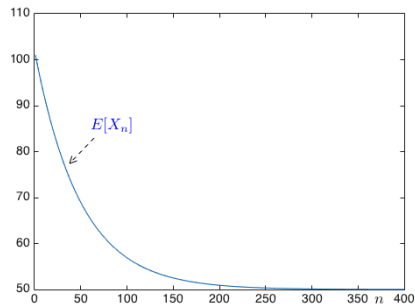


## Today

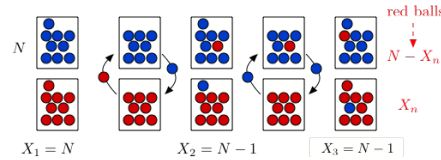
Finish up Conditional Expectation.  
Markov Chains.

## Application: Mixing

Here is the plot.



## Application: Mixing



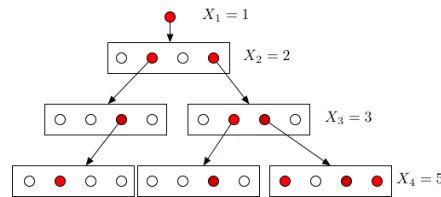
Each step, pick ball from each well-mixed urn. Transfer it to other urn.  
Let  $X_n$  be the number of red balls in the bottom urn at step  $n$ .  
What is  $E[X_n]$ ?

Given  $X_n = m$ ,  $X_{n+1} = m + 1$  w.p.  $p$  and  $X_{n+1} = m - 1$  w.p.  $q$   
where  $p = (1 - m/N)^2$  (B goes up, R down)  
and  $q = (m/N)^2$  (R goes up, B down).

Thus,  
 $E[X_{n+1}|X_n] = X_n + p - q = X_n + 1 - 2X_n/N = 1 + \rho X_n$ ,  $\rho := (1 - 2/N)$ .

## Application: Going Viral

Consider a social network (e.g., Twitter).  
You start a rumor (e.g., Rao is bad at making copies).  
You have  $d$  friends. Each of your friend retweets w.p.  $p$ .  
Each of your friends has  $d$  friends, etc.  
Does the rumor spread? Does it die out (mercifully)?



In this example,  $d = 4$ .

## Mixing

We saw that  $E[X_{n+1}|X_n] = 1 + \rho X_n$ ,  $\rho := (1 - 2/N)$ .  
Does that make sense? Decreases:  $X_n > n/2$ . Increases:  $X_n < n/2$ .  
Hence,

$$\begin{aligned} E[X_{n+1}] &= 1 + \rho E[X_n] \\ E[X_2] &= 1 + \rho N; E[X_3] = 1 + \rho(1 + \rho N) = 1 + \rho + \rho^2 N \\ E[X_4] &= 1 + \rho(1 + \rho + \rho^2 N) = 1 + \rho + \rho^2 + \rho^3 N \\ E[X_n] &= 1 + \rho + \dots + \rho^{n-2} + \rho^{n-1} N. \end{aligned}$$

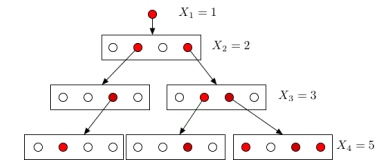
Hence,

$$E[X_n] = \frac{1 - \rho^{n-1}}{1 - \rho} + \rho^{n-1} N, n \geq 1.$$

As  $n \rightarrow \infty$ , goes to  $N/2$ .

Since  $1 - \rho = 2/N$ . And  $\rho^n \rightarrow 0$ .

## Application: Going Viral



**Fact:** Number of tweets  $X = \sum_{n=1}^{\infty} X_n$  where  $X_n$  is tweets in level  $n$ .  
Then,  $E[X] < \infty$  iff  $pd < 1$ .

**Proof:**

Given  $X_n = k$ ,  $X_{n+1} = B(kd, p)$ . Hence,  $E[X_{n+1}|X_n = k] = kpd$ .

Thus,  $E[X_{n+1}|X_n] = pdX_n$ . Consequently,  $E[X_n] = (pd)^{n-1}$ ,  $n \geq 1$ .

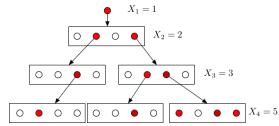
If  $pd < 1$ , then  $E[X_1 + \dots + X_n] \leq (1 - pd)^{-1} \Rightarrow E[X] \leq (1 - pd)^{-1}$ .

If  $pd \geq 1$ , then for all  $C$  one can find  $n$  s.t.

$$E[X] \geq E[X_1 + \dots + X_n] \geq C.$$

In fact, one can show that  $pd \geq 1 \Rightarrow Pr[X = \infty] > 0$ . □

### Application: Going Viral



An easy extension: Assume that everyone has an independent number  $D_i$  of friends with  $E[D_i] = d$ . Then, the same fact holds.

Why? Given  $X_n = k$ .

$D_1 = d_1, \dots, D_k = d_k$  - numbers of friends of these  $X_n$  people.

$\implies X_{n+1} = B(d_1 + \dots + d_k, p)$ . Hence,

$$E[X_{n+1} | X_n = k, D_1 = d_1, \dots, D_k = d_k] = p(d_1 + \dots + d_k).$$

Thus,  $E[X_{n+1} | X_n = k, D_1, \dots, D_k] = p(D_1 + \dots + D_k)$ .

Consequently,  $E[X_{n+1} | X_n = k] = E[p(D_1 + \dots + D_k)] = pdk$ .

Finally,  $E[X_{n+1} | X_n] = pdX_n$ , and  $E[X_{n+1}] = pdE[X_n]$ .

We conclude as before.

### CE = MMSE

#### Theorem CE = MMSE

$g(X) := E[Y|X]$  is the function of  $X$  that minimizes  $E[(Y - g(X))^2]$ .

#### Proof:

Let  $h(X)$  be any function of  $X$ . Then

$$\begin{aligned} E[(Y - h(X))^2] &= E[(Y - g(X) + g(X) - h(X))^2] \\ &= E[(Y - g(X))^2] + E[(g(X) - h(X))^2] \\ &\quad + 2E[(Y - g(X))(g(X) - h(X))]. \end{aligned}$$

But,

$$E[(Y - g(X))(g(X) - h(X))] = 0 \text{ by the projection property.}$$

Thus,  $E[(Y - h(X))^2] \geq E[(Y - g(X))^2]$ .  $\square$

### Application: Wald's Identity

Here is an extension of an identity we used in the last slide.

#### Theorem Wald's Identity

Assume that  $X_1, X_2, \dots$  and  $Z$  are independent, where

$Z$  takes values in  $\{0, 1, 2, \dots\}$

and  $E[X_n] = \mu$  for all  $n \geq 1$ .

Then,

$$E[X_1 + \dots + X_Z] = \mu E[Z].$$

#### Proof:

$E[X_1 + \dots + X_Z | Z = k] = \mu k$ .

Thus,  $E[X_1 + \dots + X_Z | Z] = \mu Z$ .

Hence,  $E[X_1 + \dots + X_Z] = E[\mu Z] = \mu E[Z]$ .  $\square$

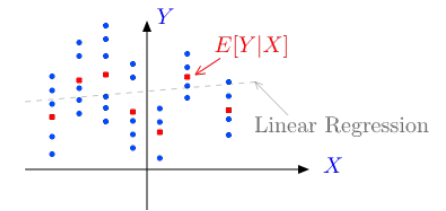
### CE = MMSE

#### Theorem

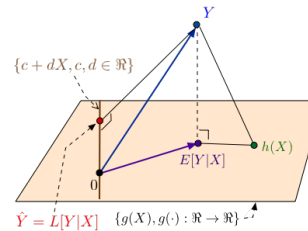
$E[Y|X]$  is the 'best' guess about  $Y$  based on  $X$ .

Specifically, it is the function  $g(X)$  of  $X$  that

minimizes  $E[(Y - g(X))^2]$ .



### $E[Y|X]$ and $L[Y|X]$ as projections



$L[Y|X]$  is the projection of  $Y$  on  $\{a + bX, a, b \in \mathbb{R}\}$ : LLSE

$E[Y|X]$  is the projection of  $Y$  on  $\{g(X), g(\cdot) : \mathbb{R} \rightarrow \mathbb{R}\}$ : MMSE.

Functions of  $X$  are linear subspace?

Vector  $(g(X(\omega_1)), \dots, g(X(\omega_n)))$ .

Coordinates  $\omega$  and  $\omega'$  with  $X(\omega) = X(\omega')$

have same value:  $v_\omega = v_{\omega'}$ .

Linear constraints! Linear Subspace.

### Summary

#### Conditional Expectation

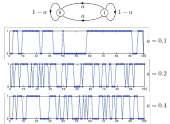
- ▶ Definition:  $E[Y|X] := \sum_y y Pr[Y = y | X = x]$
- ▶ Properties: Linearity,  $Y - E[Y|X] \perp h(X)$ ;  $E[E[Y|X]] = E[Y]$
- ▶ Some Applications:
  - ▶ Calculating  $E[Y|X]$
  - ▶ Diluting
  - ▶ Mixing
  - ▶ Rumors
  - ▶ Wald
- ▶ MMSE:  $E[Y|X]$  minimizes  $E[(Y - g(X))^2]$  over all  $g(\cdot)$

## CS70: Markov Chains.

### Markov Chains 1

1. Examples
2. Definition
3. First Passage Time

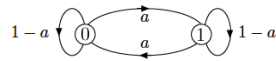
## Finite Markov Chain: Definition



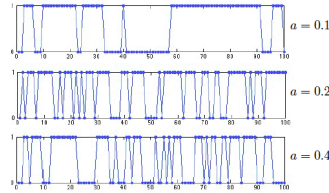
- ▶ A finite set of states:  $\mathcal{X} = \{1, 2, \dots, K\}$
- ▶ A probability distribution  $\pi_0$  on  $\mathcal{X}$ :  $\pi_0(i) \geq 0, \sum_i \pi_0(i) = 1$
- ▶ Transition probabilities:  $P(i, j)$  for  $i, j \in \mathcal{X}$   
 $P(i, j) \geq 0, \forall i, j; \sum_j P(i, j) = 1, \forall i$
- ▶  $\{X_n, n \geq 0\}$  is defined so that  
 $Pr[X_0 = i] = \pi_0(i), i \in \mathcal{X}$  (initial distribution)  
 $Pr[X_{n+1} = j | X_0, \dots, X_n = i] = P(i, j), i, j \in \mathcal{X}$ .

## Two-State Markov Chain

Here is a symmetric two-state Markov chain. It describes a random motion in  $\{0, 1\}$ . Here,  $a$  is the probability that the state changes in the next step.



Let's simulate the Markov chain:

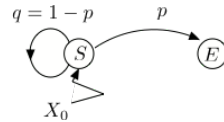


## First Passage Time - Example 1

Let's flip a coin with  $Pr[H] = p$  until we get  $H$ . How many flips, on average?

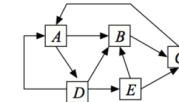
Let's define a Markov chain:

- ▶  $X_0 = S$  (start)
- ▶  $X_n = S$  for  $n \geq 1$ , if last flip was  $T$  and no  $H$  yet
- ▶  $X_n = E$  for  $n \geq 1$ , if we already got  $H$  (end)

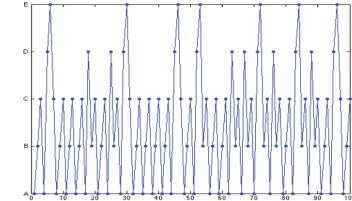


## Five-State Markov Chain

At each step, the MC follows one of the outgoing arrows of the current state, with equal probabilities.

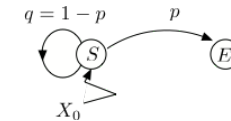


Let's simulate the Markov chain:



## First Passage Time - Example 1

Let's flip a coin with  $Pr[H] = p$  until we get  $H$ . How many flips, on average?



Let  $\beta(S)$  be the average time until  $E$ , starting from  $S$ .

Then,

$$\beta(S) = 1 + q\beta(S) + p \cdot 0.$$

(See next slide.) Hence,

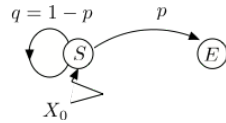
$$p\beta(S) = 1, \text{ so that } \beta(S) = 1/p.$$

Note: Time until  $E$  is  $G(p)$ .

The mean of  $G(p)$  is  $1/p$ !!!

### First Passage Time - Example 1

Let's flip a coin with  $Pr[H] = p$  until we get  $H$ . How many flips, on average?



Let  $\beta(S)$  be the average time until  $E$ . Then,

$$\beta(S) = 1 + q\beta(S) + p0.$$

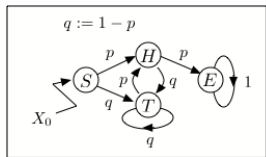
**Justification:**  $N$  – number of steps until  $E$ , starting from  $S$ .  
 $N'$  – number of steps until  $E$ , after the second visit to  $S$ .  
 And  $Z = 1\{\text{first flip} = H\}$ . Then,

$$N = 1 + (1 - Z) \times N' + Z \times 0.$$

$Z$  and  $N'$  are independent. Also,  $E[N'] = E[N] = \beta(S)$ .  
 Hence, taking expectation,

$$\beta(S) = E[N] = 1 + (1 - p)E[N'] + p0 = 1 + q\beta(S) + p0.$$

### First Passage Time - Example 2



S: Start  
 H: Last flip = H  
 T: Last flip = T  
 E: Done

Let us justify the first step equation for  $\beta(T)$ . The others are similar.

$N(T)$  – number of steps, starting from  $T$  until the MC hits  $E$ .

$N(H)$  – be defined similarly.

$N'(T)$  – number of steps after the second visit to  $T$  until MC hits  $E$ .

$$N(T) = 1 + Z \times N(H) + (1 - Z) \times N'(T)$$

where  $Z = 1\{\text{first flip in } T \text{ is } H\}$ . Since  $Z$  and  $N(H)$  are independent, and  $Z$  and  $N'(T)$  are independent, taking expectations, we get

$$E[N(T)] = 1 + pE[N(H)] + qE[N'(T)],$$

i.e.,

$$\beta(T) = 1 + p\beta(H) + q\beta(T).$$

### First Passage Time - Example 2

Let's flip a coin with  $Pr[H] = p$  until we get two consecutive  $H$ s. How many flips, on average?

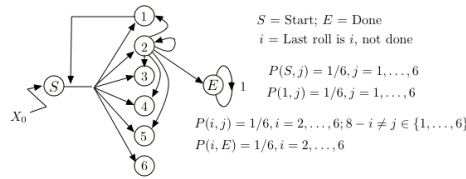
H T H T T T H T H T T T H T H H

Let's define a Markov chain:

- ▶  $X_0 = S$  (start)
- ▶  $X_n = E$ , if we already got two consecutive  $H$ s (end)
- ▶  $X_n = T$ , if last flip was  $T$  and we are not done
- ▶  $X_n = H$ , if last flip was  $H$  and we are not done

### First Passage Time - Example 3

You roll a balanced six-sided die until the sum of the last two rolls is 8. How many times do you have to roll the die, on average?



S = Start; E = Done  
 i = Last roll is  $i$ , not done

$$P(S, j) = 1/6, j = 1, \dots, 6$$

$$P(1, j) = 1/6, j = 1, \dots, 6$$

$$P(i, j) = 1/6, i = 2, \dots, 6; 8 - i \neq j \in \{1, \dots, 6\}$$

$$P(i, E) = 1/6, i = 2, \dots, 6$$

The arrows out of 3, ..., 6 (not shown) are similar to those out of 2.

$$\beta(S) = 1 + \frac{1}{6} \sum_{j=1}^6 \beta(j); \beta(1) = 1 + \frac{1}{6} \sum_{j=1}^6 \beta(j); \beta(i) = 1 + \frac{1}{6} \sum_{j=1, \dots, 6; j \neq 8-i} \beta(j), i = 2, \dots, 6.$$

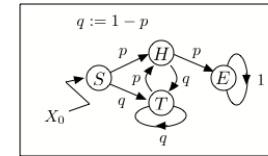
Symmetry:  $\beta(2) = \dots = \beta(6) =: \gamma$ . Also,  $\beta(1) = \beta(S)$ . Thus,

$$\beta(S) = 1 + (5/6)\gamma + \beta(S)/6; \quad \gamma = 1 + (4/6)\gamma + (1/6)\beta(S).$$

$$\Rightarrow \dots \beta(S) = 8.4.$$

### First Passage Time - Example 2

Let's flip a coin with  $Pr[H] = p$  until we get two consecutive  $H$ s. How many flips, on average? Here is a picture:



S: Start  
 H: Last flip = H  
 T: Last flip = T  
 E: Done

Let  $\beta(i)$  be the average time from state  $i$  until the MC hits state  $E$ .

We claim that (these are called the **first step equations**)

$$\beta(S) = 1 + p\beta(H) + q\beta(T)$$

$$\beta(H) = 1 + p0 + q\beta(T)$$

$$\beta(T) = 1 + p\beta(H) + q\beta(T).$$

Solving, we find  $\beta(S) = 2 + 3qp^{-1} + q^2p^{-2}$ . (E.g.,  $\beta(S) = 6$  if  $p = 1/2$ .)

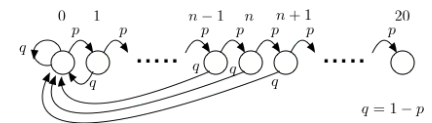
### First Passage Time - Example 4

You try to go up a ladder that has 20 rungs.

Each step, succeed or go up one rung with probability  $p = 0.9$ .

Otherwise, you fall back to the ground. **Bummer.**

Time steps to reach the top of the ladder, on average?



$$\beta(n) = 1 + p\beta(n+1) + q\beta(0), 0 \leq n < 19$$

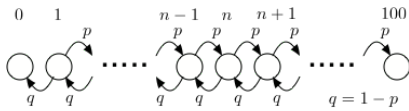
$$\beta(19) = 1 + p0 + q\beta(0)$$

$$\Rightarrow \beta(0) = \frac{p^{-20} - 1}{1 - p} \approx 72.$$

See Lecture Note 24 for algebra.

### First Passage Time - Example 5

Game of "heads or tails" using coin with 'heads' probability  $p < 0.5$ . Start with \$10. Each step, flip yields 'heads', earn \$1. Otherwise, lose \$1. What is the probability that you reach \$100 before \$0?



Let  $\alpha(n)$  be the probability of reaching 100 before 0, starting from  $n$ , for  $n = 0, 1, \dots, 100$ .

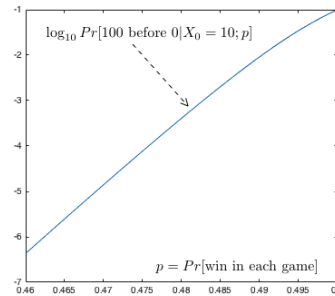
$$\alpha(0) = 0; \alpha(100) = 1.$$

$$\alpha(n) = p\alpha(n+1) + q\alpha(n-1), 0 < n < 100.$$

$$\Rightarrow \alpha(n) = \frac{1 - \rho^n}{1 - \rho^{100}} \text{ with } \rho = qp^{-1}. \text{ (See LN 24)}$$

### First Passage Time - Example 5

Game of "heads or tails" using coin with 'heads' probability  $p = .48$ . Start with \$10. Each step, flip yields 'heads', earn \$1. Otherwise, lose \$1. What is the probability that you reach \$100 before \$0?



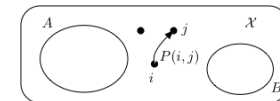
Less than 1 in a 1000. Morale of example: Money in Vegas stays in Vegas.

### First Step Equations

Let  $X_n$  be a MC on  $\mathcal{X}$  and  $A, B \subset \mathcal{X}$  with  $A \cap B = \emptyset$ . Define

$$T_A = \min\{n \geq 0 \mid X_n \in A\} \text{ and } T_B = \min\{n \geq 0 \mid X_n \in B\}.$$

Let  $\beta(i) = E[T_A \mid X_0 = i]$  and  $\alpha(i) = Pr[T_A < T_B \mid X_0 = i], i \in \mathcal{X}$ .



The FSE are

$$\beta(i) = 0, i \in A$$

$$\beta(i) = 1 + \sum_j P(i,j)\beta(j), i \notin A$$

$$\alpha(i) = 1, i \in A$$

$$\alpha(i) = 0, i \in B$$

$$\alpha(i) = \sum_j P(i,j)\alpha(j), i \notin A \cup B.$$

### Accumulating Rewards

Let  $X_n$  be a Markov chain on  $\mathcal{X}$  with  $P$ . Let  $A \subset \mathcal{X}$

Let also  $g: \mathcal{X} \rightarrow \Re$  be some function.

Define

$$\gamma(i) = E\left[\sum_{n=0}^{T_A} g(X_n) \mid X_0 = i\right], i \in \mathcal{X}.$$

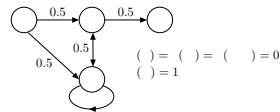
Then

$$\gamma(i) = \begin{cases} g(i), & \text{if } i \in A \\ g(i) + \sum_j P(i,j)\gamma(j), & \text{otherwise.} \end{cases}$$

### Example

Flip a fair coin until you get two consecutive  $H$ s.

What is the expected number of  $T$ s that you see?



FSE:

$$\gamma(S) = 0 + 0.5\gamma(H) + 0.5\gamma(T)$$

$$\gamma(H) = 0 + 0.5\gamma(HH) + 0.5\gamma(T)$$

$$\gamma(T) = 1 + 0.5\gamma(H) + 0.5\gamma(T)$$

$$\gamma(HH) = 0.$$

Solving, we find  $\gamma(S) = 2.5$ .

### Summary

Markov Chains

- $Pr[X_{n+1} = j \mid X_0, \dots, X_n = i] = P(i,j), i, j \in \mathcal{X}$
- $T_A = \min\{n \geq 0 \mid X_n \in A\}$
- $\alpha(i) = Pr[T_A < T_B \mid X_0 = i] \Rightarrow$  FSE
- $\beta(i) = E[T_A \mid X_0 = i] \Rightarrow$  FSE
- $\gamma(i) = E[\sum_{n=0}^{T_A} g(X_n) \mid X_0 = i] \Rightarrow$  FSE.