

# MATH180C: Introduction to Stochastic Processes II

<https://mathweb.ucsd.edu/~ynemish/teaching/180c>

Today: FSA for general MC.  
Kolmogorov equations  
Next: PK 6.3, 6.6, Durrett 4.2

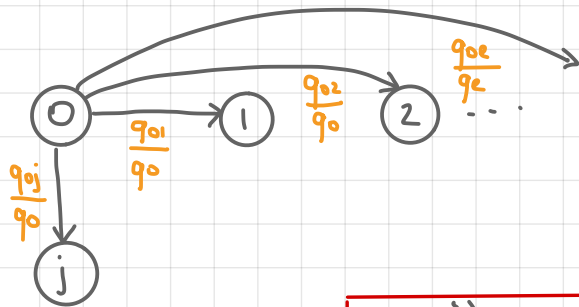
Week 3:

- HW2 due Friday, April 21 on Gradescope
- No in-person lecture on Friday, April 21

# Absorption probabilities for finite state chains

$$Q = \begin{matrix} 0 \\ \vdots \\ k-1 \\ k \\ \vdots \\ N \end{matrix} \left( \begin{array}{ccc|ccc} 0 & \dots & k-1 & k & \dots & N \\ \hline -q_0 & & & q_{ij} & & \\ \vdots & & & \vdots & & \\ q_{ij} & \dots & -q_{k-1} & & & \\ \hline & & & 0 & & 0 \\ & & & \vdots & & \\ & & & & \dots & \\ & & & & & 0 \end{array} \right)$$

Jump chain



Let  $i \in \{0, \dots, k-1\}$ ,  $j \in \{k, \dots, N\}$ .

Let  $M = \min\{n: Y_n \in \{k, \dots, N\}\}$

Denote  $u_i^{(j)} = P(Y_M = j | X_0 = i)$ .

Then FSA leads to the system

$$u_i^{(j)} = P(Y_M = j | Y_0 = i)$$

=

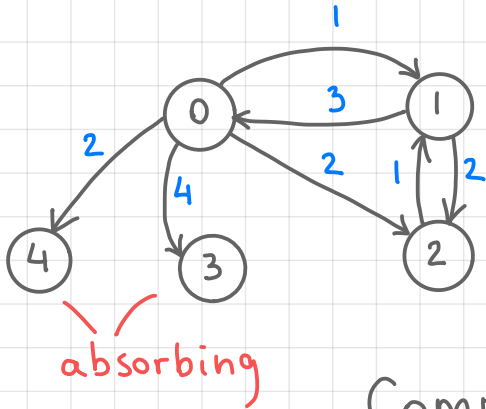
$$u_i^{(j)} = \frac{q_{ij}}{q_i} + \sum_{\substack{c=0 \\ c \neq i}}^{k-1} \frac{q_{ic}}{q_i} u_c^{(j)}$$

$P(Y_{n+1} = j | Y_n = i)$

$P(Y_{n+1} = c | Y_n = i)$

# Example

## Rate diagram



## Generator

$$Q = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{pmatrix} -9 & 1 & 2 & 4 & 2 \\ 3 & -5 & 2 & & \\ & 1 & -1 & & \\ & & & 0 & \\ & & & & 0 \end{pmatrix} \end{matrix}$$

Compute  $P(Y_M=3)$  if  $P(X_0=i)=p_i$  for  $i=0,1,2$   
 $\sum p_i=1$

Denote  $u_i = P(Y_M=3 | Y_0=i)$ .

$$\begin{cases} u_0 = \\ u_1 = \\ u_2 = \end{cases} \quad \begin{cases} \\ \\ u_2 = u_1 \end{cases} \quad P(Y_M=3) =$$

# Mean time to absorption

Similar analysis as was applied to B&D processes can be used to compute the mean time to absorption: before each jump from step  $i$  to state  $j$  the process sojourns on average in state  $i$ .

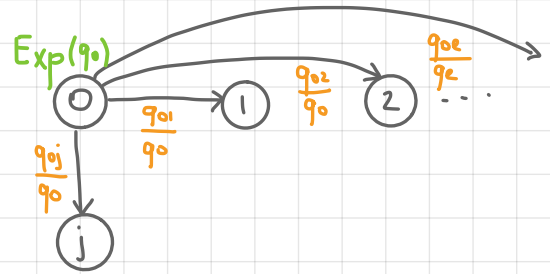
$$Q = \begin{matrix} & \begin{matrix} 0 & \dots & k-1 & k & \dots & N \end{matrix} \\ \begin{matrix} 0 \\ \vdots \\ k-1 \\ k \\ \vdots \\ N \end{matrix} & \left( \begin{array}{cccccc} -q_0 & & & & & \\ \vdots & & & & & \\ q_{ij} & \dots & -q_{k-1} & & & \\ & & & 0 & & \\ & & & & \ddots & \\ & & & & & 0 \end{array} \right) \end{matrix}$$

$$\text{Let } T = \min \{t : X_t \in \{k, \dots, N\}\}$$

$$M = \min \{n : Y_n \in \{k, \dots, N\}\}$$

Denote  $w_i =$

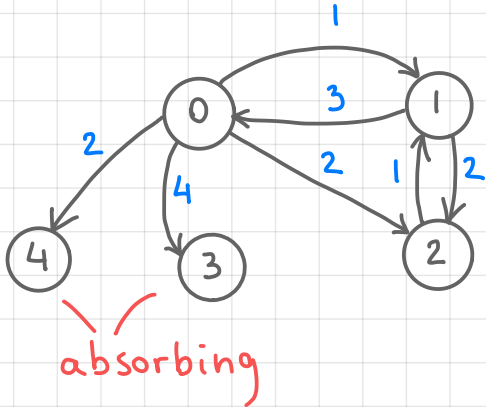
Then FSA gives



$$w_i =$$

# Example

## Rate diagram



## Generator

$$Q = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{pmatrix} 0 & 1 & 2 & 3 & 4 \\ -9 & 1 & 2 & 4 & 2 \\ 3 & -5 & 2 & & \\ & 1 & -1 & & \\ & & & 0 & \\ & & & & 0 \end{pmatrix} \end{matrix}$$

$$T = \min \{ t : X_t \in \{3, 4\} \}$$

$$w_i = E(T | X_0 = i)$$

$$\left\{ \begin{array}{l} w_0 = \\ w_1 = \\ w_2 = \end{array} \right.$$

$$\left\{ \begin{array}{l} \\ \\ w_2 = 1 + w_1 \end{array} \right.$$

## Kolmogorov equations

Jump and hold description is very intuitive, gives a very clear picture of the process, but does not answer to some very basic questions, e.g., computing  $P_{ij}(t) := P(X_t = j | X_0 = i)$ .

For computing the transition probabilities the differential equation approach is more appropriate.

In order to derive the system of differential equations for  $P_{ij}(t)$  from the infinitesimal description, we start from the familiar relation:

Chapman-Kolmogorov equation (semigroup property)

# Chapman-Kolmogorov equation

$$P_{ij}(t+s) = P(X_{t+s} = j | X_0 = i) \quad \text{condition on the value of } X_t$$

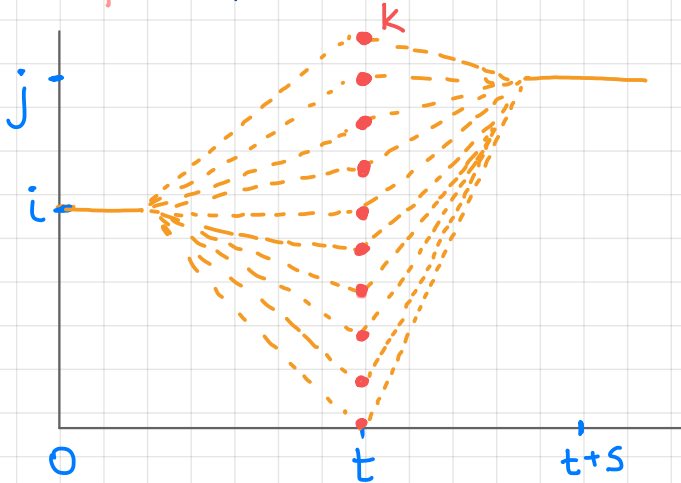
$$= \sum_{k=0}^{\infty} P(X_{t+s} = j | X_0 = i, X_t = k) P(X_t = k | X_0 = i)$$

Markov

$$= \sum_{k=0}^{\infty} P(X_{t+s} = j | X_t = k) P(X_t = k | X_0 = i)$$

stationary trans. prob.

$$= \sum_{k=0}^{\infty} P(X_s = j | X_0 = k) P(X_t = k | X_0 = i) = \sum_{k=0}^{\infty} P_{ik}(t) P_{kj}(s)$$



Or in matrix form

$$P(t+s) = P(t)P(s)$$

# Kolmogorov forward equations

Apply Chapman-Kolmogorov equations to compute

$$P_{ij}(t+h):$$

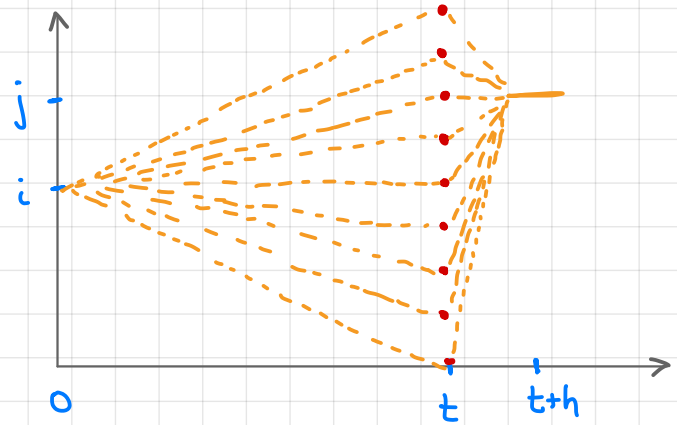
$$P_{ij}(t+h) =$$

Use infinitesimal description:

$$P_{kj}(h) = \begin{cases} q_{kj}h + o(h), & k \neq j \\ 1 + q_{jj}h + o(h), & k = j \end{cases}$$

$$(*) =$$

$$=$$

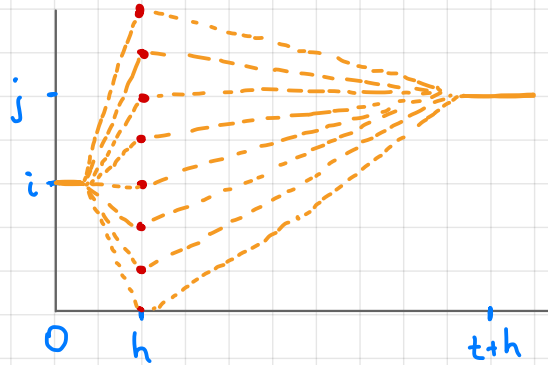


$$\frac{d}{dt}P(t) = P(t)Q$$



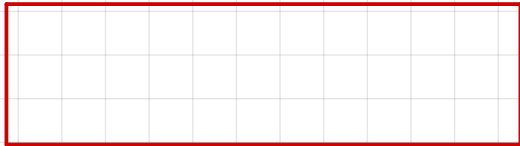
# Kolmogorov backward equations

$$\begin{aligned} P_{ij}(t+h) &= \sum_{k=0}^N P_{ik}(h) P_{kj}(t) \\ &= (1 + q_{ii}h + o(h)) P_{ij}(t) \\ &\quad + \sum_{\substack{k=0 \\ k \neq i}}^N (q_{ik}h + o(h)) P_{kj} \end{aligned}$$



$$= P_{ij}(t) + \sum_{k=0}^N q_{ik} P_{kj}(t) h + o(h)$$

↳



# Kolmogorov equations. Remarks

1.  $e^{tQ}$  satisfies both (forward and backward) equations. Indeed, omitting technical details, differentiate term-by-term

$$\frac{d}{dt} e^{tQ} = \frac{d}{dt} \left( \sum_{k=0}^{\infty} \frac{Q^k t^k}{k!} \right) =$$

$$\text{Now } \sum_{k=1}^{\infty} \frac{Q^k}{(k-1)!} t^{k-1} \stackrel{\ell=k-1}{=} \sum_{\ell=0}^{\infty} \frac{Q^{\ell+1}}{\ell!} t^{\ell} =$$

2. Redundancy is related to the stationarity of transition probabilities. If transition probabilities

$P_{ij}(s,t) = P(X_t=j | X_s=i)$  are not stationary, then

$\frac{\partial}{\partial t} P_{ij}(s,t) \rightarrow$  forward equation,  $\frac{\partial}{\partial s} P_{ij}(s,t) \rightarrow$  backward equation

## Example

Two-state MC

$$Q = \begin{pmatrix} -\alpha & \alpha \\ \beta & -\beta \end{pmatrix}$$

$$Q^2 = \begin{pmatrix} -\alpha & \alpha \\ \beta & -\beta \end{pmatrix} \begin{pmatrix} -\alpha & \alpha \\ \beta & -\beta \end{pmatrix} = \begin{pmatrix} \alpha(\alpha+\beta) & -\alpha(\alpha+\beta) \\ -\beta(\alpha+\beta) & \beta(\alpha+\beta) \end{pmatrix} =$$

↳

$$e^{tQ} = \sum_{k=0}^{\infty} \frac{Q^k t^k}{k!} =$$

=

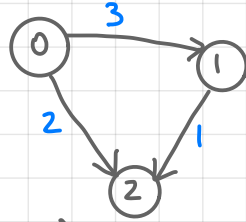
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$$= I + \frac{1}{\alpha+\beta} Q - \frac{1}{\alpha+\beta} e^{-(\alpha+\beta)t} Q$$

## Example

Let  $(X_t)_{t \geq 0}$  be a MC with generator  $Q$

$$Q = \begin{pmatrix} -5 & 3 & 2 \\ 0 & -1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$



Compute  $P_{0i}(t)$

For any  $k$ ,  $Q^k = \begin{pmatrix} * & * & * \\ 0 & * & * \\ 0 & 0 & * \end{pmatrix}$ ,  $\Rightarrow$

$$P'(t) = \begin{pmatrix} P_{00} & P_{01} & P_{02} \\ 0 & P_{11} & P_{12} \\ 0 & 0 & P_{22} \end{pmatrix} \begin{pmatrix} -5 & 3 & 2 \\ 0 & -1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$

$$P'_{00}(t) =$$

$$P'_{11}(t) = -P_{11}(t), P_{11}(0) = 1 \Rightarrow P_{11}(t) = e^{-t}$$

$$P'_{22}(t) = 0, P_{22}(0) = 1 \Rightarrow P_{22}(t) = 1$$

$$P'_{01}(t) =$$

$$P_{01}(t) =$$

$$P_{01}(t) =$$

## Forward and backward equations for B&D processes

Forward equation:

$$P_{ij}(t+h) = \sum_{k=0}^{\infty} P_{ik}(t) P_{kj}(h)$$

=

If  $\Theta_{ij} = o(h)$  (requires additional technical assumptions)

$$\begin{cases} P'_{ij}(t) = \lambda_{j-1} P_{ij-1}(t) - (\lambda_j + \mu_j) P_{ij}(t) + \mu_{j+1} P_{ij+1}(t) \\ P'_{i0}(t) = -\lambda_0 P_{i0}(t) + \mu_1 P_{i1}(t) \end{cases}, \quad \text{with } P_{ij}(0) = \delta_{ij}$$

## Forward and backward equations for B&D processes

Similarly, we derive the backward equations

$$\begin{cases} P_{ij}'(t) = \mu_i P_{i-1,j}(t) - (\lambda_i + \mu_i) P_{ij}(t) + \lambda_i P_{i+1,j}(t) \\ P_{0j}(t) = -\lambda_0 P_{0j}(t) - \lambda_0 P_{1j}(t) \quad , \quad \text{with } P_{ij}(0) = \delta_{ij} \end{cases}$$

Example Linear growth with immigration.

Recall  $\lambda_k = \lambda \cdot k + a$  ← immigration  
                    ↑ linear birth rate

$\mu_k = \mu \cdot k$   
                    ↑ linear death rate

## Example: Linear growth with immigration.

Use forward equations to compute  $E(X_t | X_0 = i)$

$$\begin{cases} P'_{ij}(t) = \lambda_{j-1} P_{i,j-1}(t) - (\lambda_j + \mu_j) P_{ij}(t) + \mu_{j+1} P_{i,j+1}(t) \\ P'_{i0}(t) = -\lambda_0 P_{i0}(t) + \mu_1 P_{i1}(t) \end{cases}$$

$$E(X_t | X_0 = i) =$$

$$P'_{ij}(t) = (\lambda(j-1) + a) P_{i,j-1}(t) - ((\lambda + \mu)j + a) P_{ij}(t) + \mu(j+1) P_{i,j+1}(t)$$

## Example: Linear growth with immigration.

$$M'(t) =$$

=

=

$$\begin{cases} M'(t) = \\ M(0) = \end{cases}$$

$$M(t) = i + at \quad \text{if } \lambda = \mu$$

$$M(t) = \frac{a}{\lambda - \mu} (e^{(\lambda - \mu)t} - 1) + i e^{(\lambda - \mu)t} \quad \text{if } \lambda \neq \mu$$