

**CS 2710 Foundations of AI**  
**Lecture 27**

**Applied AI topics**

**Milos Hauskrecht**

[milos@cs.pitt.edu](mailto:milos@cs.pitt.edu)

5329 Sennott Square

---

CS 2710 Foundations of AI

**Topics in AI**

**Five main areas:**

- **Problem solving and search**
- **Logic and knowledge representations**
- **Planning**
- **Uncertainty**
- **Learning**

**Other topics:**

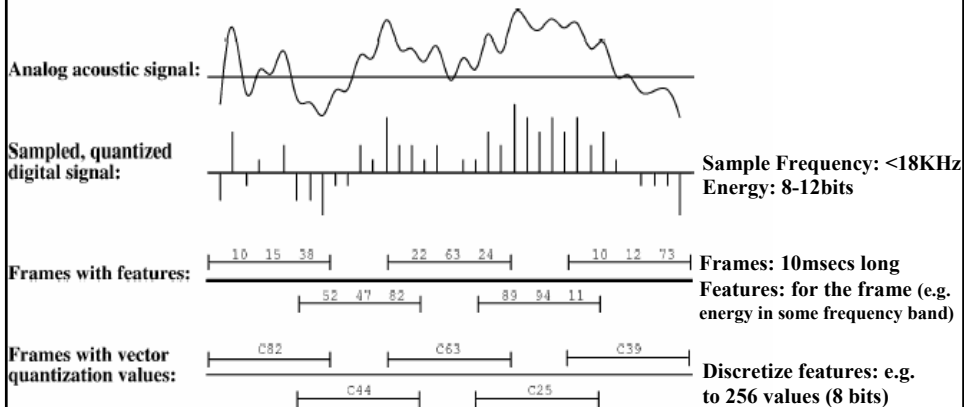
- **AI programming languages**
- **Speech recognition**
- **Natural language processing**
- **Image understanding**
- **Robotics**

---

CS 2710 Foundations of AI

## Speech recognition

- **Objective:** take acoustic signal and convert it to text



CS 2710 Foundations of AI

## Speech recognition

- We want to determine the sequence of words that is most probable given the input signal

$$P(\text{wordseq} = \mathbf{w} \mid \text{signal} = \mathbf{s})$$

- It is easier to define an **acoustic model** that relates:

$$P(\text{signal} = \mathbf{s} \mid \text{wordseq} = \mathbf{w})$$

- This is like a diagnosis problem, we can use the Bayes rule:

$$P(\text{wordseq} = \mathbf{w} \mid \text{signal} = \mathbf{s}) = \frac{P(\text{signal} = \mathbf{s} \mid \text{wordseq} = \mathbf{w})P(\text{wordseq} = \mathbf{w})}{P(\text{signal} = \mathbf{s})}$$

- Assume we have multiple possible word sequences:

$$\mathbf{w}^1, \mathbf{w}^2, \dots, \mathbf{w}^k$$

- **The best word sequence:**

$$\operatorname{argmax}_{\mathbf{w}^i} P(\text{signal} = \mathbf{s} \mid \text{wordseq} = \mathbf{w}^i)P(\text{wordseq} = \mathbf{w}^i)$$

CS 2710 Foundations of AI

## Speech recognition

- We need to define:  
 $P(\text{signal}=\mathbf{s} \mid \text{wordseq}=\mathbf{w})$  and  $P(\text{wordseq}=\mathbf{w})$   
for all possible word and signal sequences
- **Defining the probability:**  $P(\text{wordseq}=\mathbf{w})$      $\mathbf{w} = w_1w_2 \dots w_n$   
 $P(\text{wordseq} = w_1w_2 \dots w_n) = P(w_1)P(w_2 \mid w_1) \dots P(w_n \mid w_1w_2 \dots, w_{n-1})$ 
  - By the **chain rule**
- **Simplifications:**
  - **Unigram model:** a probability of each word is independent of the previous word  
 $P(\text{wordseq} = w_1w_2 \dots w_n) = P(w_1)P(w_2)P(w_3) \dots P(w_n)$
  - **Bigram model:** only the previous word matters  
 $P(\text{wordseq} = w_1w_2 \dots w_n) = P(w_1)P(w_2 \mid w_1)P(w_3 \mid w_2) \dots P(w_n \mid w_{n-1})$

CS 2710 Foundations of AI

## Speech recognition

- **Defining the probability:**  $P(\text{signal}=\mathbf{s} \mid \text{wordseq}=\mathbf{w})$   
 $\mathbf{s} = s_1s_2s_3 \dots s_m$      $\mathbf{w} = w_1w_2 \dots w_n$
  - **Two simplifications:**
    1. **Define signal signatures for individual words**  
 $P(\mathbf{s} = s_1s_2 \dots s_j \mid \text{word} = w_i)$
    2. **Divide the acoustic word models into a sequence of phones and define signal signature models for phones**  
 $P(\mathbf{p} = p_1p_2 \dots p_u \mid \text{word} = w_i)$   
 $P(\mathbf{s} = s_1s_2 \dots s_r \mid \text{phone} = p_q)$
- Conditional probabilities of sequences modeled most often as:**
- **Hidden Markov Models (HMMs)**

CS 2710 Foundations of AI

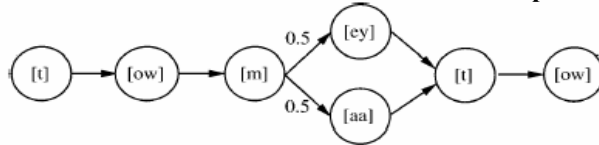
## Speech recognition

**HMM models of words**  $P(\mathbf{p} = p_1 p_2 \dots p_u \mid \text{word} = w_i)$

- **Example: word:** tomato

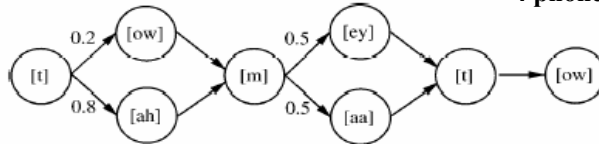
Word model with dialect variation:

2 phones sequences



Word model with coarticulation and dialect variations:

4 phones sequences



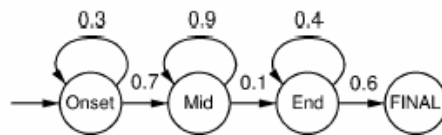
## Speech recognition

**HMM model of phones**  $P(\mathbf{s} = s_1 s_2 \dots s_r \mid \text{phone} = p_q)$

**Example:**

Phone HMM for [m]:

Many possible feature sequences:



C1 C4 C6

C1 C1 C4 C6

C1 C1 C5 C4 C6

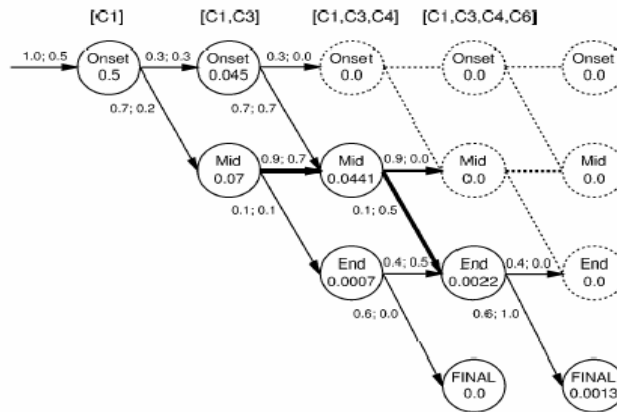
...

Output probabilities for the phone HMM:

Onset:	Mid:	End:
C1: 0.5	C3: 0.2	C4: 0.1
C2: 0.2	C4: 0.7	C6: 0.5
C3: 0.3	C5: 0.1	C7: 0.4

## Speech recognition

- **Finding the most probable path** through an HMM for [m]
- **Example:** sequence: C1 C3 C4 C6



CS 2710 Foundations of AI

## Natural language processing

**Goal:** Analyze and interpret the text in the natural language

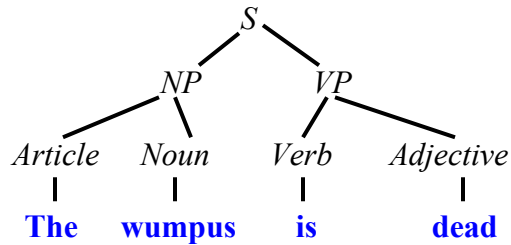
- **Input:** text sentences.
  - Speech recognition system
  - Optical character recognition (OCR)
  - Documents in the electronic form
- **Output:**
  - Knowledge extracted from the text that supports various inferences
- **Processing (multi-step process):**
  - Syntactic interpretation (parsing)
  - Semantic interpretation
  - Disambiguation & Incorporation

CS 2710 Foundations of AI

## Natural language processing

### Syntactic interpretation (parsing):

- **Input:** a sentence
- **Output:** a parse tree
- Uses grammar models for parsing the sentence to phrases and terminal symbols
- **Example:** ‘The wumpus is dead’



- Sometimes we have more than one possible parse. **Stochastic grammars** (quantify the goodness of possible parses)

CS 2710 Foundations of AI

## Natural language processing

- **Semantic interpretation:**
  - **input:** a parse tree
  - **output:** a set of meanings, e.g. in First order logic (FOL)
- **Example:** ‘The wumpus is dead’
  - Gives two possible semantic interpretations:
    - $\neg Alive(Wumpus, Now)$
    - $Tired(Wumpus, Now)$
- **Disambiguation:**
  - chooses the most probable interpretation
- **Incorporation:**
  - The extracted knowledge is checked for consistency against other pieces of knowledge before it is incorporated into the KB

CS 2710 Foundations of AI

## Image processing and vision

- **Classic image processing problem:**
  - **Analysis of image and extraction of information from the image**
  - **Can be used in many applications:**
    - Scene analysis
    - Manipulation and navigation tasks
    - Image retrieval
- **Other image processing problems:**
  - **Image enhancement:** degraded image should be improved to restore particular features
  - **Storage and Compression:** Large amounts of data need to be archived or transmitted
  - **Visualization**

## Image processing

### Image is defined by

- a **light intensity function** over the **image plane**  
(Continuous) image is typically **discretized**
- **Image plane is discretized into:**
  - Pixels arranged on the rectangular grid
  - Resolution of the grid determines the spatial quality of the discretization
- **Light intensity values are discretized into:**
  - Integers values in some interval
- **Typical (black and white) image input:**
  - 512x512 pixels
  - Light intensity: 8 bits – 512 types of gray

## Image processing

Analysis of image and extraction of information from the image

- **Segmentation:**

- Division of the image to meaningful entities in the scene
- Relies heavily on edge detection algorithms



---

CS 2710 Foundations of AI

## Image processing and vision

**Analysis of image and extraction of information from the image**

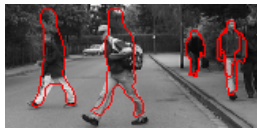
- To recognize (identify) the object from the image we need to compare it with the class pattern
- **Problem:** The position, orientation and the scale of the object in the scene may vary
- **Solution: Use a set of basic transformations:**
  - **scaling,**
  - **translation,**
  - **rotation of the object**
  - Transformations are relatively easy for 2D objects, much harder for 3-D objects
- **Other problems:** light sources and shadows

---

CS 2710 Foundations of AI

## Image processing and vision

- **More complex task:** analysis of a sequence of related images (videos)
- **Image registration:** the process of measuring visual motion between images.
- **When this is useful:**
  - Video - commercial skip
  - Detection and tracking of objects in the real world



## AI programming languages

- **Focus on symbolic processing**

### Special AI Languages:

- LISP
- Prolog
- Smalltalk