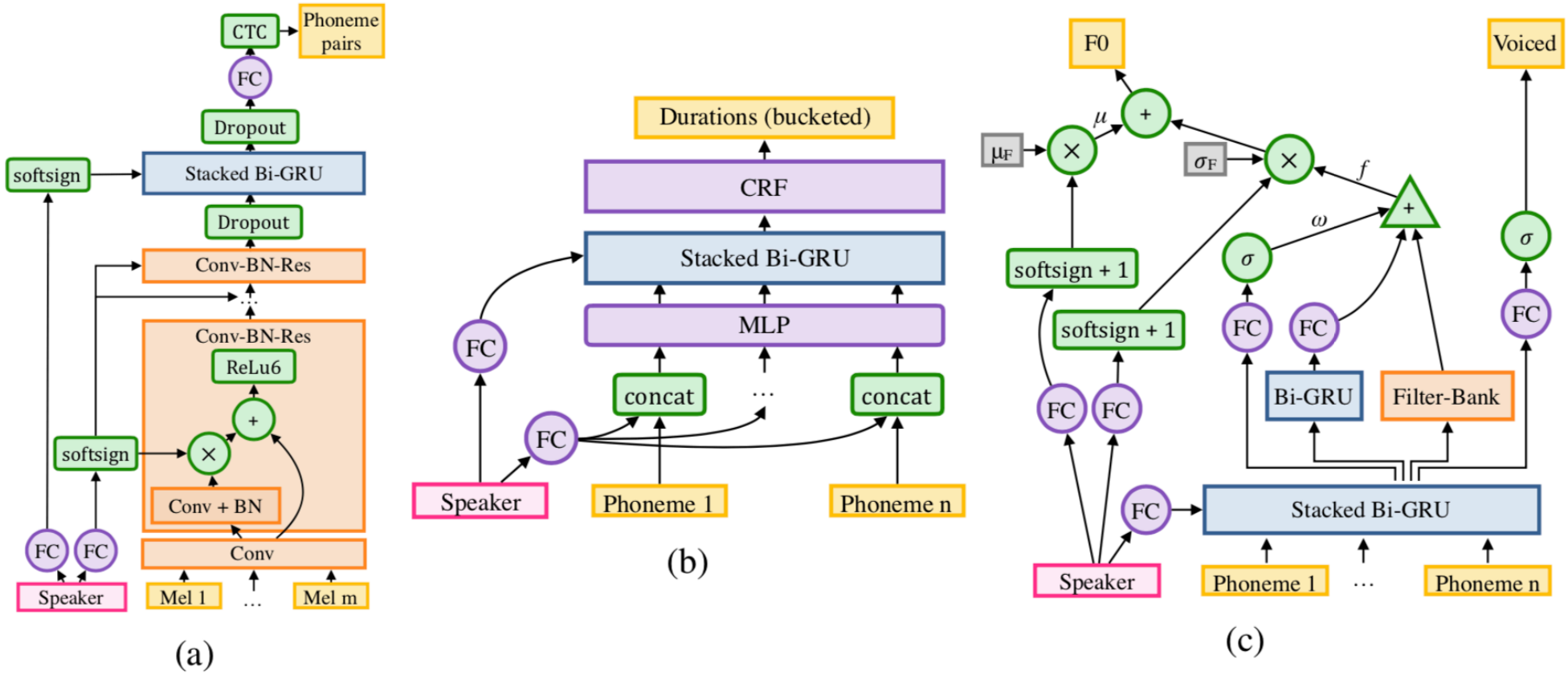


Figure 2: Architecture for the multi-speaker (a) segmentation, (b) duration, and (c) frequency model.

Figure from https://arxiv.org/abs/1705.08947

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

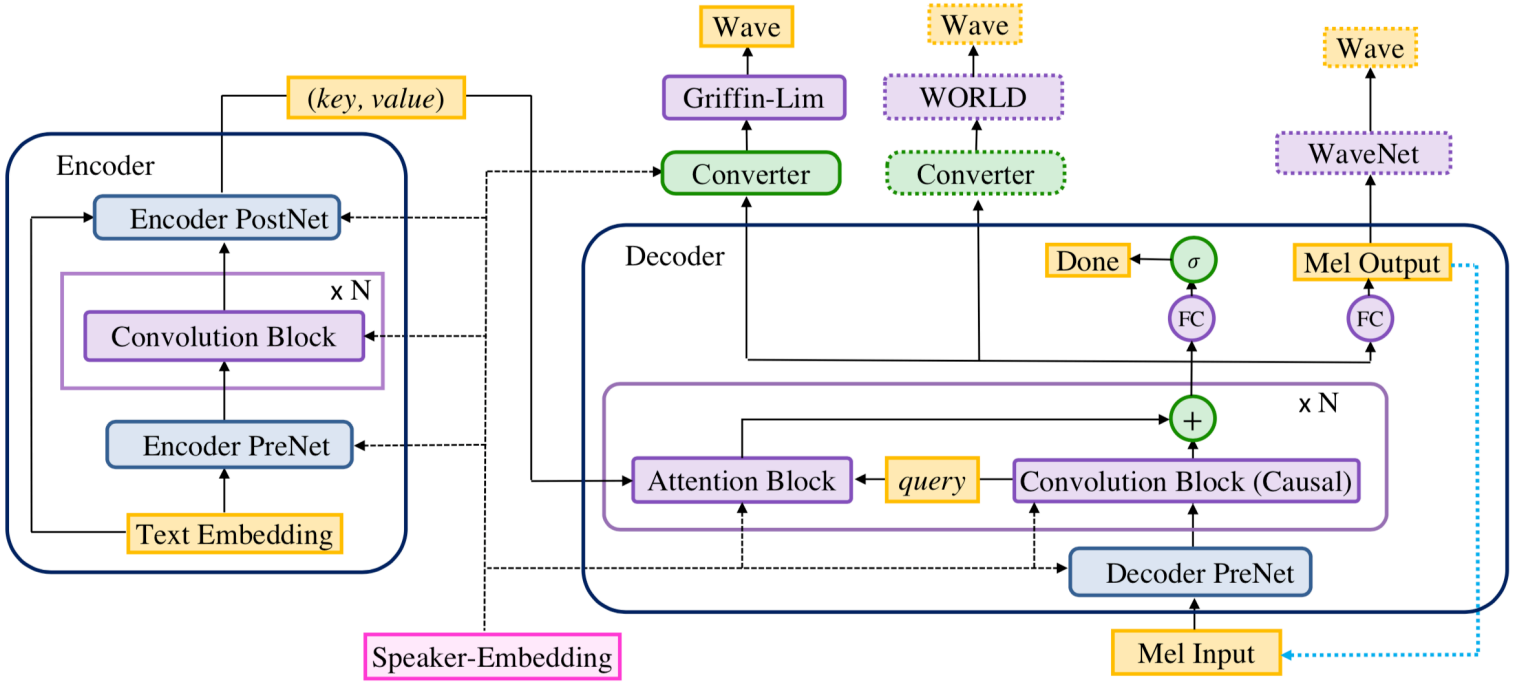


Figure from https://arxiv.org/abs/1710.07654

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

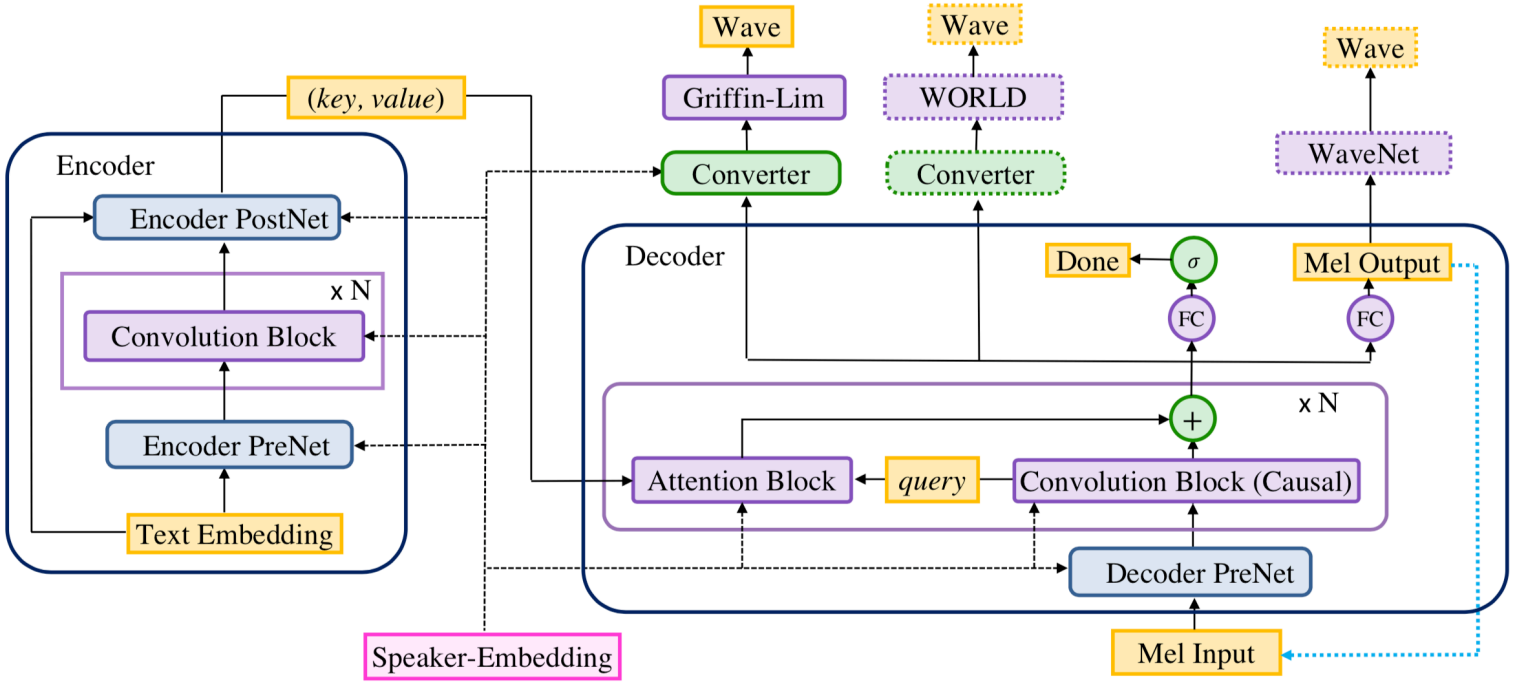
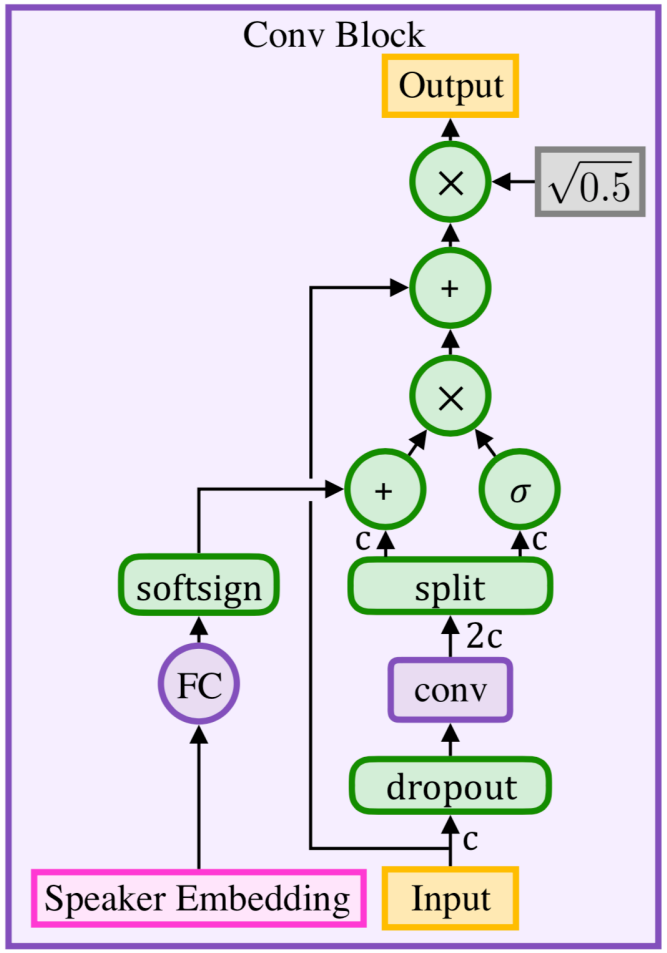


Figure from https://arxiv.org/abs/1710.07654

Example: DeepVoice 3



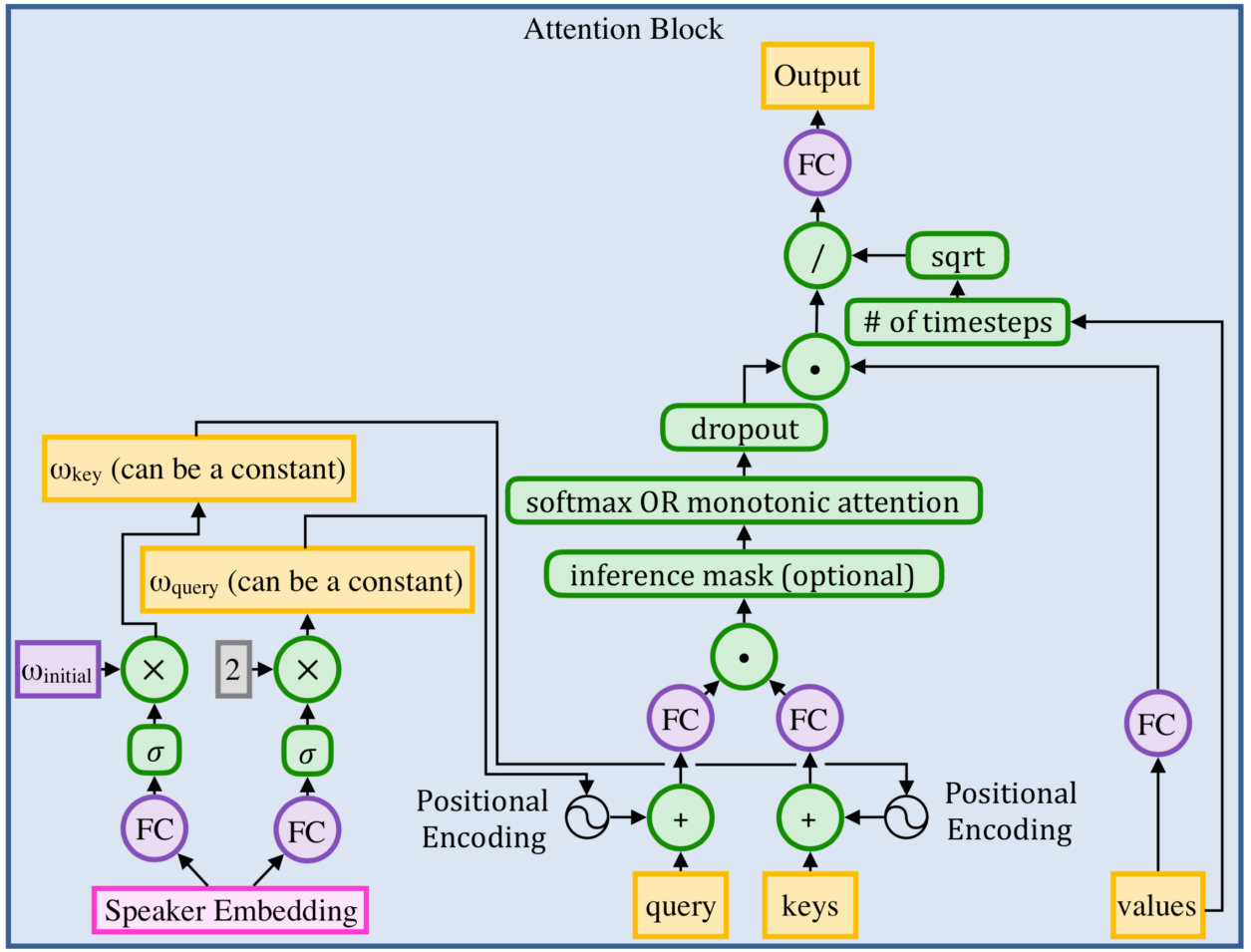
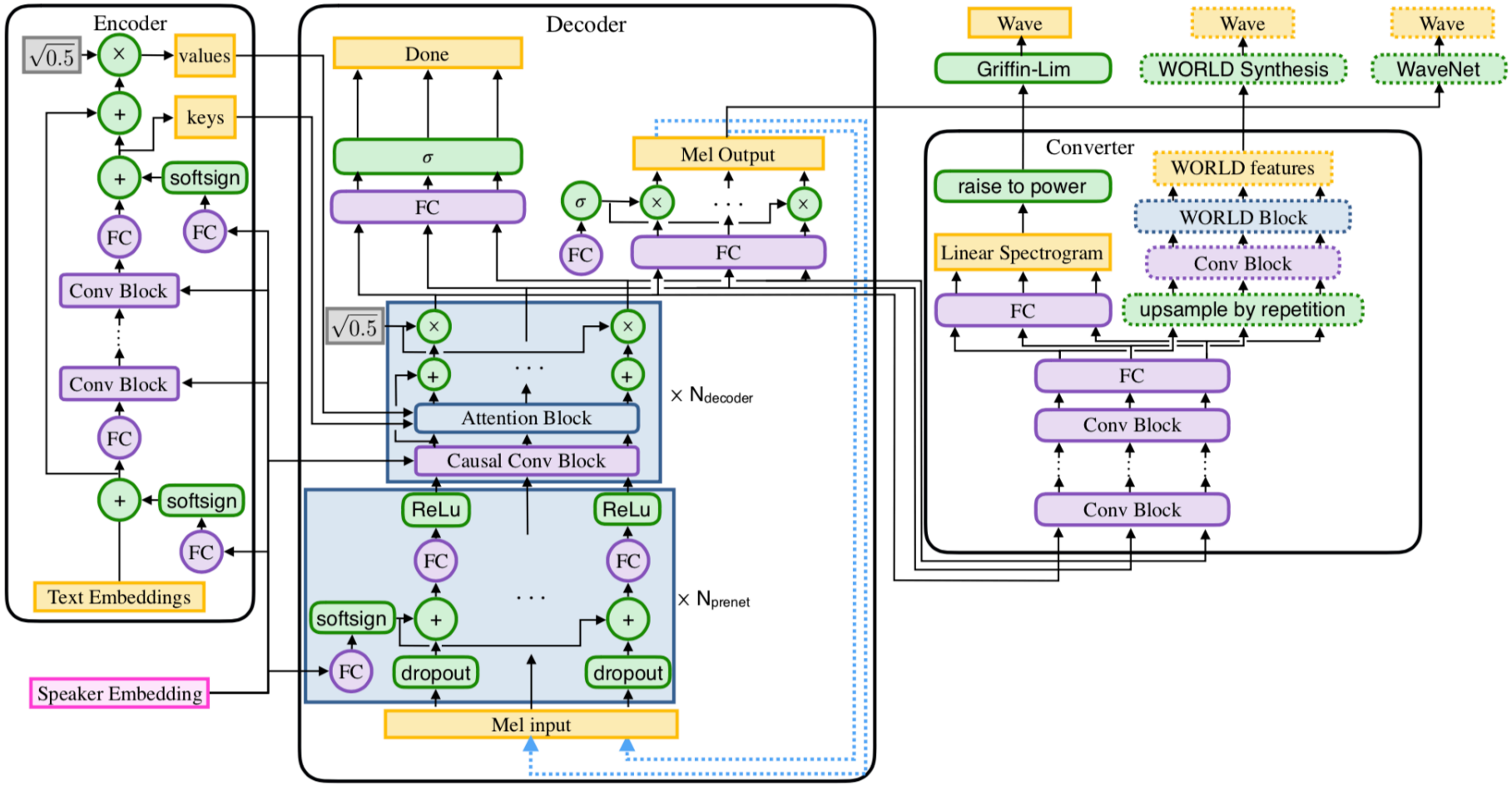


Figure from https://arxiv.org/abs/1710.07654

Example: DeepVoice 3



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