

Continuous-time Markov Chains

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Transition probability function

Determination of transition probability function

Limit probabilities and ergodicity

- ▶ **Continuous-time** positive variable $t \in [0, \infty)$
- ▶ **Time-dependent random state** $X(t)$ takes values on a countable set
 - ▶ In general denote states as $i = 0, 1, 2, \dots$, i.e., here the **state space** is \mathbb{N}
 - ▶ If $X(t) = i$ we say “the process is in state i at time t ”

- ▶ **Def:** Process $X(t)$ is a **continuous-time Markov chain (CTMC)** if

$$\begin{aligned} & P(X(t+s) = j \mid X(s) = i, X(u) = x(u), u < s) \\ &= P(X(t+s) = j \mid X(s) = i) \end{aligned}$$

- ▶ **Markov property** \Rightarrow Given the present state $X(s)$
 - \Rightarrow Future $X(t+s)$ is independent of the past $X(u) = x(u), u < s$
- ▶ In principle need to specify functions $P(X(t+s) = j \mid X(s) = i)$
 - \Rightarrow For all times t and s , for all pairs of states (i, j)

▶ Notation

- ▶ $X[s : t]$ state values for all times $s \leq u \leq t$, includes borders
 - ▶ $X(s : t)$ values for all times $s < u < t$, borders excluded
 - ▶ $X(s : t]$ values for all times $s < u \leq t$, exclude left, include right
 - ▶ $X[s : t)$ values for all times $s \leq u < t$, include left, exclude right
- ▶ **Homogeneous CTMC** if $P(X(t+s) = j \mid X(s) = i)$ invariant for all s
⇒ We restrict consideration to homogeneous CTMCs
- ▶ Still need $P_{ij}(t) := P(X(t+s) = j \mid X(s) = i)$ for all t and pairs (i, j)
⇒ $P_{ij}(t)$ is known as the **transition probability function**. More later
- ▶ **Markov property and homogeneity make description somewhat simpler**

- ▶ T_i = time until transition out of state i into any other state j
- ▶ **Def:** T_i is a random variable called **transition time** with cdf

$$P(T_i > t) = P(X(0 : t] = i \mid X(0) = i)$$

- ▶ Probability of $T_i > t + s$ given that $T_i > s$? Use cdf expression

$$\begin{aligned}P(T_i > t + s \mid T_i > s) &= P(X(0 : t + s] = i \mid X[0 : s] = i) \\&= P(X(s : t + s] = i \mid X[0 : s] = i) \\&= P(X(s : t + s] = i \mid X(s) = i) \\&= P(X(0 : t] = i \mid X(0) = i)\end{aligned}$$

- ▶ Used that $X[0 : s] = i$ given, Markov property, and homogeneity
- ▶ From definition of $T_i \Rightarrow P(T_i > t + s \mid T_i > s) = P(T_i > t)$
 \Rightarrow **Transition times are exponential random variables**

- ▶ Exponential transition times is a fundamental property of CTMCs
 - ⇒ Can be used as “algorithmic” definition of CTMCs
- ▶ Continuous-time random process $X(t)$ is a CTMC if
 - (a) Transition times T_i are exponential random variables with mean $1/\nu_i$
 - (b) When they occur, transition from state i to j with probability P_{ij}

$$\sum_{j=1}^{\infty} P_{ij} = 1, \quad P_{ii} = 0$$

- (c) Transition times T_i and transitioned state j are independent
- ▶ Define matrix \mathbf{P} grouping transition probabilities P_{ij}
 - ▶ CTMC states evolve as in a discrete-time Markov chain
 - ⇒ State transitions occur at exponential intervals $T_i \sim \exp(\nu_i)$
 - ⇒ As opposed to occurring at fixed intervals

- ▶ Consider a CTMC with transition matrix \mathbf{P} and rates ν_j
- ▶ **Def:** CTMC's embedded discrete-time MC has transition matrix \mathbf{P}
- ▶ **Transition probabilities \mathbf{P} describe a discrete-time MC**
 - ⇒ No self-transitions ($P_{ii} = 0$, \mathbf{P} 's diagonal null)
 - ⇒ Can use underlying discrete-time MCs to study CTMCs
- ▶ **Def:** State j accessible from i if accessible in the embedded MC
- ▶ **Def:** States i and j communicate if they do so in the embedded MC
 - ⇒ **Communication is a class property**
- ▶ **Recurrence, transience, ergodicity.** Class properties ... More later

- ▶ Expected value of transition time T_i is $\mathbb{E}[T_i] = 1/\nu_i$
 - ⇒ Can interpret ν_i as the rate of transition out of state i
 - ⇒ Of these transitions, a fraction P_{ij} are into state j
- ▶ **Def:** Transition rate from i to j is $q_{ij} := \nu_i P_{ij}$
- ▶ Transition rates offer yet another specification of CTMCs
- ▶ If q_{ij} are given can recover ν_i as

$$\nu_i = \nu_i \sum_{j=1}^{\infty} P_{ij} = \sum_{j=1}^{\infty} \nu_i P_{ij} = \sum_{j=1}^{\infty} q_{ij}$$

- ▶ Can also recover P_{ij} as $\Rightarrow P_{ij} = q_{ij}/\nu_i = q_{ij} \left(\sum_{j=1}^{\infty} q_{ij} \right)^{-1}$

- ▶ State $X(t) = 0, 1, \dots$. Interpret as number of individuals
- ▶ Birth and deaths occur at state-dependent rates. When $X(t) = i$
- ▶ **Births** \Rightarrow Individuals added at exponential times with mean $1/\lambda_i$
 \Rightarrow Birth or arrival rate = λ_i births per unit of time
- ▶ **Deaths** \Rightarrow Individuals removed at exponential times with rate $1/\mu_i$
 \Rightarrow Death or departure rate = μ_i deaths per unit of time
- ▶ Birth and death times are independent
- ▶ Birth and death (BD) processes are then CTMCs

- ▶ **Q:** Transition times T_i ? Leave state $i \neq 0$ when birth or death occur
- ▶ If T_B and T_D are times to next birth and death, $T_i = \min(T_B, T_D)$
⇒ Since T_B and T_D are exponential, so is T_i with rate

$$\nu_i = \lambda_i + \mu_i$$

- ▶ When leaving state i can go to $i+1$ (birth first) or $i-1$ (death first)
 - ⇒ Birth occurs before death with probability $\frac{\lambda_i}{\lambda_i + \mu_i} = P_{i,i+1}$
 - ⇒ Death occurs before birth with probability $\frac{\mu_i}{\lambda_i + \mu_i} = P_{i,i-1}$
- ▶ Leave state 0 only if a birth occurs, then

$$\nu_0 = \lambda_0, \quad P_{01} = 1$$

- ⇒ If CTMC leaves 0, goes to 1 with probability 1
- ⇒ Might not leave 0 if $\lambda_0 = 0$ (e.g., to model extinction)

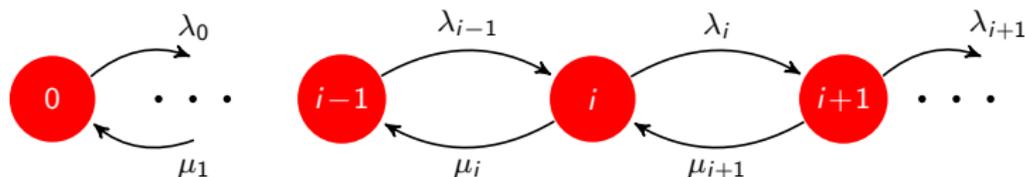
- ▶ Rate of transition from i to $i + 1$ is (recall definition $q_{ij} = \nu_i P_{ij}$)

$$q_{i,i+1} = \nu_i P_{i,i+1} = (\lambda_i + \mu_i) \frac{\lambda_i}{\lambda_i + \mu_i} = \lambda_i$$

- ▶ Likewise, rate of transition from i to $i - 1$ is

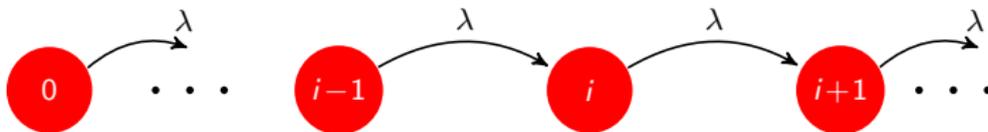
$$q_{i,i-1} = \nu_i P_{i,i-1} = (\lambda_i + \mu_i) \frac{\mu_i}{\lambda_i + \mu_i} = \mu_i$$

- ▶ For $i = 0 \Rightarrow q_{01} = \nu_0 P_{01} = \lambda_0$



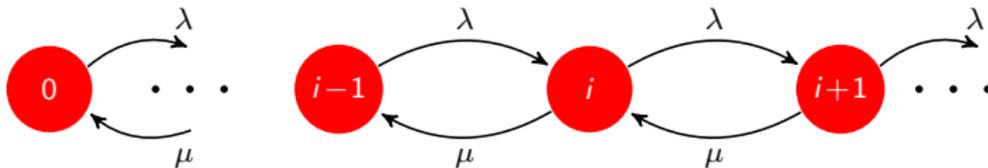
- ▶ Somewhat more natural representation. **Similar to discrete-time MCs**

- ▶ A **Poisson process** is a BD process with $\lambda_i = \lambda$ and $\mu_i = 0$ constant
- ▶ State $N(t)$ counts the total number of events (arrivals) by time t
 - ⇒ Arrivals occur a rate of λ per unit time
 - ⇒ Transition times are the i.i.d. exponential interarrival times



- ▶ The Poisson process is a CTMC

- ▶ An **M/M/1 queue** is a BD process with $\lambda_i = \lambda$ and $\mu_i = \mu$ constant
- ▶ State $Q(t)$ is the number of customers in the system at time t
 - ⇒ Customers arrive for service at a rate of λ per unit time
 - ⇒ They are serviced at a rate of μ customers per unit time



- ▶ The M/M is for Markov arrivals/Markov departures
 - ⇒ Implies a Poisson arrival process, exponential services times
 - ⇒ The 1 is because there is only one server

Continuous-time Markov chains

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Limit probabilities and ergodicity

- ▶ Two equivalent ways of specifying a CTMC
- 1) Transition time averages $1/\nu_i$ + transition probabilities P_{ij}
 - ⇒ Easier description
 - ⇒ Typical starting point for CTMC modeling
- 2) Transition probability function $P_{ij}(t) := P(X(t+s) = j \mid X(s) = i)$
 - ⇒ More complete description for all $t \geq 0$
 - ⇒ Similar in spirit to P_{ij}^n for discrete-time Markov chains
- ▶ **Goal:** compute $P_{ij}(t)$ from transition times and probabilities
 - ⇒ Notice two obvious properties $P_{ij}(0) = 0$, $P_{ii}(0) = 1$

Roadmap to determine $P_{ij}(t)$

- ▶ Goal is to obtain a differential equation whose solution is $P_{ij}(t)$
 - ⇒ Study change in $P_{ij}(t)$ when time changes slightly
- ▶ Separate in two subproblems (divide and conquer)
 - ⇒ Transition probabilities for small time h , $P_{ij}(h)$
 - ⇒ Transition probabilities in $t + h$ as function of those in t and h
- ▶ We can combine both results in two different ways
 - 1) Jump from 0 to t then to $t + h$ ⇒ Process runs a little longer
 - ⇒ Changes where the process is going to ⇒ Forward equations
 - 2) Jump from 0 to h then to $t + h$ ⇒ Process starts a little later
 - ⇒ Changes where the process comes from ⇒ Backward equations

Theorem

The transition probability functions $P_{ii}(t)$ and $P_{ij}(t)$ satisfy the following limits as t approaches 0

$$\lim_{t \rightarrow 0} \frac{P_{ij}(t)}{t} = q_{ij}, \quad \lim_{t \rightarrow 0} \frac{1 - P_{ii}(t)}{t} = \nu_i$$

- ▶ Since $P_{ij}(0) = 0$, $P_{ii}(0) = 1$ above limits are derivatives at $t = 0$

$$\left. \frac{\partial P_{ij}(t)}{\partial t} \right|_{t=0} = q_{ij}, \quad \left. \frac{\partial P_{ii}(t)}{\partial t} \right|_{t=0} = -\nu_i$$

- ▶ Limits also imply that for small h (recall Taylor series)

$$P_{ij}(h) = q_{ij}h + o(h), \quad P_{ii}(h) = 1 - \nu_i h + o(h)$$

- ▶ Transition rates q_{ij} are “instantaneous transition probabilities”
⇒ Transition probability coefficient for small time h

- ▶ **Q:** Probability of an event happening in infinitesimal time h ?
- ▶ Want $P(T < h)$ for small h

$$P(T < h) = \int_0^h \lambda e^{-\lambda t} dt \approx \lambda h$$

$$\Rightarrow \text{Equivalent to } \left. \frac{\partial P(T < t)}{\partial t} \right|_{t=0} = \lambda$$

- ▶ Sometimes also write $P(T < h) = \lambda h + o(h)$

$$\Rightarrow o(h) \text{ implies } \lim_{h \rightarrow 0} \frac{o(h)}{h} = 0$$

\Rightarrow Read as “negligible with respect to h ”

- ▶ **Q:** Two independent events in infinitesimal time h ?

$$P(T_1 \leq h, T_2 \leq h) \approx (\lambda_1 h)(\lambda_2 h) = \lambda_1 \lambda_2 h^2 = o(h)$$

Proof.

- ▶ Consider a small time h , and recall $T_i \sim \exp(\nu_i)$
- ▶ Since $1 - P_{ii}(h)$ is the probability of transitioning out of state i

$$1 - P_{ii}(h) = P(T_i < h) = \nu_i h + o(h)$$

⇒ Divide by h and take limit to establish the second identity

- ▶ For $P_{ij}(t)$ notice that since two or more transitions have $o(h)$ prob.

$$P_{ij}(h) = P(X(h) = j \mid X(0) = i) = P_{ij}P(T_i < h) + o(h)$$

- ▶ Again, since T_i is exponential $P(T_i < h) = \nu_i h + o(h)$. Then

$$P_{ij}(h) = \nu_i P_{ij} h + o(h) = q_{ij} h + o(h)$$

⇒ Divide by h and take limit to establish the first identity



Theorem

For all times s and t the transition probability functions $P_{ij}(t + s)$ are obtained from $P_{ik}(t)$ and $P_{kj}(s)$ as

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

- ▶ As for discrete-time MCs, to go from i to j in time $t + s$
 - ⇒ Go from i to some state k in time t ⇒ $P_{ik}(t)$
 - ⇒ In the remaining time s go from k to j ⇒ $P_{kj}(s)$
 - ⇒ Sum over all possible intermediate states k

Proof.

$$\begin{aligned} P_{ij}(t+s) &= P(X(t+s) = j \mid X(0) = i) && \text{Definition of } P_{ij}(t+s) \\ &= \sum_{k=0}^{\infty} P(X(t+s) = j \mid X(t) = k, X(0) = i) P(X(t) = k \mid X(0) = i) && \text{Law of total probability} \\ &= \sum_{k=0}^{\infty} P(X(t+s) = j \mid X(t) = k) P_{ik}(t) && \text{Markov property of CTMC} \\ &&& \text{and definition of } P_{ik}(t) \\ &= \sum_{k=0}^{\infty} P_{kj}(s) P_{ik}(t) && \text{Definition of } P_{kj}(s) \end{aligned}$$

□

- ▶ Let us combine the last two results to express $P_{ij}(t + h)$
- ▶ Use Chapman-Kolmogorov's equations for $0 \rightarrow t \rightarrow h$

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

- ▶ Substitute infinitesimal time expressions for $P_{jj}(h)$ and $P_{kj}(h)$

$$P_{ij}(t + h) = P_{ij}(t)(1 - \nu_j h) + \sum_{k=0, k \neq j}^{\infty} P_{ik}(t)q_{kj}h + o(h)$$

- ▶ Subtract $P_{ij}(t)$ from both sides and divide by h

$$\frac{P_{ij}(t + h) - P_{ij}(t)}{h} = -\nu_j P_{ij}(t) + \sum_{k=0, k \neq j}^{\infty} P_{ik}(t)q_{kj} + \frac{o(h)}{h}$$

- ▶ Right-hand side equals a “derivative” ratio. Let $h \rightarrow 0$ to prove ...

Theorem

The transition probability functions $P_{ij}(t)$ of a CTMC satisfy the system of differential equations (for all pairs i, j)

$$\frac{\partial P_{ij}(t)}{\partial t} = \sum_{k=0, k \neq j}^{\infty} q_{kj} P_{ik}(t) - \nu_j P_{ij}(t)$$

- ▶ Interpret each summand in Kolmogorov's forward equations
 - ▶ $\partial P_{ij}(t)/\partial t$ = rate of change of $P_{ij}(t)$
 - ▶ $q_{kj} P_{ik}(t)$ = (transition into k in $0 \rightarrow t$) \times
(rate of moving into j in next instant)
 - ▶ $\nu_j P_{ij}(t)$ = (transition into j in $0 \rightarrow t$) \times
(rate of leaving j in next instant)
- ▶ Change in $P_{ij}(t) = \sum_k$ (moving into j from k) $-$ (leaving j)
- ▶ Kolmogorov's forward equations valid in most cases, but not always

- ▶ For **forward** equations used Chapman-Kolmogorov's for $0 \rightarrow t \rightarrow h$
- ▶ For **backward** equations we use $0 \rightarrow h \rightarrow t$ to express $P_{ij}(t+h)$ as

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

- ▶ Substitute infinitesimal time expression for $P_{ii}(h)$ and $P_{ik}(h)$

$$P_{ij}(t+h) = (1 - \nu_i h)P_{ij}(t) + \sum_{k=0, k \neq i}^{\infty} q_{ik} h P_{kj}(t) + o(h)$$

- ▶ Subtract $P_{ij}(t)$ from both sides and divide by h

$$\frac{P_{ij}(t+h) - P_{ij}(t)}{h} = -\nu_i P_{ij}(t) + \sum_{k=0, k \neq i}^{\infty} q_{ik} P_{kj}(t) + \frac{o(h)}{h}$$

- ▶ Right-hand side equals a “derivative” ratio. Let $h \rightarrow 0$ to prove ...

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The transition probability functions $P_{ij}(t)$ of a CTMC satisfy the system of differential equations (for all pairs i, j)

$$\frac{\partial P_{ij}(t)}{\partial t} = \sum_{k=0, k \neq i}^{\infty} q_{ik} P_{kj}(t) - \nu_i P_{ij}(t)$$

- ▶ Interpret each summand in **Kolmogorov's backward equations**
 - ▶ $\partial P_{ij}(t)/\partial t =$ rate of change of $P_{ij}(t)$
 - ▶ $q_{ik} P_{kj}(t) =$ (transition into j in $h \rightarrow t$) \times
(rate of **transition into k in initial instant**)
 - ▶ $\nu_i P_{ij}(t) =$ (transition into j in $h \rightarrow t$) \times
(rate of **leaving i in initial instant**)
- ▶ **Forward equations** \Rightarrow change in $P_{ij}(t)$ if finish h later
- ▶ **Backward equations** \Rightarrow change in $P_{ij}(t)$ if start h earlier
- ▶ Where process goes (**forward**) vs. where process comes from (**backward**)

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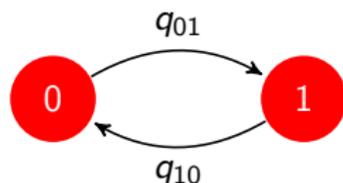
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Limit probabilities and ergodicity

Ex: Simplest possible CTMC has only two states. Say 0 and 1

- ▶ Transition rates are q_{01} and q_{10}
- ▶ Given q_{01} and q_{10} can find rates of transitions out of $\{0, 1\}$



$$\nu_0 = \sum_j q_{0j} = q_{01}, \quad \nu_1 = \sum_j q_{1j} = q_{10}$$

- ▶ Use Kolmogorov's equations to find **transition probability functions**

$$P_{00}(t), \quad P_{01}(t), \quad P_{10}(t), \quad P_{11}(t)$$

- ▶ **Transition probabilities out of each state sum up to one**

$$P_{00}(t) + P_{01}(t) = 1, \quad P_{10}(t) + P_{11}(t) = 1$$

- ▶ Kolmogorov's forward equations (process runs a little longer)

$$P'_{ij}(t) = \sum_{k=0, k \neq j}^{\infty} q_{kj} P_{ik}(t) - \nu_j P_{ij}(t)$$

- ▶ For the two state CTMC

$$\begin{aligned} P'_{00}(t) &= q_{10} P_{01}(t) - \nu_0 P_{00}(t), & P'_{01}(t) &= q_{01} P_{00}(t) - \nu_1 P_{01}(t) \\ P'_{10}(t) &= q_{10} P_{11}(t) - \nu_0 P_{10}(t), & P'_{11}(t) &= q_{01} P_{10}(t) - \nu_1 P_{11}(t) \end{aligned}$$

- ▶ Probabilities out of 0 sum up to 1 \Rightarrow eqs. in first row are equivalent
- ▶ Probabilities out of 1 sum up to 1 \Rightarrow eqs. in second row are equivalent
 \Rightarrow Pick the equations for $P'_{00}(t)$ and $P'_{11}(t)$

- ▶ Use \Rightarrow Relation between transition rates: $\nu_0 = q_{01}$ and $\nu_1 = q_{10}$
 \Rightarrow Probs. sum 1: $P_{01}(t) = 1 - P_{00}(t)$ and $P_{10}(t) = 1 - P_{11}(t)$

$$P'_{00}(t) = q_{10}[1 - P_{00}(t)] - q_{01}P_{00}(t) = q_{10} - (q_{10} + q_{01})P_{00}(t)$$

$$P'_{11}(t) = q_{01}[1 - P_{11}(t)] - q_{10}P_{11}(t) = q_{01} - (q_{10} + q_{01})P_{11}(t)$$

- ▶ Can obtain exact same pair of equations from backward equations
- ▶ First-order linear differential equations \Rightarrow Solutions are exponential
- ▶ For $P_{00}(t)$ propose candidate solution (just differentiate to check)

$$P_{00}(t) = \frac{q_{10}}{q_{10} + q_{01}} + ce^{-(q_{10} + q_{01})t}$$

\Rightarrow To determine c use initial condition $P_{00}(0) = 1$

- ▶ Evaluation of candidate solution at initial condition $P_{00}(0) = 1$ yields

$$1 = \frac{q_{10}}{q_{10} + q_{01}} + c \Rightarrow c = \frac{q_{01}}{q_{10} + q_{01}}$$

- ▶ Finally transition probability function $P_{00}(t)$

$$P_{00}(t) = \frac{q_{10}}{q_{10} + q_{01}} + \frac{q_{01}}{q_{10} + q_{01}} e^{-(q_{10} + q_{01})t}$$

- ▶ Repeat for $P_{11}(t)$. Same exponent, different constants

$$P_{11}(t) = \frac{q_{01}}{q_{10} + q_{01}} + \frac{q_{10}}{q_{10} + q_{01}} e^{-(q_{10} + q_{01})t}$$

- ▶ As time goes to infinity, $P_{00}(t)$ and $P_{11}(t)$ converge exponentially
⇒ Convergence rate depends on magnitude of $q_{10} + q_{01}$

- ▶ Recall $P_{01}(t) = 1 - P_{00}(t)$ and $P_{10}(t) = 1 - P_{11}(t)$
- ▶ **Limiting (steady-state) probabilities** are

$$\begin{aligned}\lim_{t \rightarrow \infty} P_{00}(t) &= \frac{q_{10}}{q_{10} + q_{01}}, & \lim_{t \rightarrow \infty} P_{01}(t) &= \frac{q_{01}}{q_{10} + q_{01}} \\ \lim_{t \rightarrow \infty} P_{11}(t) &= \frac{q_{01}}{q_{10} + q_{01}}, & \lim_{t \rightarrow \infty} P_{10}(t) &= \frac{q_{10}}{q_{10} + q_{01}}\end{aligned}$$

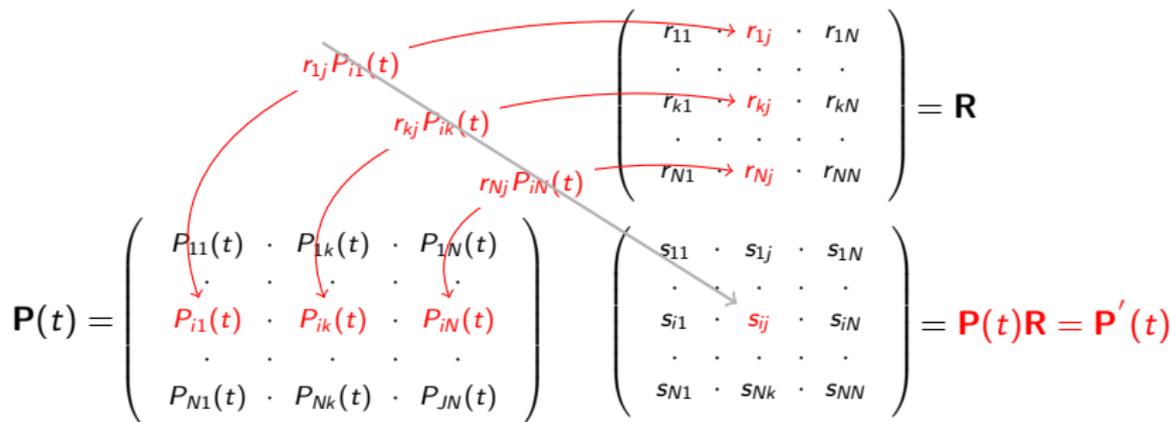
- ▶ **Limit distribution exists and is independent of initial condition**
⇒ Compare across diagonals

Kolmogorov's forward equations in matrix form

- Restrict attention to finite CTMCs with N states
 \Rightarrow Define matrix $\mathbf{R} \in \mathbb{R}^{N \times N}$ with elements $r_{ij} = q_{ij}$, $r_{ii} = -\nu_i$
- Rewrite Kolmogorov's **forward** eqs. as (process runs a little longer)

$$P'_{ij}(t) = \sum_{k=1, k \neq j}^N q_{kj} P_{ik}(t) - \nu_j P_{ij}(t) = \sum_{k=1}^N r_{kj} P_{ik}(t)$$

- Right-hand side defines elements of a matrix product

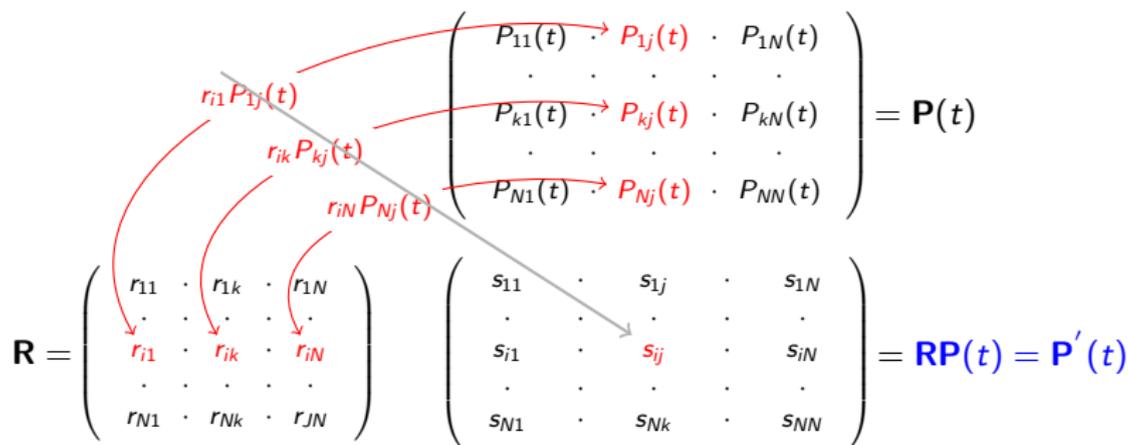


$$\begin{aligned}
 & \left(\begin{array}{ccc} r_{1j} P_{i1}(t) & r_{kj} P_{ik}(t) & r_{nj} P_{iN}(t) \end{array} \right) \begin{pmatrix} r_{11} \rightarrow r_{1j} \cdot r_{1N} \\ \cdot \cdot \cdot \cdot \cdot \\ r_{k1} \rightarrow r_{kj} \cdot r_{kN} \\ \cdot \cdot \cdot \cdot \cdot \\ r_{N1} \rightarrow r_{Nj} \cdot r_{NN} \end{pmatrix} = \mathbf{R} \\
 \mathbf{P}'(t) = & \begin{pmatrix} P_{11}(t) \cdot P_{1k}(t) \cdot P_{1N}(t) \\ \cdot \cdot \cdot \cdot \cdot \\ P_{i1}(t) \cdot P_{ik}(t) \cdot P_{iN}(t) \\ \cdot \cdot \cdot \cdot \cdot \\ P_{N1}(t) \cdot P_{Nk}(t) \cdot P_{NJ}(t) \end{pmatrix} \begin{pmatrix} s_{11} \cdot s_{1j} \cdot s_{1N} \\ \cdot \cdot \cdot \cdot \cdot \\ s_{i1} \cdot s_{ij} \cdot s_{iN} \\ \cdot \cdot \cdot \cdot \cdot \\ s_{N1} \cdot s_{Nk} \cdot s_{NN} \end{pmatrix} = \mathbf{P}(t)\mathbf{R} = \mathbf{P}'(t)
 \end{aligned}$$

- ▶ Similarly, Kolmogorov's **backward** eqs. (process starts a little later)

$$P'_{ij}(t) = \sum_{k=1, k \neq i}^N q_{ik} P_{kj}(t) - \nu_i P_{ij}(t) = \sum_{k=1}^N r_{ik} P_{kj}(t)$$

- ▶ Right-hand side also defines a matrix product



$$\mathbf{R} = \begin{pmatrix} r_{11} & \cdot & r_{1k} & \cdot & r_{1N} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ r_{i1} & \cdot & r_{ik} & \cdot & r_{iN} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ r_{N1} & \cdot & r_{Nk} & \cdot & r_{NN} \end{pmatrix} \begin{pmatrix} P_{11}(t) & \cdot & P_{1j}(t) & \cdot & P_{1N}(t) \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ P_{k1}(t) & \cdot & P_{kj}(t) & \cdot & P_{kN}(t) \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ P_{N1}(t) & \cdot & P_{Nj}(t) & \cdot & P_{NN}(t) \end{pmatrix} = \mathbf{P}(t)$$

$$\mathbf{R} = \begin{pmatrix} r_{11} & \cdot & r_{1k} & \cdot & r_{1N} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ r_{i1} & \cdot & r_{ik} & \cdot & r_{iN} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ r_{N1} & \cdot & r_{Nk} & \cdot & r_{NN} \end{pmatrix} \begin{pmatrix} s_{11} & \cdot & s_{1j} & \cdot & s_{1N} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ s_{i1} & \cdot & s_{ij} & \cdot & s_{iN} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ s_{N1} & \cdot & s_{Nk} & \cdot & s_{NN} \end{pmatrix} = \mathbf{R}\mathbf{P}(t) = \mathbf{P}'(t)$$

- ▶ Matrix form of Kolmogorov's **forward** equation $\Rightarrow \mathbf{P}'(t) = \mathbf{P}(t)\mathbf{R}$
- ▶ Matrix form of Kolmogorov's **backward** equation $\Rightarrow \mathbf{P}'(t) = \mathbf{R}\mathbf{P}(t)$
 - \Rightarrow More similar than apparent
 - \Rightarrow But not equivalent because matrix product not commutative
- ▶ Notwithstanding both equations have to **accept the same solution**

- ▶ Kolmogorov's equations are first-order linear differential equations
 - ⇒ They are **coupled**, $P'_{ij}(t)$ depends on $P_{kj}(t)$ for all k
 - ⇒ **Accepts exponential solution** ⇒ Define **matrix exponential**

- ▶ **Def:** The matrix exponential $e^{\mathbf{A}t}$ of matrix $\mathbf{A}t$ is the series

$$e^{\mathbf{A}t} = \sum_{n=0}^{\infty} \frac{(\mathbf{A}t)^n}{n!} = \mathbf{I} + \mathbf{A}t + \frac{(\mathbf{A}t)^2}{2} + \frac{(\mathbf{A}t)^3}{2 \times 3} + \dots$$

- ▶ Derivative of matrix exponential with respect to t

$$\frac{\partial e^{\mathbf{A}t}}{\partial t} = \mathbf{0} + \mathbf{A} + \mathbf{A}^2 t + \frac{\mathbf{A}^3 t^2}{2} + \dots = \mathbf{A} \left(\mathbf{I} + \mathbf{A}t + \frac{(\mathbf{A}t)^2}{2} + \dots \right) = \mathbf{A}e^{\mathbf{A}t}$$

- ▶ Putting \mathbf{A} on right side of product shows that $\Rightarrow \frac{\partial e^{\mathbf{A}t}}{\partial t} = e^{\mathbf{A}t} \mathbf{A}$

- ▶ Propose solution of the form $\mathbf{P}(t) = e^{\mathbf{R}t}$
- ▶ $\mathbf{P}(t)$ solves **backward** equations, since derivative is

$$\frac{\partial \mathbf{P}(t)}{\partial t} = \frac{\partial e^{\mathbf{R}t}}{\partial t} = \mathbf{R}e^{\mathbf{R}t} = \mathbf{R}\mathbf{P}(t)$$

- ▶ It also solves **forward** equations

$$\frac{\partial \mathbf{P}(t)}{\partial t} = \frac{\partial e^{\mathbf{R}t}}{\partial t} = e^{\mathbf{R}t}\mathbf{R} = \mathbf{P}(t)\mathbf{R}$$

- ▶ Notice that $\mathbf{P}(0) = \mathbf{I}$, as it should ($P_{ii}(0) = 1$, and $P_{ij}(0) = 0$)

- ▶ Suppose $\mathbf{A} \in \mathbb{R}^{n \times n}$ is diagonalizable, i.e., $\mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{U}^{-1}$
 - ⇒ Diagonal matrix $\mathbf{D} = \text{diag}(\lambda_1, \dots, \lambda_n)$ collects eigenvalues λ_i
 - ⇒ Matrix \mathbf{U} has the corresponding eigenvectors as columns
- ▶ We have the following neat identity

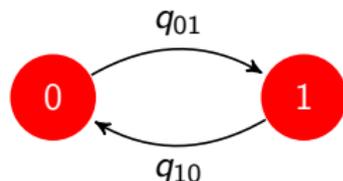
$$e^{\mathbf{A}t} = \sum_{n=0}^{\infty} \frac{(\mathbf{U}\mathbf{D}\mathbf{U}^{-1}t)^n}{n!} = \mathbf{U} \left(\sum_{n=0}^{\infty} \frac{(\mathbf{D}t)^n}{n!} \right) \mathbf{U}^{-1} = \mathbf{U}e^{\mathbf{D}t}\mathbf{U}^{-1}$$

- ▶ But since \mathbf{D} is diagonal, then

$$e^{\mathbf{D}t} = \sum_{n=0}^{\infty} \frac{(\mathbf{D}t)^n}{n!} = \begin{pmatrix} e^{\lambda_1 t} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & e^{\lambda_n t} \end{pmatrix}$$

Ex: Simplest CTMC with two states 0 and 1

- ▶ Transition rates are $q_{01} = 3$ and $q_{10} = 1$



- ▶ Recall transition time rates are $\nu_0 = q_{01} = 3$, $\nu_1 = q_{10} = 1$, hence

$$\mathbf{R} = \begin{pmatrix} -\nu_0 & q_{01} \\ q_{10} & -\nu_1 \end{pmatrix} = \begin{pmatrix} -3 & 3 \\ 1 & -1 \end{pmatrix}$$

- ▶ Eigenvalues of \mathbf{R} are 0, -4 , eigenvectors $[1, 1]^T$ and $[-3, 1]^T$. Thus

$$\mathbf{U} = \begin{pmatrix} 1 & -3 \\ 1 & 1 \end{pmatrix}, \quad \mathbf{U}^{-1} = \begin{pmatrix} 1/4 & 3/4 \\ -1/4 & 1/1 \end{pmatrix}, \quad e^{\mathbf{D}t} = \begin{pmatrix} 1 & 0 \\ 0 & e^{-4t} \end{pmatrix}$$

- ▶ The solution to the forward equations is

$$\mathbf{P}(t) = e^{\mathbf{R}t} = \mathbf{U}e^{\mathbf{D}t}\mathbf{U}^{-1} = \begin{pmatrix} 1/4 + (3/4)e^{-4t} & 3/4 - (3/4)e^{-4t} \\ 1/4 - (1/4)e^{-4t} & 3/4 + (1/4)e^{-4t} \end{pmatrix}$$

- ▶ $\mathbf{P}(t)$ is transition prob. from states at time 0 to states at time t
- ▶ Define **unconditional probs.** at time t , $p_j(t) := P(X(t) = j)$
⇒ Group in vector $\mathbf{p}(t) = [p_1(t), p_2(t), \dots, p_j(t), \dots]^T$
- ▶ Given initial distribution $\mathbf{p}(0)$, find $p_j(t)$ conditioning on initial state

$$p_j(t) = \sum_{i=0}^{\infty} P(X(t) = j | X(0) = i) P(X(0) = i) = \sum_{i=0}^{\infty} P_{ij}(t) p_i(0)$$

- ▶ Using compact matrix-vector notation ⇒ $\mathbf{p}(t) = \mathbf{P}^T(t)\mathbf{p}(0)$
⇒ Compare with discrete-time MC ⇒ $\mathbf{p}(n) = (\mathbf{P}^n)^T \mathbf{p}(0)$

Continuous-time Markov chains

Transition probability function

Determination of transition probability function

Limit probabilities and ergodicity

- ▶ Recall the **embedded discrete-time MC** associated with any CTMC
 - ⇒ Transition probs. of MC form the matrix \mathbf{P} of the CTMC
 - ⇒ No self transitions ($P_{ii} = 0$, \mathbf{P} 's diagonal null)
- ▶ States $i \leftrightarrow j$ communicate in the CTMC if $i \leftrightarrow j$ in the MC
 - ⇒ Communication partitions MC in classes
 - ⇒ **Induces CTMC partition as well**
- ▶ **Def:** CTMC is irreducible if embedded MC contains a single class
- ▶ State i is recurrent if it is recurrent in the embedded MC
 - ⇒ Likewise, define transience and positive recurrence for CTMCs
- ▶ Transience and recurrence shared by elements of a MC class
 - ⇒ **Transience and recurrence are class properties of CTMCs**
- ▶ **Periodicity not possible in CTMCs**

Theorem

Consider irreducible, positive recurrent CTMC with transition rates ν_i and q_{ij} . Then, $\lim_{t \rightarrow \infty} P_{ij}(t)$ exists and is independent of the initial state i , i.e.,

$$P_j = \lim_{t \rightarrow \infty} P_{ij}(t) \quad \text{exists for all } (i, j)$$

Furthermore, steady-state probabilities $P_j \geq 0$ are the unique nonnegative solution of the system of linear equations

$$\nu_j P_j = \sum_{k=0, k \neq j}^{\infty} q_{kj} P_k, \quad \sum_{j=0}^{\infty} P_j = 1$$

- ▶ **Limit distribution exists** and **is independent of initial condition**
 - ⇒ Obtained as solution of system of linear equations
 - ⇒ Like discrete-time MCs, but equations slightly different

- ▶ As with MCs difficult part is to prove that $P_j = \lim_{t \rightarrow \infty} P_{ij}(t)$ exists
- ▶ Algebraic relations obtained from **Kolmogorov's forward** equations

$$\frac{\partial P_{ij}(t)}{\partial t} = \sum_{k=0, k \neq j}^{\infty} q_{kj} P_{ik}(t) - \nu_j P_{ij}(t)$$

- ▶ If limit distribution exists we have, independent of initial state i

$$\lim_{t \rightarrow \infty} \frac{\partial P_{ij}(t)}{\partial t} = 0, \quad \lim_{t \rightarrow \infty} P_{ij}(t) = P_j$$

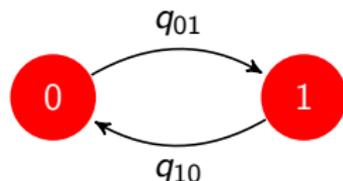
- ▶ Considering the limit of Kolmogorov's forward equations yields

$$0 = \sum_{k=0, k \neq j}^{\infty} q_{kj} P_k - \nu_j P_j$$

- ▶ Reordering terms the limit distribution equations follow

Ex: Simplest CTMC with two states 0 and 1

- ▶ Transition rates are q_{01} and q_{10}
- ▶ From transition rates find mean transition times $\nu_0 = q_{01}$, $\nu_1 = q_{10}$
- ▶ Stationary distribution equations



$$\begin{aligned} \nu_0 P_0 &= q_{10} P_1, & \nu_1 P_1 &= q_{01} P_0, & P_0 + P_1 &= 1, \\ q_{01} P_0 &= q_{10} P_1, & q_{10} P_1 &= q_{01} P_0 \end{aligned}$$

- ▶ Solution yields $\Rightarrow P_0 = \frac{q_{10}}{q_{10} + q_{01}}$, $P_1 = \frac{q_{01}}{q_{10} + q_{01}}$
- ▶ Larger rate q_{10} of entering 0 \Rightarrow Larger prob. P_0 of being at 0
- ▶ Larger rate q_{01} of entering 1 \Rightarrow Larger prob. P_1 of being at 1

- ▶ **Def:** Fraction of time $T_i(t)$ spent in state i by time t

$$T_i(t) := \frac{1}{t} \int_0^t \mathbb{I}\{X(\tau) = i\} d\tau$$

⇒ $T_i(t)$ a time/ergodic average, $\lim_{t \rightarrow \infty} T_i(t)$ is an ergodic limit

- ▶ If CTMC is irreducible, positive recurrent, the ergodic theorem holds

$$P_i = \lim_{t \rightarrow \infty} T_i(t) = \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t \mathbb{I}\{X(\tau) = i\} d\tau \quad \text{a.s.}$$

- ▶ Ergodic limit coincides with limit probabilities (almost surely)

- ▶ Consider function $f(i)$ associated with state i . Can write $f(X(t))$ as

$$f(X(t)) = \sum_{i=1}^{\infty} f(i) \mathbb{I}\{X(t) = i\}$$

- ▶ Consider the time average of $f(X(t))$

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t f(X(\tau)) d\tau = \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t \sum_{i=1}^{\infty} f(i) \mathbb{I}\{X(\tau) = i\} d\tau$$

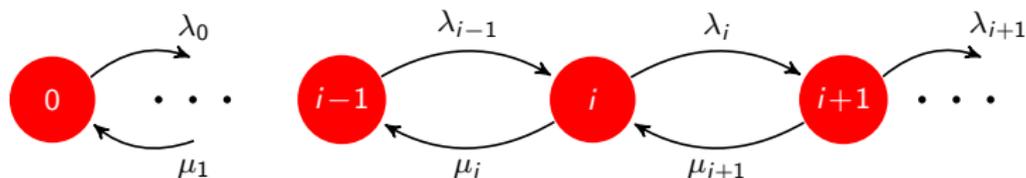
- ▶ Interchange summation with integral and limit to say

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t f(X(\tau)) d\tau = \sum_{i=1}^{\infty} f(i) \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t \mathbb{I}\{X(\tau) = i\} d\tau = \sum_{i=1}^{\infty} f(i) P_i$$

- ▶ **Function's ergodic limit = Function's expectation under limiting dist.**

- ▶ Recall limit distribution equations $\Rightarrow \nu_j P_j = \sum_{k=0, k \neq j}^{\infty} q_{kj} P_k$
- ▶ P_j = fraction of time spent in state j
- ▶ ν_j = rate of transition out of state j given CTMC is in state j
 $\Rightarrow \nu_j P_j$ = rate of transition out of state j (unconditional)
- ▶ q_{kj} = rate of transition from k to j given CTMC is in state k
 $\Rightarrow q_{kj} P_k$ = rate of transition from k to j (unconditional)
 $\Rightarrow \sum_{k=0, k \neq j}^{\infty} q_{kj} P_k$ = rate of transition into j , from all states
- ▶ Rate of transition out of state j = Rate of transition into state j
- ▶ Balance equations \Rightarrow Balance nr. of transitions in and out of state j

- ▶ Birth/deaths occur at state-dependent rates. When $X(t) = i$
- ▶ **Births** \Rightarrow Individuals added at exponential times with mean $1/\lambda_i$
 \Rightarrow Birth rate = upward transition rate = $q_{i,i+1} = \lambda_i$
- ▶ **Deaths** \Rightarrow Individuals removed at exponential times with mean $1/\mu_i$
 \Rightarrow Death rate = downward transition rate = $q_{i,i-1} = \mu_i$
- ▶ Transition time rates $\Rightarrow \nu_i = \lambda_i + \mu_i, i > 0$ and $\nu_0 = \lambda_0$



- ▶ Limit distribution/balance equations: **Rate out of j** = **Rate into j**

$$(\lambda_i + \mu_i)P_i = \lambda_{i-1}P_{i-1} + \mu_{i+1}P_{i+1}$$

$$\lambda_0 P_0 = \mu_1 P_1$$

- ▶ Start expressing all probabilities in terms of P_0

- ▶ Equation for P_0

$$\lambda_0 P_0 = \mu_1 P_1$$

- ▶ Sum eqs. for P_1
and P_0

$$\begin{aligned}\lambda_0 P_0 &= \mu_1 P_1 \\ (\lambda_1 + \mu_1) P_1 &= \lambda_0 P_0 + \mu_2 P_2\end{aligned}$$

$$\lambda_1 P_1 = \mu_2 P_2$$

- ▶ Sum result and
eq. for P_2

$$\begin{aligned}\lambda_1 P_1 &= \mu_2 P_2 \\ (\lambda_2 + \mu_2) P_2 &= \lambda_1 P_1 + \mu_3 P_3\end{aligned}$$

$$\lambda_2 P_2 = \mu_3 P_3$$

⋮

- ▶ Sum result and
eq. for P_i

$$\begin{aligned}\lambda_{i-1} P_{i-1} &= \mu_i P_i \\ (\lambda_i + \mu_i) P_i &= \lambda_{i-1} P_{i-1} + \mu_{i+1} P_{i+1}\end{aligned}$$

$$\lambda_i P_i = \mu_{i+1} P_{i+1}$$

- ▶ Recursive substitutions on **red** equations on the right

$$P_1 = \frac{\lambda_0}{\mu_1} P_0$$

$$P_2 = \frac{\lambda_1}{\mu_2} P_1 = \frac{\lambda_1 \lambda_0}{\mu_2 \mu_1} P_0$$

⋮

$$P_{i+1} = \frac{\lambda_i}{\mu_{i+1}} P_i = \frac{\lambda_i \lambda_{i-1} \dots \lambda_0}{\mu_{i+1} \mu_i \dots \mu_1} P_0$$

- ▶ To find P_0 use $\sum_{i=0}^{\infty} P_i = 1 \Rightarrow 1 = P_0 + \sum_{i=1}^{\infty} \frac{\lambda_i \lambda_{i-1} \dots \lambda_0}{\mu_{i+1} \mu_i \dots \mu_1} P_0$

$$\Rightarrow P_0 = \left[1 + \sum_{i=1}^{\infty} \frac{\lambda_i \lambda_{i-1} \dots \lambda_0}{\mu_{i+1} \mu_i \dots \mu_1} \right]^{-1}$$

- ▶ Continuous-time Markov chain
- ▶ Markov property
- ▶ Time-homogeneous CTMC
- ▶ Transition probability function
- ▶ Exponential transition time
- ▶ Transition probabilities
- ▶ Embedded discrete-time MC
- ▶ Transition rates
- ▶ Birth and death process
- ▶ Poisson process
- ▶ M/M/1 queue
- ▶ Chapman-Kolmogorov equations
- ▶ Kolmogorov's forward equations
- ▶ Kolmogorov's backward equations
- ▶ Limiting probabilities
- ▶ Matrix exponential
- ▶ Unconditional probabilities
- ▶ Recurrent and transient states
- ▶ Ergodicity
- ▶ Balance equations