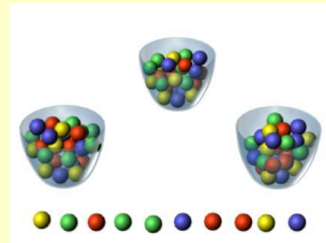
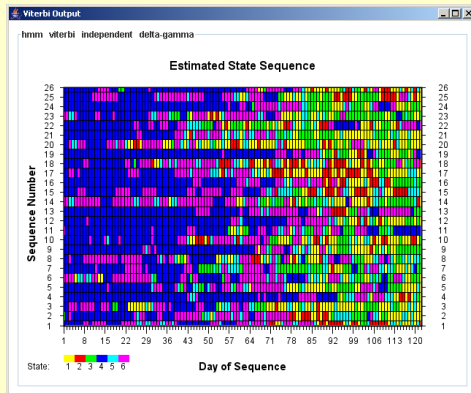


## Hidden Markov Model

- The simplest dynamic Bayesian network
- Application in speech recognition, handwriting, gesture recognition...



## Hidden Markov Model

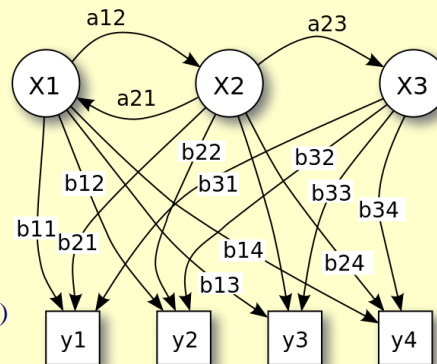
- In a room that is not visible to an observer there is a genie. The room contains urns  $X_1, X_2, X_3, \dots$  each of which contains a known mix of balls, each ball labeled  $y_1, y_2, y_3, \dots$ . The genie chooses an urn in that room and randomly draws a ball from that urn.

Observer can observe the sequence of the balls but not the sequence of urns from which they were drawn.

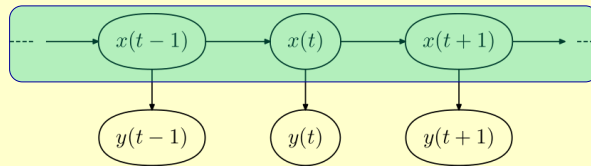
States =  $\{X_1, X_2, X_3\}$

Observations =  $\{y_1, y_2, y_3, y_4\}$

**Transition probabilities**  $a_{ij} = P(X_i \rightarrow X_j)$   
**Emission probabilities**  $b_{ij} = P(X_i \rightarrow y_j)$



## Hidden Markov Model



Hidden state sequence  $x(t-1), x(t), x(t+1)$ . Markov process which is hidden behind a green screen is determined by the current state and transition matrix  $\mathbf{P}$ . We are only able to observe the  $y(t)$  which are related to the hidden states by emission matrix  $\mathbf{E}$ .

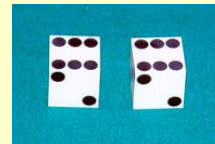
States =  $\{x_1, x_2, x_3\}$

Observations =  $\{y_1, y_2, y_3, y_4\}$

**Transition probabilities**  $\mathbf{P}_{ij} = P(X_i \rightarrow X_j)$

**Emission probabilities**  $\mathbf{E}_{ij} = P(X_i \rightarrow y_j)$

## Example: The dishonest casino



A casino has two dice:

- Fair die  
 $P(1) = P(2) = P(3) = P(4) = P(5) = P(6) = 1/6$
- Loaded die  
 $P(1) = P(2) = P(3) = P(4) = P(5) = 1/10$   
 $P(6) = 1/2$

Casino player switches between fair and loaded die with probability  $1/20$  at each turn

### Game:

1. You bet \$1
2. You roll (always with a fair die)
3. Casino player rolls (maybe with fair die, maybe with loaded die)
4. Highest number wins \$2

## Question # 1 – Decoding

### GIVEN

A sequence of rolls by the casino player

$O = 455264621461461361366616646616366163661636165156151151461235623$



### QUESTION

What portion of the sequence was generated with the fair die, and what portion with the loaded die?

Given  $HMM = (P, E, p_0)$  and observation  $O$ .

Find optimal state sequence  $X$  for the underlying Markov process.

## Question # 2 – Evaluation

### GIVEN

A sequence of rolls by the casino player

$O = 4552646214614613613666166466163661636616361651561511514612356234$

Prob =  $1.3 \times 10^{-35}$

### QUESTION

How likely is this sequence, given our model of how the casino works?

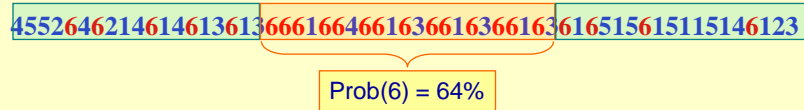
$HMM = (P, E, p_0)$

$P(O / HMM) = ?$

## Question # 3 – Training

### GIVEN

A sequence of rolls by the casino player

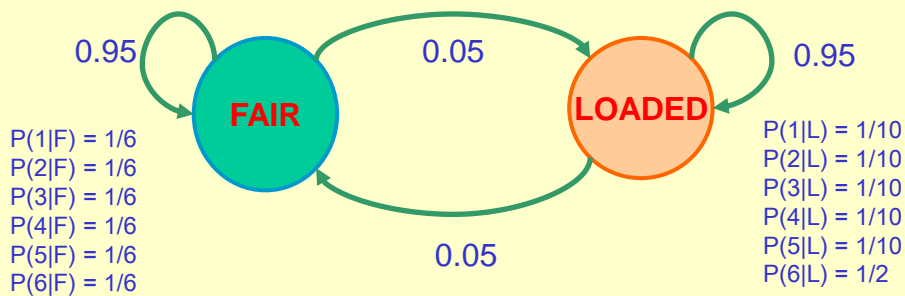


### QUESTION

How “loaded” is the loaded die? How “fair” is the fair die? How often does the casino player change from fair to loaded, and back?

Given  $O$  and number states.

$$HMM = (P, E, p_0) = ?$$



$$P = \begin{matrix} F \\ L \end{matrix} \begin{pmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{pmatrix}$$

$$E = \begin{matrix} F \\ L \end{matrix} \begin{matrix} 1 & 2 & 3 & 4 & 5 & 6 \\ \begin{pmatrix} \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} \\ .1 & .1 & .1 & .1 & .1 & .5 \end{pmatrix} \end{matrix}$$

## Question # 2 – Evaluation

Initial distribution  $p_0 = (1,0)$  – we start with fair dice

Consider observation sequence  $O = 4552$

and state sequence  $X = \{F, F, L, L\}$

$$\begin{aligned} P(4552 \cap FFLL) &= \\ &= p_0(F) * E(F4) * P(FF) * E(F5) * P(FL) * E(L5) * P(LL) * E(L2) = \\ &= 1 \cdot \frac{1}{6} \cdot 0.95 \cdot \frac{1}{6} \cdot 0.05 \cdot \frac{1}{10} \cdot 0.95 \cdot \frac{1}{10} = 1.25 \cdot 10^{-5} \end{aligned}$$

$$P(4552 \cap FFFL)$$

...

all 16 variation

By summing over all possible state sequence we obtain  $P(O_1, O_2, O_3, O_4)$

## Question # 2 – Evaluation forward algorithm

Given: HMM:  $p_0$  - Initial distribution

$P$  - Transition matrix (nxn)

$P(i,j) = P(\text{state } i \rightarrow \text{state } j)$

$E$  - Emission matrix (nxm)

$E(i,j) = P(\text{state } i \rightarrow O_j)$

sequence of observation  $O = (O_1, O_2, \dots, O_T)$

Find  $P(O_1, O_2, \dots, O_T)$

For  $t = 1, 2, \dots, T$  define vector  $\alpha(t)$ , where  $\alpha_i(t) = P(O_1, \dots, O_t, i \text{ state})$

$$\alpha(1) = (p_{0_1} \cdot E(1, O_1), p_{0_2} \cdot E(2, O_1), \dots, p_{0_n} \cdot E(n, O_1)) = p_0 \cdot E(:, O_1)$$

$$\alpha_j(t) = E(j, O_t) \cdot \sum_{i=1..n} \alpha_i(t-1) \cdot P(i, j)$$

$$\alpha(t) = E(:, O_t) \cdot \alpha(t-1) \cdot P$$

$$P(O_1, O_2, \dots, O_T) = \sum_{i=1..n} \alpha_i(T)$$

## Question # 2 – Evaluation forward algorithm

$$\alpha(1) = (p_{0_1} \cdot E(1, O_1), p_{0_2} \cdot E(2, O_1), \dots, p_{0_n} \cdot E(n, O_1)) = p_0 \cdot E(:, O_1)$$

$$\alpha(t) = E(:, O_t) \cdot \alpha(t-1) \cdot P$$

$$P = \begin{matrix} F & \begin{pmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{pmatrix} \\ L \end{matrix}$$

```
p0 = [1, 0];
```

```
observ = [4, 5, 1, 2, 6, 6, 6];
```

```
alpha(:, 1) = p0 .* E(:, observ(1))
```

```
alpha(:, 2) = alpha(:, 1) .* P .* E(:, observ(2))
```

```
sum(alpha(:, T))
```

$$\alpha = \begin{pmatrix} \frac{1}{6} & \dots & \dots & \dots & \alpha_F(T) \\ 0 & \dots & \dots & \dots & \alpha_L(T) \end{pmatrix}$$

$$E = \begin{matrix} F & \begin{pmatrix} \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} \\ \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} \end{pmatrix} \\ L & \begin{pmatrix} .1 & .1 & .1 & .1 & .1 & .5 \end{pmatrix} \end{matrix}$$

## Question # 1 – Decoding

Initial state  $p_0 = (1, 0)$  – we start with fair dice

Given  $HMM = (P, E, p_0)$  and observation  $O$ .

Find optimal state sequence  $X$  for the underlying Markov process.

```
P=[0.95, 0.05; 0.05, 0.95];
```

```
E=[1/6, 1/6, 1/6, 1/6, 1/6, 1/6; 1/10, 1/10, 1/10, 1/10, 1/10, 1/2];
```

```
observ=[4, 5, 1, 2, 6, 6, 6];
```

```
pStates = hmmdecode(observ, P, E); % P(X/O)
```

```
estStates = hmmviterbi(observ, P, E);
```

|             |   |      |      |      |      |      |      |      |
|-------------|---|------|------|------|------|------|------|------|
|             | F | 0.95 | 0.89 | 0.79 | 0.62 | 0.33 | 0.24 | 0.22 |
| pStates =   | L | 0.04 | 0.11 | 0.21 | 0.38 | 0.67 | 0.76 | 0.78 |
| estStates = |   | 1    | 1    | 1    | 1    | 2    | 2    | 2    |

## Hidden Markov Model - example

- States = {'OK';'defect';'serious defect'}
- Observations = {1,2,3,4}

$$P = \begin{pmatrix} 0.9 & 0.1 & 0.1 \\ 0 & 0.9 & 0.1 \\ 0 & 0 & 1 \end{pmatrix}$$

a) Transition probabilities  $P_{ij} = P(X_i \rightarrow X_j)$

b) Emission probabilities  $E_{ij} = P(X_i \rightarrow y_j)$

$$E = \begin{matrix} OK & \begin{pmatrix} 0.9 & 0.1 & 0 & 0 \\ 0.5 & 0.2 & 0.2 & 0.1 \\ 0 & 0.1 & 0.1 & 0.8 \end{pmatrix} \\ defect \\ ser.def \end{matrix}$$

```
%generovani skryte posloupnosti states a pozorovane  
posloupnosti observ
```

```
[observ,states] = hmmgenerate(100,P,E)
```

```
[estimateP,estimateE] = hmestimate(observ,states);
```

HiddenMarkov.m