# Building Speech Systems

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  - Conveys lot more information than mere text content
- Economical
  - Inexpensive transmission and reception of information
  - Voice communication is the reason behind success of mobile phones

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  - Information that can be represented by a set of discrete symbols
  - Conveys textual message in the speech signal
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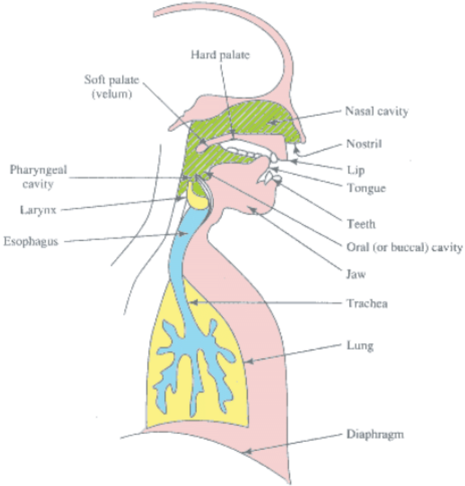
- Background Information - Acoustic environment around the speaker

# Acoustic Theory of Speech Production

# Speech Production Mechanism



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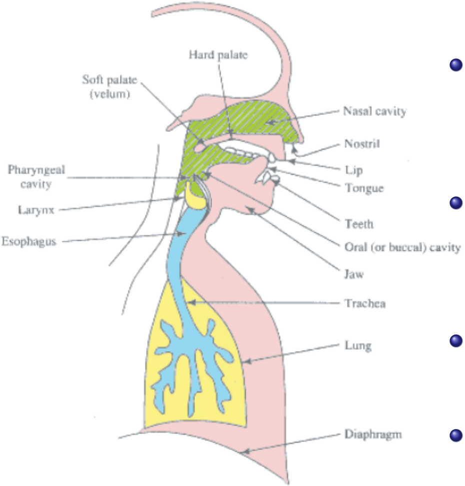
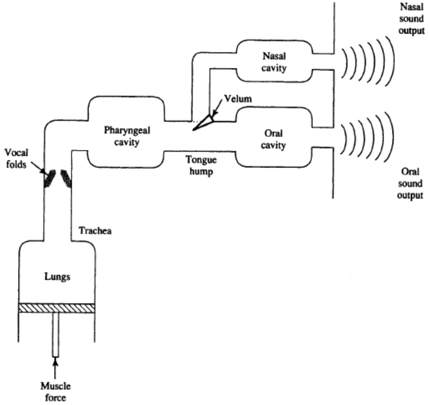


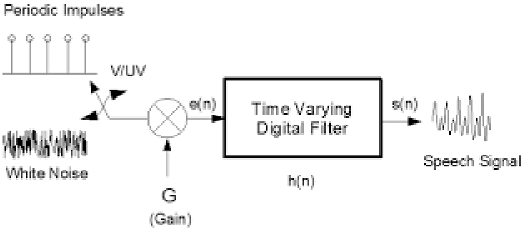

- Speech is the most sophisticated motor activity in the human body
- The motions are lightening fast and totally fluid, yet highly accurate
- Nasal cavity is much larger than oral cavity
- Animation

# Block Diagram of Speech Production




- Lungs act as source of energy
- Vocal folds chop the airflow from lungs into quasi periodic puffs of excitation
- Shape of the vocal tract determines the sound that is produced
- Velum is big enough is decouple nasal cavity, but not oral cavity

# Source-Filter Model of Speech Production



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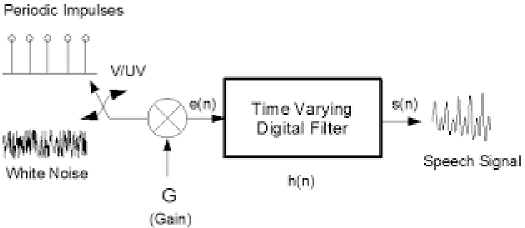


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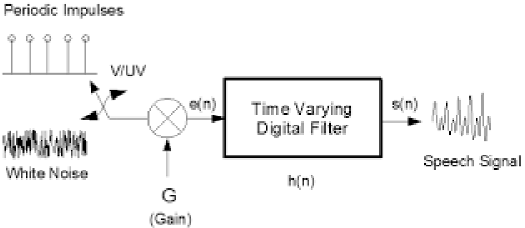


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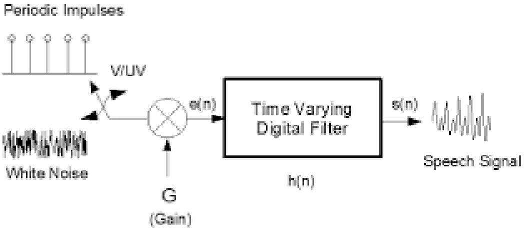


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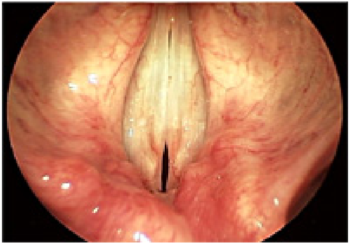
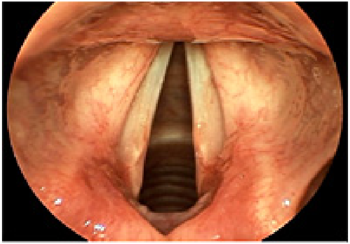
- The state of the vocal cords, the positions, shapes and sizes of the various articulators – all change slowly over time, thereby producing the desired speech sounds
- Need to determine the state of VT from waveform - inverse problem

# Vocal Folds - View & Operation





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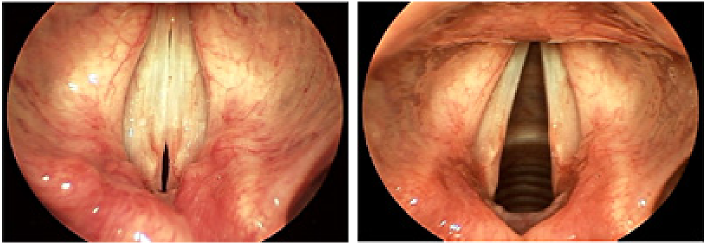
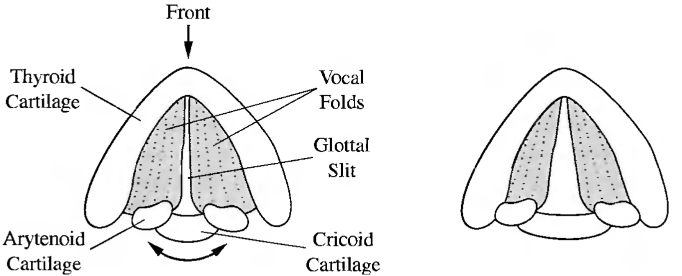
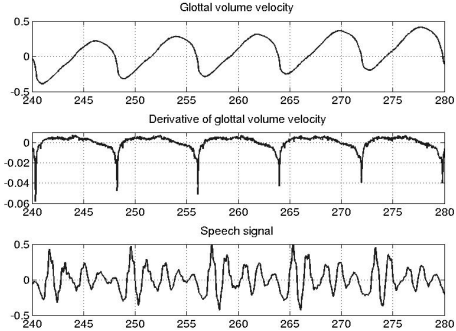





Video - 1 Video - 2

# Voice Source - Male vs Female

Male Speaker

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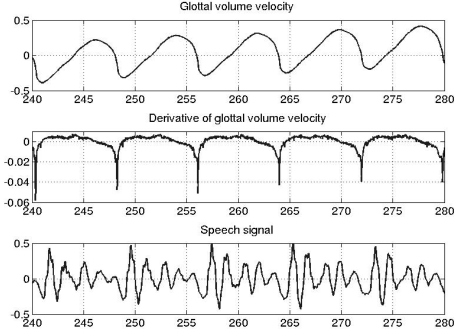


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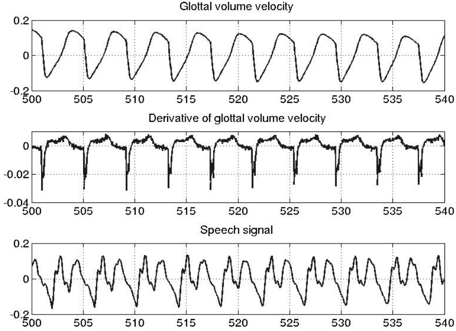


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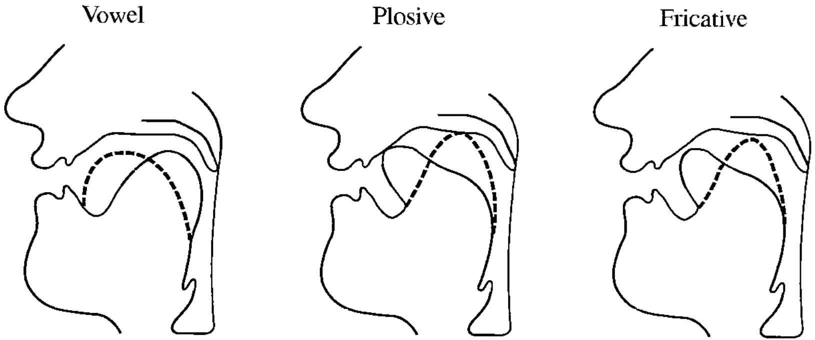
# Important Vocal-Tract Configurations



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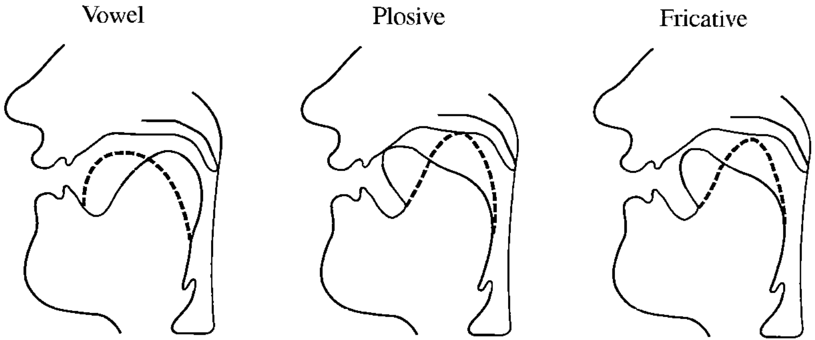
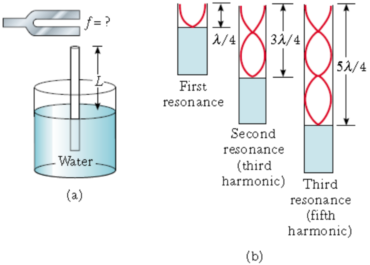



- Vowel - Relatively Open vocal-tract
- Plosive (Stop consonant) - VT is closed at some point
- Fricative - Constricted vocal tract

# Resonances of a Uniform Tube



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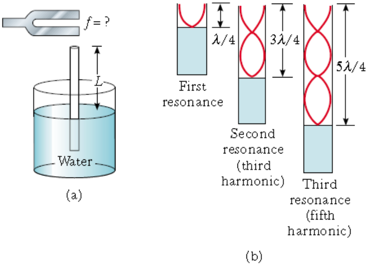

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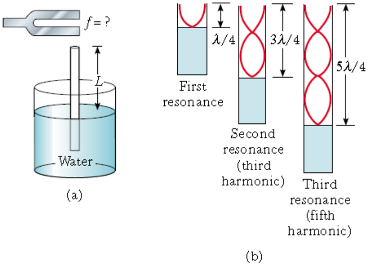


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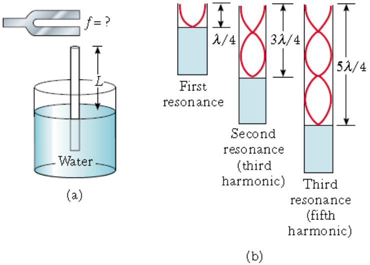


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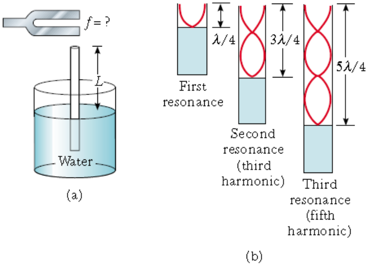


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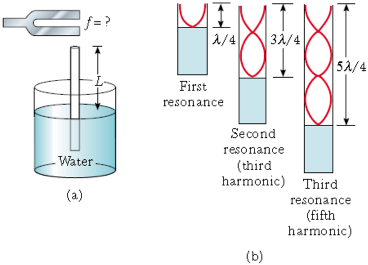


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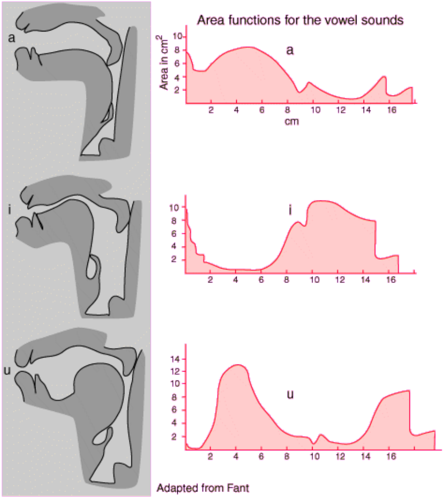
- If the tuning fork has the right frequency, the air column in the tube resonates loudly
- A standing wave pattern - maximum air displacement at open end & no air displacement at closed end.
- The tube acts like an acoustic filter - the frequency response of which depends on its dimensions

# Two-Tube Vowel Models



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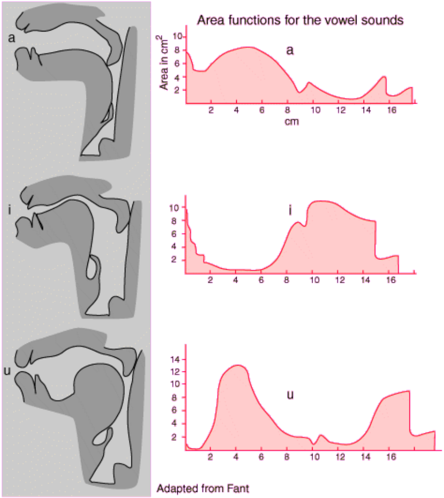


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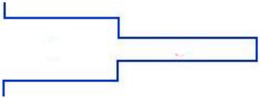

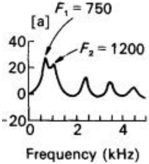

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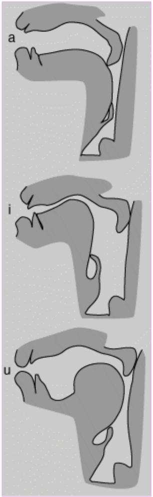


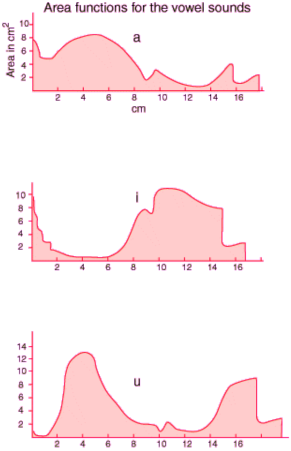


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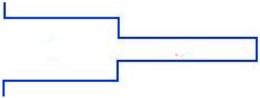

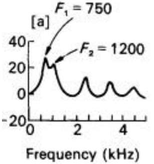


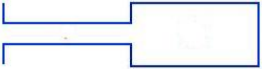

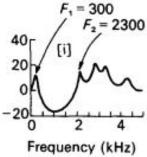

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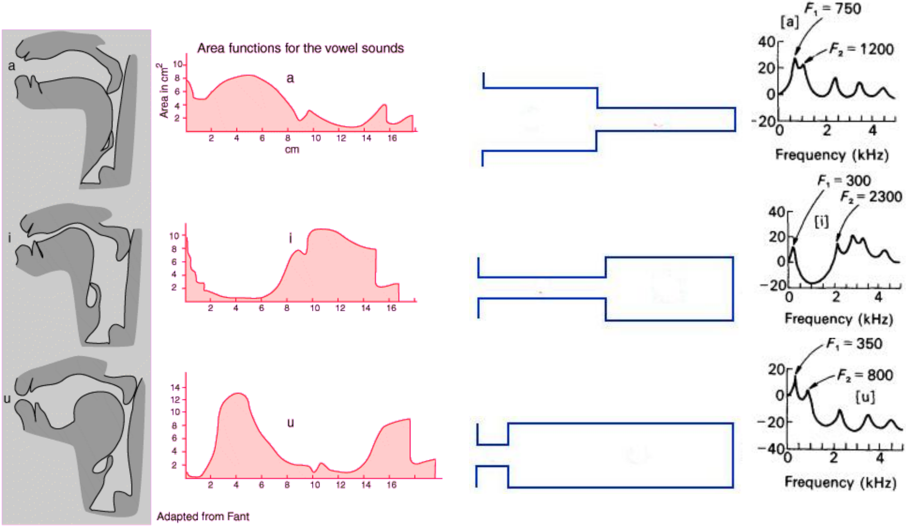
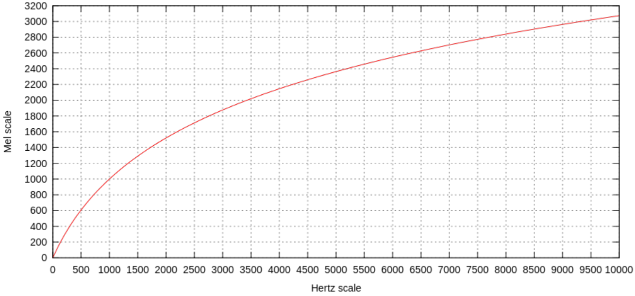


# Feature Extraction

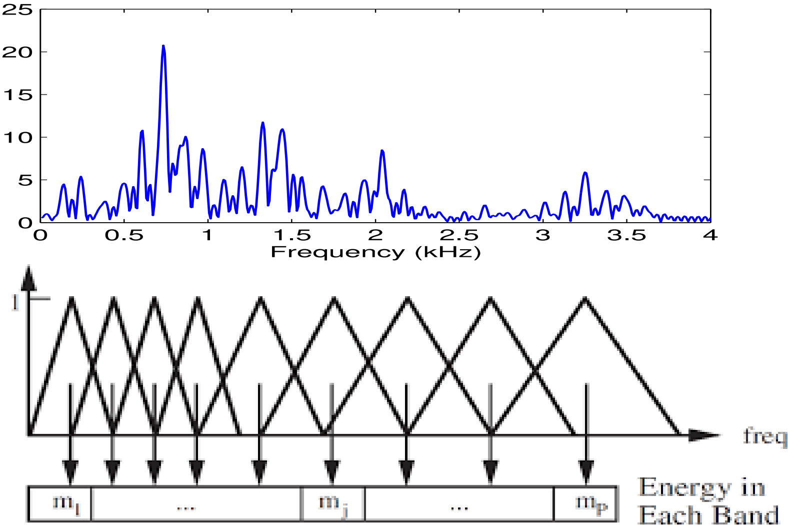
# Mel Scale

- Human beings can resolve low-frequency sounds better
- Mel scale incorporates this feature of human perception
- Mel scale is linear up to 1000 Hz, and logarithmic after that
- Filters are placed uniformly-spaced along Mel scale

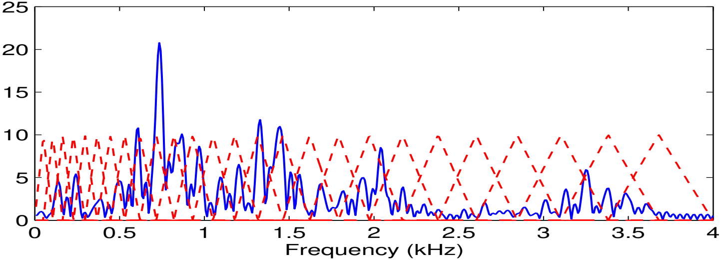



$$m = 2595 \log_{10}\left(1 + \frac{f}{700}\right)$$

# Mel Filters


25
20
15
10
5
0
0
0.5
1
1.5
2
2.5
3
3.5
4
Frequency (kHz)
1
freq
$m_1$
...
$m_j$
...
$m_P$
Energy in
Each Band

# Mel-Filter Bank Energy Coefficients



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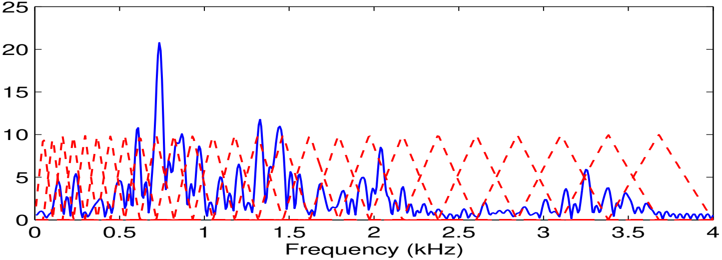


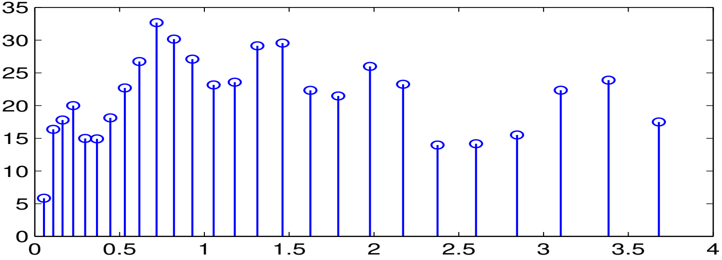

# Mel Frequency Cepstral Coefficients

MFCCs from waveform

- 20-30 ms window: $s[n]$
- N-point DFT - $S[k]$
- Squared magnitude $|S[k]|^2$
- **S**: symmetric half of $|S[k]|^2$

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$\mathbf{W}$ is the Mel-weight matrix

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- Log energy - $\mathbf{S}_l = \log \mathbf{S}_m$
- Compute IDCT: $\mathbf{S}_c = \mathbf{D}_{M\times M}\mathbf{S}_l$
- Retain first few coefficients $\hat{\mathbf{S}}_c$

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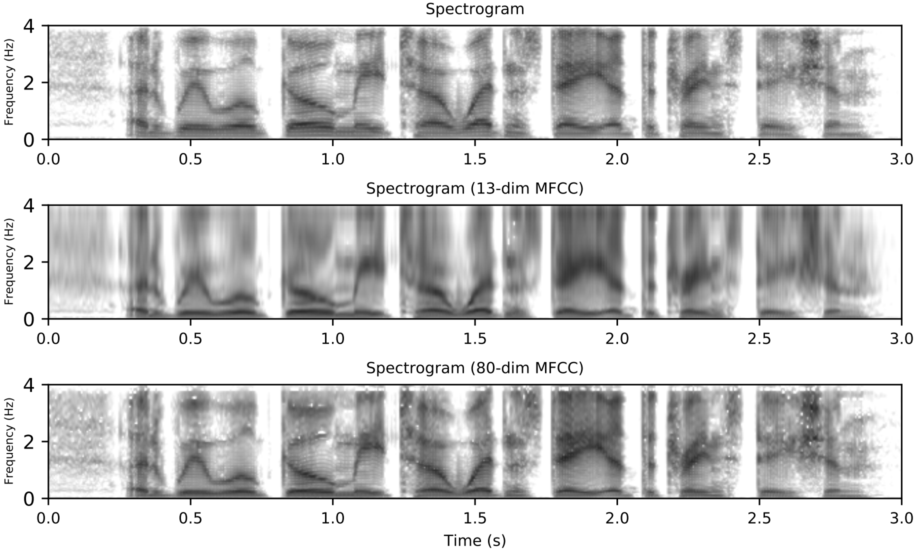
- Square root: $|S[k]|$
- Phase information is missing
- Griffin-Lim algo.: $e^{j\angle S[k]}$
- Inverse DFT: $\hat{s}[n]$

# Effect of Cepstral Order



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  - Recent DNN approaches extract features from the raw-waveform.

# Feature Extraction using Librosa

- Extract MFCC feature vectors using Librosa library

```
import librosa
y, sr = librosa.load('speech.wav', sr=16000)
mfcc = librosa.feature.mfcc(y=y, sr=sr)
mfcc_delta = librosa.feature.delta(mfcc)
mfcc_delta2 = librosa.feature.delta(mfcc, order=2)
```

- Concatenate MFCC and delta features to form 60-dim vector

# Speaker Recognition

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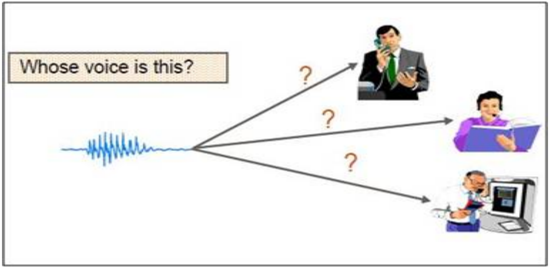
- Not an easy task: Humans make 23% errors on unfamiliar voices
- Speaker-specific information in the speech signal
  - **Anatomical differences:** VT size & shape, vocal-fold thickness, pitch..
  - **Learned speaking habits:** dialect, prosody, speaking rate, disfluencies

# Types of Speaker Recognition Systems

- **Text-independent speaker recognition**
  - Text content of enrollment and test utterances need not match
  - Recognition system does not know text spoken at test time
  - Offers a flexible system, but difficult to realize
  - Useful in forensic applications
  - Statistical pattern matching techniques are used
- **Text-dependent speaker recognition**
  - Enrollment and test utterances should be of same text
  - Recognition system knows the text spoken at test time
  - Knowledge of known text improves the performance
  - Applications involving cooperative users (banking, mobile phones)
  - Template matching techniques, like DTW, are used

# Text-Independent Speaker Identification



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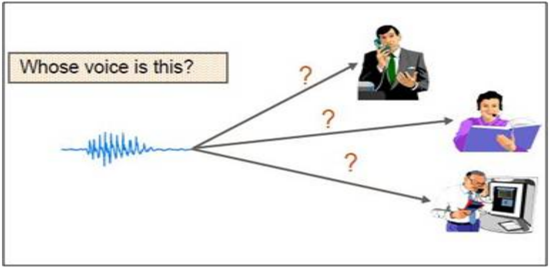


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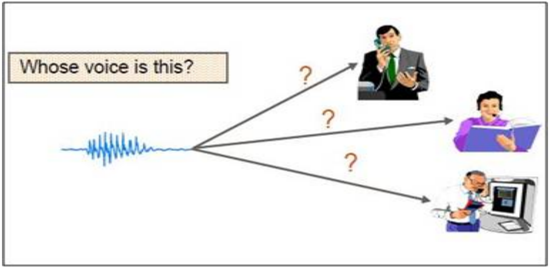


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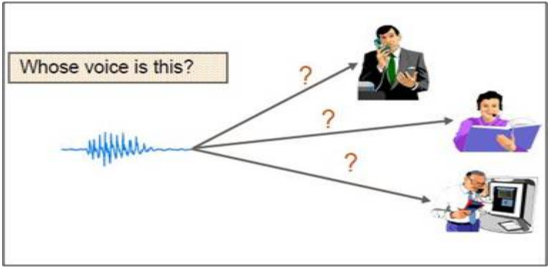


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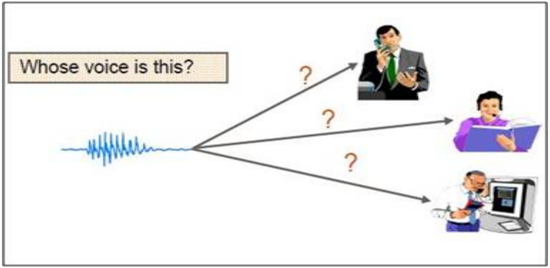


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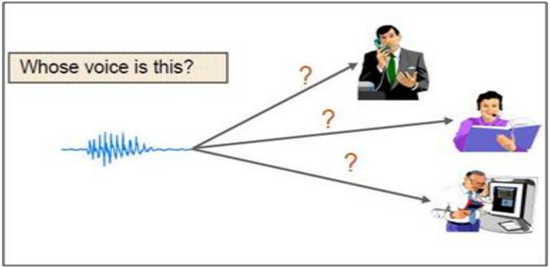


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- The enrollment and test utterances could be of different length
- Estimate the pdf of features from enrollment utterance
- Evaluate probability of drawing test data from the estimated pdf
- Assign speaker-$k$ if $p(\text{test data}/\lambda_k)$ is the highest

# Speaker Identification using GMMs

- Extract features from the speakers data
- Estimate pdf of the features of each speaker using GMM
- Let the speaker models be denoted by $\lambda_k, \quad k = 1, 2, \cdots, K$
- Let $X$ denotes the set of features extracted from a test utterance
- Assign test utterance to the model with maximum likelihood

$$\text{Speaker Id} = \arg\max_k p(X/\lambda_k)$$

- Issues with this approach
  - Likelihoods from different *model estimates* are not comparable
  - All the models might not have got trained to the same extent
  - The variance of the data could be different across speakers
  - Speaker models may yield consistently higher/lower likelihoods

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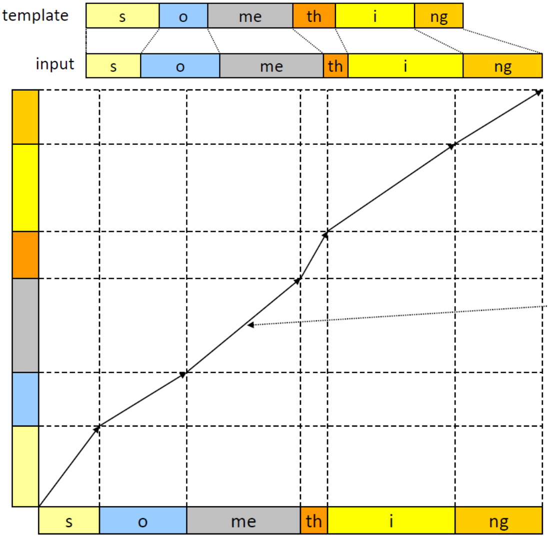
- Adapt UBM to each spaker to build speaker-specific model

```
spkr1 = sklearn.mixture.GaussianMixture(
        n_components=64, max_iter=1, covariance_type='
        means_init=ubm.means_, weights_init=ubm.weight
        precisions_init=ubm.precisions_)
spkr1.fit(X1)
```

# Isolated Word Recognition

# Isolated Word Recognition Using DTW



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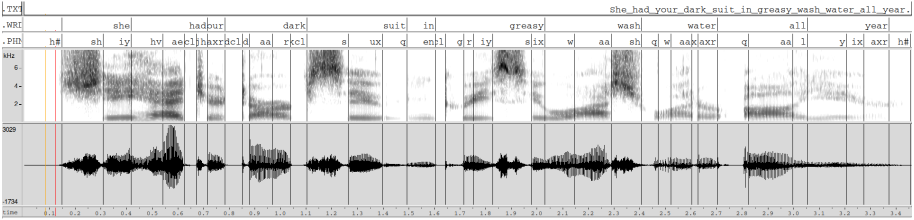

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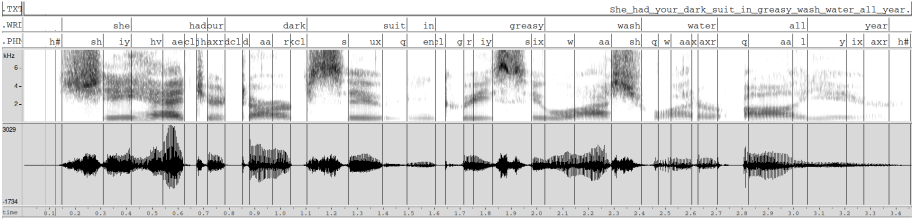


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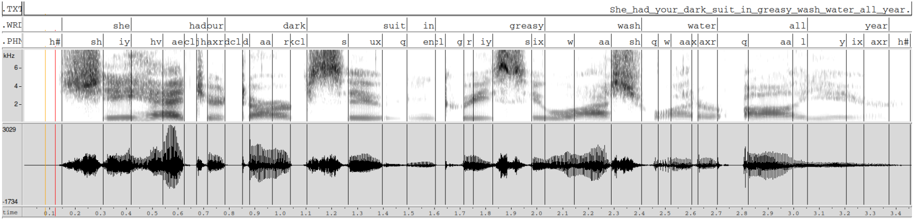


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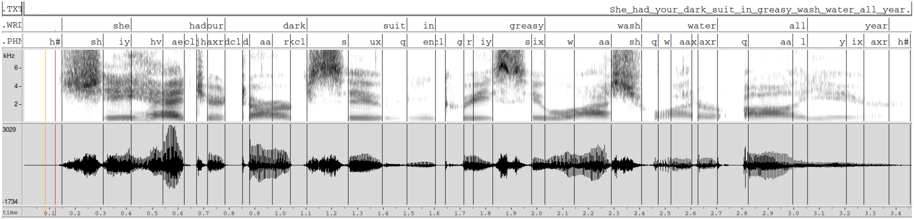


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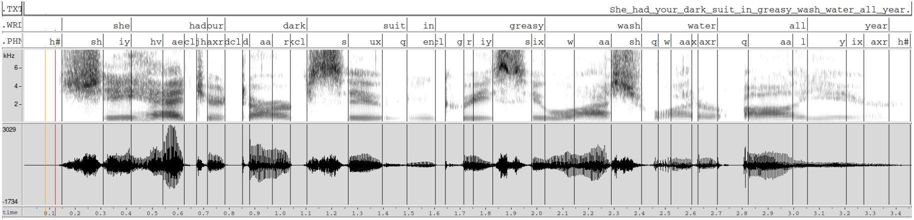


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- Time-domain samples → Feature representation → Subword units → Words → Sentences

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- Most-likely word sequence can be determined by maximizing

$$W^* = \arg\max_W \underbrace{P[W]}_{LM} \underbrace{p(\mathbf{O}/W)}_{AM}$$

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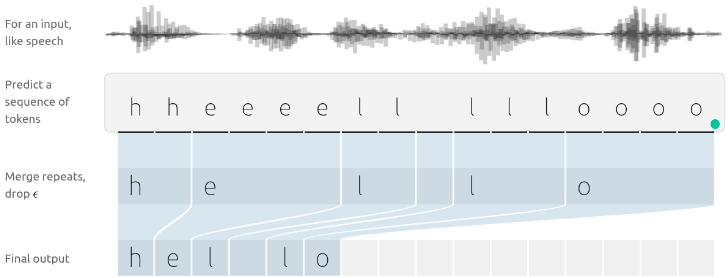
- $P[W]$ is estimated using Markov models
- End-to-end neural network models directly estimate $P[W/\mathbf{O}]$

# Towards End-to-End Speech Recognition



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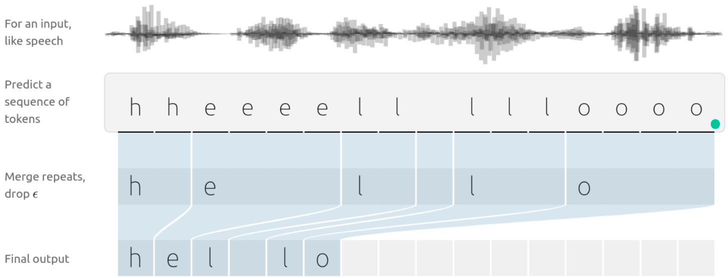


- Map acoustic observation sequence $O = (\mathbf{o}_1, \mathbf{o}_2, \cdots, \mathbf{o}_T)$ to alphabet sequence $W = (w_1, w_2, \cdots w_U)$, where $W_k \in \{S_1, S_2, \cdots S_{26}\}$
  - The sequences $O$ and $W$ are of different length
  - The ratio of lengths of $O$ and $W$ can vary
  - Do not have access to accurate alignment between $O$ and $W$

## Sequence Model

- Train a model to infer word sequence $W$ from observation sequence $O$
- That is, the model should maximize $P[W/O]$
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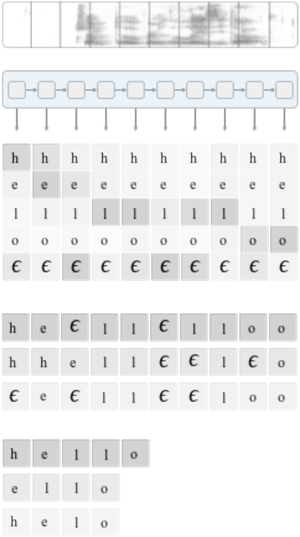
- RNNs/CNNs are used to map the observations to word posteriors
  - Cross-entropy loss cannot be used as it requires ground-truth alignment

# Connectionist Temporal Classification (CTC))




We start with an input sequence, like a spectrogram of audio.

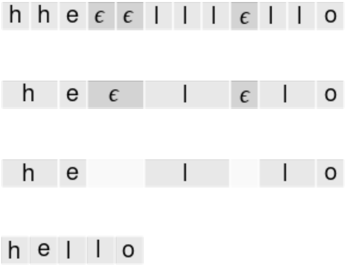
The input is fed into an RNN, for example.

The network gives $p_t(a \mid X)$, a distribution over the outputs {h, e, l, o, $\epsilon$ } for each input step.

With the per time-step output distribution, we compute the probability of different sequences

By marginalizing over alignments, we get a distribution over outputs.

# CTC Alignment Steps




First, merge repeat characters.

Then, remove any $\epsilon$ tokens.

The remaining characters are the output.

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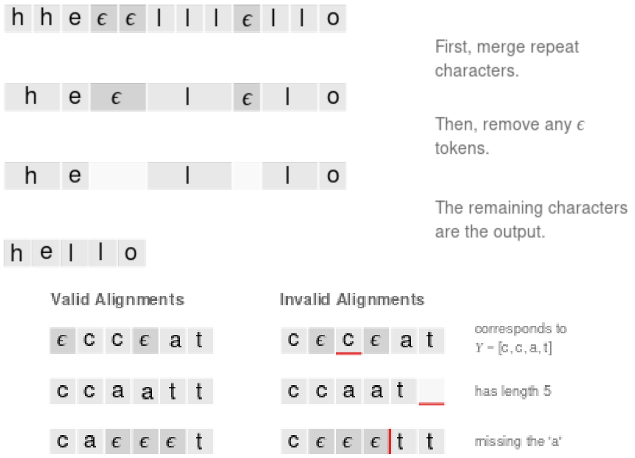

## CTC Loss

- Probability of a word sequence W given the observation sequence O

$$P[W/O] = \sum_{\text{all valid paths}} \prod_{t=1}^{T} P[w_t/\mathbf{o}_1, \mathbf{o}_2, \cdots \mathbf{o}_T]$$

- During training, manual transcription of words/sentences is known
  - Restrict output posterior computation to the alphabet in those words
  - Form the trellis by arranging posteriors in the order of alphabet
  - Evaluate the probabilities along all the paths resuting in the given word
  - Compute the gradients, and backpropagate to maximize the probability
- Negative logarithm of the $P[W/O]$ is referred to as CTC loss

$$\mathcal{L}(\theta) = -\frac{1}{\mathcal{B}} \sum_{(O,W)\in\mathcal{B}} P[W/O]$$

# Inference

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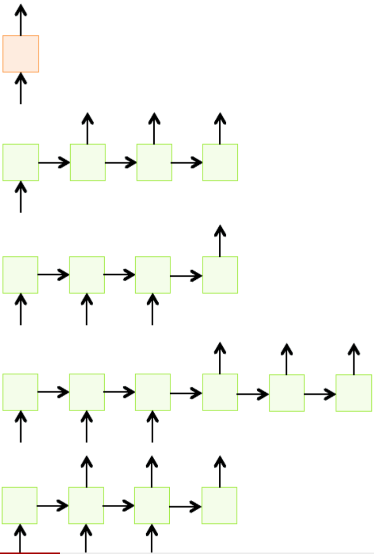
  - It results in alignment with highest probability
  - Collapse the repeats and remove $\epsilon$ to get $W$
  - Works well when most probability mass is allotted to a single alignment

# RNN Configurations



| | |
|---|---|
| Single - Single | Feed-forward Network |
| Single - Multiple | Image Captioning |
| Multiple - Single | Sentiment Classification |
| Multiple - Multiple | Translation |
| | Image Captioning |

# Thank You!