

MATH180C: Introduction to Stochastic Processes II

[Lecture A00: math-old.ucsd.edu/~ynemish/teaching/180cA](http://math-old.ucsd.edu/~ynemish/teaching/180cA)

[Lecture B00: math-old.ucsd.edu/~ynemish/teaching/180cB](http://math-old.ucsd.edu/~ynemish/teaching/180cB)

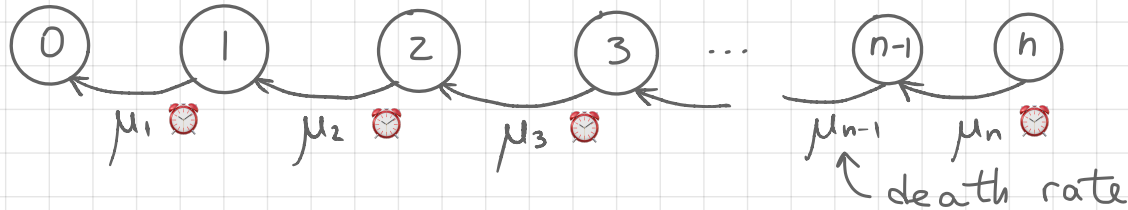
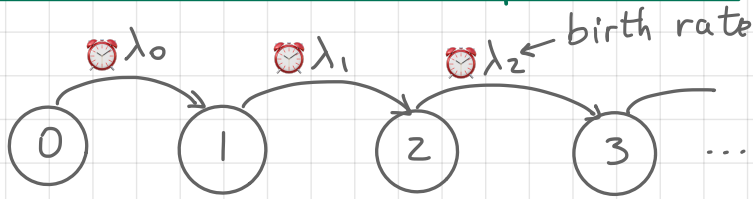
Today: Birth and death processes.
Strong Markov property.
Hitting probabilities

Next: PK 6.5, 6.6, Durrett 4.1

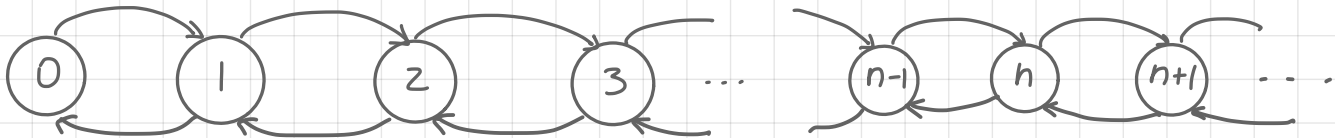
Week 2:

- homework 1 (due Friday April 8)

Birth and death processes



Combine both



Birth and death processes

Infinitesimal definition

Def. Let $(X_t)_{t \geq 0}$ be a continuous time MC, $X_t \in \{0, 1, 2, \dots\}$ with stationary transition probabilities. Then $(X_t)_{t \geq 0}$ is called a birth and death process with birth rates (λ_k) and death rates (μ_k) if

$$1. P_{i, i+1}(h) = \lambda_i h + o(h)$$

$$2. P_{i, i-1}(h) = \mu_i h + o(h)$$

$$3. P_{i, i}(h) = 1 - (\lambda_i + \mu_i)h + o(h)$$

$$4. P_{ij}(0) = \delta_{ij} \quad (P(X_0=j | X_0=i) = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases})$$

$$5. \mu_0 = 0, \lambda_0 > 0, \lambda_i, \mu_i > 0$$

Example: Linear growth with immigration

Dynamics of a certain population is described by the following principles:

during any small period of time of length h

- each individual gives birth to one new member with probability $\beta h + o(h)$ independently of other members;
- each individual dies with probability $\alpha h + o(h)$ independently of other members;
- one external member joins the population with probability $a h + o(h)$

Can be modeled as a Markov process

Example: Linear growth with immigration

Let $(X_t)_{t \geq 0}$ denote the size of the population.

Using a similar argument as for the Yule/pure death models:

• $P_{n,n+1}(h) = n\beta h + ah + o(h)$

← pure birth growth

↑ immigration growth

• $P_{n,n-1}(h) = n\alpha h + o(h)$

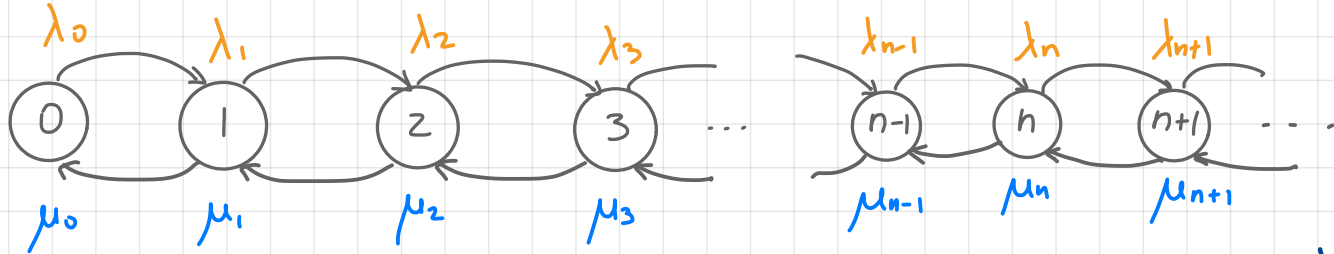
• $P_{n,n}(h) = 1 - (n\beta h + ah + n\alpha h) + o(h)$

↳ birth and death process with

$$\lambda_n = n\beta + a$$

$$\mu_n = n\alpha$$

Alternative (jump and hold) characterization



Sojourn times S_k are independent,

$$\frac{\lambda}{\lambda + \mu} = \frac{\mu}{\lambda + \mu} = \frac{\lambda'}{\lambda' + \mu'} = \frac{\mu'}{\lambda' + \mu'}$$

\swarrow $\text{Exp}(\lambda)$ \searrow $\text{Exp}(\mu)$

Each transition has two parts

- wait in state i for time $\sim \text{Exp}(\lambda_i + \mu_i)$
- then choose where to go:

go \rightarrow $(i+1)$ with probability $\frac{\lambda_i}{\lambda_i + \mu_i}$

go \leftarrow $(i-1)$ with probability $\frac{\mu_i}{\lambda_i + \mu_i}$

Stopping times

Def (Informal). Let $(X_t)_{t \geq 0}$ be a stochastic process and let $T \geq 0$ be a random variable. We call T a **stopping time** if the event

$$\{T \leq t\}$$

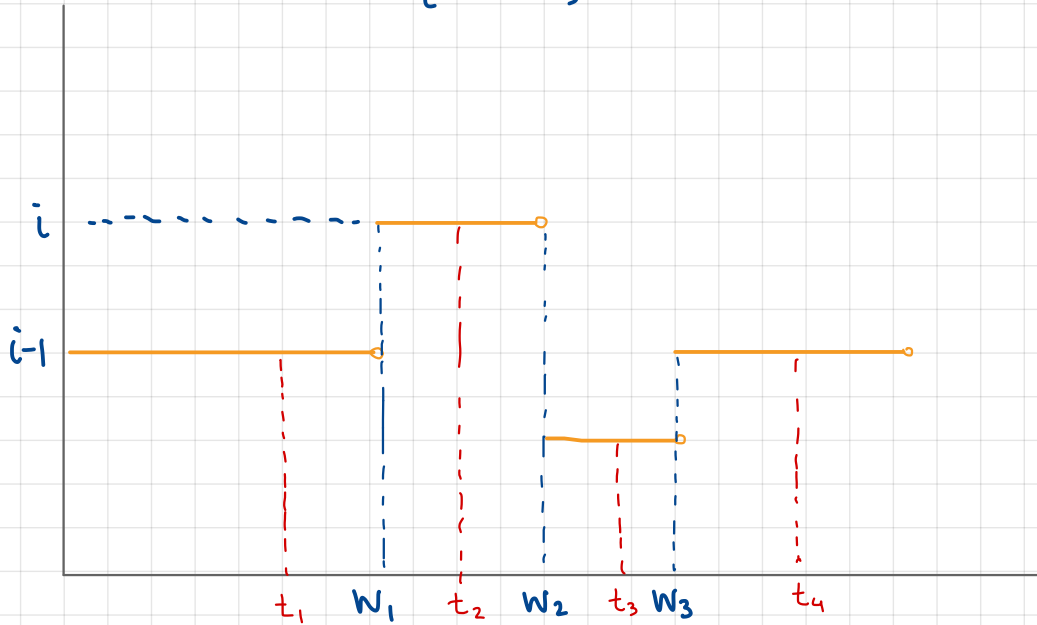
can be determined from the knowledge of the process up to time t (i.e., from $\{X_s : 0 \leq s \leq t\}$)

Examples: Let $(X_t)_{t \geq 0}$ be right-continuous

1. $\min\{t \geq 0 : X_t = i\}$ is a stopping time
2. W_k is a stopping time
3. $\sup\{t \geq 0 : X_t = i\}$ is not a stopping time

Stopping times

$$\{T \leq t\}$$



Strong Markov property

Theorem (no proof)

Let $(X_t)_{t \geq 0}$ be a MC, let T be a stopping time of $(X_t)_{t \geq 0}$. Then, conditional on $T < \infty$ and $X_T = i$,

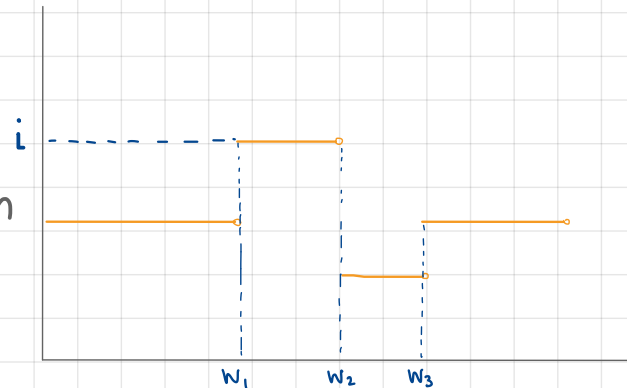
$$(X_{T+t})_{t \geq 0}$$

(i) is independent of $\{X_s, 0 \leq s \leq T\}$

(ii) has the same distribution as $(X_t)_{t \geq 0}$ starting from i .

Example

$(X_{W_i+t})_{t \geq 0}$ has the same distribution as $(X_t)_{t \geq 0}$ conditioned on $X_0 = i$ and is indep. of what happened before

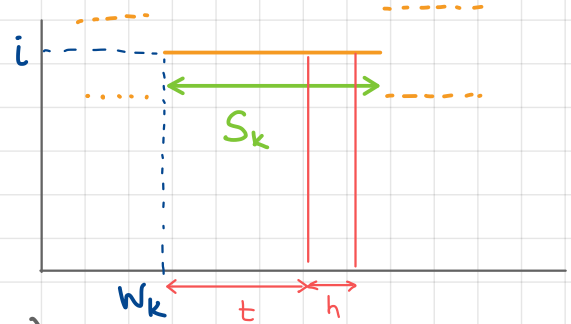


Alternative (jump and hold) characterization

"Proof"

Denote $G_i(t) := P(S_k > t | X_{W_k} = i)$

$$G_i(t+h) = P(S_k > t+h | X_{W_k} = i)$$



$$S_{\text{Markov}} = P(\text{no jumps on } [0, t+h] | X_0 = i) \quad \uparrow \text{stopping time}$$

$$\text{Markov} = P(\text{no jumps on } [0, t] | X_0 = i) P(\text{no jumps on } [0, h] | X_0 = i)$$

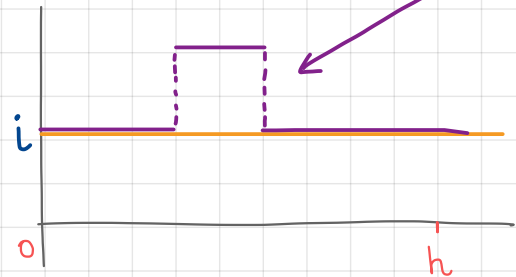
$$= P(S_0 > t | X_0 = i) P(S_0 > h | X_0 = i) = G_i(t) \underbrace{P_{i,i}(h)}_{1 - (\lambda + \mu_i)h + o(h)}$$

$$= G_i(t) - (\lambda + \mu_i) G_i(t) h + G_i(t) o(h)$$

$$\hookrightarrow G_i'(t) = -(\lambda + \mu_i) G_i(t), \quad G_i(0) = 1$$

$$P_{i,i}(h) = \lambda h + o(h)$$

$$P_{i+1,i}(h) = \mu_i h + o(h)$$



Alternative (jump and hold) characterization

"Proof" cont.

$$e^x = 1 + x + \frac{x^2}{2} + \dots + \frac{x^n}{n!} + \dots$$

$$G_i'(t) = -(\lambda_i + \mu_i) G_i(t), \quad G_i(0) = 1$$

$$\hookrightarrow G_i(t) = e^{-(\lambda_i + \mu_i)t} = P(S_k > t \mid X_{W_k} = i)$$

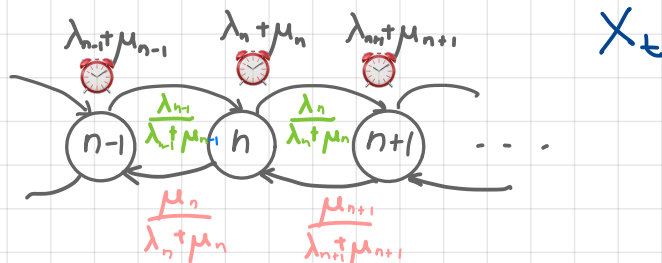
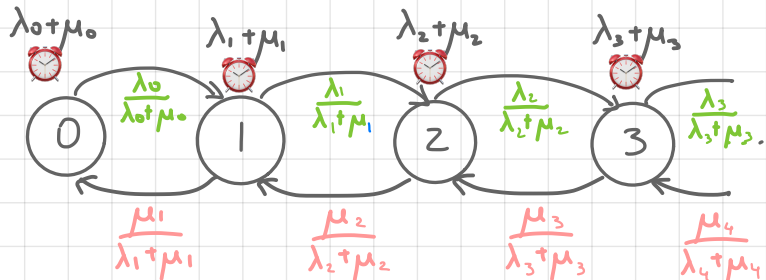
✓ $\hookrightarrow S_k \sim \text{Exp}(\lambda_i + \mu_i)$ (given that the process sojourns in i)

Suppose the process waits $\text{Exp}(\lambda_i + \mu_i)$, then
jumps to $i+1$ with probability $\lambda_i / (\lambda_i + \mu_i)$
to $i-1$ with probability $\mu_i / (\lambda_i + \mu_i)$

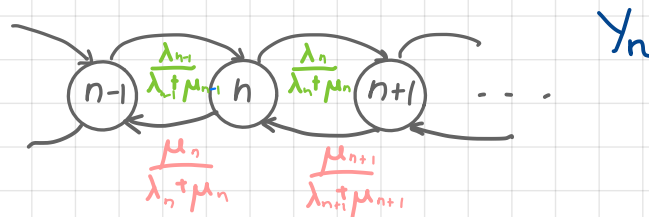
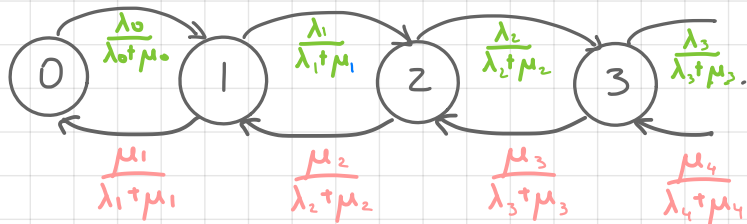
$$\begin{aligned} P_{i,i+1}(h) &= P(S_k \leq h \mid X_{W_k} = i) P(\text{jump to } i+1) \\ &= (1 - e^{-(\lambda_i + \mu_i)h}) \frac{\lambda_i}{\lambda_i + \mu_i} = ((\lambda_i + \mu_i)h + o(h)) \frac{\lambda_i}{\lambda_i + \mu_i} = \lambda_i h + o(h) \end{aligned} \quad \checkmark$$

$$P_{i,i-1}(h) = P(S_k \leq h \mid X_{W_k} = i) P(\text{jump to } i-1) = ((\lambda_i + \mu_i)h + o(h)) \frac{\mu_i}{\lambda_i + \mu_i} = \mu_i h + o(h)$$

Related discrete time MC.



Def. Let $(X_t)_{t \geq 0}$ be a continuous time MC, let $W_n, n \geq 0$, be the corresponding waiting (arrival, jump) times. Then we call $(Y_n)_{n \geq 0}$ defined by $Y_n = X_{W_n}, Y_0 = X_0, n \geq 1$ the **jump chain** of $(X_t)_{t \geq 0}$.



↑ random walk

Related discrete time MC.

$(X_t)_{t \geq 0}$ and its jump chain $(Y_n)_{n \geq 0}$ execute the same transitions.

Let $(X_t)_{t \geq 0}$ be a birth and death process. Then the transition probability matrix of the random walk $(Y_n)_{n \geq 0}$ is given by

$$P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 & \dots \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ \vdots \end{matrix} & \begin{pmatrix} & & & & & \dots \\ & \frac{\lambda_0}{\lambda_0 + \mu_0} & & & & \dots \\ \frac{\mu_1}{\lambda_1 + \mu_1} & & \frac{\lambda_1}{\lambda_1 + \mu_1} & & & \dots \\ & \frac{\mu_2}{\lambda_2 + \mu_2} & & \frac{\lambda_2}{\lambda_2 + \mu_2} & & \dots \\ & & \frac{\mu_3}{\lambda_3 + \mu_3} & & \frac{\lambda_3}{\lambda_3 + \mu_3} & \dots \\ & \vdots & \vdots & \ddots & \vdots & \ddots \end{pmatrix} \end{matrix}$$

Absorption probabilities for B&D processes

Let $(X_t)_{t \geq 0}$ be a birth and death process, and assume that the state 0 is absorbing, $\lambda_0 = 0$. Then

$$\begin{aligned} P((X_t)_{t \geq 0} \text{ gets absorbed in } 0 \mid X_0 = i) \\ = P((Y_n)_{n \geq 0} \text{ gets absorbed in } 0 \mid Y_0 = i) \end{aligned}$$

↳ use the first step analysis to compute the absorption probabilities for $(Y_n)_{n \geq 0}$ (and for $(X_t)_{t \geq 0}$)

Denote $u_i = P(Y_n \text{ is absorbed in } 0 \mid Y_0 = i)$

Then
$$u_0 = 1, \quad u_n = \frac{\mu_n}{\lambda_n + \mu_n} u_{n-1} + \frac{\lambda_n}{\lambda_n + \mu_n} u_{n+1}$$

Absorption probabilities for B&D processes

$$u_0 = 1, \quad u_n = \frac{\mu_n}{\lambda_n + \mu_n} u_{n-1} + \frac{\lambda_n}{\lambda_n + \mu_n} u_{n+1}$$

Rewrite $(\lambda_n + \mu_n) u_n = \mu_n u_{n-1} + \lambda_n u_{n+1}$

$$\lambda_n (u_{n+1} - u_n) = \mu_n (u_n - u_{n-1})$$

$$u_{n+1} - u_n = \frac{\mu_n}{\lambda_n} (u_n - u_{n-1})$$

$$= \underbrace{\frac{\mu_n}{\lambda_n} \cdot \frac{\mu_{n-1}}{\lambda_{n-1}} \cdots \frac{\mu_1}{\lambda_1}}_{\rho_n} (u_1 - u_0)$$

$$(*) \quad u_{n+1} - u_n = \rho_n (u_1 - 1)$$

Note that $\sum_{k=1}^{n-1} (u_{k+1} - u_k) = u_n - u_1 = (u_1 - 1) \sum_{n=1}^{n-1} \rho_n$

If $\sum_{n=1}^{\infty} \rho_n = \infty$, then $u_1 = 1$ and from (*) $u_n = 1 \quad \forall n \geq 0$.

Absorption probabilities for B&D processes

Let $\sum_{k=1}^{\infty} p_k < \infty$. If we assume that $u_n \rightarrow 0, n \rightarrow \infty$, then by

taking $n \rightarrow \infty$

$$u_n - u_1 = (u_1 - 1) \sum_{k=1}^{n-1} p_k$$

$$u_1 = \frac{\sum_{k=1}^{\infty} p_k}{1 + \sum_{k=1}^{\infty} p_k}$$

$$\text{and } u_n = u_1 + (u_1 - 1) \sum_{k=1}^{n-1} p_k = \frac{\sum_{k=1}^{\infty} p_k + \left(\sum_{k=1}^{\infty} p_k + 1 - \sum_{k=1}^{\infty} p_k \right) \sum_{k=1}^{n-1} p_k}{1 + \sum_{k=1}^{\infty} p_k}$$

$$= \frac{\sum_{k=1}^{\infty} p_k - \sum_{k=1}^{n-1} p_k}{1 + \sum_{k=1}^{\infty} p_k} = \frac{\sum_{k=n}^{\infty} p_k}{1 + \sum_{k=1}^{\infty} p_k}$$