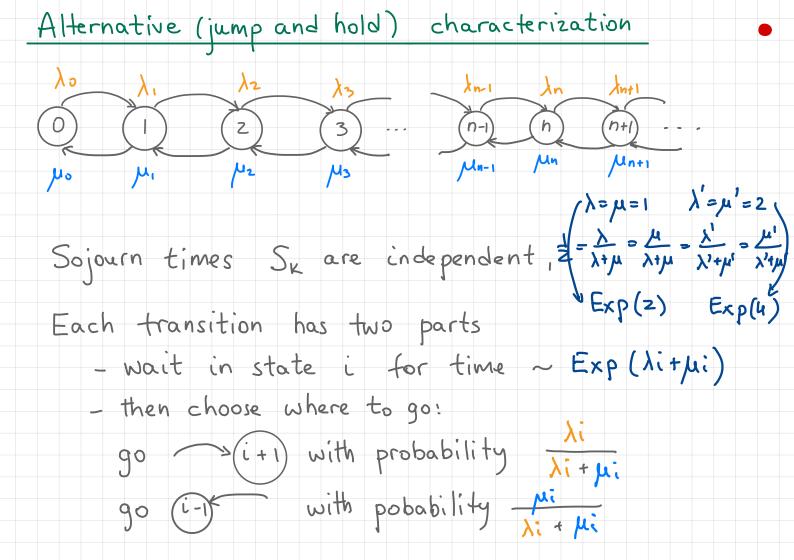
MATH180C: Introduction to Stochastic Processes II

Lecture A00: math-old.ucsd.edu/~ynemish/teaching/180cA Lecture B00: math-old.ucsd.edu/~ynemish/teaching/180cB

Today: Birth and death processes.
Absorption times.
General CTMC. Matrix
exponentials
Next: PK 6.6, Durrett 4.1

Week 2:

homework 1 (due Friday April 8)



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 $\{X_s: o \leq s \leq t\}$)

Examples: Let (Xt)+20 be right-continuous

- 1. min {t20: Xt=i} is a stopping time
- 2. Wk is a stopping time
- 3. sup {t20: X = i is not a stopping time

Strong Markov property Theorem (no proof) Let (Xt)to be a MC, let T be a stopping time of (Xt)t≥o. Then, conditional on T<∞ and X+=i, (X_{T+t})_{t≥0} (i) is independent of {Xs, 0 \le S \le T} (ii) has the same distribution as (Xt)tzo starting from i. Example (Xw, +t) +20 has the same distribution as (Xt)tes conditioned on Xo=i and is indep of what happened before

Related discrete time MC. Ant My-1 Ant My Ant My+1 $\lambda_0 + \mu_0$ $\lambda_1 + \mu_1$ $\lambda_2 + \mu_2$ $\lambda_3 + \mu_3$ $\begin{array}{c|c}
\lambda_0 \\
\lambda_1 + \mu_1 \\
\hline
\end{array}$ $\begin{array}{c|c}
\lambda_1 \\
\lambda_1 + \mu_2 \\
\hline
\end{array}$ $\begin{array}{c|c}
\lambda_2 \\
\lambda_3 \\
\lambda_4 + \mu_2
\end{array}$ (n-1) 1 1 m (n+1) --- $\frac{\mu_1}{\lambda_1 + \mu_1}$ $\frac{\mu_2}{\lambda_2 + \mu_2}$ $\frac{\mu_3}{\lambda_3 + \mu_3}$ $\frac{\mu_4}{\lambda_4 + \mu_4}$ Def. Let (Xt)t20 be a continuous time MC, let Wn, n20, be the corresponding waiting (arrival, jump) times. Then we call (Yn) nzo defined by the jump chain of (X+)+20. $\frac{\lambda_0}{\lambda_0 t \mu_0} = \frac{\lambda_1}{\lambda_1 t \mu_1} = \frac{\lambda_2}{\lambda_2 t \mu_2} = \frac{\lambda_3}{\lambda_3 t \mu_3}.$ $\lambda_1 + \mu_1$ $\lambda_2 + \mu_2$ $\lambda_3 + \mu_3$ $\lambda_4 + \mu_4$ C random walk

Mean time until absorption Let (Xt)t20 be a birth and death process. Denote T= min{t20: X+=0} absorption time and $W_i := E(T \mid X_o = i)$. Let (Yn) nzo be the jumps chain for (Xt)t20. N:= min { n > 0 : Yn = 0 } Then $W_i = E\left(\sum_{k=0}^{N-1} S_k \mid X_{o=i}\right) = \frac{1}{\lambda_i + \mu_i} + E\left(\sum_{k=1}^{N-1} S_k \mid X_{o=i}\right)$ = $\frac{1}{\lambda_{i} + \mu_{i}} + E\left(\sum_{k=1}^{N} S_{k} | X_{o} = i, Y_{i} = i+1\right) P(Y_{i} = i+1 | Y_{o} = i)$ + E (\(\S_k \) \(\X_0 = \i, \Y_1 = \i-1 \) P (\Y_1 = \i-1 \) \(\Y_0 = \i) Mean time until absorption

$$\int Wi = \frac{1}{\lambda i + \mu i} + \frac{\lambda i}{\lambda i + \mu i} + \frac{\mu i}{\lambda i + \mu i} + \frac{\mu i}{\lambda i + \mu i} + \frac{\mu i}{\lambda i + \mu i}$$

$$W_0 = 0$$

Alternatively,
$$E(T|X_0=i) = E\left(\sum_{k=0}^{N-1} \frac{1}{\lambda_{y_k} + \mu_{y_k}} |Y_0=i\right)$$

 $wi = E\left(\sum_{k=0}^{N-1} g(Y_k) \mid Y_0 = i\right),$ which leads to (the same) system of equations $W_i = g(i) + \sum_{j=1}^{n} P_{ij} W_j$

New apply the first step analysis for the general MC

First step analysis for birth and death processes

Let $(X_t)_{t\geq 0}$ be a birth and death process of rates $((\lambda_i, \mu_i))$ with $\lambda_0 = 0$ (state 0 absorbing).

Denote T= min{t: Xt=0}, u= P(Xt gets absorbed in 0 (Xo=i)

Denote
$$T = \min\{t: X_t = 0\}$$
, $u_i = P(X_t \text{ gets absorbed in } 0 | X_0 = i)$
 $Wi = E(T | X_0 = i)$ and $p_j = \frac{\mu_1 \mu_2 - \mu_j}{\lambda_1 \lambda_2 - \mu_j}$. Then

$$\sum_{j=1}^{\infty} p_j \qquad \qquad \sum_{j=1}^{\infty} \frac{1}{\lambda_j p_j} \prod_{k=1}^{\infty} p_k \sum_{j=k+1}^{\infty} \frac{1}{\lambda_j p_j} \prod_{j=1}^{\infty} \frac{1}{\lambda_j p_j} \prod_{k=1}^{\infty} \frac{1}{\lambda_j p_j} \prod_{j=1}^{\infty} \frac{1}{\lambda_j p_j} \prod_{k=1}^{\infty} \frac{1}{\lambda_j p_j} \prod_{j=1}^{\infty} \frac{1}{\lambda_j p_j} \prod_{j=1}^{$$

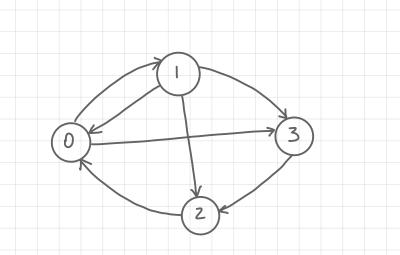
 $U_{i} = \begin{cases} \sum_{j=1}^{\infty} \beta_{j} & \text{if } \sum_{j=1}^{\infty} \beta_{j} \\ \text{if } \sum_{j=1}^{\infty} \beta_{j} & \text{where } \beta_{i} \end{cases}$ $U_{i} = \begin{cases} \sum_{j=1}^{\infty} \beta_{j} & \text{where } \beta_{i} \\ \text{where } \beta_{i} & \text{where } \beta_{i} \end{cases}$ $U_{i} = \begin{cases} \sum_{j=1}^{\infty} \beta_{j} & \text{where } \beta_{i} \\ \text{where } \beta_{i} & \text{where } \beta_{i} \end{cases}$ $U_{i} = \begin{cases} \sum_{j=1}^{\infty} \beta_{j} & \text{where } \beta_{i} \\ \text{where } \beta_{i} & \text{where } \beta_{i} \end{cases}$ $U_{i} = \begin{cases} \sum_{j=1}^{\infty} \beta_{j} & \text{where } \beta_{i} \\ \text{where } \beta_{i} & \text{where } \beta_{i} \end{cases}$ $U_{i} = \begin{cases} \sum_{j=1}^{\infty} \beta_{j} & \text{where } \beta_{i} \\ \text{where } \beta_{i} & \text{where } \beta_{i} \end{cases}$ $U_{i} = \begin{cases} \sum_{j=1}^{\infty} \beta_{j} & \text{where } \beta_{i} \\ \text{where } \beta_{i} & \text{where } \beta_{i} \end{cases}$

Birth and death processes. Results

- infinitesimal transition probability description - sojourn time description (jump and hold)
 - sojourn times are independent exponential r.v.s $P(i \rightarrow i+1) = \frac{\lambda i}{\lambda i + \mu_i} \quad P(i \rightarrow i-1) = \frac{\mu_i}{\lambda i + \mu_i}$
- system of differential equations for pure birth/death e.g. $P_i'(t) = -\lambda_i P_i(t) + \lambda_{i-1} P_{i-1}(t)$
- distributions of Xt for linear birth (geometric) and linear death (binomial) processes
- first step analysis giving absorption probabilities and mean time to absorption
- explosion, Strong Markov property etc.

General continuous time MC

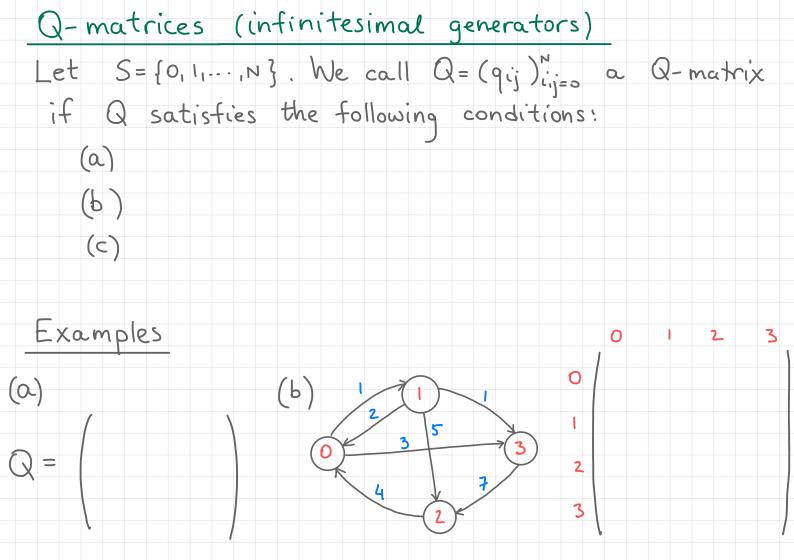
Assume for simplicity that the state space is finite



birth and death process

general MC

How to define? How to analyze?



Matrix exponentials

Let Q = (qij)ij=, be a matrix. Then the series converges componentwise, and we denote

its sum
$$\sum_{k=0}^{\infty} \frac{Q^k}{k!} = :$$
 the matrix exponential of Q .

In particular, we can define for t20.

Thm. Define
$$P(t) = e^{tQ}$$
. Then

(i) for all s, t

(ii) $(P(t))_{t\geq 0}$ is the unique solution to the equations

(i) for all s,t (ii) (P(t)) is the unique solution to the equations , and $\begin{cases} \frac{d}{dt} P(t) = \end{cases}$ $\left(\frac{d}{dt}P(t)=\right)$ P(0) =P(0) = .

Matrix exponentials

Properties are easy to remember -> scalar exponential

(i)
$$e^{(t+s)Q} = e^{tQ} = e^{sQ} = e^{tQ} = e^{(t+s)\alpha} = e^{tA} = e^{sA}$$

(note that in general $AB \neq BA$ for matrices A,B)

(ii)
$$\frac{d}{dt}e^{tQ} = Qe^{tQ} = e^{tQ}$$
 ($\frac{d}{dt}e^{tA} = ae^{tA}$)

(ii)
$$\frac{d}{dt}e^{tQ} = Qe^{tQ} = e^{tQ} \left(\frac{d}{dt}e^{t} = \lambda e^{tA}\right)$$

 $e^{0Q} = I \left(e^{0} = I\right)$

$$e = I \qquad (e^{\circ} = I)$$
Example

$$e = I \qquad (e = 1)$$
Example

$$\begin{array}{c}
e = I \\
e = I
\end{array}$$
Example

Example
$$(a) O = (O)$$

$$(a) Q = (0)$$

$$(\alpha) Q = (0)$$

$$(a) Q = (0)$$

$$(b) Q_2 = \begin{pmatrix} \lambda_1 & \lambda_2 \\ 0 & \lambda_2 \end{pmatrix}$$

Matrix exponentials Results on the previous slide hold for any matrix Q. Thm. Matrix Q is a Q-matrix iff $P(t) = e^{tQ}$ is a stochastic matrix $\forall t$

