

# STATS 217: Introduction to Stochastic Processes I

## Lecture 12

## Exit times

- Let  $(X_n)_{n \geq 0}$  be a DTMC on a finite state space  $S = \{1, \dots, N\}$  with transition matrix  $P$ .
- Suppose that all the recurrent states of  $S$  are absorbing.
- Without loss of generality, this means that there is some  $r < N$  such that states  $\{1, \dots, r\}$  are transient, states  $\{r + 1, \dots, N\}$  are recurrent, and  $P_{x,x} = 1$  for all  $x > r$ .
- Therefore, the transition matrix  $P$  decomposes as

$$P = \begin{bmatrix} Q & R \\ 0 & I \end{bmatrix}$$

where  $Q$  is an  $r \times r$  matrix,  $R$  is an  $r \times (N - r)$  matrix, and  $I$  is the  $(N - r) \times (N - r)$  identity matrix.

## Exit times

- Let  $T$  be the first time that the chain reaches one of the absorbing states.
- We know that  $\mathbb{P}[T < \infty] = 1$ .
- Last time we studied the exit distribution starting from  $i \in S$  i.e.,

$$U_{i,j} = \mathbb{P}[X_T = j \mid X_0 = i].$$

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- Today, we will study the **exit time** i.e. the random variable  $T$  itself.
- We already saw an example in the very first lecture when we discussed the expected time for a gambler to lose either  $\$B$  or win  $\$A$  when betting  $\$1$  on the outcomes of independent, fair coin tosses.

Exit times throughout:  $1, \dots, r$  are transient

$r+1, \dots, N$  are absorbing

$$P = \begin{pmatrix} Q & R \\ 0 & I \end{pmatrix} \begin{array}{l} Q \text{ is} \\ r \times r \\ \text{matrix.} \end{array}$$

- Fix  $i \in \{1, \dots, r\}$ . What is  $\mathbb{P}[T > t_0 \mid X_0 = i]$ ?
- Equivalently, this is the probability that  $X_1, \dots, X_{t_0} \in \{1, \dots, r\}$  given that  $X_0 = i$ .

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→ + law of total prob.
- Using the Markov property, this probability is exactly

→ look at all possible values

of  $X_1, X_2, \dots, X_{t_0}$

→ sum over all possible trajectories

$$\sum_{i_1, \dots, i_{t_0} \in \{1, \dots, r\}} \underbrace{P_{i, i_1}}_{P_i P_{i_1}} \dots \underbrace{P_{i_{t_0-1}, i_{t_0}}}$$

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- Using the Markov property, this probability is exactly

$$(*) \quad \sum_{\substack{i_1, \dots, i_{t_0} \in \{1, \dots, r\}}} P_{i, i_1} \dots P_{i_{t_0-1}, i_{t_0}} \quad (\text{path counting}).$$

$$P = \begin{pmatrix} |Q| & R \\ \hline 0 & I \end{pmatrix}$$

- A more convenient way of writing this is as

$$\mathbb{P}[T > t_0 \mid X_0 = i] = \sum_{j=1}^r (Q^{t_0})_{i,j}.$$

$$(Q^{t_0})_{i,j} = \sum_{i_1, \dots, i_{t_0-1}} Q_{i, i_1} Q_{i_1, i_2} \dots Q_{i_{t_0-1}, j}$$

$Q$  is an  
 $r \times r$   
matrix

## Exit times

- What is  $\mathbb{E}[T \mid X_0 = i]$ ? Call this expectation  $g(i)$ .
- We know that  $g(r + 1) = \dots = g(N) = 0$ .



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- On the other hand, by first step analysis, we have for any  $1 \leq i \leq r$  that

$$\mathbb{E}[T \mid X_0 = i] = \tilde{1} + \sum_{j=1}^r \underbrace{P_{i,j}}_w g(j). \quad \left( \begin{array}{l} \text{note that only} \\ \text{summing over} \\ \text{transient states.} \end{array} \right)$$

take a step.  $\rightarrow$  if hit  $r+1, \dots, N$ , then done

$\rightarrow$  else hit  $1, \dots, r$ , in which case, restart from  $X_1$ .

## Exit times

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- On the other hand, by first step analysis, we have for any  $1 \leq i \leq r$  that

$$g(i) = 1 + \sum_{j=1}^r P_{i,j} g(j).$$

last time : for exit distribution  
 $h(i) = \mathbb{E}[h(X_1) \mid X_0 = i]$

- Since for all  $1 \leq i \leq r$ ,

$$g(i) = 1 + \mathbb{E}[g(X_1) \mid X_0 = i],$$

it follows from the same argument as in the last lecture that a solution to the above system of linear equations with the boundary conditions  $g(r+1) = \dots = g(N) = 0$  must satisfy  $g(i) = \mathbb{E}[T \mid X_0 = i]$ .

## Exit times

we know that  $g(r+1) = \dots = g(N) = 0$ .

$$P = \begin{pmatrix} Q & R \\ 0 & I \end{pmatrix}$$

- Another way of writing the previous result is as follows.
- Let  $\vec{w} = (\underbrace{g(1), \dots, g(r)}_{\text{components}}) \in \mathbb{R}^r$  and let  $\vec{b} = (\underbrace{1, 1, \dots, 1}_{\text{components}}) \in \mathbb{R}^r$ . Then,

$$|\vec{w} = \vec{b} + Q\vec{w}| \text{ i.e. } (I - Q)\vec{w} = \vec{b}.$$

*i*<sup>th</sup> component ↙

$$g(i) = \underline{1} + \sum_{j=1}^r p_{ij} g(j)$$
$$= \underline{1} + \sum_{j=1}^r \underline{Q_{ij}} g(j)$$

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- Therefore,

$$\vec{w} = (I - Q)^{-1}\vec{b},$$

provided that  $(I - Q)^{-1}$  exists.

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$$\left\{ \frac{1}{1-x} = 1 + x + x^2 + \dots \right\}$$

for  $|x| < 1$ .

↙ "plug  $x = Q$ "

provided that  $(I - Q)^{-1}$  exists.

- Since  $(I - Q) \cdot (I + Q + Q^2 + Q^3 + \dots) = I$ , it follows that  $I - Q$  is invertible if  $I + Q + Q^2 + \dots$  converges.

~ neumann series expansion of  $(I - a)^{-1}$

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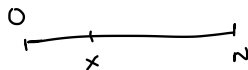
- Since  $(I - Q) \cdot (I + Q + Q^2 + Q^3 + \dots) = I$ , it follows that  $I - Q$  is invertible if  $I + Q + Q^2 + \dots$  converges.
- In our case, this convergence indeed holds since

$$0 \leq (Q^t)_{i,j} \leq \mathbb{P}[T > t \mid X_0 = i] \rightarrow 0 \text{ as } t \rightarrow \infty.$$

optimal

## Biased Gambler's ruin

- Let us return to the problem of the Gambler's ruin, except now, the bets are biased.
- Concretely, the gambler starts with  $\$x$  and in each round, independently, wins  $\$1$  with probability  $p$  and loses  $\$1$  with probability  $q$ .
- She stops playing once she either reaches  $\$N$  or  $\$0$ .



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- We want to compute

$$g(x) = \mathbb{E}[T \mid X_0 = x].$$

- We have,  $g(N) = g(0) = 0$  and for  $1 \leq x \leq N - 1$ ,

$$g(x) = 1 + pg(x + 1) + qg(x - 1).$$



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- Check that this is satisfied by

$$h(x) = \frac{x}{q-p} - \frac{\textcircled{N}}{q-p} \cdot \frac{1 - (q/p)^x}{1 - (q/p)^N}.$$

$\left(\frac{q}{p}\right)^x$  also showed up in the exit distribution.

## Biased Gambler's ruin

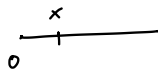
$$\frac{q}{p} = 1.01 \text{ (say)}$$

$$\frac{x}{q-p} - \frac{N^x}{(1.01)^N} \cdot C$$

- As an example, consider the case when  $p < q$ .
- Then, as  $N \rightarrow \infty$ , we see that  $h(x) \rightarrow \frac{x}{q-p}$ .

## Biased Gambler's ruin

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- Also, by the formula from last time



$\infty$   
→  
 $\infty$

$$\lim_{N \rightarrow \infty} \mathbb{P}[V_N < V_0 \mid X_0 = x] = \lim_{N \rightarrow \infty} \frac{1 - (q/p)^x}{1 - (q/p)^N} = 0.$$

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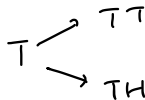
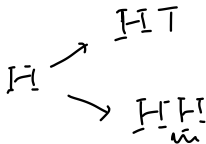
- Intuition: As  $N \rightarrow \infty$ , we lose all our money with probability tending to 1. Moreover, since the expected loss per game is  $(q - p)$  and since we start off with  $x$ , the expected number of steps it takes to lose all our money is  $x/(q - p)$ .

## Patterns in coin tossing

$TT$  : waiting time of 2.

$HT$  $HTTT$  : waiting time of 6.

- You are tossing an unbiased coin repeatedly. What is the expected number of tosses to see the pattern  $TT$ ? What is the expected number of tosses to see the pattern  $HT$ ?



# Patterns in coin tossing

- You are tossing an unbiased coin repeatedly. What is the expected number of tosses to see the pattern  $TT$ ? What is the expected number of tosses to see the pattern  $HT$ ?
- The transition matrix is

$x_1, x_2, x_3, x_4$   
~~~~~  
~~~~~

$$P = \begin{bmatrix} \overline{HH} & HH & HT & TH & TT \\ \overline{HT} & 1/2 & 1/2 & 0 & 0 \\ TH & 1/2 & 1/2 & 0 & 0 \\ TT & 0 & 0 & 1/2 & 1/2 \end{bmatrix}$$

## Patterns in coin tossing

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- The transition matrix is

$$P = \begin{bmatrix} HH & HT & TH & TT \\ HH & 1/2 & 1/2 & 0 \\ HT & 0 & 0 & 1/2 \\ TH & 1/2 & 1/2 & 0 \\ TT & 0 & 0 & 1 \end{bmatrix} = \begin{pmatrix} Q & R \\ 0 & I \end{pmatrix}$$

Handwritten annotations: A circled 'Q' is above the top-left 3x3 submatrix. A circled 'R' is to the right of the top-right 3x1 column. A circled '0' is to the right of the bottom-left 1x3 row. A circled 'I' is to the right of the bottom-right 1x1 element. Arrows point from these annotations to their respective parts in the matrix.

- In the case when we are waiting for  $TT$ , we modify the chain to make  $TT$  an absorbing state. In the case when we are waiting for  $HT$ , we modify the chain to make  $HT$  an absorbing state.

## Patterns in coin tossing

- Let  $\tau_{TT}$  denote the number of steps until we see  $TT$ .
- Let  $\vec{w} = (w_{HH}, w_{HT}, w_{TH})$  where  $w_{HH} = \mathbb{E}[\tau_{TT} \mid X_1 X_2 = HH]$  and so on.



# Patterns in coin tossing

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- Let  $\vec{w} = (w_{HH}, w_{HT}, w_{TH})$  where  $w_{HH} = \mathbb{E}[\tau_{TT} \mid X_1 X_2 = HH]$  and so on.
- Then, by our previous discussion,  $(I - Q)^{-1} \vec{b}$

$$\vec{w} = (I - Q)^{-1} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} + \begin{pmatrix} 2 \\ 2 \\ 2 \end{pmatrix},$$

starting state consists of 2 coin tosses.

where

$$Q = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 0 & 0 & 1/2 \\ 1/2 & 1/2 & 0 \end{bmatrix}$$

## Patterns in coin tossing

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where

$$Q = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 0 & 0 & 1/2 \\ 1/2 & 1/2 & 0 \end{bmatrix} \quad I - Q = \begin{pmatrix} 1/2 & -1/2 & 0 \\ 0 & 1 & -1/2 \\ -1/2 & -1/2 & 1 \end{pmatrix}$$

- Solving this, we get

$$\vec{w} = \begin{pmatrix} 8 \\ 6 \\ 8 \end{pmatrix} \begin{matrix} \leftarrow \mathbb{E}[\tau_{TT} \mid X_1 X_2 = HH] \\ \leftarrow \mathbb{E}[\tau_{TT} \mid X_1 X_2 = HT] \\ TH \end{matrix}$$

# Patterns in coin tossing

- Let  $\tau_{TT}$  denote the number of steps until we see  $TT$ .
- Conditioning on the outcome of the first two tosses and using the law of total probability,

$$\mathbb{E}[\tau_{TT}] = \frac{\begin{array}{c} HH \rightarrow \\ HT \downarrow \\ TH \swarrow \\ TT \rightarrow \end{array} 8 + 6 + 8 + 2}{4} = 6.$$

# Patterns in coin tossing

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$$\mathbb{E}[\tau_{TT}] = \frac{8 + 6 + 8 + 2}{4} = 6.$$

- A similar computation shows that

$$\mathbb{E}[\tau_{HT}] = 4.$$

$\rightarrow Q :$

HH	TH	TT
HH		
TH		
TT		

(A 3x3 matrix with columns labeled HH, TH, TT)

$$(\mathbb{I} - Q)^{-1} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} 2 \\ 2 \\ 2 \end{pmatrix}$$