## CS344: Introduction to Artificial

## Intelligence <br> (associated lab: CS386)

Pushpak Bhattacharyya<br>CSE Dept.,

IIT Bombay
Lecture 6-7: Hidden Markov Model
$18^{\text {th }}$ and $20^{\text {th }}$ Jan, 2011

## Observations leading to why probability is needed

- Many intelligence tasks are sequence labeling tasks
- Tasks carried out in layers
- Within a layer, there are limited windows of information
- This naturally calls for strategies for dealing with uncertainty
- Probability and Markov process give a way


## "I went with my friend to the bank to withdraw some money, but was disappointed to find it closed"



## HMM

## A Motivating Example

Colored Ball choosing

Urn 1
\# of Red = 30
\# of Green $=50$
\# of Blue $=20$

Urn 2
\# of Red = 10
\# of Green $=40$
\# of Blue = 50

Urn 3
\# of Red =60
\# of Green $=10$
\# of Blue $=30$

Probability of transition to another Urn after picking a ball:

|  | $\mathrm{U}_{1}$ | $\mathrm{U}_{2}$ | $\mathrm{U}_{3}$ |
| :--- | :--- | :--- | :--- |
| $\mathrm{U}_{1}$ | 0.1 | 0.4 | 0.5 |
| $\mathrm{U}_{2}$ | 0.6 | 0.2 | 0.2 |
| $\mathrm{U}_{3}$ | 0.3 | 0.4 | 0.3 |

## Example (contd.)



and |  | $R$ | $G$ | $B$ |
| :--- | :--- | :--- | :--- |
| $U_{1}$ | 0.3 | 0.5 | 0.2 |
| $U_{2}$ | 0.1 | 0.4 | 0.5 |
| $U_{3}$ | 0.6 | 0.1 | 0.3 |

Observation : RRGGBRGR

State Sequence : ??

Not so Easily Computable.

## Diagrammatic representation (1/2)



## Diagrammatic representation (2/2)



## Example (contd.)

- Here :
- $S=\{U 1, U 2, U 3\} \quad A=$
- $V=\{R, G, B\}$
- For observation:
- $\mathrm{O}=\left\{\mathrm{o}_{1} \ldots \mathrm{o}_{n}\right\}$
- And State sequence
- $\mathrm{Q}=\left\{\mathrm{q}_{1} \ldots \mathrm{q}_{\mathrm{n}}\right\} \quad \mathrm{B}=$
- $\Pi$ ist $_{\pi_{i}=P\left(q_{1}=U_{i}\right)}$

|  | $\mathrm{U}_{1}$ | $\mathrm{U}_{2}$ | $\mathrm{U}_{3}$ |
| :--- | :--- | :--- | :--- |
| $\mathrm{U}_{1}$ | 0.1 | 0.4 | 0.5 |
| $\mathrm{U}_{2}$ | 0.6 | 0.2 | 0.2 |
| $\mathrm{U}_{3}$ | 0.3 | 0.4 | 0.3 |
|  | $R$ | $G$ | $B$ |
| $\mathrm{U}_{1}$ | 0.3 | 0.5 | 0.2 |
| $\mathrm{U}_{2}$ | 0.1 | 0.4 | 0.5 |
| $\mathrm{U}_{3}$ | 0.6 | 0.1 | 0.3 |

## Observations and states

| $\mathrm{O}_{1}$ | $\mathrm{O}_{2}$ | $\mathrm{O}_{3}$ | $\mathrm{O}_{4}$ | $\mathrm{O}_{5}$ | $\mathrm{O}_{6}$ | $\mathrm{O}_{7}$ | $\mathrm{O}_{8}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| R | R | G | G | B | R | G | R |

$\begin{array}{llllllll}\text { OBS: } & R & R & G & G & B & R & G \\ R \\ \text { State: } & S_{1} & S_{2} & S_{3} & S_{4} & S_{5} & S_{6} & S_{7} \\ S_{8}\end{array}$
$S_{i}=U_{1} / U_{2} / U_{3}$; A particular state
S : State sequence
O: Observation sequence
S* = "best" possible state (urn) sequence
Goal: Maximize $\mathrm{P}\left(\mathrm{S}^{*} \mid 0\right)$ by choosing "best" S

## Goal

- Maximize $P(S \mid O)$ where $S$ is the State Sequence and $O$ is the Observation Sequence

$$
S^{*}=\arg \max _{S}(P(S \mid O))
$$

## False Start

|  | $\mathrm{O}_{1}$ | $\mathrm{O}_{2}$ | $\mathrm{O}_{3}$ | $\mathrm{O}_{4}$ | $\mathrm{O}_{5}$ | $\mathrm{O}_{6}$ | $\mathrm{O}_{7}$ | $\mathrm{O}_{8}$ |
| :--- | :---: | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| OBS: | R | R | G | G | B | R | G | R |
| State: | $\mathrm{S}_{1}$ | $\mathrm{~S}_{2}$ | $\mathrm{~S}_{3}$ | $\mathrm{~S}_{4}$ | $\mathrm{~S}_{5}$ | $\mathrm{~S}_{6}$ | $\mathrm{~S}_{7}$ | $\mathrm{~S}_{8}$ |
| $P(S \mid O)=$ | $P\left(S_{1-8} \mid O_{1-8}\right)$ |  |  |  |  |  |  |  |
| $P(S \mid O)=$ | $P\left(S_{1} \mid O\right) . P\left(S_{2} \mid S_{1}, O\right) . P\left(S_{3} \mid S_{1-2, O)} \ldots P\left(S_{8} \mid S_{1-7, O}\right)\right.$ |  |  |  |  |  |  |  |

By Markov Assumption (a state depends only on the previous state)

$$
P(S \mid O)=P\left(S_{1} \mid O\right) \cdot P\left(S_{2} \mid S_{1}, O\right) \cdot P\left(S_{3} \mid S_{2}, O\right) \ldots P\left(S_{8} \mid S_{7}, O\right)
$$

## Baye's Theorem <br> $P(A \mid B)=P(A) \cdot P(B \mid A) / P(B)$

$\mathrm{P}(\mathrm{A})$-: Prior
$\mathrm{P}(\mathrm{B} \mid \mathrm{A})$-: Likelihood
$\operatorname{argmax}_{f} P(S \mid O)=\operatorname{argmax}_{S} P(S) \cdot P(O \mid S)$

## State Transitions Probability

$$
\begin{aligned}
& P(S)=P\left(S_{1-8}\right) \\
& P(S)=P\left(S_{1}\right) P\left(S_{2} \mid S_{1}\right) P\left(S_{3} \mid S_{1-2}\right) P\left(S_{4} \mid S_{1-3}\right) . . P\left(S_{8} \mid S_{1-7}\right)
\end{aligned}
$$

By Markov Assumption (k=1)

$$
P(S)=P\left(S_{1}\right) P\left(S_{2} \mid S_{1}\right) P\left(S_{3} \mid S_{2}\right) P\left(S_{4} \mid S_{3}\right) . . P\left(S_{8} \mid S_{7}\right)
$$

## Observation Sequence probability

$$
P(O \mid S)=P\left(O_{1} \mid S_{1-8}\right) \cdot P\left(O_{2} \mid O_{1}, S_{1-8}\right) P\left(O_{3} \mid O_{1-2}, S_{1-8}\right) . . P\left(O_{8} \mid O_{1-7}, S_{1-8}\right)
$$

Assumption that ball drawn depends only on the Urn chosen
$P(O \mid S)=P\left(O_{1} \mid S_{1}\right) \cdot P\left(O_{2} \mid S_{2}\right) \cdot P\left(O_{3} \mid S_{3}\right) \ldots P\left(O_{8} \mid S_{8}\right)$
$P(S \mid O)=P(S) \cdot P(O \mid S)$
$P(S \mid O)=P\left(S_{1}\right) \cdot P\left(S_{2} \mid S_{1}\right) \cdot P\left(S_{3} \mid S_{2}\right) \cdot P\left(S_{4} \mid S_{3}\right) \ldots P\left(S_{8} \mid S_{7}\right)$.
$P\left(O_{1} \mid S_{1}\right) \cdot P\left(O_{2} \mid S_{2}\right) \cdot P\left(O_{3} \mid S_{3}\right) \ldots P\left(O_{8} \mid S_{8}\right)$

## Grouping terms

|  | $\mathrm{O}_{0}$ | $\mathrm{O}_{1}$ | $\mathrm{O}_{2}$ | $\mathrm{O}_{3}$ | $\mathrm{O}_{4}$ | $\mathrm{O}_{5}$ | $\mathrm{O}_{6}$ | $\mathrm{O}_{7}$ | $\mathrm{O}_{8}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
|  |  |  |  |  |  |  |  |  |  |
| Obs: $\varepsilon$ | R | R | G | G | B | R | G | R |  |
| State: $\mathrm{S}_{0}$ | $\mathrm{~S}_{1}$ | $\mathrm{~S}_{2}$ | $\mathrm{~S}_{3}$ | $\mathrm{~S}_{4}$ | $\mathrm{~S}_{5}$ | $\mathrm{~S}_{6}$ | $\mathrm{~S}_{7}$ | $\mathrm{~S}_{8}$ | $\mathrm{~S}_{9}$ |

P(S).P(O|S)
$=\left[P\left(\mathrm{O}_{0} \mid \mathrm{S}_{0}\right) \cdot \mathrm{P}\left(\mathrm{S}_{1} \mid \mathrm{S}_{0}\right)\right]$. $\left[P\left(\mathrm{O}_{1} \mid \mathrm{S}_{1}\right) . \quad \mathrm{P}\left(\mathrm{S}_{2} \mid \mathrm{S}_{1}\right)\right]$. $\left[P\left(\mathrm{O}_{2} \mid \mathrm{S}_{2}\right) . \quad \mathrm{P}\left(\mathrm{S}_{3} \mid \mathrm{S}_{2}\right)\right]$. $\left[P\left(\mathrm{O}_{3} \mid \mathrm{S}_{3}\right) \cdot \mathrm{P}\left(\mathrm{S}_{4} \mid \mathrm{S}_{3}\right)\right]$. $\left[P\left(\mathrm{O}_{4} \mid \mathrm{S}_{4}\right) \cdot \mathrm{P}\left(\mathrm{S}_{5} \mid \mathrm{S}_{4}\right)\right]$. $\left[P\left(O_{5} \mid S_{5}\right) \cdot P\left(S_{6} \mid S_{5}\right)\right]$. $\left[P\left(\mathrm{O}_{6} \mid \mathrm{S}_{6}\right) \cdot \mathrm{P}\left(\mathrm{S}_{7} \mid \mathrm{S}_{6}\right)\right]$. $\left[\mathrm{P}\left(\mathrm{O}_{7} \mid \mathrm{S}_{7}\right) \cdot \mathrm{P}\left(\mathrm{S}_{8} \mid \mathrm{S}_{7}\right)\right]$. $\left[P\left(\mathrm{O}_{8} \mid \mathrm{S}_{8}\right) \cdot \mathrm{P}\left(\mathrm{S}_{9} \mid \mathrm{S}_{8}\right)\right]$.

We introduce the states $\mathrm{S}_{0}$ and $\mathrm{S}_{9}$ as initial and final states respectively.
After $\mathrm{S}_{8}$ the next state is $\mathrm{S}_{9}$ with probability 1, i.e., $P\left(S_{9} \mid S_{8}\right)=1$
$\mathrm{O}_{0}$ is $\varepsilon$-transition

## Introducing useful notation

|  | $\mathrm{O}_{0}$ | $\mathrm{O}_{1}$ | $\mathrm{O}_{2}$ | $\mathrm{O}_{3}$ | $\mathrm{O}_{4}$ | $\mathrm{O}_{5}$ | $\mathrm{O}_{6}$ | $\mathrm{O}_{7}$ | $\mathrm{O}_{8}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
|  |  |  |  |  |  |  |  |  |  |
| Obs: $\varepsilon$ | R | R | G | G | B | R | G | R |  |
| State: $\mathrm{S}_{0}$ | $\mathrm{~S}_{1}$ | $\mathrm{~S}_{2}$ | $\mathrm{~S}_{3}$ | $\mathrm{~S}_{4}$ | $\mathrm{~S}_{5}$ | $\mathrm{~S}_{6}$ | $\mathrm{~S}_{7}$ | $\mathrm{~S}_{8}$ | $\mathrm{~S}_{9}$ |



## Probabilistic FSM



The question here is:
"what is the most likely state sequence given the output sequence seen"

## Developing the tree



## Tree structure contd...



The problem being addressed by this tree is $S^{*}=\arg \max P\left(S \mid a_{1}-a_{2}-a_{1}-a_{2, \mu}\right)$ $\mathrm{a} 1-\mathrm{a} 2-\mathrm{a} 1-\mathrm{a} 2$ is the output sequence and $\mu$ the model or the machine

Path found:
(working backward)


Problem statement: Find the best possible sequence

$$
S^{*}=\arg \max P(S \mid O, \mu)
$$

$s$
where, $S \rightarrow$ State Seq, $O \rightarrow$ Output Seq, $\mu \rightarrow$ Model or Machine


T is defined as $P\left(S_{i} \xrightarrow{a_{k}} S_{j}\right) \quad \forall i, j, k$

