“Hidden Markov Models for Speech Recognition”

by B.H. Juang and L.R. Rabiner

Papers We Love Bucharest

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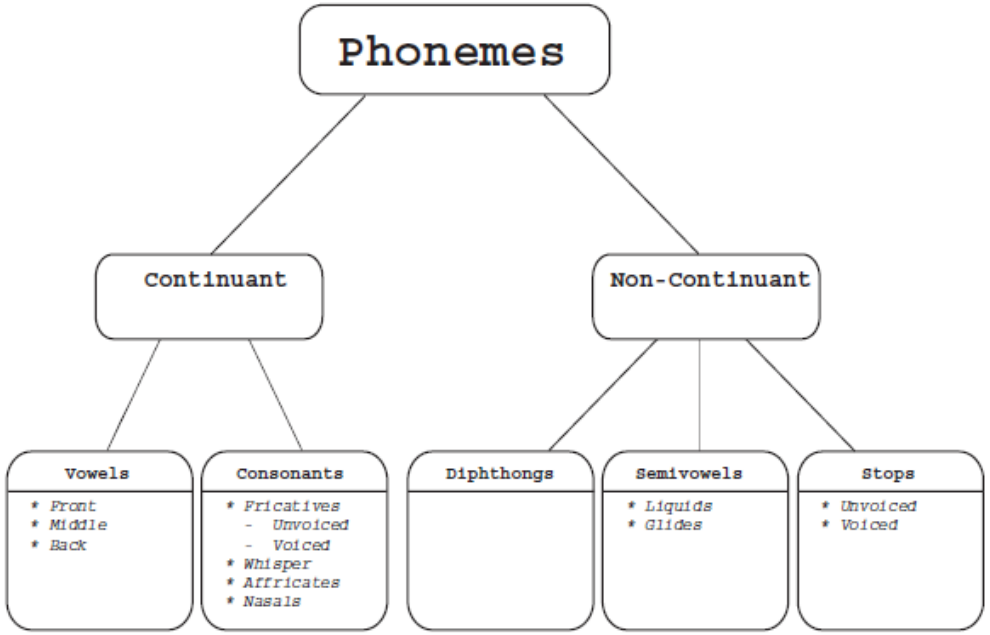
TechHub

The history of Automated Speech Recognition (ASR)

- 1950-1960 Baby Talk (only digits)
- 1970 Speech Recognition Takes Off (1011 words)
- 1980 **Big Revolution** - Prediction based approach
  - Discovery the use of HMM in Speech Recognition
  - See *Automatic Speech Recognition—A Brief History of the Technology Development by B.H. Juang and Lawrence R. Rabiner*
- 1990s: Automatic Speech Recognition Comes to the Masses
- 2000 computer toped out 80% accuracy
- Now Siri, Google Voice, Cortana

Speech signal

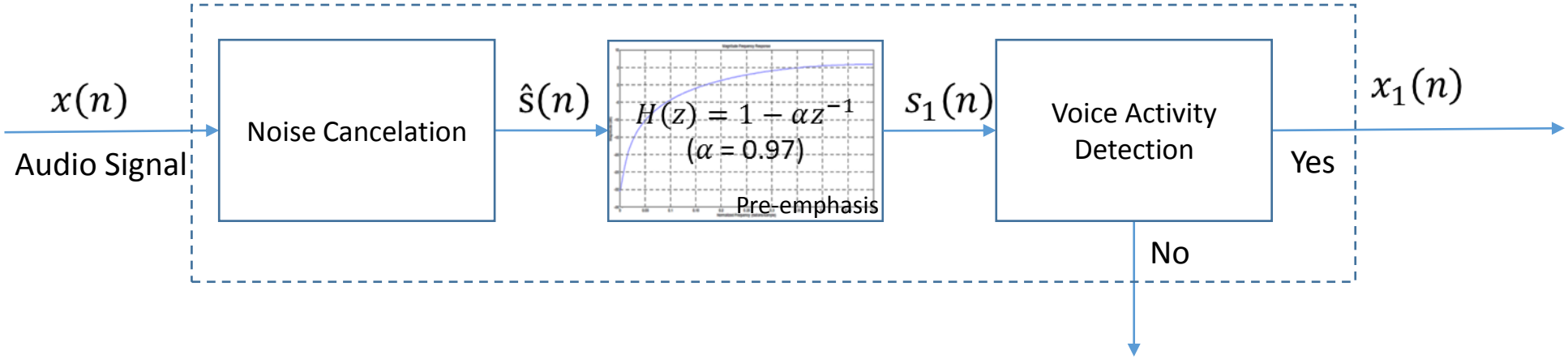
- The voice band is 0-4000 Hz
  - In telephony 300 – 3400 Hz
  - The sampling according to Nyquist –Shannon sampling theorem should be at least 8000 Hz (twice as signal frequency)
- Phoneme
  - The smallest unit of a phonetic language



ASR Model


Audio Signal
Preprocessing
Voice signal
Features Extraction
Features Vector
Detection Engine
Words

ASR Model – Preprocessing



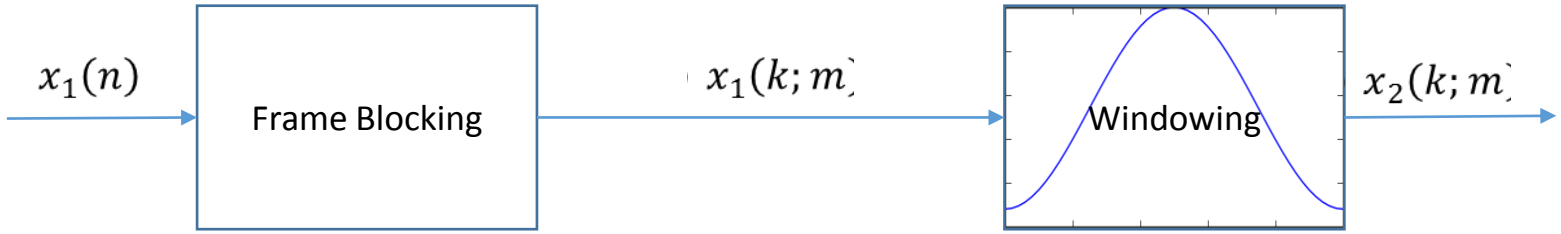
It is assumed that the initial part of the signal (usually 200 ms) is noise and silence.

$$VAD(m) = \begin{cases} 1, & W_{s_1}(m) \geq t_w \\ 0, & W_{s_1}(m) < t_w \end{cases}$$

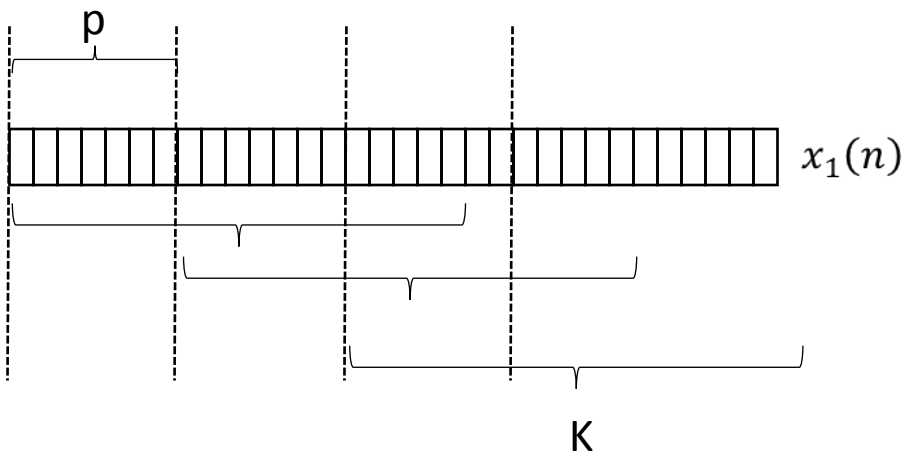
, where t_w is equal with W_{s_1} computed for the first 200 ms.

The W_{s_1} usually depends on signal energy, power, zero crossing rate

ASR Model – Features Extraction. Frame Blocking and Windowing



Each frame is K samples long and overlaps the previous one with P samples



In order to remove discontinuities a Hamming window is applied

$$w(k) = 0.54 - 0.46\cos\left(\frac{2\pi k}{K-1}\right)$$

$$x_2(k;m) = x_1(k;m) \cdot w(k)$$

ASR – Model – Features Extraction

Extract the sensitive information from the signal

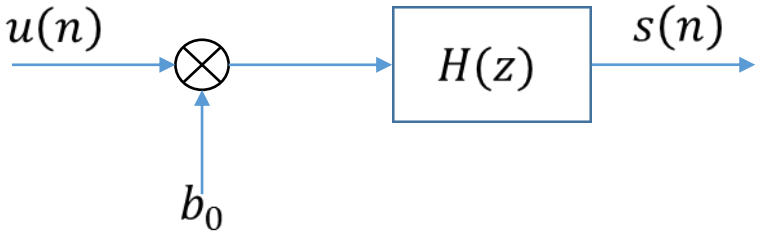
- This information is presented as a double vector

There are three main approaches

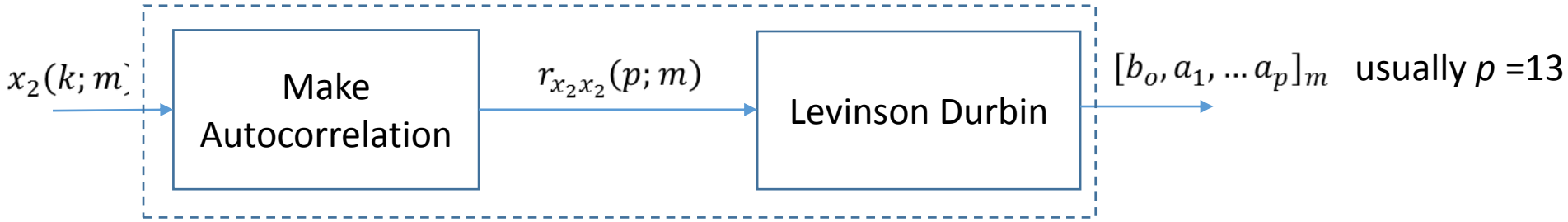
- Linear Prediction Coding (LPC)
- Mel Frequency Cepstral Coefficient (MFCC)
- Perceptual Linear Prediction (PLP)

ASR – Model – Features Extraction - LPC

The idea is to determine the transfer function $H(z)$ of the sound. Given a speech sample at time n, $s(n)$ can be modelled as a linear combination of the past p speech samples.



$$s(n) = b_0 u(n) + \sum_{1}^{\bar{p}} a_i s(n-i)$$



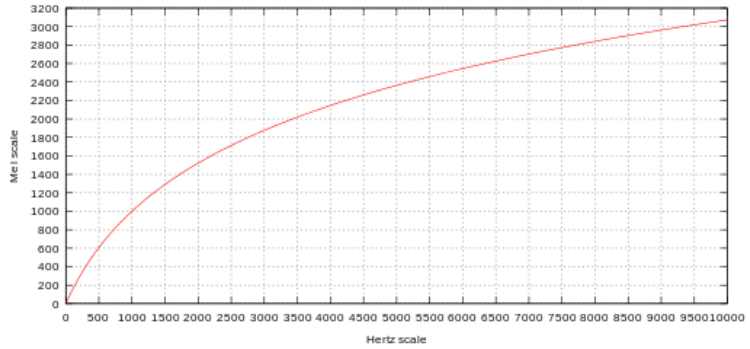
usually p =13

ASR – Model – Features Extraction - MFCC

- Mel scale
  - Is a perceptual scale of pitches judged by listener to be equal in distance from one another
  - Converts f hertz into m mel.

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

$$f = 700 \cdot (10^{\frac{m}{2595}} - 1)$$



Hz	20	160	394	670	1000	1420	1900	2450	3120	4000	5100	6600	9000	14000
mel	0	250	500	750	1000	1250	1500	1750	2000	2250	2500	2750	3000	3250

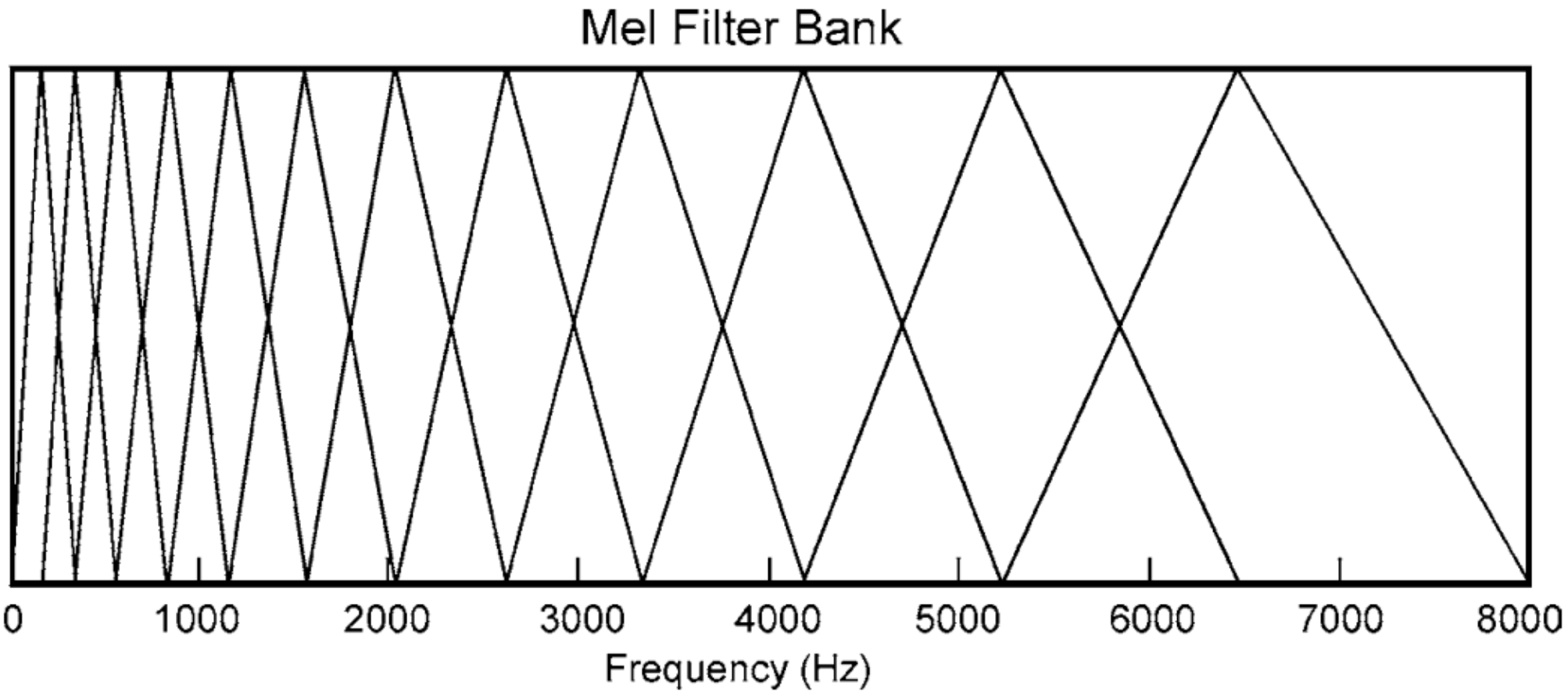
ASR – Model – Features Extraction – MFCC Mel Filter banks

Steps

1. Establish a lower and a higher frequency (typically 0 - 4000 Hz)
2. Convert this interval to a mel interval
3. Divide this interval in equal parts (typically 26 - 40 filter banks)
4. Convert back to hertz
5. Define the filter bank function

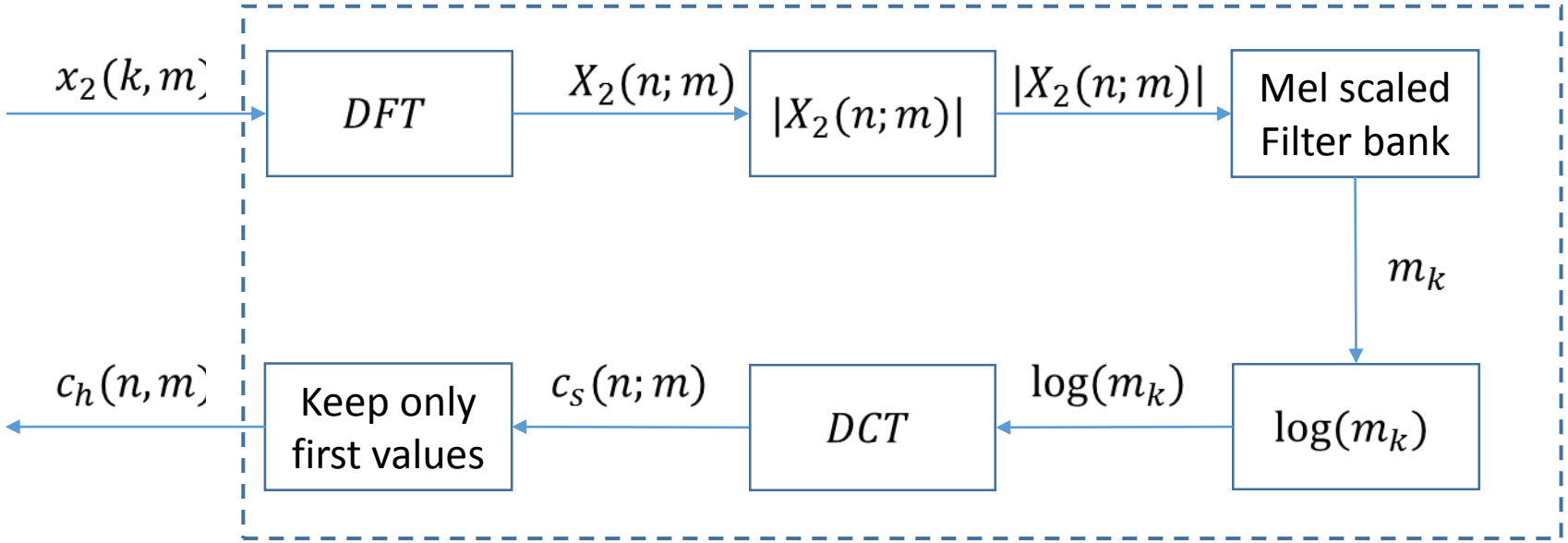
$$H_m(k) = \begin{cases} 0, & k < f(m-1) \\ \dfrac{k - f(m-1)}{f(m) - f(m-1)}, & f(m-1) \le k \le f(m) \\ \dfrac{f(m+1) - k}{f(m+1) - f(m)}, & f(m) \le k \le f(m+1) \\ 0, & k > f(m+1) \end{cases}$$

ASR – Model – Features Extraction – MFCC Mel Filter banks



ASR – Model – Features Extraction - MFCC

Features Extraction Flow



- Signal Energy E, $\Delta c_h(n,m)$and $\Delta\Delta c_h(n,m)$coefficients are usually included in the output

ASR – Model – Detection Engine

- Pattern matching
- Hidden Markov Models
- Neural Networks

Markov Model

Markov Model is used to model randomly changing systems where future states depend only on the present state.

$$X = [X_1 \dots X_N] \; X_t \in S = \{s_1, s_2, \dots, s_N\}$$

X is called a *Markov Process*

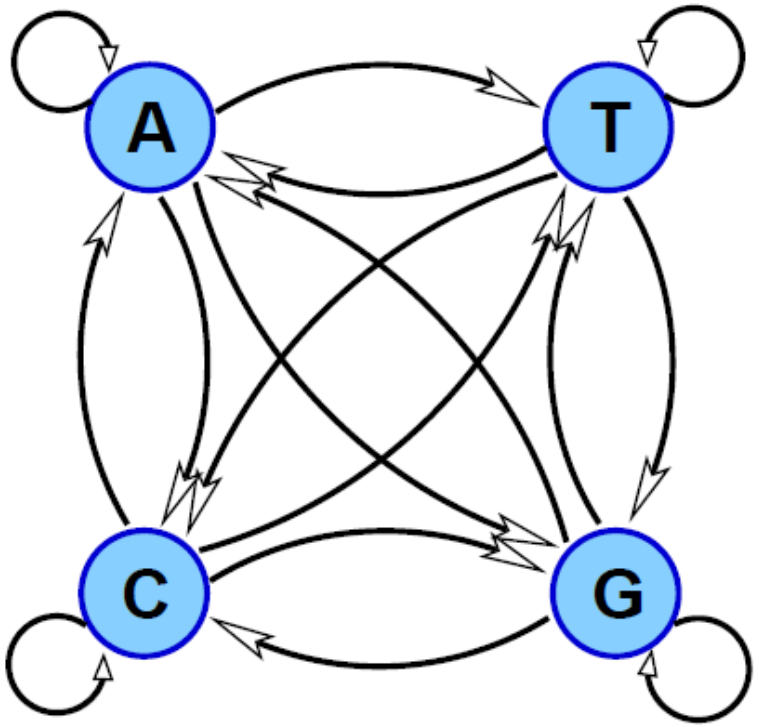
S = set of states

Π = initial state probabilities:

$\pi_i = P(X_1 = s_i); \sum_1^N \pi_i = 1$

A = transition probabilities:

$a_{ij} = P(X_{t+1} = s_j | X_t = s_i); \sum_1^N a_{ij} = 1 \; \forall i$



Hidden Markov Model

V = output alphabet = $\{v_1, v_2, \ldots, v_m\}$

B = output emission probabilities:

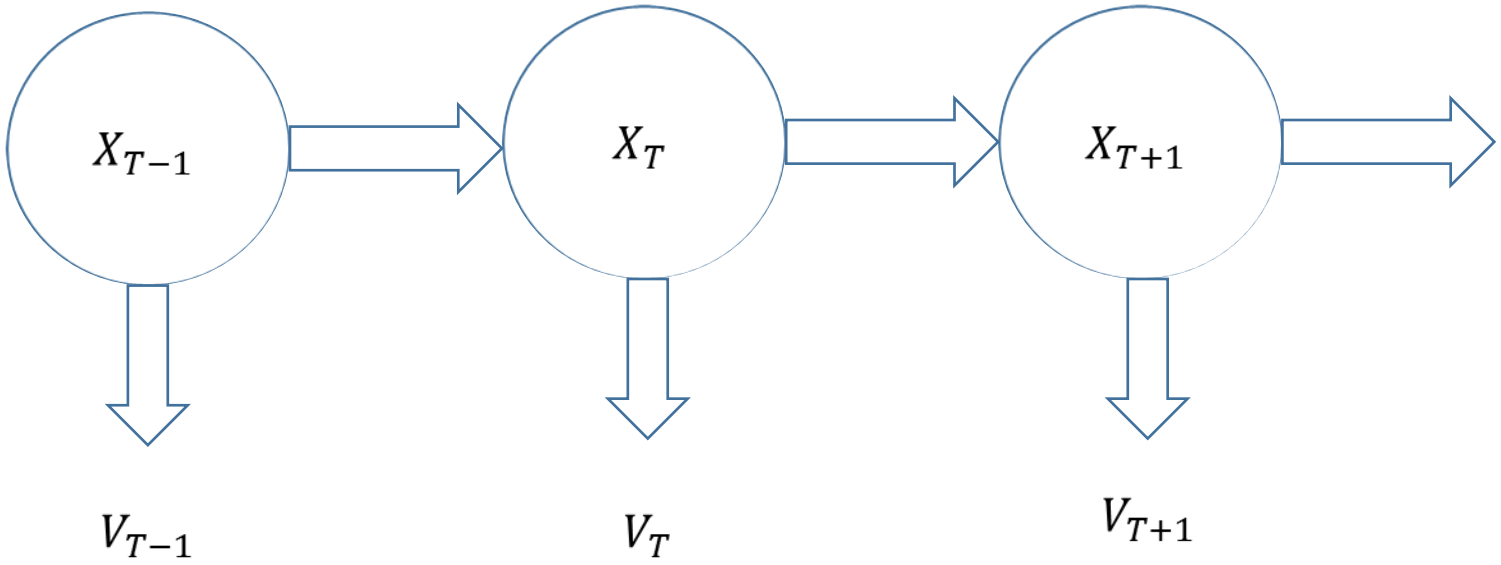
$$b_{ij} = P(O_t = v | X_t = s_i, X_{t+1} = s_j)$$

Notice that B doesn't depend on time.

The states of the system are hidden and we observe only the emissions.

Hidden Markov Model

t = 1;
start in state s_1 with probability π_i (i.e., $X_1 = i$);
forever do
move from state s_i to state s_j with prob. a_{ij} (i.e., $X_{t+1} = j$);
emit observation symbol O_t = v with probability b_{ij};
t = t + 1;



Hidden Markov Model

Questions

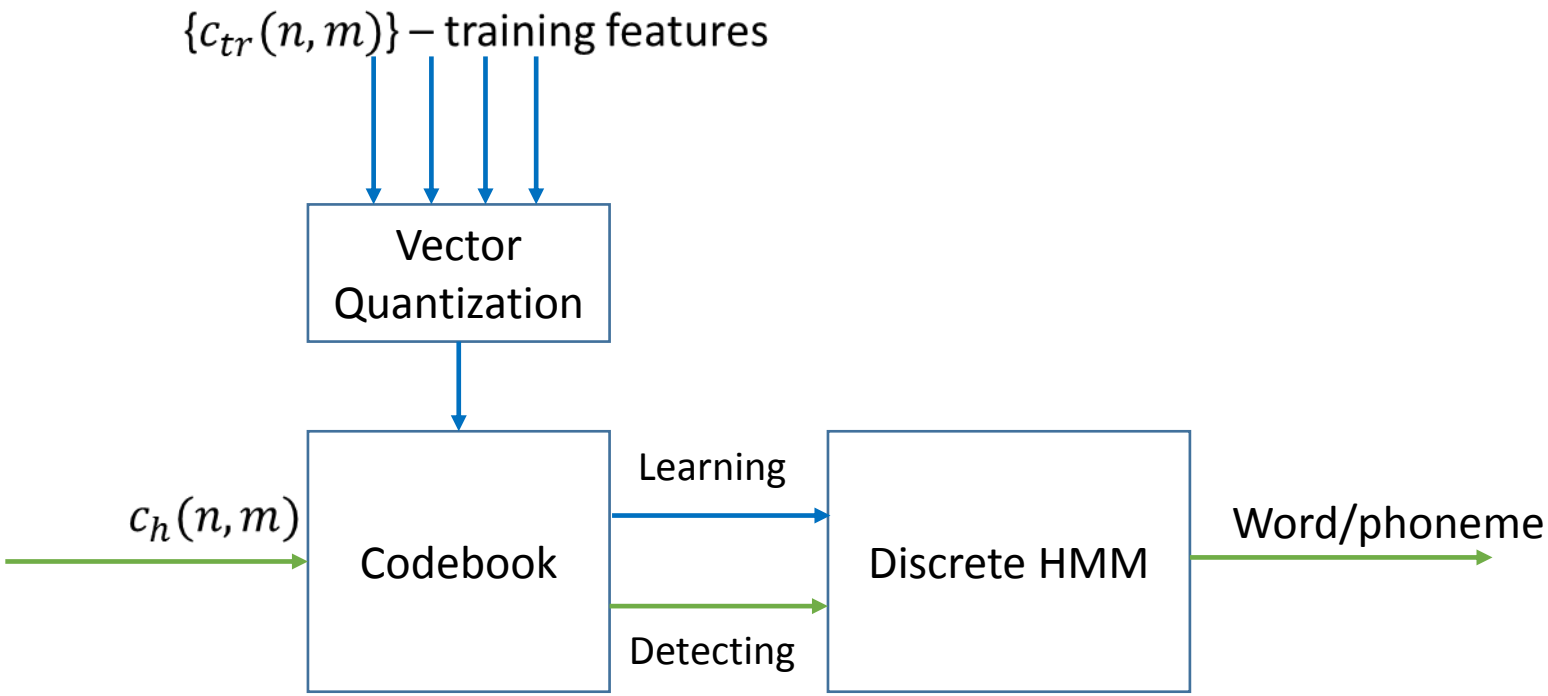
1. Given the current and last *t-i* emissions, what is the probability of the system beeing in state X_t?
2. Knowing the current state X_t what is the probability to observe the following *n* emissions $V_{t+1:n}$?
3. Knowing the emissions sequence what is the most likely states sequence?
4. Knowing the emissions sequence $V_{1:n}$ what is the probability of the system to be in state X_k where k<n?

Hidden Markov Model

For each question there is a separated dynamic programming algorithm.

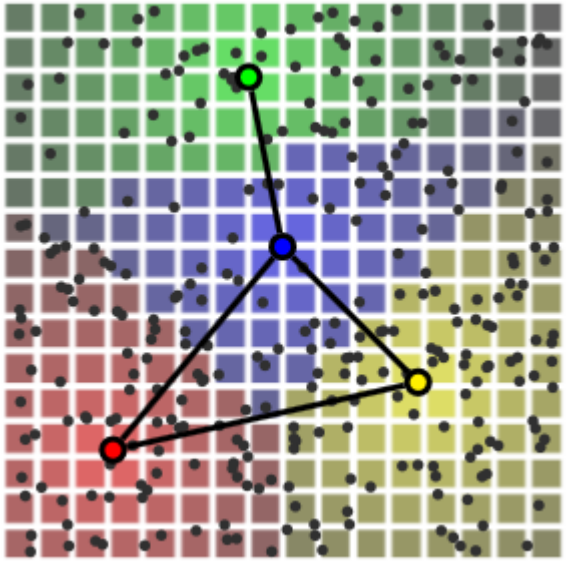
1. Forward Algorithm (recursive computation)
2. Backward Algorithm (recursive computation)
3. Viterbi algorithm
4. Forward – Backward Algorithm based on 1 and 2
5. Baum-Welch Algorithm based on 4

ASR – Model – HMM Detection Engine



ASR – Model – HMM Detection Engine Vector Quantization

- Apply vector quantization and define the Codebook
  - Usually the length of the Codebook is several hundreds
  - Apply K-Means algorithm



ASR – Model – HMM Detection Engine Training

Given a HMM $\lambda = (N, A, B)$

Record samples for a specific word or phoneme.

Using the quantized features extracted train the model using Viterbi or Baum-Welch.

- quantized features play the role of an Observations Sequence

- usually the number of training samples is 10. The samples can be grouped in two categories (man and woman).

Label (tag) the model with the corresponding word or phoneme.

ASR – Model – HMM Detection Engine Detection

Given a quantized features sequence iterates throw each existing HMM and find out which has the maximum probability.

Detection properties

- Detection is very fast (also easy to parallelize)
- Accuracy 80 % in the base implementation
- Limitations – doesn’t take in consideration observation duration

ASR – Model – HMM Detection Engine Demo

- https://github.com/AdamStefan/Speech-Recognition