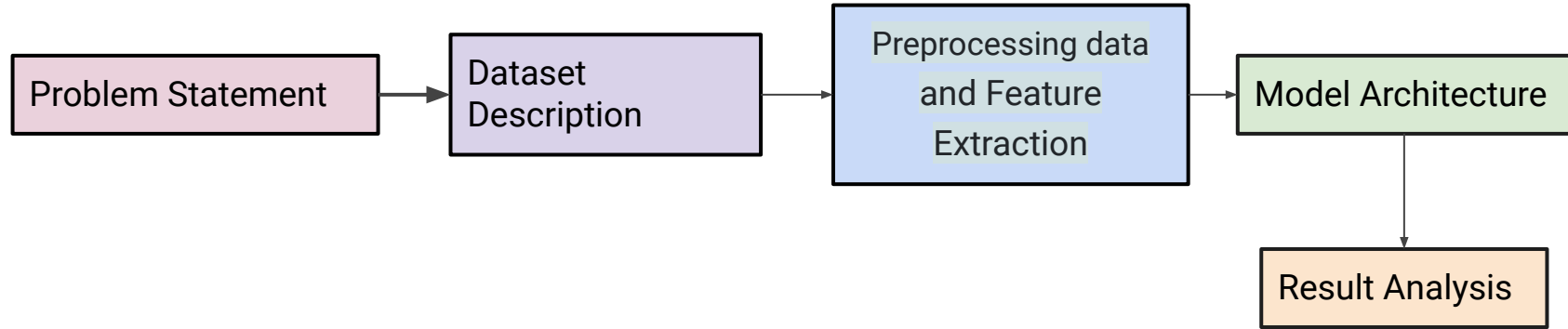


Bengali Spoken Digit Classification: A Hidden Markov Model Approach

By
Dibyendu Das
Under the Guidance Of
Dr. Sujoy Biswas

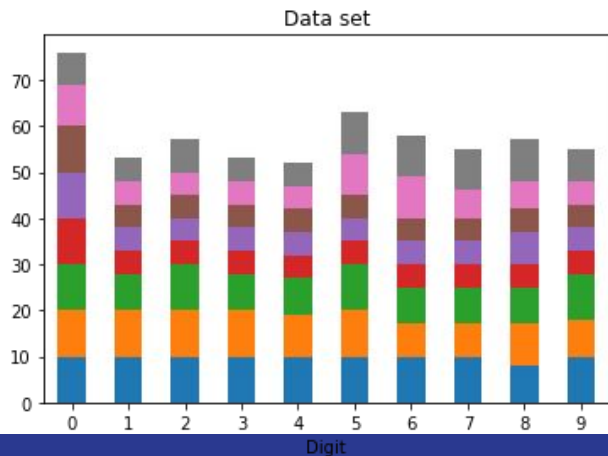
M.Sc in Big Data Analytics
Ramakrishna Mission Vivekananda Educational and Research Institute



Dataset Description

Dataset Description

- A dataset containing 600 audio file (.wav format) was created for the experiment.
- Eight people from various parts of the State were asked to give their voice recordings Using “QuickRec” App.



Bengali word	Bengali pronunciation	English word	English numerical
শূন্য	shun-no	zero	0
এক	a-k	one	1
দুই	du-i	two	2

Preprocessing and Feature Extraction

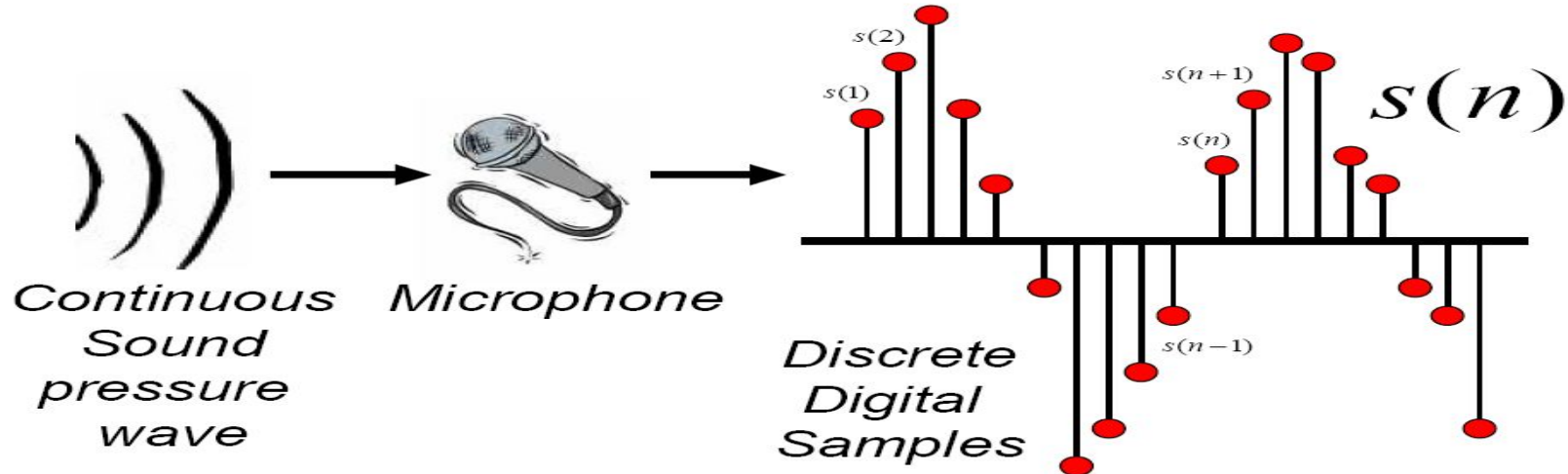
Discrete Representation of Signal :

Analog-to-digital conversion has two steps :

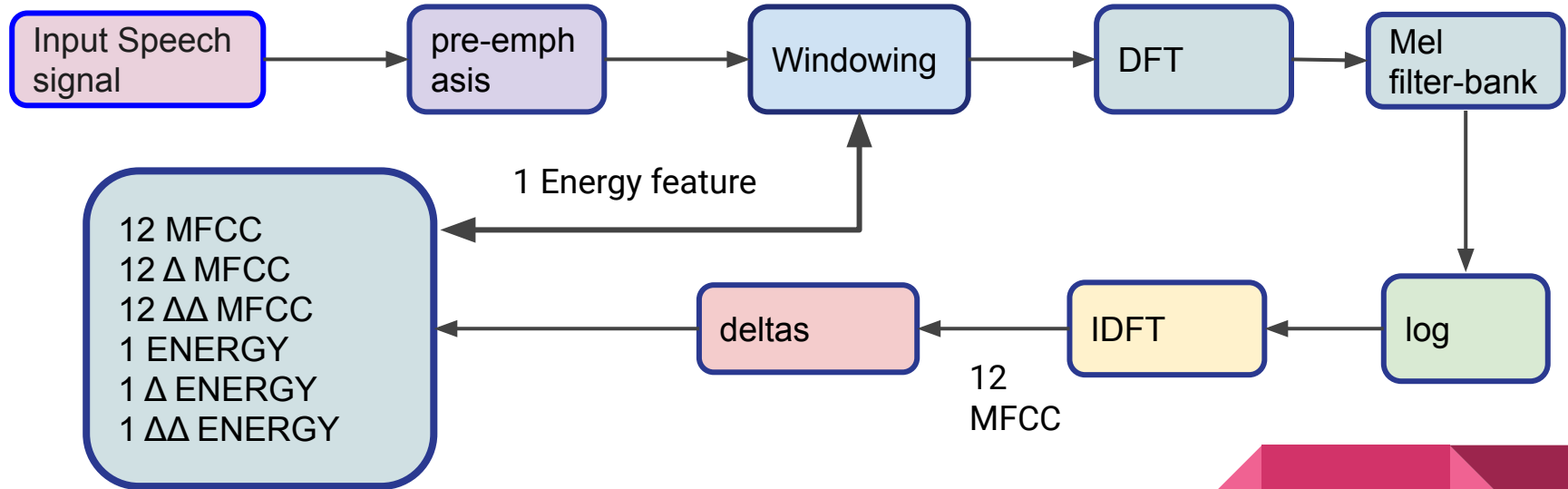
Sampling = $2 * \text{Nyquist}$
frequency



Quantization = store the
amplitude value as 8 bit or 16 bit



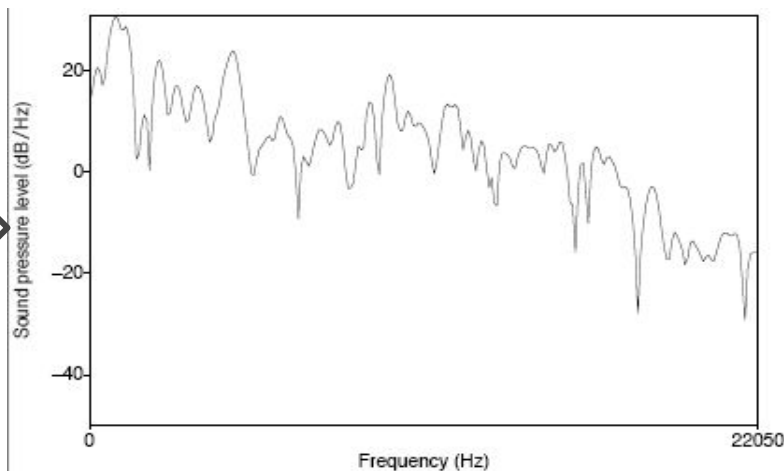
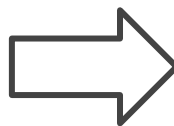
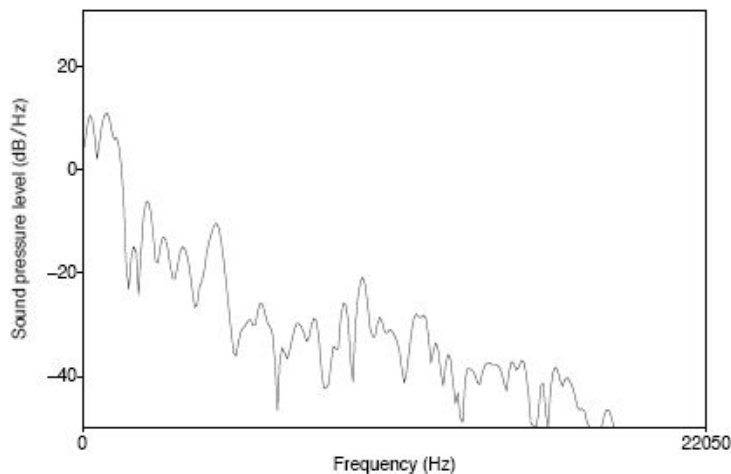
Preprocessing data and MFCC Feature Extraction :



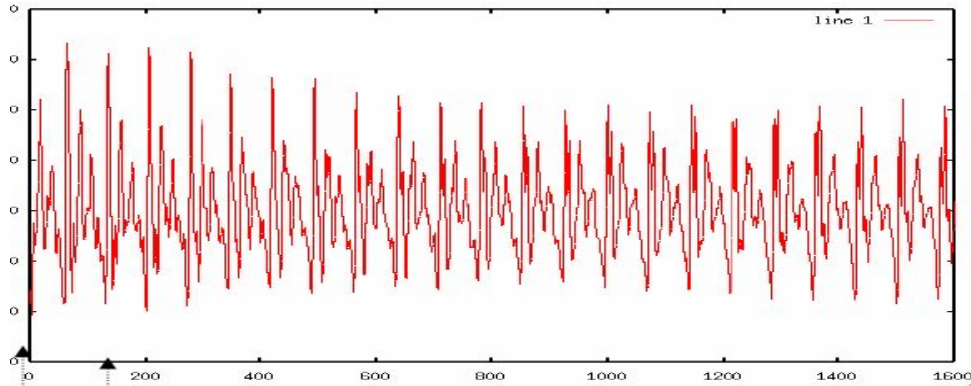
Preemphasis :

- The spectrum for voiced segments has more energy at lower frequencies than higher frequencies. This is called **spectral tilt**
- Spectral tilt is caused by the nature of the glottal pulse

Spectral slice from the vowel [aa]

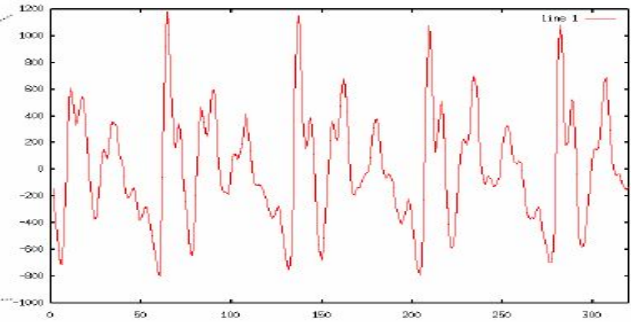
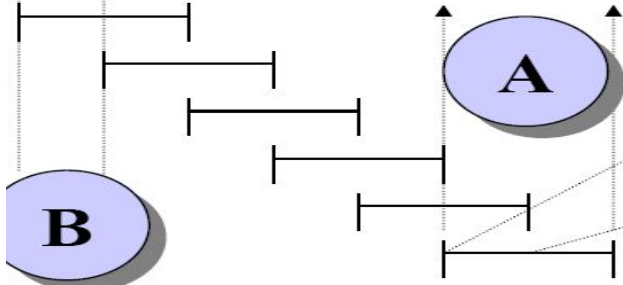


Windowing :



A ~ 20 – 25 ms

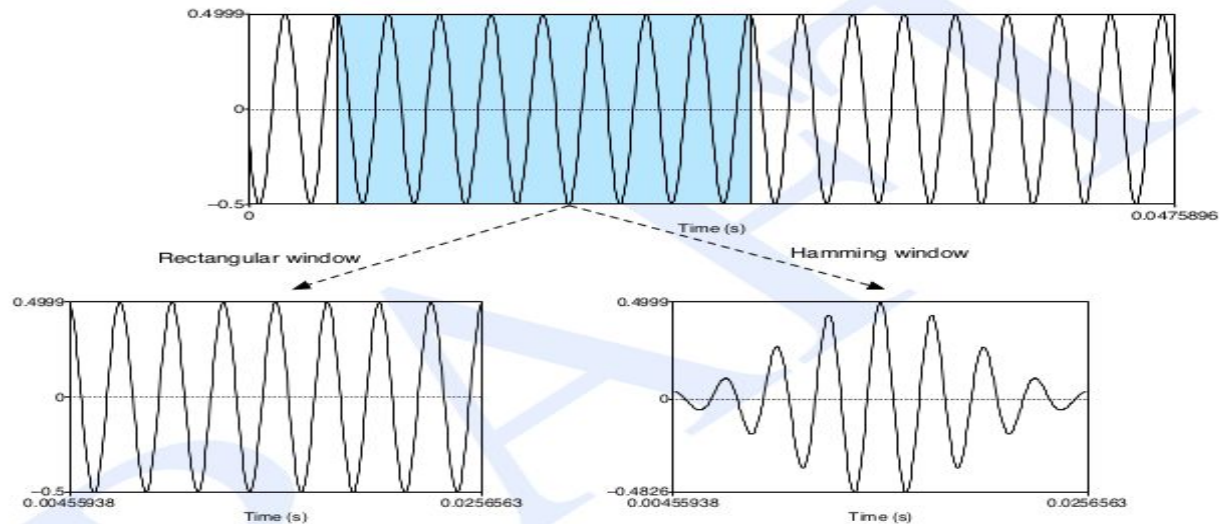
B ~ 10 ms



Common window shapes :

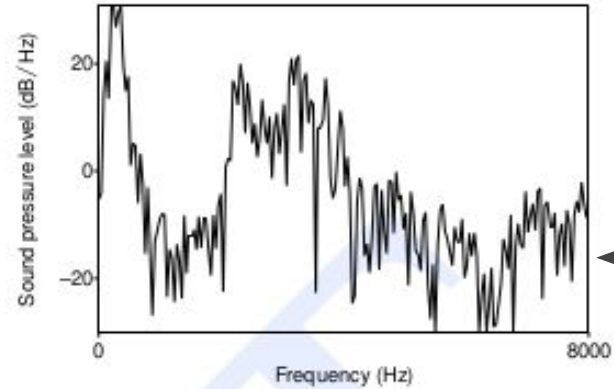
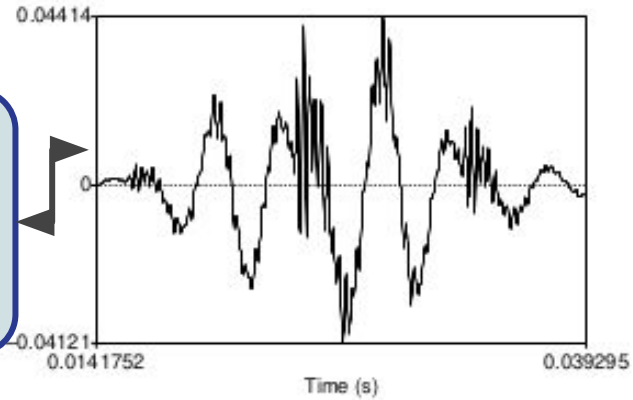
$$\text{rectangular} \quad w[n] = \begin{cases} 1 & 0 \leq n \leq L-1 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{hamming} \quad w[n] = \begin{cases} 0.54 - 0.46 \cos\left(\frac{2\pi n}{L}\right) & 0 \leq n \leq L-1 \\ 0 & \text{otherwise} \end{cases}$$



DFT :

25 ms
windowed
portion



Spectrum
compute
d by DFT

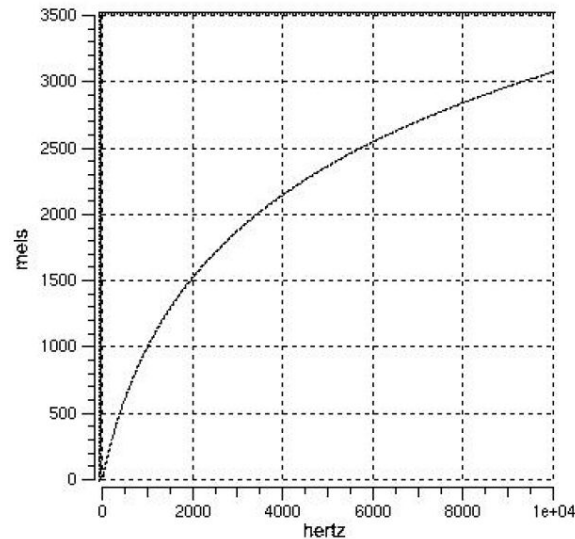
Mel Scale :

- Human hearing is not equally sensitive to all frequency bands
- Less sensitive at higher frequencies, roughly > 1000 Hz
- I.e. human perception of frequency is non-linear:

A mel is a unit of pitch

Definition: Pairs of sounds perceptually equidistant in pitch
Are separated by an equal number of mels

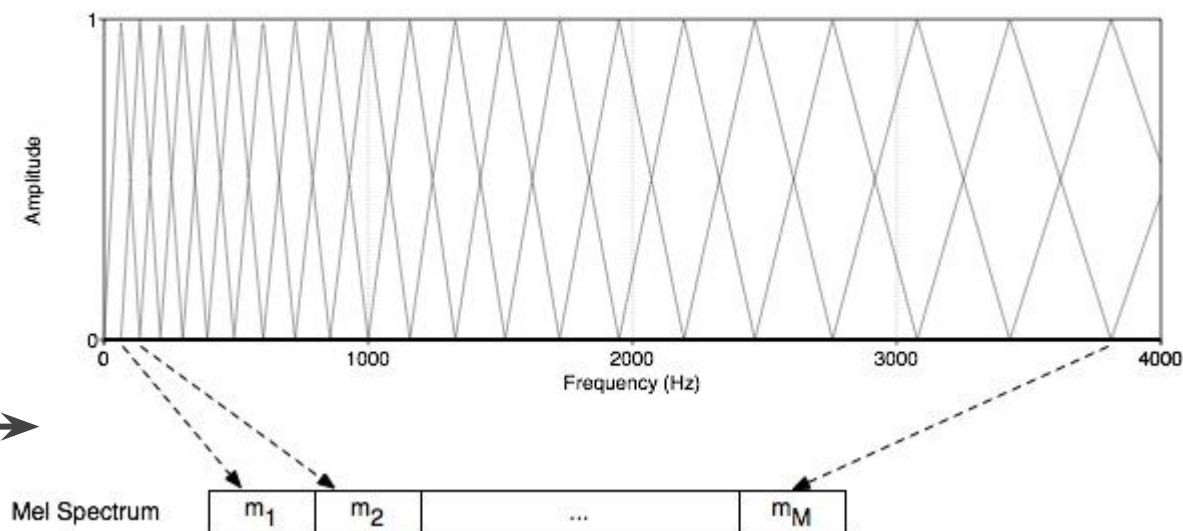
$$\text{Mel}(f) = 1127 \ln \left(1 + (f/1000) \right)$$



Mel Filter bank

Uniformly spaced before 1 kHz
logarithmic scale after 1 kHz

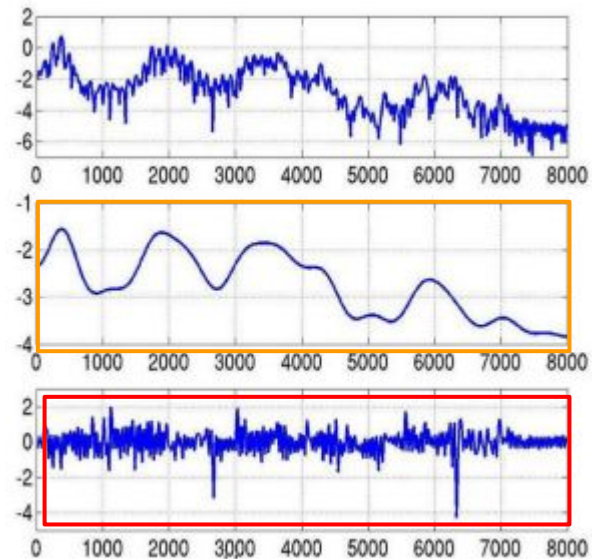
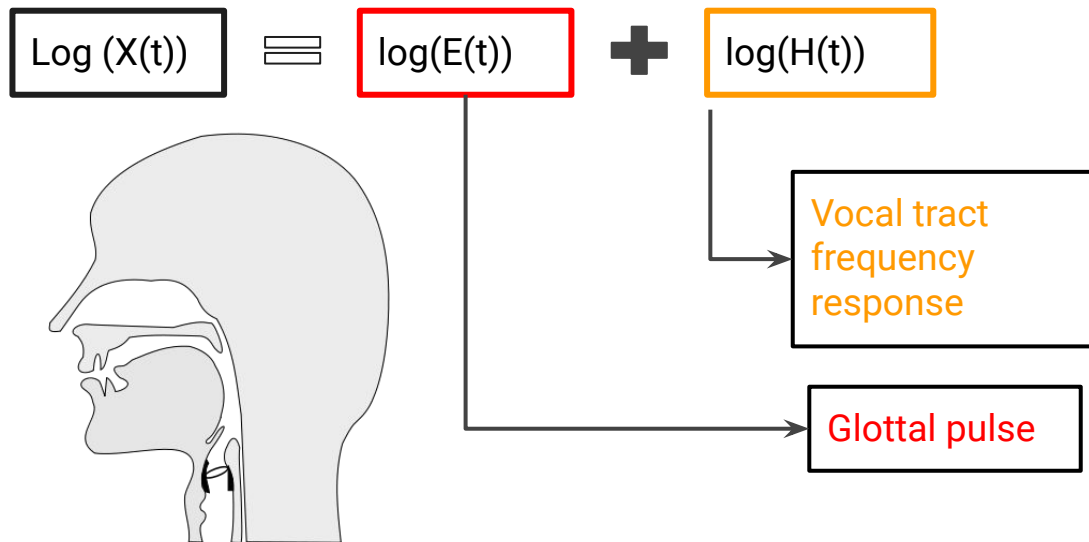
Each triangular filter
collects energy from
given frequency
range



The Cepstrum : IDFT

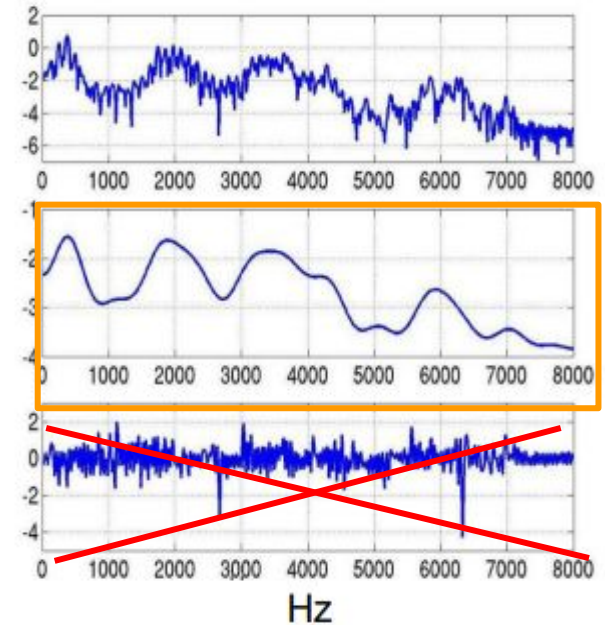
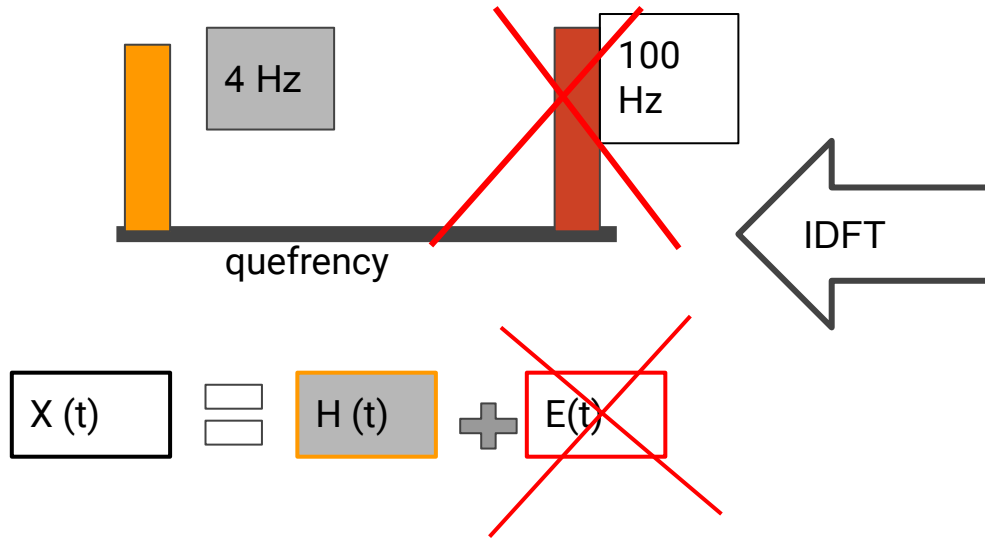
Speech = Convolution of **vocal tract frequency response** with **glottal pulse**

$$x(t) = e(t) * h(t) \rightarrow X(t) = E(t) * H(t) \rightarrow \log(X(t)) = \log(E(t)) + \log(H(t))$$



HZ

The Cepstrum :



Feature :

- The cepstral coefficients do not capture energy
- So we add an energy feature
- Also, we know that speech signal is not constant
- So we want to add the changes in features (the slopes).
- We call these delta features

$$d(t) = \frac{c(t+1) - c(t-1)}{2}$$

$c(t)$ = cepstral value at time t

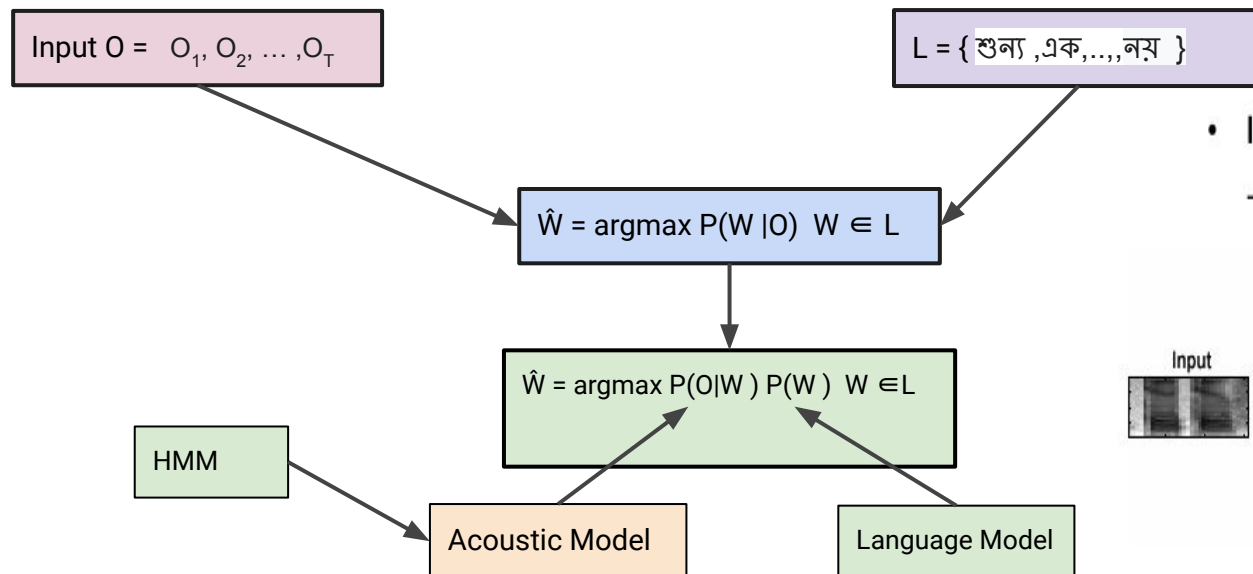
12 MFCC
12 Δ MFCC
12 $\Delta\Delta$ MFCC
1 ENERGY
1 Δ ENERGY
1 $\Delta\Delta$ ENERGY

- We also add double-delta acceleration feature

HMM Architecture

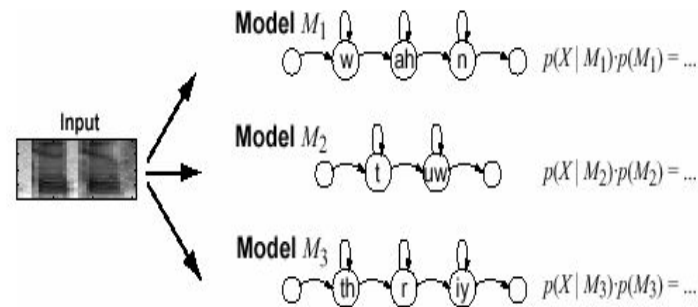
Our main goal :

“What is the most likely word out of all words in the language L given some acoustic input O?”



- Isolated word

- choose best $p(M|X) \propto p(X|M)p(M)$



Overall Architecture :

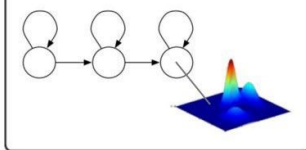
Forward Algorithm

Likelihood : Given an HMM $\lambda = (A, B)$ and a observation sequence O , determine the likelihood $P(O | \lambda)$.

Baum-Welch Algorithm

Learning : Given an observation sequence O and the set of states in the HMM, Learn HMM parameter A and B

Acoustic model



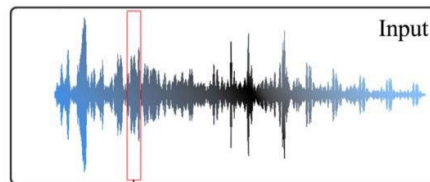
Lexicon

smile s m ay l

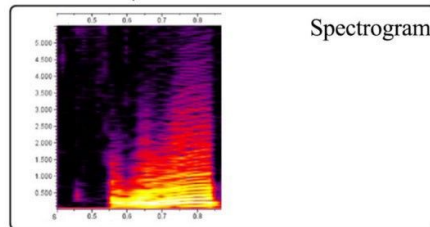
Tutorial on HMM

Link :
https://docs.google.com/presentation/d/1JUBvTYGM1cepgNkQ39oM3zVpAzEWJni_dF51pz5_scg/e/dit?usp=sharing

Input



Spectrogram



39 features

Features extraction

Decoding search

Word sequence

$$W^* = \arg \max_W P(W | X)$$

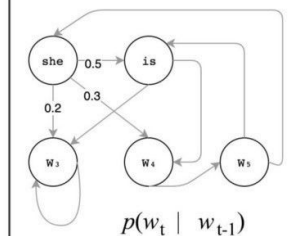
$$W^* = \arg \max_W p(X|W) P(W)$$

word sequence

acoustic model

language model

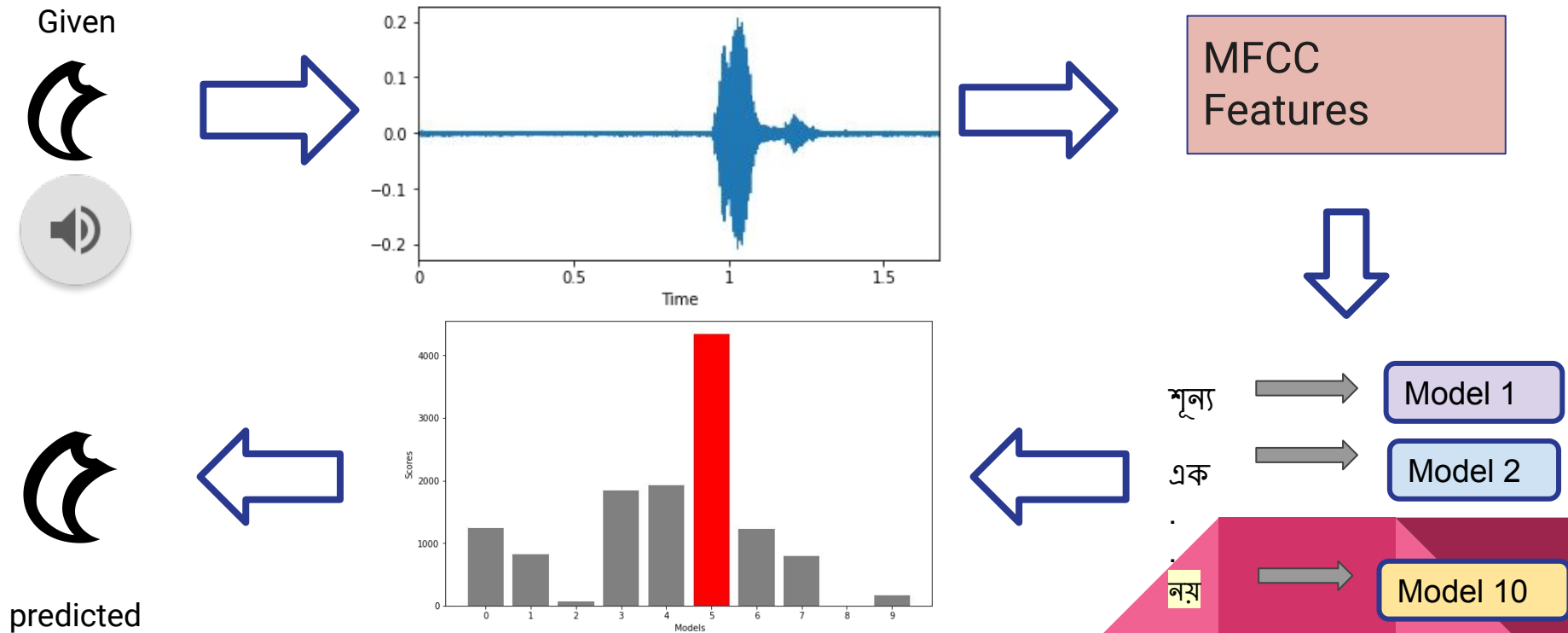
Language model



Viterbi Algorithm:

Given an observation sequence O and an HMM $\lambda = (A, B)$, discover the best hidden sequence Q

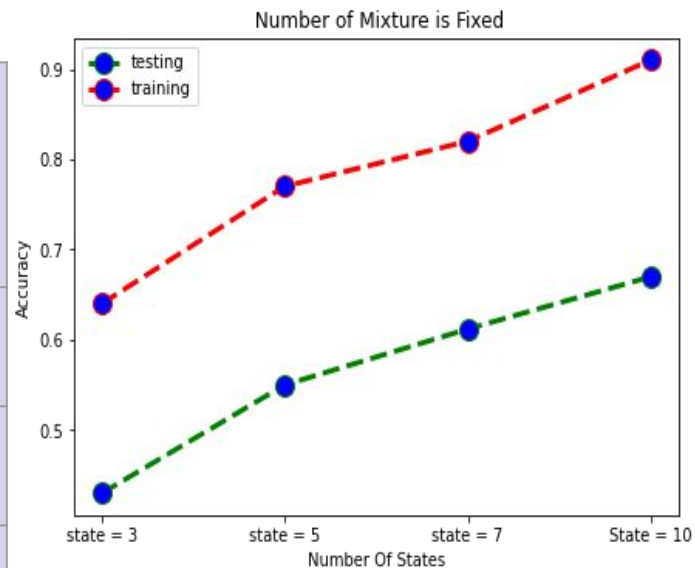
Example :



Result Analysis

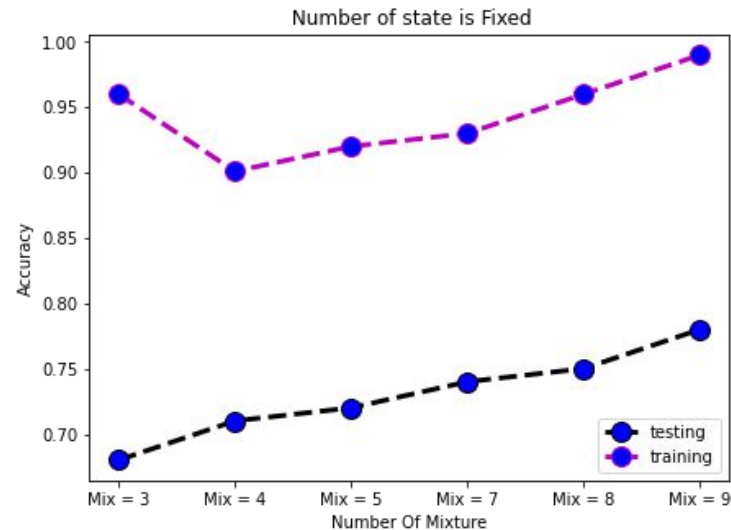
Total Data = 600
Train Data = 478
Test Data = 122

Number Of States	Number Of Mixture	Number Of Iteration	Training Accuracy	Testing Accuracy
3	2	100	64%	43%
5	2	100	77%	55%
7	2	100	82%	61%
10	2	100	91%	67%



Changing Parameters :

Number Of States	Number Of Mixture	Number Of Iteration	Training Accuracy	Testing Accuracy
10	3	100	96%	68%
10	4	100	90%	71%
10	8	100	96%	74%
10	9	400	96%	76%

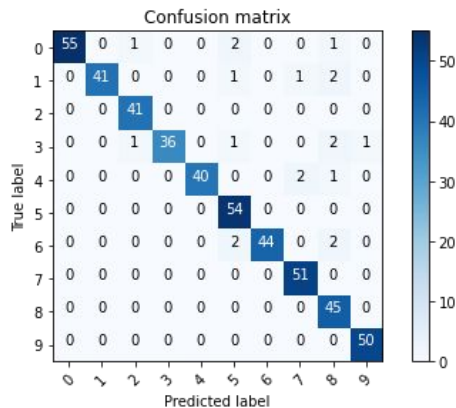


Data = 478

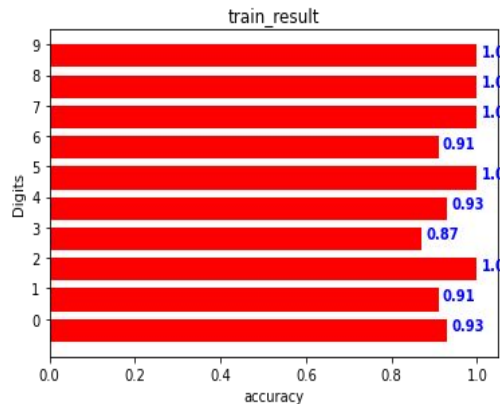
Training Analysis

Accuracy = 96%

Confusion Matrix
for training set



Digit wise
accuracy for
training set

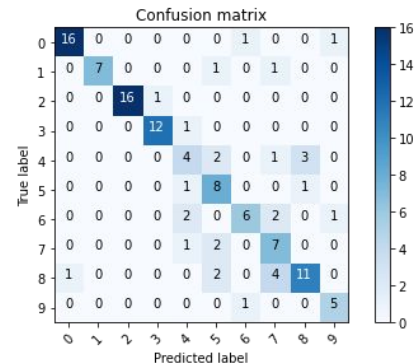


Data = 122

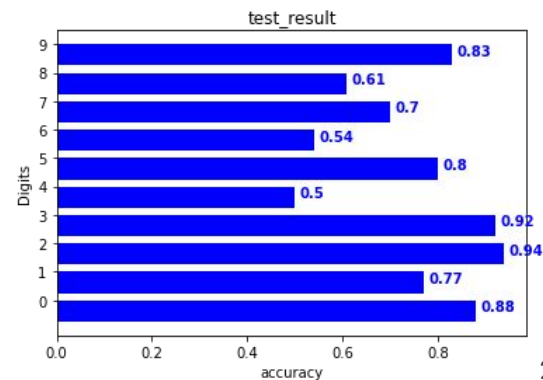
Testing Analysis

Accuracy = 76%

Confusion
Matrix for test
set



Digit wise
accuracy for
test set



Any Questions





Thank
You