

Stochastic processes

- t is time.
- $X()$ is a *stochastic process* if $X(t)$ is a random variable for every t .
- t is a scalar — it can be discrete or continuous.
- $X(t)$ can be discrete or continuous, scalar or vector.

- A *Markov process* is a stochastic process in which the probability of finding X at some value at time $t + \delta t$ depends only on the value of X at time t .
- Or, let $x(s)$, $s \leq t$, be the history of the values of X before time t and let A be a possible value of X .
Then
$$\text{prob}\{X(t + \delta t) = A | X(s) = x(s), s \leq t\} = \text{prob}\{X(t + \delta t) = A | X(t) = x(t)\}$$

- In words: if we know what \mathbf{X} was at time t , we don't gain any more useful information about $\mathbf{X}(t + \delta t)$ by *also* knowing what \mathbf{X} was at any time earlier than t .

Markov processes

States and transitions

Discrete state, discrete time

- States can be numbered 0, 1, 2, 3, ... (*or with multiple indices if that is more convenient*).
- Time can be numbered 0, 1, 2, 3, ... (*or 0, Δ , 2Δ , 3Δ , ... if more convenient*).
- The probability of a transition from j to i in one time unit is often written P_{ij} , where

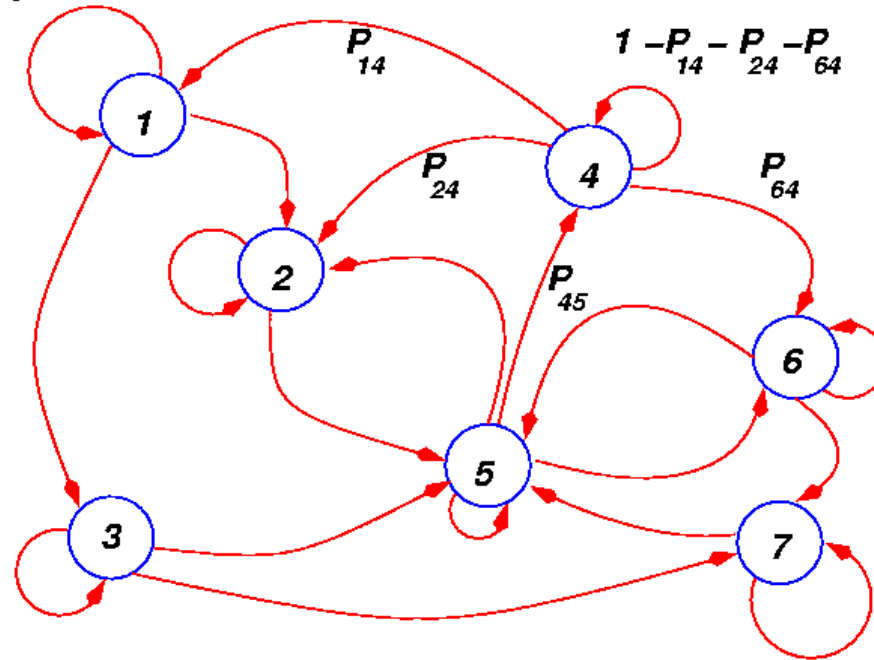
$$P_{ij} = \text{prob}\{X(t + 1) = i | X(t) = j\}$$

Markov processes

States and transitions

Discrete state, discrete time

Transition graph



P_{ij} is a probability. Note that $P_{ii} = 1 - \sum_{m, m \neq i} P_{mi}$.

- Define $\pi_i(t) = \text{prob}\{X(t) = i\}$
- Transition equations: $\pi_i(t + 1) = \sum_j P_{ij}\pi_j(t)$.
- *Steady state*: $\pi_i = \lim_{t \rightarrow \infty} \pi_i(t)$, if it exists.
- Steady-state transition equations: $\pi_i = \sum_j P_{ij}\pi_j$.
- Steady-state balance equations:
$$\pi_i \sum_{m, m \neq i} P_{mi} = \sum_{j, j \neq i} P_{ij}\pi_j$$

Markov processes

States and transitions

Discrete state, continuous time

- States can be numbered $0, 1, 2, 3, \dots$ (or with multiple indices if that is more convenient).
- Time is a real number, defined on $(-\infty, \infty)$ or a smaller interval.
- The probability of a transition from j to i during $[t, t + \delta t]$ is approximately $\lambda_{ij}\delta t$, where δt is small, and

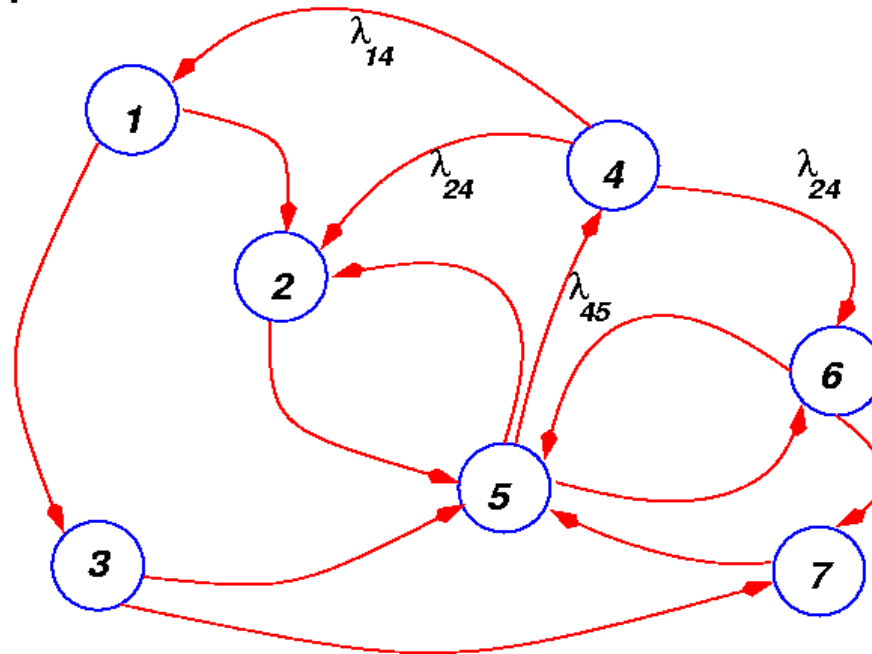
$$\lambda_{ij}\delta t \approx \text{prob}\{X(t + \delta t) = i | X(t) = j\}$$

Markov processes

States and transitions

Discrete state, continuous time

Transition graph



λ_{ij} is a probability *rate*. $\lambda_{ij}\delta t$ is a probability.

Markov processes

States and transitions

Discrete state, continuous time

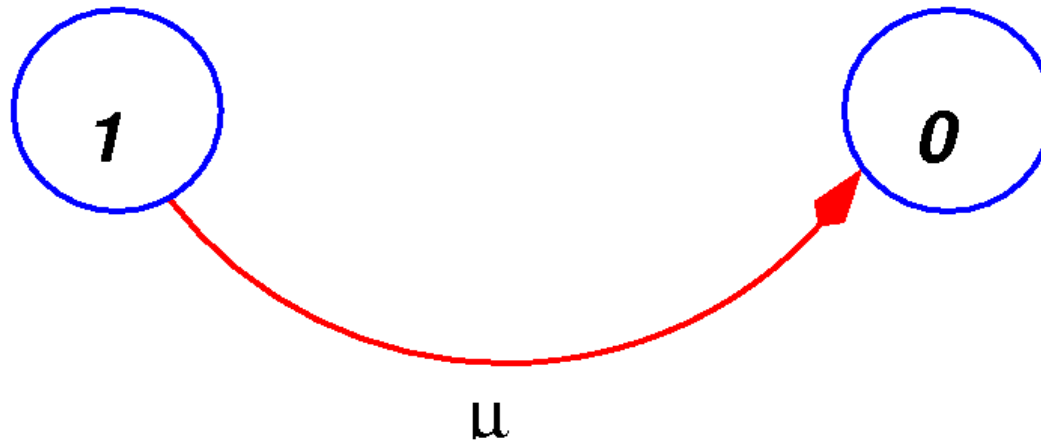
- Define $\pi_i(t) = \text{prob}\{X(t) = i\}$
- It is convenient to define $\lambda_{ii} = -\sum_{j \neq i} \lambda_{ji}$
- Transition equations: $\frac{d\pi_i(t)}{dt} = \sum_j \lambda_{ij} \pi_j(t)$.
- **Steady state:** $\pi_i = \lim_{t \rightarrow \infty} \pi_i(t)$, if it exists.
- Steady-state transition equations: $\mathbf{0} = \sum_j \lambda_{ij} \pi_j$.
- Steady-state balance equations:
$$\pi_i \sum_{m, m \neq i} \lambda_{mi} = \sum_{j, j \neq i} \lambda_{ij} \pi_j$$

Markov processes

States and transitions

Discrete state, continuous time

Exponential random variable: the time to move from state 1 to state 0.



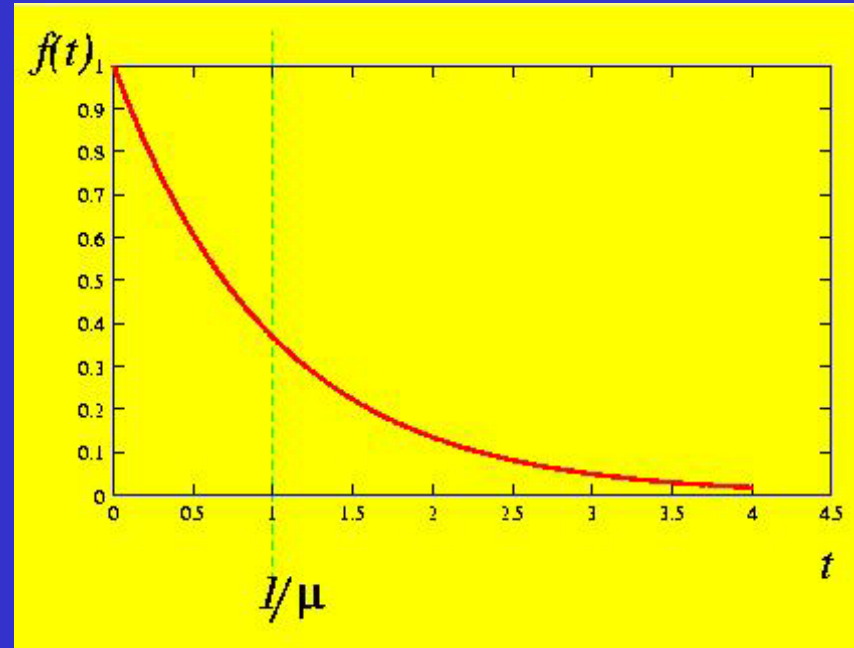
The Exponential Distribution

$$T \sim \text{exp}(\mu)$$

$$f(t) = \mu e^{-\mu t}, t \geq 0 \quad \mu > 0$$

$$F(t) = \text{Pr}(T \leq t) = 1 - e^{-\mu t}$$

$$E[T] = \frac{1}{\mu} \quad \text{Var}(T) = \frac{1}{\mu^2}$$



Properties

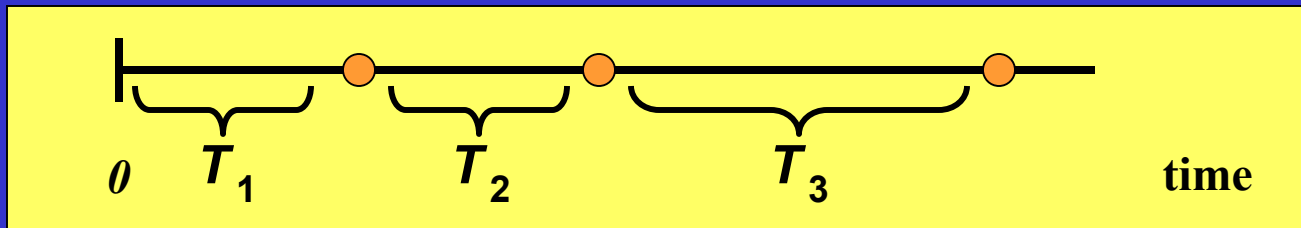
1) Memoryless (or Markov) Property $\text{Pr}(T > t + s \mid T > s) = \text{Pr}(T > t)$

2) If T_1, \dots, T_n independent and $T_i \sim \text{exp}(\mu_i)$

then $\text{Min}\{T_1, \dots, T_n\} \sim \text{exp}(\mu_1 + \dots + \mu_n)$

3) $\text{Pr}\{T \leq t + \Delta t \mid T > t\} \cong \mu \Delta t$

The Poisson Process



$$T_i \sim iid \exp(\lambda)$$

$N(t)$ = number of events by time t

$$= \begin{cases} 0 & \text{if } T_1 > t \\ \sup \{n \geq 1 : T_1 + \dots + T_n \leq t\} & \text{if } T_1 \leq t \end{cases}$$

$N(t)$ is a Poisson Process

$$\Pr\{N(t) = n\} = \frac{(\lambda t)^n e^{-\lambda t}}{n!}$$

$N(t) \sim$ Poisson random variable with mean λt

λ = Arrival rate

M/M/1 Queue

1) Customers arrive according to a Poisson Process

$$\lambda = \text{arrival rate}$$

2) There is one server

3) Service times are exponential

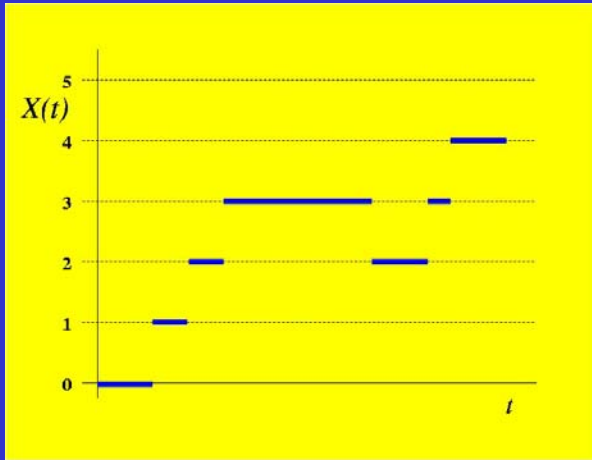
$$\mu = \text{service rate}$$

4) First-come first-served (FCFS)

5) Infinite waiting room

6) Long-run behavior

Birth and Death Process



$X(t)$ = # of customers in a queueing system

Continuous time

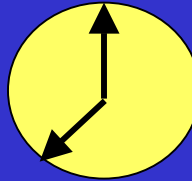
Discrete State Space = $\{0,1,2,\dots\}$

2 independent clocks when in state i

$\lambda_i, i \geq 0$ birth (arrival) rates

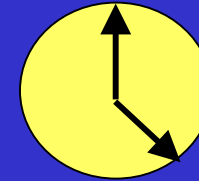
$\mu_i, i \geq 1$ death (service) rates

Arrival



$$B_i \sim \exp(\lambda_i)$$

Service



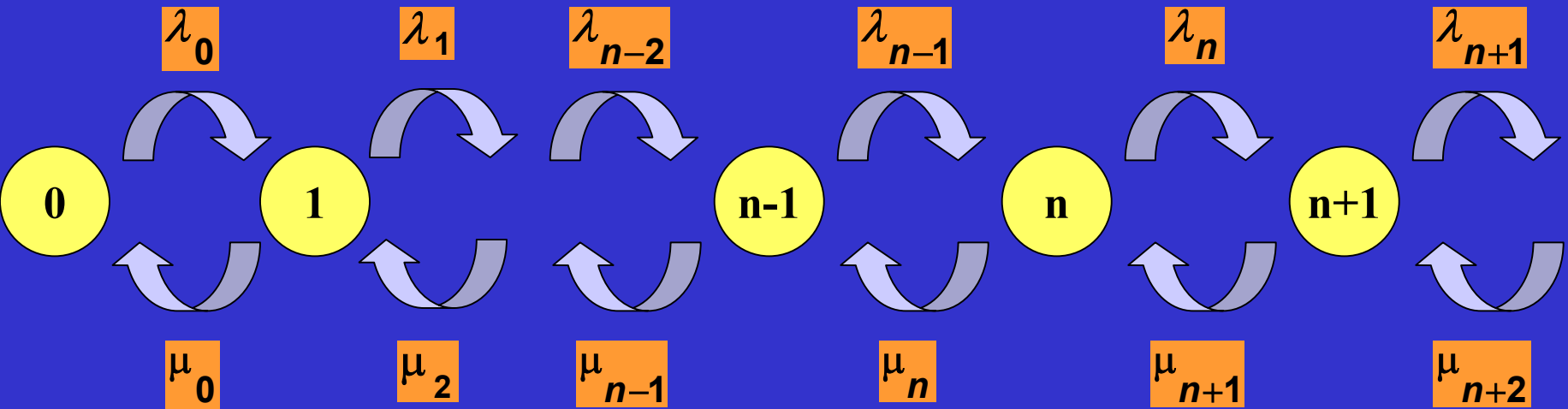
$$D_i \sim \exp(\mu_i)$$

H_i = Holding time in state i = $\text{Min}(B_i, D_i) \sim \exp(\lambda_i + \mu_i)$

$$\Pr(\text{arrival}) = \Pr(B_i < D_i) = \frac{\lambda_i}{\lambda_i + \mu_i}$$

$$\Pr(\text{departure}) = \Pr(D_i < B_i) = \frac{\mu_i}{\lambda_i + \mu_i}$$

Steady-State Solution to Birth and Death Process



Flow Balance Equations: Flow into state n = Flow out of state n

P_n = Steady-state probability of being in state n

$$\lambda_0 P_0 = \mu_1 P_1$$

$$\lambda_{n-1} P_{n-1} + \mu_{n+1} P_{n+1} = (\lambda_n + \mu_n) P_n$$

Steady-State Solution to Birth and Death Process... Continued

Solution:

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

$$P_n = \frac{\lambda_{n-1}}{\mu_n} P_{n-1}$$

$$P_{n+1} = \frac{\lambda_n}{\mu_{n+1}} P_n + \frac{1}{\mu_{n+1}} \underbrace{(\mu_n P_n - \lambda_{n-1} P_{n-1})}_{=0}$$

So:

$$P_n = \frac{\lambda_0 \cdots \lambda_{n-1}}{\mu_1 \cdots \mu_n} P_0 \triangleq \pi_n P_0$$

$$\pi_0 = 1$$

$$\sum_{n=0}^{\infty} P_n = \sum_{n=0}^{\infty} \pi_n P_0 = 1$$

So:

$$P_0 = \left(\sum_{n=0}^{\infty} \pi_n \right)^{-1}$$

Solution to M/M/1 Queue

M/M/1 Queue = Birth - Death Process with

$$\lambda_n = \lambda, \mu_n = \mu$$

$$\rho = \frac{\lambda}{\mu} = \text{utilization rate}$$

$$P_n = \rho^n P_0$$

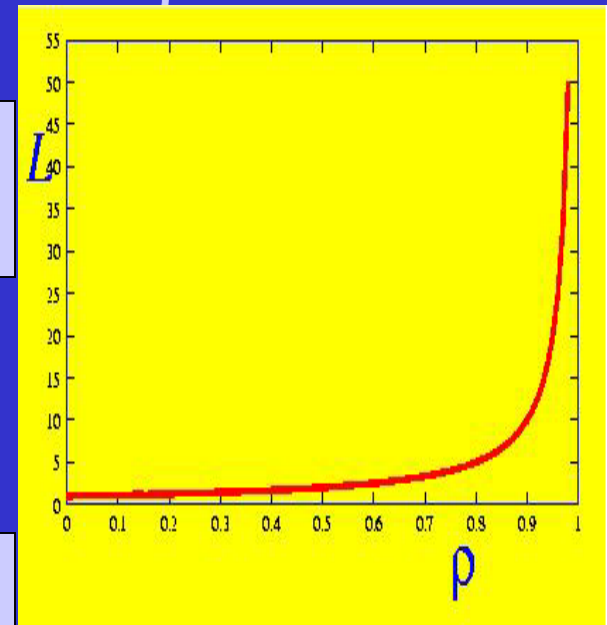
$$P_0 = \left(\sum_{n=0}^{\infty} \rho^n \right)^{-1} = 1 - \rho$$

$$P_n = \text{Pr}(n \text{ customers in system}) = \rho^n (1 - \rho)$$

~ geometric distribution

$$L = E[\text{number of customers in system}] = \frac{\rho}{1 - \rho}$$

If $\rho < 1$



Little's Formula

W = Steady-state mean waiting time in the system

Little's Formula: $L = \lambda W$

$$W = \frac{1}{\mu(1-\rho)} \text{ for } M/M/1$$

L_q = steady - state mean number of customers in queue

W_q = steady - state mean waiting time in queue

$$W_q = W - \frac{1}{\mu} = \frac{\rho}{\mu(1-\rho)} \text{ for } M/M/1$$

$$L_q = \lambda W_q = \frac{\rho^2}{1-\rho} \text{ for } M/M/1$$

- **Generalization of Model M/M/c System**
- **c identical servers in parallel, each with service rate μ**
- **See Exhibit 3 of Harvard note for exact performance measures**

Approximations for Single-Station Models

M/M/c

$$W_q = \frac{\rho^{\sqrt{2(c+1)}-1}}{c\mu(1-\rho)}$$

G/G/1

scv = squared coefficient of variation = $\frac{\text{Var}}{\text{mean}^2}$
= 1 if exponential

c_a^2 = scv of interarrival time distribution

c_s^2 = scv of service time distribution

$$W_q = \left(\frac{c_a^2 + c_s^2}{2} \right) \frac{\rho}{\mu(1-\rho)}$$

G/G/c

$$W_q = \left(\frac{c_a^2 + c_s^2}{2} \right) \frac{\rho^{\sqrt{2(c+1)}-1}}{c\mu(1-\rho)}$$