

random variable $\begin{cases} \text{discrete r.v.} \Rightarrow \text{pmf}, P(X=x) = p(x) \\ \text{continuous r.v.} \Rightarrow \text{pdf}, P(a \leq X \leq b) = \int_a^b f(x)dx \end{cases}$ $\begin{cases} p(x) \geq 0, \sum p(x) = 1 \\ f(x) \geq 0, \int_{-\infty}^{\infty} f(x)dx = 1 \end{cases}$

$$\text{cdf}, F(x) = P(X \leq x) = P(-\infty < x \leq x)$$

$$\text{pmf}, E[X] = \sum x p(x), E[g(X)] = \sum g(x) p(x). F(x) = \frac{1}{-\infty} P(X \leq x)$$

$$\text{pdf}, E[X] = \int_{-\infty}^{\infty} xf(x)dx, E[g(X)] = \int_{-\infty}^{\infty} g(x)f(x)dx \quad F(x) = \int_{-\infty}^x f(y)dy$$

$$E[X] = \int_{-\infty}^{\infty} xf(x)dx \text{ or } \sum x p(x)$$

$$\text{Var}(X) = E[X^2] - (E[X])^2$$

$$sd(X) = \sqrt{\text{Var}(X)}$$

$$\text{coefficient of variation: } C_x = \frac{sd(X)}{E[X]}$$

$$X \sim U(a,b), \quad \text{pdf } f(x) = \begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & \text{o.w.} \end{cases} \quad \text{cdf } F(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ 1 & x > b \end{cases}$$

$$X \sim \exp(\lambda), \quad \text{pdf } f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & \text{o.w.} \end{cases} \quad \text{cdf } F(x) = \begin{cases} 1 - e^{-\lambda x} & x \geq 0 \\ 0 & \text{o.w.} \end{cases}$$

$$\left. \begin{array}{l} E[X] = 1/\lambda \quad \text{Var}(X) = 1/\lambda^2 \quad (\text{E}[X]: 1^{\text{st}} \text{ moment}, \text{E}[X^2]: 2^{\text{nd}} \text{ moment}, \dots, \text{E}[X^n]: n^{\text{th}} \text{ moment}) \\ E[X] = \int_{-\infty}^{\infty} xf(x)dx = \int_0^{\infty} x \lambda e^{-\lambda x} dx = [-\lambda e^{-\lambda x}]_0^{\infty} + \int_0^{\infty} \lambda^2 e^{-\lambda x} dx = [-\frac{1}{\lambda} e^{-\lambda x}]_0^{\infty} = 0 + \frac{1}{\lambda} = \frac{1}{\lambda} \\ E[X^2] = \int_{-\infty}^{\infty} x^2 f(x)dx = \int_0^{\infty} x^2 \cdot \lambda e^{-\lambda x} dx = [\lambda^2 \cdot (-e^{-\lambda x})]_0^{\infty} + \int_0^{\infty} 2\lambda e^{-\lambda x} dx = \frac{2}{\lambda} \int_0^{\infty} \lambda \cdot \lambda e^{-\lambda x} dx = \frac{2}{\lambda^2} \\ \therefore \text{Var}(X) = \frac{2}{\lambda^2} - \left(\frac{1}{\lambda}\right)^2 = 1/\lambda^2 \quad \text{cf) } n^{\text{th}} \text{ moment: } n!/\lambda^n \end{array} \right.$$

$$\left. \begin{array}{l} \text{r.v. } X \sim \exp(\lambda) \text{ is memoryless} \Rightarrow P(X > s+t | X > t) = P(X > s) \quad \text{for } (s, t \geq 0) \\ \text{pf) } P(X > s+t | X > t) = \frac{P(X > s+t \cap X > t)}{P(X > t)} = \frac{P(X > s+t)}{P(X > t)} = \frac{1 - F(s+t)}{1 - F(t)} = \frac{e^{-\lambda(s+t)}}{e^{-\lambda t}} = e^{-\lambda s} \\ P(X > s) = (-F(s)) = e^{-\lambda s} \\ \therefore P(X > s+t | X > t) = P(X > s) \quad \text{if } X \sim \exp(\lambda) \end{array} \right.$$

$$X_1 \sim \exp(\lambda_1) \& X_2 \sim \exp(\lambda_2) \rightarrow X_1 \& X_2 \text{ independent} \rightarrow P(X_1 < X_2) = \frac{\lambda_1}{\lambda_1 + \lambda_2}$$

$$X_1 \sim \exp(\lambda_1) \& X_2 \sim \exp(\lambda_2) \rightarrow X_1 \& X_2 \text{ independent} \rightarrow \min(X_1, X_2) \sim \exp(\lambda_1 + \lambda_2)$$

$$X \sim \text{Poi}(\lambda) \quad \text{pmf}, \quad P(X=k) = p(k) = \frac{\lambda^k e^{-\lambda}}{k!} \quad \text{for } k=0,1,2,\dots \quad F(x) = P(X \leq x) = \sum_{k=0}^{\lfloor x \rfloor} \frac{\lambda^k e^{-\lambda}}{k!}$$

$$\sum_{k=0}^{\infty} P(X=k) = \sum_{k=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} = e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} = e^{-\lambda} \cdot e^{\lambda} = 1 \quad (\because \sum_{k=0}^{\infty} \frac{1}{k!} = e, \quad \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} = e^{\lambda} \text{ by Taylor series})$$

$$E[X] = \sum_{k=0}^{\infty} k P(X=k) = \sum_{k=0}^{\infty} k \cdot \lambda \cdot \frac{\lambda^{k-1} e^{-\lambda}}{(k-1)!} = \sum_{k=1}^{\infty} k \cdot \frac{\lambda^k e^{-\lambda}}{k!} = \sum_{k=1}^{\infty} \lambda \cdot \frac{\lambda^{k-1} e^{-\lambda}}{(k-1)!}$$

$$\Rightarrow y = \lambda - 1, \quad E[X] = \lambda \cdot \sum_{y=0}^{\infty} \frac{\lambda^y e^{-\lambda}}{y!} = \lambda$$

$$E[X^2] = \sum_{k=0}^{\infty} k^2 P(X=k) = \sum_{k=0}^{\infty} k^2 \cdot \frac{\lambda^k e^{-\lambda}}{k!} = \sum_{k=1}^{\infty} k^2 \cdot \lambda \cdot \frac{\lambda^{k-1} e^{-\lambda}}{(k-1)!}$$

$$\Rightarrow y = \lambda + 1, \quad E[X^2] = \sum_{y=0}^{\infty} y^2 \frac{\lambda^y e^{-\lambda}}{y!} = \lambda \left[\sum_{y=0}^{\infty} y \cdot \frac{\lambda^y e^{-\lambda}}{y!} + \sum_{y=0}^{\infty} \frac{\lambda^y e^{-\lambda}}{y!} \right] = \lambda(\lambda + 1)$$

$$\text{Var}(X) = \lambda(\lambda + 1) - \lambda^2 = \lambda$$

Bayes' Rule $F_i \cap F_j = \emptyset$ for any $i \neq j$, $P(F_1 \cup \dots \cup F_n) = 1$

$$P(E) = \sum_{i=1}^n P(E \cap F_i) = \sum_{i=1}^n P(E|F_i) P(F_i)$$

$$X \sim U(20, 40) \quad \text{pdf } f(x) = \begin{cases} \frac{1}{20} & 20 \leq x \leq 40 \\ 0 & \text{otherwise} \end{cases} \quad \text{cf)} \quad A \wedge B = \min(A, B) \quad A \vee B = \max(A, B)$$

$$x^+ = \max(x, 0) \quad x^- = \min(x, 0)$$

$$E(X \wedge 25) = \int_{-\infty}^{\infty} \min(x, 25) f(x) dx = \int_{20}^{40} \min(x, 25) \cdot \frac{1}{20} dx = \int_{20}^{25} \frac{1}{20} x dx + \int_{25}^{40} \frac{25}{20} dx$$

$$= \frac{1}{20} \left(\left[\frac{1}{2} x^2 \right]_{20}^{25} + [25x]_{25}^{40} \right) = 24.375$$

$$E((25-x)^+) = \int_{-\infty}^{\infty} \max(25-x, 0) f(x) dx = \int_{20}^{40} \max(25-x, 0) \cdot \frac{1}{20} dx = \frac{1}{20} \left(\int_{20}^{25} 25-x dx + \int_{25}^{40} 0 dx \right)$$

$$= \frac{1}{20} \left[25x - \frac{1}{2} x^2 \right]_{20}^{25} = \frac{5}{4}$$

Stationary distribution. $\pi P = \pi$, $\sum \pi_i = 1$

representing not unique solution. Let $\pi_1 + \pi_2 + \pi_3 + \pi_4 = \pi_1 + \frac{2}{5}\pi_1 + \pi_3 + \frac{4}{7}\pi_3 = 1$

i) Let $p := \pi_1$ $p \in [0, 1]$

$$\begin{aligned} \pi_1 &= p \\ \pi_2 &= \frac{2}{5}p \\ \pi_3 &= \frac{3}{7}(1 - \frac{2}{5}p) \\ \pi_4 &= \frac{4}{7}(1 - \frac{2}{5}p) \end{aligned}$$

$$\pi = \left[p, \frac{2}{5}p, \frac{3}{7}(1 - \frac{2}{5}p), \frac{4}{7}(1 - \frac{2}{5}p) \right]$$

for any $p \in [0, 1]$

ii) Let $p := \pi_1 + \pi_2 = \frac{5}{7}\pi_1$

$$\begin{aligned} \pi_1 &= \frac{5}{7}p \\ \pi_2 &= \frac{2}{7}p \\ \pi_3 &= \frac{3}{7}(1 - p) \\ \pi_4 &= \frac{4}{7}(1 - p) \end{aligned}$$

$$\pi = \left[\frac{5}{7}p, \frac{2}{7}p, \frac{3}{7}(1 - p), \frac{4}{7}(1 - p) \right]$$

for any $p \in [0, 1]$

$$|r| < 1, \quad S = a + ar + ar^2 + \dots \quad \therefore S = \sum_{n=0}^{\infty} ar^n = \frac{a}{1-r} \quad (|r| < 1)$$

$$\begin{aligned} -rS &= ar + ar^2 + \dots \\ (1-r)S &= a \end{aligned}$$

$$r \neq 1, \quad S = a + ar + ar^2 + \dots + ar^{n-1} \quad \therefore S = \sum_{n=1}^{\infty} ar^{n-1} = \frac{a}{1-r} (1-r^n)$$

$$\begin{aligned} -rS &= ar + ar^2 + \dots + ar^{n-1} + ar^n \\ (1-r)S &= a - ar^n \end{aligned}$$

$$|r| < 1 \quad S = r + 2r^2 + 3r^3 + \dots \quad \therefore S = \frac{r}{(1-r)^2}$$

$$\begin{aligned} -rS &= r^2 + 2r^3 + \dots \\ (1-r)S &= r + r^2 + r^3 + \dots = \sum_{n=0}^{\infty} r \cdot r^n = \frac{r}{1-r} \end{aligned}$$

Newsvendor Model ... optimal ordering on perishable goods/services

information needed =	demand	[11, 15]	w/ each 20% of chance
	retail price	\$2	
	wholesale price / material cost	\$1	
	salvage value.	\$0.5	

profit = revenue - cost = (sales revenue + salvage revenue) - (material cost)

$$= (2 \times \min(X, D) + (X-D) \times 0.5) - 1 \times X$$

Stock < demand ... understock unit cost \$1 = C_u

Stock < demand (D)	20% (11)	20% (12)	20% (13)	20% (14)	20% (15)	Expected profit
(11)	$2 \times 11 + 0 \times 0.5 - 1 \times 11$ = 11	11	11	11	11	11
(12)	$2 \times 11 + 1 \times 0.5 - 1 \times 12$ = 10.5	$2 \times 12 + 0 \times 0.5 - 1 \times 12$ = 12	12	12	12	11.7
(13)	$2 \times 11 + 2 \times 0.5 - 1 \times 13$ = 10	$2 \times 12 + 1 \times 0.5 - 1 \times 13$ = 11.5	$2 \times 13 + 0 \times 0.5 - 1 \times 13$ = 13	13	13	12.1
(14)	$2 \times 11 + 3 \times 0.5 - 1 \times 14$ = 9.5	$2 \times 12 + 2 \times 0.5 - 1 \times 14$ = 11	$2 \times 13 + 1 \times 0.5 - 1 \times 14$ = 12.5	$2 \times 14 + 0 \times 0.5 - 1 \times 14$ = 14	14	12.2
(15)	$2 \times 11 + 4 \times 0.5 - 1 \times 15$ = 9	$2 \times 12 + 3 \times 0.5 - 1 \times 14$ = 10.5	$2 \times 13 + 2 \times 0.5 - 1 \times 15$ = 12	$2 \times 14 + 1 \times 0.5 - 1 \times 15$ = 13.5	$2 \times 15 + 0 \times 0.5 - 1 \times 15$ = 15	12

Stock > demand ... overstock unit cost \$0.5 = C_o

continuous distribution, $F(y) = \frac{C_o}{C_o + C_u}$

discrete distribution, $F(y) \geq \frac{C_o}{C_o + C_u}$

Queueing Theory Variables

Demand: inter-arrival time

Capacity: inter-departure times (service time), # servers, queue size

⇒ notation: inter-arrival time / service time / # servers / queue size

$\begin{cases} G & \text{general distribution} \\ M & \text{exponential distribution} \\ D & \text{deterministic (constant)} \end{cases}$

"unstable": # waiting customers for the system diverges to infinity or not converging

"stable": not unstable.

"traffic intensity", ρ : demand / capacity

if $\rho < 1$: stable

$\rho = 1$: unstable, unless inter-arrival time & service times are deterministic.

$\rho > 1$: unstable

M/M/1/∞ system. ⇒ $\rho = \frac{\lambda}{\mu} = \frac{1/\mathbb{E}(U)}{1/\mathbb{E}(V)}$, λ = arrival rate, μ = service rate
 U = inter-arrival time. V = inter-departure time.
 $\lambda = 1/\mathbb{E}U$, $\mu = 1/\mathbb{E}V$

"Utilization of server, U " = $\min(1, \rho)$

Kingman's high-traffic approximation formula.: how long customer needs to wait prior to begin of the service
 $(\rho < 1, \text{ but } \rho \text{ close to } 1.)$

$$\mathbb{E}W_q = \mathbb{E}V \times \left(\frac{\rho}{1-\rho}\right) \times \left(\frac{C_a^2 + C_s^2}{2}\right), \quad \begin{aligned} W_q &= \text{long-run average waiting time} \\ C_a &= \text{coefficient of variation of inter-arrival time} \\ C_s &= \text{coefficient of variation of service time} \end{aligned}$$

Little's Law, $L = \lambda W$.

L = # people

λ = arrival rate

W = time spent

$$\textcircled{1} L_{\text{queue}} = \lambda \cdot W_{\text{queue}}$$

$$\textcircled{2} L_{\text{service}} = \lambda \cdot W_{\text{service}}$$

$$\textcircled{3} L_{\text{system}} = L_{\text{queue}} + L_{\text{service}} \quad \& \quad W_{\text{system}} = W_{\text{queue}} + W_{\text{service}},$$

$$\textcircled{4} L_{\text{sys}} = \lambda \cdot W_{\text{sys}}$$

$$W_{\text{queue}} = \mathbb{E}U,$$

$$W_{\text{service}} = \mathbb{E}V,$$

System = queue + services

"Throughput, TH": if system is stable & infinite waiting space, then throughput = λ

otherwise, throughput $< \lambda$

$$\text{one server, } \rho = \frac{\lambda}{\mu} \Rightarrow TH = \begin{cases} \lambda & (\text{if } \rho < 1) \\ \mu & (\text{if } \rho \geq 1) \end{cases} = \min(\lambda, \mu)$$

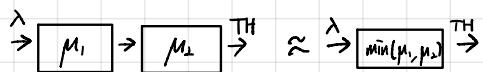
* $\rho \leq 1$ & $\rho > 1$ is incorrect, in my opinion.

$\rho = 1$ is unstable status.

The result will not change, but I think the condition should be revised

$$\text{two server, } \rho = \frac{\lambda}{\mu_1 + \mu_2} \Rightarrow TH = \begin{cases} \lambda & (\text{if } \rho < 1) \\ \mu_1 + \mu_2 & (\text{if } \rho \geq 1) \end{cases} = \min(\lambda, \mu_1 + \mu_2)$$

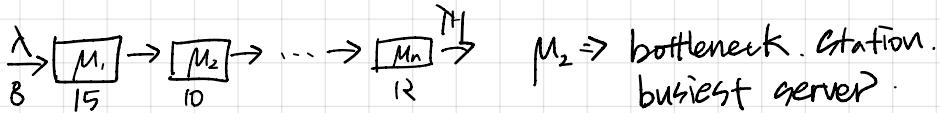
two server
(in sequence)



demand = λ , capacity = $\min(\mu_1, \mu_2)$

$$P = \frac{\lambda}{\mu_1 + \mu_2}, \quad \text{TH} = \begin{cases} \lambda & \text{if } P < 1 \\ \min(\mu_1, \mu_2) & \text{if } P \geq 1 \end{cases} = \min(\lambda, \mu_1, \mu_2)$$

n server
(in sequence)

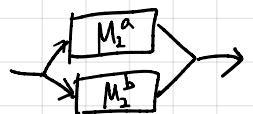


busiest server?

demand = λ , capacity = $\min(\mu_1, \mu_2, \dots, \mu_n)$

sol) line balancing . \Rightarrow

$$P = \frac{\lambda}{\min(\mu_1, \mu_2, \dots, \mu_n)}, \quad \text{TH} = \min(\lambda, \mu_1, \mu_2, \dots, \mu_n)$$



Kingman's equation : $EW_q = E[V] \left(\frac{\rho^2 + \rho}{1-\rho} \right) \Rightarrow$ if ρ is closed to 1, EW_q is exponentially increasing

Highway traffic example : 100 cars/min in I-75 200 cars/min in I-85
3000 cars in merged area

using Little's law ($= L = \lambda W$), 3000 cars = (100+200) cars/min \times 10 min.

Stochastic Process : Time + Random . \nwarrow discrete time : $X_n : n \geq 0, n \in \mathbb{N}$
 \searrow continuous time : $X_t : t \geq 0, t \in \mathbb{R}^+$

State : value of X_n (discrete) State space : set of all possible values of X_n

Martov property : for discrete time stochastic process.

X_{n+1} depends only on state of X_n .

$$X_{n+1} = f(X_n, \text{randomness})$$

$$\begin{aligned} P(X_{n+1}=j \mid X_0=i_0, X_1=j_1, \dots, X_n=i) &= P(X_{n+1}=j \mid X_n=i) \\ &\quad \underbrace{\text{irrelevant history}}_{\text{outdated info.}} \\ &= P(X_3=j \mid X_2=i) = P(X_2=j \mid X_1=i) \end{aligned}$$

DTMC, Discrete Time Martov Chain : discrete time stochastic process with Martov chain

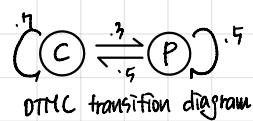
Transition Probability, $p_{ij} = P(X_{n+1}=j \mid X_n=i) = P(X_n=j \mid X_{n-1}=i) = P(X_i=j \mid X_0=i)$
Transition Probability $P = [p_{ij}] \in \mathbb{R}^{|\mathcal{S}| \times |\mathcal{S}|}$

Initial distribution : info of chain at time 0.

$\alpha_0 :=$ dist of X_0 as a row vector.

Soda example

\mathbb{R}^+	C	P
C	0.7	0.3
P	0.5	0.5



DTMC transition diagram

$$\text{matrix } A \begin{bmatrix} & C & P \\ C & 0.7 & 0.3 \\ P & 0.5 & 0.5 \end{bmatrix}$$

DTMC transition matrix

$$P(X_{n+1}=P | X_n=C) = 0.3 = A_{CP}$$

$$S = \{C, P\}$$

1x1x1 matrix

row sum=1 ... stochastic!

elements $\in [0, 1]$

Stochastic Process : Time + Random.

Discrete Time : $\{X_n : n \geq 0, n \in \mathbb{N}\} = \{X_0, X_1, X_2, \dots\}$

Continuous Time : $\{X_t : t \geq 0, t \in \mathbb{R}^+\} = \{X_0, \dots, X_{1/2}, \dots, X_{3.14}, \dots\}$

State: value of X_n . State Space S : a set of all possible states.

Markov property: the nearest future depends on the present.

for discrete time $\{X_n : n \geq 0, n \in \mathbb{N}\} \Rightarrow X_{n+1}$ depends only on the state of X_n . X_{n+1} is function of X_n & some randomness. $X_{n+1} = f(X_n, \text{random})$

$$\Rightarrow P(X_{n+1}=j | X_0=i_0, X_1=i_1, \dots, X_n=i_n) = P(X_{n+1}=j | X_n=i)$$

outdated info. most recent history

Discrete Time Markov chain, DTMC

⇒ discrete time stochastic process with Markov property

Transition probability $P_{ij} = P(X_{n+1}=j | X_n=i) = P(X_n=j | X_{n-1}=i) = P(X_1=j | X_0=i)$ Transition probability matrix $P = [P_{ij}] \in \mathbb{R}^{S \times S}$

Initial Distribution: info of where the chain starts at time 0.

$$P(X_0=C) = 0.6, P(X_0=P) = 0.4 \Rightarrow \alpha_0 = (1, 0) \quad \text{... } P(X_1=C) = \alpha_0 \begin{pmatrix} 0.7 \\ 0.3 \end{pmatrix} = 0.62.$$

$$\alpha_1 = \alpha_0 P, \alpha_2 = \alpha_1 P = \alpha_0 P^2, \alpha_3 = \alpha_2 P = \alpha_0 P^3 = \alpha_0 P^2, \dots, \alpha_n = \alpha_0 P^{n-1}$$

Stationary Distribution: State space S , transition probability matrix P ,

$$\pi = (\pi_i, i \in S) \text{ if } \pi_i \geq 0, \text{ all } i \in S, \sum_{i \in S} \pi_i = 1, \pi = \pi P$$

⇒ dynamic equilibrium, steady states. $(\text{inflow})_i = (\text{outflow})_i$ for all $i \in S \Rightarrow \# \text{ of stationary dist.} = 0, 1, \infty$ Soda with stationary dist. $\pi = (\pi_C, \pi_P) \Rightarrow \pi_C, \pi_P \geq 0, \pi_C + \pi_P = 1, (\pi_C, \pi_P) \begin{pmatrix} 0.7 & 0.3 \\ 0.5 & 0.5 \end{pmatrix} = (\pi_C, \pi_P) \Rightarrow \pi_C = 5/8, \pi_P = 3/8$

$$P = \begin{bmatrix} P_{CC} & P_{CP} \\ P_{PC} & P_{PP} \end{bmatrix} = \begin{bmatrix} 0.7 & 0.3 \\ 0.5 & 0.5 \end{bmatrix}$$

$(\text{outflow})_{\text{coke}} = (\text{inflow})_{\text{coke}}$ & $\pi_C + \pi_P = 1 \Rightarrow \pi_C = 5/8, \pi_P = 3/8$

$\pi_C \cdot P_{CP} = \pi_P \cdot P_{PC}$

n-step transition probability: $P(X_{n+k}=j | X_k=i) = P_{ij}^n, \lim_{n \rightarrow \infty} (1-\lambda) P^n \cong \text{stationary dist.}$ Soda $\Rightarrow P = \begin{bmatrix} 0.7 & 0.3 \\ 0.5 & 0.5 \end{bmatrix}, P^\infty = \begin{bmatrix} 5/8 & 3/8 \\ 3/8 & 5/8 \end{bmatrix} = \begin{bmatrix} -\pi & -\pi \\ -\pi & -\pi \end{bmatrix} > \text{identical rows!}$ unique (only 1) stationary dist. exist!
not always P^∞ converges.

DTMC with state space S & transition probability matrix P

$\pi = \pi(\pi_i, i \in S)$, $\pi_i \geq 0$ for all $i \in S$, $\sum \pi_i = 1$, $\pi P = \pi \Rightarrow$ stationary distribution
 ... dynamic equilibrium. Steady State. $(\text{inflow})_i = (\text{outflow})_i$, unique or inf solution.

Compute stationary dist. ① use $[\pi_i \geq 0, \sum \pi_i = 1, \pi P = \pi]$
 ② use $[(\text{inflow})_i = (\text{outflow})_i, \sum \pi_i = 1]$

n-step transition probability: $P(X_{k+n} = j | X_k = i) = P_{ij}^n$... from i state to j state in n -step.

Some case) $P = \begin{bmatrix} .7 & .3 \\ .5 & .5 \end{bmatrix}$ $P^{10} = \begin{bmatrix} 5/8 & 3/8 \\ 5/8 & 3/8 \end{bmatrix}$ identical rows.

initial dist. doesn't matter in long run - calculate limiting prob. by stationary dist.

$$\begin{aligned} (\pi_1, \pi_2, \pi_3, \pi_4) \left(\begin{array}{cccc} 0.5 & 0.5 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 \\ 0.5 & 0.5 & 0.5 & 0 \\ 0.5 & 0 & 0.5 & 0 \end{array} \right) = (\pi_1, \pi_2, \pi_3, \pi_4) \quad & \text{Periodic MC. Limiting prob. NOT Exist.} \\ \Rightarrow \pi = (1/4 \ 1/4 \ 1/4 \ 1/4) \quad & \text{if } n \rightarrow \infty \frac{P^{n+1} + P^{n+2} + \dots + P^{n+d}}{d} = \left(\begin{array}{c} -\pi \\ \vdots \end{array} \right) \\ & (d = \text{period}) \end{aligned}$$

Stationary dist unique

$$\begin{aligned} (\pi_C, \pi_P, \pi_B, \pi_M) \left(\begin{array}{cccc} 0.7 & 0.3 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 \\ 0 & 0 & 0.6 & 0.4 \\ 0 & 0 & 0.3 & 0.7 \end{array} \right) = (\pi_C, \pi_P, \pi_B, \pi_M) \quad & \text{2-reducible MC} \Rightarrow 2 \text{ classes exist} \\ \Rightarrow \alpha = \pi_C + \pi_P \quad 1-\alpha = \pi_B + \pi_M \quad & \text{("C} \xrightarrow[0.5]{0.3} \text{P"}, "B} \xrightarrow[0.6]{0.4} \text{M"} \text{)} \\ \pi = \left(\begin{array}{c} 5/8 \alpha \\ 3/8 \alpha \\ 3/7 (1-\alpha) \\ 4/7 (1-\alpha) \end{array} \right) \sim \alpha \quad & \text{Limiting prob. exist depending on initial state.} \\ & \text{Stationary dist. not unique } (\alpha) \end{aligned}$$

Accessibility: A state i can reach state j in some future. & write $i \rightarrow j$ if $\exists n \text{ s.t. } P_{ij}^n > 0$.
 State i & j are said to communicate & write $i \leftrightarrow j$ if $i \rightarrow j$, $j \rightarrow i$
 Class: group of states communicate

Reducibility: MC X_n is irreducible if all states communicate. (\exists only one class)

Periodicity: State $i \in S$, period $d(i) := \text{gcd}\{n \mid P_{ii}^n > 0\}$

MC X_n is periodic if $\exists i \text{ with } d(i) > 1$

\Rightarrow class property. class shares period. $i \leftrightarrow j \Rightarrow d(i) = d(j)$

If a finite state DTMC X_n is aperiodic & irreducible, $\left\{ \begin{array}{l} \text{limiting prob. exist.} \\ \text{stationary dist. is unique.} \end{array} \right.$

$\left. \begin{array}{l} \text{stationary dist. = limiting prob.} \end{array} \right.$

\Rightarrow The long-run fraction of time that the MC spends in each state.

calculate limiting prob. by solving stationary dist.

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Due Date: 2025-11-24

Simple Random Walk: $S = \{\dots, -1, 0, 1, 2, \dots\}$, $\dots \xrightarrow{\frac{p}{2}} -1 \xrightarrow{\frac{p}{2}} 0 \xrightarrow{\frac{p}{2}} 1 \xrightarrow{\frac{p}{2}} 2 \xrightarrow{\frac{p}{2}} \dots$

$q = 1-p$, if $p=q \Rightarrow$ symmetric
if $p \neq q \Rightarrow$ asymmetric

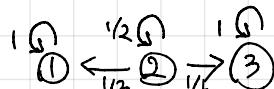
$$\begin{bmatrix} \cdots & -2 & -1 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ -2 & \cdots & q & p \\ -1 & \cdots & q & p \\ 0 & \cdots & q & p \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

State i
 recurrent : prob. getting back from i to $i = 1$ (always be a way to get back to i)
 absorbing state: recurrent & $P_{ii}=1$ (cannot leave state i)
 transient : prob. getting back from i to $i < 1$ (possible to be no way to get back to i)
 recurrent & transient \Rightarrow class property. ($i \leftrightarrow j$)

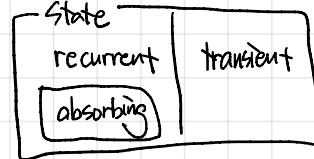
Compute P^∞

$$\text{ex)} P = \begin{pmatrix} 1 & 0 & 0 \\ 1/3 & 1/2 & 1/6 \\ 0 & 0 & 1 \end{pmatrix}$$

1. transition diagram.
2. period, R/A/T
3. identify class
4. compute P^∞



period=1 class = {1} {2} {3}
 R/A/T A T A



$$P^\infty = \begin{bmatrix} 1 & 0 & 0 \\ f_{2,1} & 0 & f_{2,3} \\ 0 & 0 & 1 \end{bmatrix} \quad f_{2,1} = P_{2,1}^\infty, \quad f_{2,3} = P_{2,3}^\infty, \quad f_{2,1} + f_{2,3} = 1$$

$$\begin{aligned}
 f_{2,1} &= P(X_\infty=1 | X_0=2) = P(X_\infty=1, X_1=1 | X_0=2) + P(X_\infty=1, X_1=2 | X_0=2) + P(X_\infty=1, X_1=3 | X_0=2) \\
 &= P(X_\infty=1 | X_1=1, X_0=2) P(X_1=1 | X_0=2) + \\
 &\quad P(X_\infty=1 | X_1=2, X_0=2) P(X_1=2 | X_0=2) + \\
 &\quad P(X_\infty=1 | X_1=3, X_0=2) P(X_1=3 | X_0=2) \quad (\because P(A \cap B \cap C) = P(A|B \cap C)P(B|C)) \\
 &= P(X_\infty=1 | X_1=1,) P(X_1=1 | X_0=2) + \\
 &\quad P(X_\infty=1 | X_1=2,) P(X_1=2 | X_0=2) + \\
 &\quad P(X_\infty=1 | X_1=3,) P(X_1=3 | X_0=2) \quad (\because \text{Markov property}) \\
 &= 1 \times 1/3 + f_{2,1} \times 1/3 + 0 \times 1/6 \Rightarrow f_{2,1} = 2/3 \quad f_{2,3} = 1/3 \quad (\because f_{2,1} + f_{2,3} = 1)
 \end{aligned}$$

Remarks. In a MC finite state space, not all states can be transient.

A recurrent state is accessible from all states in its class,
but is not accessible from recurrent states in other classes.

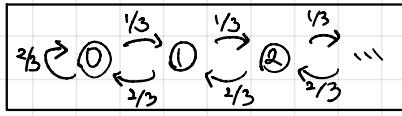
A transient state is not accessible from any recurrent state.

At least one, recurrent states are accessible from a given transient state.

1. $S = (-\infty, \infty)$ $p \neq 0.5$ all states are transient
2. $S = (-\infty, \infty)$ $p = 0.5$ all states are null recurrent (# stationary dist.)
3. $S = [0, \infty)$ $p > 0.5$ all states are transient
4. $S = [0, \infty)$ $p = 0.5$ all states are null recurrent (# stationary dist.)
5. $S = [0, \infty)$ $p < 0.5$ all states are positive recurrent. (= stationary dist.)

5. $\Rightarrow S = \{0, 1, 2, \dots\}$ $p = 1/3 < 0.5$

using flow equation,



inflow = outflow

$$\text{State 0} \quad \frac{2}{3}\pi_0 + \frac{2}{3}\pi_1 = \frac{2}{3}\pi_0 + \frac{1}{2}\pi_0 \Rightarrow \pi_0 = \frac{1}{2}\pi_0$$

$$\sum \pi_i = \pi_0 + \frac{1}{2}\pi_0 + \frac{1}{4}\pi_0 + \frac{1}{8}\pi_0 + \dots = \frac{1}{1-1/2}\pi_0 = 1 \Rightarrow \pi_0 = 1/2$$

$$\text{State 1} \quad \frac{1}{2}\pi_0 + \frac{2}{3}\pi_2 = \frac{2}{3}\pi_1 + \frac{1}{3}\pi_1 \Rightarrow \pi_1 = 1/4\pi_0$$

$$\pi_i = (\frac{1}{2})^{i+1} \text{ for all } i \in \mathbb{N}^+$$

$$\text{State 2} \quad \frac{1}{2}\pi_1 + \frac{2}{3}\pi_3 = \frac{2}{3}\pi_2 + \frac{1}{3}\pi_2 \Rightarrow \pi_2 = 1/8\pi_0$$

$$\pi = \{1/2, 1/4, 1/8, 1/16, \dots\}$$

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reminder: $X \sim \exp(\lambda)$, $P(X > s+t | X > t) = P(X > s)$ for all $s, t \geq 0$

$X_1 \sim \exp(\lambda_1)$, $X_2 \sim \exp(\lambda_2)$, $P(X_1 < X_2) = \lambda_1 / (\lambda_1 + \lambda_2)$, $\min(X_1, X_2) \sim \exp(\lambda_1 + \lambda_2)$

$$\begin{aligned} X_1 + X_2 &= \min(X_1, X_2) + \max(X_1, X_2) \Rightarrow E[X_1 + X_2] = 1 / (\lambda_1 + \lambda_2) + E[\max(X_1, X_2)] \Rightarrow Y_{\lambda_1} + Y_{\lambda_2} = 1 / (\lambda_1 + \lambda_2) + E[\max(X_1, X_2)] \\ &\Rightarrow E[\max(X_1, X_2)] = Y_{\lambda_1} + Y_{\lambda_2} - 1 / (\lambda_1 + \lambda_2) \end{aligned}$$

Discrete random var $X \sim \text{Poi}(\lambda)$ if pmf $P(X=k) = \frac{\lambda^k e^{-\lambda}}{k!}$ for $k=0, 1, 2, \dots \Rightarrow EX = \text{Var}(X) = \lambda$
 $N = \{N(t), t \geq 0\}$ counting process, if $N(0)=0$ & $N(t)$ is non-decreasing with integer value.
 \Rightarrow Poisson Process with rate λ , $\text{PP}(\lambda)$. if $\begin{cases} N(t_2) - N(t_1) \sim \text{Poi}(\lambda(t_2-t_1)) \text{ for any } 0 < t_1 < t_2 \Rightarrow \text{stationary increment.} \\ \text{for } t_1 < t_2 < t_3 < t_4, N(t_2) - N(t_1) \& N(t_4) - N(t_2) \text{ independent increment.} \end{cases}$

N is $\text{PP}(\lambda=2/\text{min})$

- Prob. 1 arrival in first 3 min : $P[N(3)-N(0)=1] = P[X=1 | X \sim \text{Poi}(2(3-0)=6)] = \frac{6^1 e^{-6}}{1!}$
- Prob. 2 arrival in [0, 2] & at least 3 arrival in [1, 3]
- $\begin{array}{c|ccccc} & 1 & 2 & 3 & 4 & 5 \\ \hline 2 & 1 & 0 & 2 & 3 & 4 \\ 1 & 1 & 1 & 2 & 3 & 4 \\ 0 & 2 & 2 & 1 & 1 & 0 \end{array} \quad P[N(2)-N(0)=2, N(3)-N(1) \geq 3] = P[N(1)-N(0)=2, N(2)-N(1)=0, N(3)-N(2) \geq 3] \quad P[N(1)-N(0)=1, N(2)-N(1)=1, N(3)-N(2) \geq 2]$
 $P[N(1)-N(0)=0, N(2)-N(1)=2, N(3)-N(2) \geq 1] = \frac{2^2 e^{-2}}{2!} \cdot \frac{2^2 e^{-2}}{0!} \cdot \left(1 - \frac{2^0 e^0}{0!} - \frac{2^1 e^1}{1!} - \frac{2^2 e^2}{2!}\right) + \frac{2^1 e^{-1}}{1!} \cdot \frac{2^1 e^{-1}}{1!} \cdot \left(1 - \frac{2^0 e^0}{0!} - \frac{2^1 e^1}{1!}\right) + \frac{2^0 e^{-2}}{0!} \cdot \frac{2^2 e^{-2}}{2!} \cdot \left(1 - \frac{2^0 e^0}{0!}\right)$
- Prob. no arrival in [0, 4] : made in counting domain \Rightarrow Prob. 1st arrival at least 4 min : made in time domain
 $\Rightarrow P[N(4)-N(0)=0] = P[X=0 | X \sim \text{Poi}(2(4-0)=8)] = \frac{8^0 e^{-8}}{0!}$
- Prob. 1st arrival takes at least t min $\Rightarrow P[N(t)-N(0)=0] = P[X=0 | X \sim \text{Poi}(\lambda(t-0)=2t)] = \frac{(2t)^0 e^{-2t}}{0!} = e^{-2t}$
- Dist of T_i := time to 1st arrival $\Rightarrow P[T_i > t] = e^{-\lambda t}$, $P[T_i \leq t] = 1 - P[T_i > t] = 1 - e^{-\lambda t}$
 \Rightarrow Time to 1st arrival in $\text{PP}(\lambda) \sim \exp(\lambda)$ If T_i be the time to first arrival,
 $P(T_i \leq t) = P(N(t)-N(0) > 0) = 1 - P(N(t)-N(0)=0) = 1 - P(X=0 | X \sim \text{Poi}(\lambda t)) = 1 - \frac{(\lambda t)^0 e^{-\lambda t}}{0!} = 1 - e^{-\lambda t}$
 $\therefore T_i \sim \exp(\lambda)$

For $n > 1$, let T_n denoted the elapsed time between $(n-1)^{\text{th}}$ & n^{th} event. $\{T_n, n=1, 2, 3, \dots\}$ = sequence of interarrival times.

$\therefore T_n \sim \exp(\lambda)$ for all $n=1, 2, 3, \dots$

independent increments : independent of all that has previously occurred. \Rightarrow no memory.

stationary increments : same distribution as the original process.

Merging PP.

$N_A = \{N_A(t), t \geq 0\}$ is $\text{PP}(\lambda_A)$, $N_B = \{N_B(t), t \geq 0\}$ is $\text{PP}(\lambda_B)$. they are independent. $\Rightarrow N = \{N(t) = N_A(t) + N_B(t)\}$ is $\text{PP}(\lambda_A + \lambda_B)$

Thinning PP.

$N = \{N(t), t \geq 0\}$ is $\text{PP}(\lambda)$, each arrival choose subset A (prob=p) or B (prob=q=1-p)

$\Rightarrow N_A = \{N_A(t), t \geq 0\}$ is $\text{PP}(p\lambda)$, $N_B = \{N_B(t), t \geq 0\}$ is $\text{PP}(q\lambda)$

counting process $N = \{N(t), t \geq 0\}$ with rate λ , $\text{PP}(\lambda)$ if $N(0)=0$, $N(t)$ has independent increment, $N(t+s)-N(s) \sim \text{Poi}(\lambda t)$

Non-homogeneous Poisson Process: $\lambda \rightarrow \lambda(t)$. function for arrival rate that changes over time.

\Rightarrow Counting process $N = \{N(t), t \geq 0\}$ is NHPP($\lambda(t)$) if $\begin{cases} N(0)=0 \\ N(t) \text{ has independent increment.} \end{cases}$

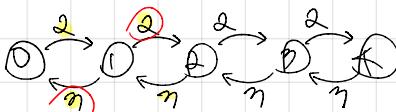
example. $\lambda(t) = \begin{cases} 6t & (0 \leq t \leq 1) \\ 60 & (t > 1) \end{cases}$

$$\begin{aligned} P\left[N\left(\frac{1}{6}\right) - N\left(\frac{1}{6}\right) = k\right] &= P\left[\text{Poi}\left(\int_{\frac{1}{6}}^{\frac{1}{6}} \lambda(u) du\right)\right] \\ &= P\left[\text{Poi}\left(\int_{\frac{1}{6}}^1 6u du + \int_{\frac{1}{6}}^{\frac{1}{6}} 60 du\right) = k\right] \end{aligned}$$

$$\begin{aligned} &= P\left[\text{Poi}\left(115/6\right) = k\right] = \underbrace{\left(\frac{115}{6}\right)^k e^{-115/6}}_{k!} \end{aligned}$$

cf) $X_1 \sim \exp(\lambda_1)$, $X_2 \sim \exp(\lambda_2)$ X_1 & X_2 independent. $\Rightarrow P(X_1 < X_2) = \frac{\lambda_1}{\lambda_1 + \lambda_2}$
 total n customers ($n \geq 1$) in 1-server post office. $T_A \sim \exp(2)$, $T_S \sim \exp(3)$ $n \swarrow n-1$ (service complete)
 $P(n \rightarrow n+1) = \frac{2}{3}$, $P(n \rightarrow n-1) = \frac{3}{5}$ distribution of time to transition = $\min(T_A, T_S) \sim \exp(2+3)$ $n \swarrow n+1$ (customer arrival)

M/M/1/3. $S = \{0, 1, 2, 3, 4\}$ CTMC's rate diagram:



time to transition from 0	rate matrix G : $(\sum_{row=0} = 0)$
exp(2)	$\begin{bmatrix} -2 & 2 & 0 & 0 & 0 \\ 3 & -5 & 2 & 0 & 0 \\ 0 & 3 & -5 & 2 & 0 \\ 0 & 0 & 3 & -5 & 2 \\ 0 & 0 & 0 & 3 & -3 \end{bmatrix}$
1	
2	
3	
4	$\Rightarrow \pi G = 0$

flow balance	inflow	=	outflow.
State 0	$3\pi_1$	=	$2\pi_0$
State 1	$2\pi_0 + 3\pi_2$	=	$3\pi_1 + 2\pi_3$
State 2	$2\pi_1 + 3\pi_3$	=	$3\pi_2 + 2\pi_4$
State 3	$2\pi_2 + 3\pi_4$	=	$3\pi_3 + 2\pi_1$
State 4	$2\pi_3$	=	$3\pi_4$
$\sum \pi_i = 1$	$\pi = [\pi_0, \pi_1, \pi_2, \pi_3, \pi_4]$		

CTMC:

continuous time stochastic process $\{X(t), t \geq 0\}$ in state space S

all $t \geq 0$, $i \in S$. $X(u) \in S$ for $0 \leq u \leq t$

$$P[X(t+s) > t | X(s) = i, X(u) = x(u), 0 \leq u \leq s] = P[X(t+s) > t | X(s) = i]$$

\Rightarrow depending on most recent info.

Time to transition $\sim \text{exp}$. Markov property = exp. dist. Time to transition.

Stationary distribution, $(\pi) \Rightarrow \pi = \pi P(t) \& \pi G = 0$. $P(t) = \text{CTMC transition matrix. } = e^{tG}$

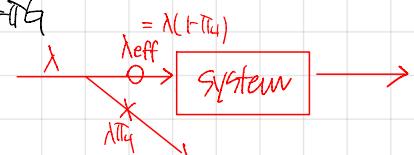
proof). claim, $\pi = \pi P(t)$ for all $t \geq 0 \Rightarrow \pi G = 0$.

$$\pi = \pi P(t) = \pi e^{tG} \Rightarrow \frac{d}{dt} \pi = \frac{d}{dt} \pi P(t) = \frac{d}{dt} \pi e^{tG} \Rightarrow 0 = \pi e^{tG} \cdot G \Rightarrow t=0, 0=\pi G$$

system empty? π_0 , system busy? $1-\pi$. customer not accepted? π_4 .

$$L_{sys} = 0 \cdot \pi_0 + 1 \cdot \pi_1 + 2 \cdot \pi_2 + 3 \cdot \pi_3 + 4 \cdot \pi_4. \quad L_{queue} = 0 \cdot \pi_0 + 0 \cdot \pi_1 + 1 \cdot \pi_2 + 2 \cdot \pi_3 + 3 \cdot \pi_4.$$

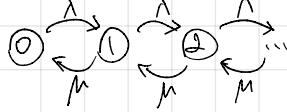
$$W_{sys} = \frac{L_{sys}}{\lambda_{eff}}, \quad W_{queue} = \frac{L_{queue}}{\lambda_{eff}}, \quad W_{svc} = W_{sys} - W_{queue}, \quad \lambda_{eff} = \lambda - \pi_4, \quad \lambda_{eff} = \lambda(1-\pi_4)$$



M/M/1/∞ Arrival is PP(λ /min), Service is PP(μ /min) $\Rightarrow T_A \sim \exp(\lambda)$, $T_S \sim \exp(\mu)$ $P = \frac{\lambda}{\mu} < 1$ for stability.

$X(t)$: # customers in the sys at time t . $\{X(t), t \geq 0\}$ is CTMC with state space $S = \{0, 1, 2, \dots\}$

rate diagram:



stationary dist.

$$\begin{aligned} \{0\} &\rightarrow \{1, 2, \dots\} & \lambda \pi_0 &= \mu \pi_1 \\ \{1\} &\rightarrow \{2, 3, \dots\} & \lambda \pi_1 &= \mu \pi_2 \\ \{2\} &\rightarrow \{3, 4, \dots\} & \lambda \pi_2 &= \mu \pi_3 \end{aligned}$$

$$\pi_i = \left(\frac{\lambda}{\mu}\right)^i \pi_0$$

$$\sum_{i=0}^{\infty} \pi_i = \frac{\pi_0}{1 - \frac{\lambda}{\mu}} = 1 \Rightarrow \pi_0 = \frac{1}{1 - \frac{\lambda}{\mu}}, \quad \pi_i = \left(\frac{\lambda}{\mu}\right)^i \pi_0 = \rho^i \pi_0$$

$$L_{sys} = 0 \cdot \pi_0 + 1 \cdot \pi_1 + 2 \cdot \pi_2 + \dots = 0(1-\rho) + 1 \cdot \rho(1-\rho) + 2 \rho^2(1-\rho) = \frac{\rho}{1-\rho} = \frac{\lambda}{\mu-\lambda} \quad (\because S-pS)$$

$$W_{sys} = L_{sys}/\lambda = \frac{\rho}{1-\rho} \times \frac{1}{\lambda} = \frac{\lambda}{\mu-\lambda} \times \frac{1}{\lambda} = \frac{1}{\mu-\lambda}$$

$$L_{queue} = 0 \cdot \pi_0 + 0 \cdot \pi_1 + 1 \cdot \pi_2 + 2 \cdot \pi_3 + \dots = \frac{\rho^2}{1-\rho}/\lambda = \frac{\rho^2}{\mu(1-\rho)} \quad (\because S-pS)$$

$$W_{queue} = L_{queue}/\lambda = \frac{\rho^2}{\mu(1-\rho)} \times \frac{1}{\lambda} = \frac{\lambda}{\mu(\mu-\lambda)} \quad (W_q = E[V] \cdot \frac{\rho}{1-\rho} \left(\frac{C_s + C_q}{2} \right))$$

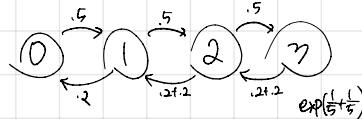
Stable dist \Rightarrow stationary dist.
 Unstable dist \Rightarrow non-stationary dist.

finite CTMC \Rightarrow unique stationary dist.
 infinite stable CTMC \Rightarrow stationary dist.

M/M/2/1

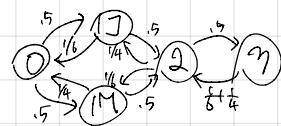
Arrival is $PP(\frac{1}{2})$, each service $\sim \exp(\frac{1}{2})$

$$S = \{0, 1, 2, 3\}$$



Arrival is $PP(\frac{1}{2})$, Join $\sim \exp(\frac{1}{2})$ Many servers

$$S = \{0, 1, 2, 3\}$$

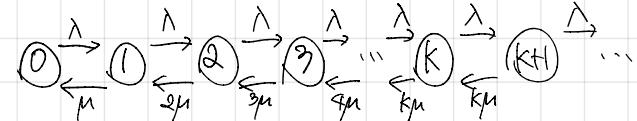


M/M/K/∞

Arrival is $PP(\lambda)$, service $\sim \exp(\mu)$ $S = \{0, 1, 2, \dots\}$

$$\Rightarrow \lambda_n = \lambda$$

$$\begin{cases} n\mu & (0 \leq n < k) \\ k\mu & (n \geq k) \end{cases}$$



Cutting method

$$\left| \begin{array}{c} L \rightarrow R = R \rightarrow L \\ \{0, \dots, n-1\} \rightarrow \{n, \dots\} \quad | \quad \lambda_{n-1} T_{n-1} = \mu_n T_n \\ \lambda_n T_{n-1} = \mu_n T_n \end{array} \right. \Rightarrow T_n = \frac{\lambda_n}{\mu_n} T_{n-1} = \frac{\lambda_0 \lambda_1 \dots \lambda_{n-1}}{\mu_1 \mu_2 \mu_3 \dots \mu_n} T_0 = \begin{cases} n < k, T_n = \frac{\lambda^n}{n! \mu^n} T_0 < \frac{1}{n!} \left(\frac{\lambda}{\mu}\right)^n T_0 \\ n \geq k, T_n = \frac{\lambda^n}{k! k^{n-k} \mu^n} T_0 = \frac{1}{k! k^{n-k}} \left(\frac{\lambda}{\mu}\right)^n T_0 \end{cases}$$

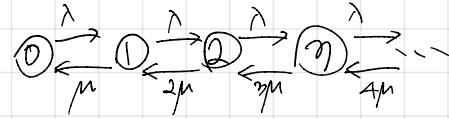
$$\sum_{n=0}^{\infty} T_n = 1 = T_0 \left(\sum_{n=0}^{k-1} \frac{1}{n!} \left(\frac{\lambda}{\mu}\right)^n + \sum_{n=k}^{\infty} \frac{1}{k! k^{n-k}} \left(\frac{\lambda}{\mu}\right)^n \right)$$

$$L_q = \frac{\lambda}{\mu} (n-k) T_n, \quad W_q = \frac{L_q}{\lambda}, \quad W_{sys} = W_q + \frac{1}{\mu}, \quad L_{sys} = W_{sys} \times \lambda = L_q + \frac{\lambda}{\mu}$$

M/M/∞/∞ self service

$S = \{0, 1, 2, \dots\}$ $n =$ customer in system & service
 λ_n . arrival rate = λ . μ_n . service rate = $n\mu$.

\Rightarrow always stable (\because server $\rightarrow \infty$)



Cutting Method

$$\begin{array}{|c|c|c|} \hline & L \rightarrow R & R \rightarrow L \\ \hline \{0\} \rightarrow \{1, 2, 3, \dots\} & \lambda T_0 & \mu T_1 \\ \{0, 1\} \rightarrow \{2, 3, 4, \dots\} & \lambda T_1 & 2\mu T_2 \\ \{0, 1, 2\} \rightarrow \{3, 4, 5, \dots\} & \lambda T_2 & 3\mu T_3 \\ \hline \end{array} \quad \left\{ \begin{array}{l} T_0 = \frac{\lambda}{\mu} T_0 \\ T_1 = \frac{1}{2} \left(\frac{\lambda}{\mu}\right) T_0 = \frac{1}{2} \left(\frac{\lambda}{\mu}\right)^2 T_0 \\ T_2 = \frac{1}{3} \left(\frac{\lambda}{\mu}\right) T_0 = \frac{1}{3!} \left(\frac{\lambda}{\mu}\right)^3 T_0 \end{array} \right\} \Rightarrow T_i = \frac{1}{i!} \left(\frac{\lambda}{\mu}\right)^i T_0$$

$$\sum_{i=0}^{\infty} T_i = T_0 \sum_{i=0}^{\infty} \frac{1}{i!} \left(\frac{\lambda}{\mu}\right)^i = 1, \quad T_0 = e^{-\frac{\lambda}{\mu}}, \quad (\because \sum_{n=0}^{\infty} \frac{\lambda^n}{n!} = e^{\lambda})$$

$$\therefore T_i = \frac{1}{i!} \left(\frac{\lambda}{\mu}\right)^i e^{-\frac{\lambda}{\mu}} \Rightarrow Pois\left(\frac{\lambda}{\mu}\right)$$

$$L_{sys} = \frac{\lambda}{\mu}, \quad L_q = 0, \quad W_{sys} = \frac{1}{\mu}, \quad W_q = 0$$

$$L_{av} = \frac{\lambda}{\mu}, \quad L_{av} = \frac{1}{\mu}$$