STATS 217: Introduction to Stochastic Processes I

Lecture 11

Let $(X_n)_{n\geq 0}$ be a DTMC on S with transition matrix P.

• $s \in S$ is recurrent if $f_{s \to s} = 1$, where $f_{s \to s} = \mathbb{P}[\tau_{\{s\},s} < \infty]$.

• We saw that s is recurrent if and only if

$$\mathbb{E}[N(s) \mid X_0 = s] = \infty,$$

where N(s) is the number of visits to s.

Let $(X_n)_{n\geq 0}$ be a DTMC on S with transition matrix P.

• $s \in S$ is recurrent if $f_{s \to s} = 1$, where $f_{s \to s} = \mathbb{P}[\tau_{\{s\},s} < \infty]$.

• We saw that s is recurrent if and only if

$$\mathbb{E}[N(s) \mid X_0 = s] = \infty,$$

where N(s) is the number of visits to s.

• While proving that a recurrent and $a \rightarrow b$ implies $b \rightarrow a$, we used that

$$\mathbb{P}[N(a) = \infty \mid X_0 = a] = 1.$$

Note that this is stronger than saying that $\mathbb{E}[N(a) = \infty \mid X_0 = a] = \infty$.

• Why is this stronger statement true? It suffices to show that $\mathbb{P}[N(a) < \infty | X_0 = a] = 0.$

- Why is this stronger statement true? It suffices to show that $\mathbb{P}[N(a) < \infty | X_0 = a] = 0.$
- By definition, {N(a) < ∞} = ∪_{n∈Z≥0} {N(a) = n}.
 We also know that for any n∈ Z≥0

$$\mathbb{P}[N(a) = n \mid X_0 = a] = f_{a \to a}^n - f_{a \to a}^{n+1} = 0.$$

.

- Why is this stronger statement true? It suffices to show that $\mathbb{P}[N(a) < \infty | X_0 = a] = 0.$
- By definition, $\{N(a) < \infty\} = \cup_{n \in \mathbb{Z}^{\geq 0}} \{N(a) = n\}.$
- We also know that for any $n\in\mathbb{Z}^{\geq0}$

$$\mathbb{P}[N(a)=n\mid X_0=a]=f_{a\to a}^n-f_{a\to a}^{n+1}=0.$$



• Therefore,

$$\mathbb{P}[N(a) < \infty \mid X_0 = 0] = \sum_{n \in \mathbb{Z}^{\ge 0}} \mathbb{P}[N(a) = n \mid X_0 = a]$$
$$= \sum_{n \in \mathbb{Z}^{\ge 0}} 0$$
$$= 0.$$

- In the first lecture, we studied the Gambler's ruin: consider a gambler who bets on the outcome of fair coin tosses. What is the probability that she loses \$100 before winning \$200?
- We can study such questions more generally.

- In the first lecture, we studied the Gambler's ruin: consider a gambler who bets on the outcome of fair coin tosses. What is the probability that she loses \$100 before winning \$200?
- We can study such questions more generally.
- For instance, generalizing our argument from Gambler's ruin shows the following.
- Let $(X_n)_{n\geq 0}$ be a DTMC on a finite state space S. Let $a \neq b \in S$ and let $C = S \{a, b\}$. Let V_a be the first time (including 0) that a is visited and similarly for V_b .

- In the first lecture, we studied the Gambler's ruin: consider a gambler who bets on the outcome of fair coin tosses. What is the probability that she loses \$100 before winning \$200?
- We can study such questions more generally.
- For instance, generalizing our argument from Gambler's ruin shows the following.
- Let $(X_n)_{n\geq 0}$ be a DTMC on a finite state space S. Let $a \neq b \in S$ and let $C = S \{a, b\}$. Let V_a be the first time (including 0) that a is visited and similarly for V_b . Suppose that h(a) = 1, h(b) = 0 and for all $x \in C$,

$$h(x) = \sum_{y \in S} p_{x,y} h(y).$$

- In the first lecture, we studied the Gambler's ruin: consider a gambler who bets on the outcome of fair coin tosses. What is the probability that she loses \$100 before winning \$200?
- We can study such questions more generally.
- For instance, generalizing our argument from Gambler's ruin shows the following.
- Let $(X_n)_{n\geq 0}$ be a DTMC on a finite state space S. Let $a \neq b \in S$ and let $C = S \{a, b\}$. Let V_a be the first time (including 0) that a is visited and similarly for V_b . Suppose that h(a) = 1, h(b) = 0 and for all $x \in C$,

$$\begin{cases} h(x) = \sum_{y \in S} p_{x,y} h(y). \quad ``first step \\ analysis'' \end{cases}$$

If there exists some N such that $\mathbb{P}[\min\{V_a, V_b\} < N \mid X_0 = x] > 0$ for all $x \in C$, then "heads 300 minus, $h(x) = \mathbb{P}[V_a < V_b \mid X_0 = x]$. The proble of hitting then you win"

- Let $T = \min\{V_a, V_b\}$.
- Since P[T < N | X₀ = x] > 0 for all x ∈ C, the same argument as Problem 1 of HW1 shows that P[T < ∞] = 1.

- Let $T = \min\{V_a, V_b\}$.
- Since P[T < N | X₀ = x] > 0 for all x ∈ C, the same argument as Problem 1 of HW1 shows that P[T < ∞] = 1.
- The equation

$$h(x) = \sum_{y \in S} p_{x,y} h(y) \quad \forall x \in C.$$

can be rewritten as

$$h(x) = \mathbb{E}[h(X_1) \mid X_0 = x] \quad \forall x \in C.$$

$$= \sum_{i=1}^{n} \left[p \left(X_{\underline{p}} = y \mid y_{\delta} = x \right) h(y) \right]$$

$$= \sum_{i=1}^{n} p_{x_i} y^{h(y)}.$$

- Let $T = \min\{V_a, V_b\}$.
- Since P[T < N | X₀ = x] > 0 for all x ∈ C, the same argument as Problem 1 of HW1 shows that P[T < ∞] = 1.
- The equation

$$h(x) = \sum_{y \in S} p_{x,y} h(y) \quad \forall x \in C.$$

can be rewritten as

$$h(x) = \mathbb{E}[h(X_1) \mid X_0 = x] \quad \forall x \in C.$$

• Iterating this, we have for all $x \in C$,

$$h(X_1) = \begin{cases} X_1 \in \mathcal{C} \\ IE[h(X_2) \mid X_1] \end{cases}$$

$$\begin{array}{l} x_{\tau} \in \{a, b\} \\ h(a) = 1, h(b) = 0 \end{array} \xrightarrow{h(x) = \mathbb{E}[h(X_{\tau}) \mid X_0 = x]} \cdot \left\{ \begin{array}{c} h(x_{\tau}) \mid x_{\tau} = a, x_{\tau}x \\ = \mathbb{P}[X_{\tau} = a \mid X_0 = x] \\ = \mathbb{P}[V_a < V_b \mid X_0 = x] \cdot + for b \end{array} \right.$$

Example

Consider the following crude model of opinion dynamics.

- There is a population of N individuals, each with one of two opinions: A or B.
- Initially, $1 \le x \le N 1$ individuals have opinion A and N x individuals have opinion B.
- At each time step, the individuals update their opinion by sampling without replacement from the current opinions.

Example

Consider the following crude model of opinion dynamics.

- There is a population of N individuals, each with one of two opinions: A or B.
- Initially, $1 \le x \le N 1$ individuals have opinion A and N x individuals have opinion B.
- At each time step, the individuals update their opinion by sampling without replacement from the current opinions.
- This just means that if x people have opinion A today, then at the next time step, the probability that y people have opinion A is

$$p_{x,y} := \binom{N}{y} \left(\frac{x}{N}\right)^{y} \left(\frac{N-x}{N}\right)^{N-y}$$

Example

Consider the following crude model of opinion dynamics.

- There is a population of N individuals, each with one of two opinions: A or B.
- Initially, $1 \le x \le N 1$ individuals have opinion A and N x individuals have opinion B.
- At each time step, the individuals update their opinion by sampling without replacement from the current opinions.
- This just means that if x people have opinion A today, then at the next time step, the probability that y people have opinion A is

$$p_{x,y} := \binom{N}{y} \left(\frac{x}{N}\right)^{y} \left(\frac{N-x}{N}\right)^{N-y} = \left[\left(\int \beta i \operatorname{norm} \left(N, \frac{x}{N} \right) = y \right] \right]$$

• What is the probability that everyone in the population eventually holds opinion *A*?

- Let X_n denote the number of people with opinion A at time n.
- Then, X_n is a DTMC.
- We are interested in finding $\mathbb{P}[V_N < V_0 \mid X_0 = x]$.

- Let X_n denote the number of people with opinion A at time n.
- Then, X_n is a DTMC.
- We are interested in finding $\mathbb{P}[V_N < V_0 \mid X_0 = x]$.
- By the theorem, it suffices to find a function h(x) with h(N) = 1, h(0) = 0 and for all 1 ≤ x ≤ N − 1,

$$h(x) = \sum_{y \in S} p_{x,y} h(y).$$

$$h(x) = \sum_{i}^{l} \mathbb{P} \left[Binom(N, x) = y \right] h(y).$$

$$h(y) = y \qquad h(n) = 1$$

$$h(y) = y \qquad h(0) = 0$$

- Let X_n denote the number of people with opinion A at time n.
- Then, X_n is a DTMC.
- We are interested in finding $\mathbb{P}[V_N < V_0 \mid X_0 = x]$.
- By the theorem, it suffices to find a function h(x) with h(N) = 1, h(0) = 0and for all $1 \le x \le N - 1$,

$$h(x) = \sum_{y \in S} p_{x,y} h(y)$$

• Since $p_{x,y} = \mathbb{P}[\text{Binom}(N, x/N) = y]$, you can check easily that h(x) = x/N is a valid choice. by + mm, $h(x) = \oint \left[V_N < V_0 \mid x_0 = x \right]$



- Let (X_n)_{n≥0} be a DTMC on a finite state space S = {1,..., 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 $\{1, \ldots, r\}$ are transient, states $\{r + 1, \ldots, N\}$ are recurrent, and $P_{x,x} = 1$ for all x > r.

- Let (X_n)_{n≥0} be a DTMC on a finite state space S = {1,..., 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 $\{1, \ldots, r\}$ are transient, states $\{r + 1, \ldots, N\}$ are recurrent, and $P_{x,x} = 1$ for all x > r.
- Therefore, the transition matrix P decomposes as

prob. of going from
$$P = \begin{bmatrix} Q & R \\ O & I \end{bmatrix}$$

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.

- Let T be the first time that the chain reaches one of the absorbing states. We know that $\mathbb{P}[T < \infty] = 1$.
- Our goal is to understand, for all j > r,

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

- Let T be the first time that the chain reaches one of the absorbing states. We know that $\mathbb{P}[T < \infty] = 1$.
- Our goal is to understand, for all j > r,

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

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

$$\mathcal{R} \neq i, \dots, \mathcal{N}$$

• By definition, we must have $U_{j,j} = 1$ and $U_{i,j} = 0$ for all i > r, $i \neq j$. h(k) = 0 "

- Let T be the first time that the chain reaches one of the absorbing states. We know that $\mathbb{P}[T < \infty] = 1$.
- Our goal is to understand, for all j > r,

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

- By definition, we must have $U_{j,j} = 1$ and $U_{i,j} = 0$ for all i > r, $i \neq j$.
- On the other hand, for any $i \leq r$, we have by first step analysis that

$$P = \begin{pmatrix} \boxed{\mathbb{Q}} \\ 0 \\ 1 \end{pmatrix} \qquad \qquad U_{i,j} = P_{i,j} + \sum_{\substack{k \leq r \\ k \leq r}} P_{i,k} U_{k,j} \end{cases} (\textbf{x})$$
$$= \frac{R_{i,j}}{\underline{x}} + \sum_{\substack{k \leq r \\ k \leq r}} Q_{i,\underline{k}} U_{k,j}, \zeta$$

- Let T be the first time that the chain reaches one of the absorbing states. We know that $\mathbb{P}[T < \infty] = 1$.
- Our goal is to understand, for all j > r,

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

- By definition, we must have $U_{j,j} = 1$ and $U_{i,j} = 0$ for all i > r, $i \neq j$.
- On the other hand, for any $i \leq r$, we have by first step analysis that

$$U_{i,j} = P_{i,j} + \sum_{k \le r} P_{i,k} U_{k,j}$$
$$= R_{i,j} + \sum_{k \le r} Q_{i,j} U_{k,j},$$

and by the same argument as before, a solution to these equations with the given boundary conditions gives $\mathbb{P}[X_T = j \mid X_0 = i]$.

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 = ι-γ
- She stops playing once she either reaches \$*N* or \$0.

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.
- We want to compute

$$h(x) = \mathbb{P}[V_N < V_0 \mid X_0 = x].$$

• As before, h(N) = 1, h(0) = 0 and for $1 \le x \le N - 1$,

$$h(x) = ph(x+1) + qh(x-1).$$

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.
- We want to compute

$$h(x) = \mathbb{P}[V_N < V_0 \mid X_0 = x].$$

• As before,
$$h(N) = 1$$
, $h(0) = 0$ and for $1 \le x \le N - 1$,
 $h(x) = ph(x+1) + qh(x-1)$.
• $h(x) = ph(x+1) + qh(x-1)$.
• $h(x) = h(x)$
• Check that this is satisfied by
 $h(x) = \frac{\theta^x - 1}{\theta^N - 1}$, $\theta = \frac{q}{p}$.
• $h(x) = \frac{\theta^x - 1}{\theta^N - 1}$, $\theta = \frac{q}{p}$.
• $h(x) = \frac{\theta^x - 1}{\theta^N - 1}$, $\theta = \frac{q}{p}$.
• $h(x) = \frac{\theta^x - 1}{\theta^N - 1}$, $\theta = \frac{q}{p}$.
• $h(x) = \frac{\theta^x - 1}{\theta^N - 1}$, $\theta = \frac{q}{p}$.

- As an example, imagine that you are betting \$1 on each round of roulette, where there are 18 red, 18 black, and 2 green holes.
- In this case p = 18/38.

- As an example, imagine that you are betting \$1 on each round of roulette, where there are 18 red, 18 black, and 2 green holes.
- In this case p = 18/38.
- So, for instance,

$$\mathbb{P}[V_{100} < V_{50} \mid X_0 = 50] = \frac{(20/18)^{50} - 1}{(20/18)^{100} - 1} = 0.005128,$$

which is almost 100 times less likely than when p = 19/38.