

Queueing Systems

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Today:

- ▶ Finite state continuous time Markov chains
- ▶ Queueing Processes
- ▶ M/M/s systems
- ▶ M/G/1 system

After fall break

- ▶ To be announced



Finite Continuous Time Markov Chains

$$P_{ij}(t) = \mathbb{P}\{X(t+s) = j | X(s) = i\}$$

- (a) $P_{ij}(t) \geq 0$
- (b) $\sum_{j=0}^N P_{ij}(t) = 1$
- (c) $P_{ik}(s+t) = \sum_{j=0}^N P_{ij}(s)P_{jk}(t)$
- (d) $\lim_{t \rightarrow 0+} P_{ij}(t) = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases}$

(c) is the Chapman-Kolmogorov equations, in matrix form

$$\mathbf{P}(t+s) = \mathbf{P}(t)\mathbf{P}(s)$$



$$\mathbf{P}'(t) = \mathbf{P}(t)\mathbf{A} \text{ (forward equations)}$$

$$\mathbf{P}'(t) = \mathbf{A}\mathbf{P}(t) \text{ (backward equations)}$$

$$\mathbf{P} = e^{\mathbf{A}t} = \sum_{n=0}^{\infty} \frac{\mathbf{A}^n t^n}{n!} = \mathbf{I} + \sum_{n=1}^{\infty} \frac{\mathbf{A}^n t^n}{n!}$$

Stationary Distribution

$$\mathbf{0} = \boldsymbol{\pi} \mathbf{A} = (\pi_0, \pi_1, \dots, \pi_N) \begin{vmatrix} -q_0 & q_{01} & \cdots & q_{0N} \\ q_{10} & -q_1 & \cdots & q_{1N} \\ \vdots & \vdots & \cdots & \vdots \\ q_{N0} & q_{N1} & \cdots & q_{NN} \end{vmatrix}$$

elementwise

$$\pi_j q_j = \sum_{i \neq j} \pi_i q_{ij} \text{ with } q_j = \sum_{k \neq j} q_{jk}$$



Infinitesimal Description

$$\begin{aligned}\mathbb{P}\{X(t+h) = j | X(t) = i\} &= q_{ij}h + o(h) \text{ for } i \neq j \\ \mathbb{P}\{X(t+h) = i | X(t) = i\} &= (1 - q_i h) + o(h)\end{aligned}$$

Sojourn Description

1. Embedded Markov chain of state sequences ξ_i has one step transition probabilities $p_{ij} = \frac{q_{ij}}{q_i}$
2. Successive sojourn times S_{ξ_i} are exponentially distributed with mean $\frac{1}{q_{\xi_i}}$.



Two State Markov Chain

$$\mathbf{A} = \begin{vmatrix} -\alpha & \alpha \\ \beta & -\beta \end{vmatrix}$$

$$\mathbf{A}^2 = \begin{vmatrix} \alpha^2 + \alpha\beta & -\alpha^2 - \alpha\beta \\ -\beta^2 - \alpha\beta & \beta^2 + \alpha\beta \end{vmatrix} = -(\alpha + \beta) \begin{vmatrix} -\alpha & \alpha \\ \beta & -\beta \end{vmatrix}$$

Thus

$$\mathbf{A}^n = [-(\alpha + \beta)]^{n-1} \mathbf{A}$$

And

$$\begin{aligned}\mathbf{P}(t) &= \mathbf{I} - \frac{1}{\alpha + \beta} \sum_{n=1}^{\infty} \frac{[-(\alpha + \beta)t]^n}{n!} \mathbf{A} \\ &= \mathbf{I} - \frac{1}{\alpha + \beta} \left(e^{-(\alpha+\beta)t} - 1 \right) \mathbf{A} \\ &= \mathbf{I} + \frac{1}{\alpha + \beta} \mathbf{A} - \frac{1}{\alpha + \beta} \mathbf{A} e^{-(\alpha+\beta)t}\end{aligned}$$



Summary of most Important Results

$$\mathbf{P}(t) = e^{\mathbf{A}t} \rightarrow \mathbf{1}\boldsymbol{\pi} \quad \text{for } t \rightarrow \infty$$

Under an assumption of irreducibility



Additional Reading

Kai Lai Chung: “Markov Chains with Stationary Transition Probabilities”



Queueing process

1. Input Process
2. Service Process
3. Queue Discipline

Kendall notation: $A/B/s$

1. Number of customers/items in system
2. Throughput
3. Utilization
4. Customer waiting time, probability of being served



Little's Theorem

$$L = \lambda W$$



M/M/1 System

Steady state equations:

$$\pi_k = \lim_{t \rightarrow \infty} \mathbb{P}\{X(t) = k\} \text{ for } k = 0, 1, \dots$$

$$\pi_k \mu = \pi_{k-1} \lambda, \quad \pi_k = \theta_k \pi_0$$

with

$$\theta_k = \left(\frac{\lambda}{\mu}\right)^k$$

such that

$$\pi_0 \sum_{k=0}^{\infty} \theta_k = 1 \Leftrightarrow \pi_0 = \frac{1}{\sum_{k=0}^{\infty} \theta_k} = \frac{1}{\frac{1}{1 - \frac{\lambda}{\mu}}} = 1 - \frac{\lambda}{\mu} \text{ for } \lambda < \mu$$

$$\pi_k = \left(\frac{\lambda}{\mu}\right)^k \left(1 - \frac{\lambda}{\mu}\right) = \rho^k (1 - \rho) \text{ with } \rho = \frac{\lambda}{\mu}$$

A geometric distribution



Total Time in M/M/1 System

$$\mathbb{P}\{T \leq t | n \text{ ahead}\} = \int_0^t \mu \frac{(\mu\tau)^n}{n!} e^{-\mu\tau} d\tau$$

$$\begin{aligned}\mathbb{P}\{T \leq t\} &= \sum_{n=0}^{\infty} \mathbb{P}\{T \leq t | n \text{ ahead}\} \mathbb{P}\{n \text{ ahead}\} \\ &= \sum_{n=0}^{\infty} \left[\int_0^t \mu \frac{(\mu\tau)^n}{n!} e^{-\mu\tau} d\tau \right] \left(1 - \frac{\lambda}{\mu}\right) \left(\frac{\lambda}{\mu}\right)^n \\ &= \int_0^t \mu \left(1 - \frac{\lambda}{\mu}\right) e^{-\mu\tau} \sum_{n=0}^{\infty} \frac{(\mu\tau)^n}{n!} \left(\frac{\lambda}{\mu}\right)^n \\ &= \int_0^t (\mu - \lambda) e^{-(\mu-\lambda)\tau} d\tau \\ &= 1 - e^{-(\mu-\lambda)t}\end{aligned}$$



Mean performance measures

$$W = \frac{1}{\mu - \lambda}$$

From Little's theorem

$$L = \lambda W = \frac{\lambda}{\mu - \lambda} = \frac{\rho}{1 - \rho}$$

which we could also have gotten directly from the distribution π_k

M/M/1 Busy Period

$$\mathbb{E}[l_1] = \frac{1}{\lambda}$$

$$\lim_{t \rightarrow \infty} p_0(t) = \pi_0 = \frac{\mathbb{E}[l_1]}{\mathbb{E}[l_1] + \mathbb{E}[B_1]}$$

$$1 - \frac{\lambda}{\mu} = \frac{\frac{1}{\lambda}}{\frac{1}{\lambda} + \mathbb{E}[B_1]}$$

$$\mathbb{E}[B_1] = \frac{1}{\mu - \lambda}$$



$$\lambda_k = \lambda \quad \mu_k = k\mu$$

$$\pi_k \lambda = \pi_{k+1} (k+1)\mu \quad \theta_k = \frac{\left(\frac{\lambda}{\mu}\right)^k}{k!}$$

$$\sum_{k=0}^{\infty} \pi_k = \pi_0 \sum_{k=0}^{\infty} \theta_k = \pi_0 \sum_{k=0}^{\infty} \frac{\left(\frac{\lambda}{\mu}\right)^k}{k!} = \pi_0 e^{\frac{\lambda}{\mu}}$$

$$\pi_k = \frac{\left(\frac{\lambda}{\mu}\right)^k}{k!} e^{-\frac{\lambda}{\mu}}$$

a Poisson distribution



M/M/s System

$$\lambda_k = \lambda, \mu_k = \begin{cases} k\mu & \text{for } k < s \\ s\mu & \text{for } s \leq k \end{cases}$$

$$\pi_0 = \left\{ \sum_{j=0}^{s-1} \frac{1}{j!} \left(\frac{\lambda}{\mu} \right)^j + \frac{\left(\frac{\lambda}{\mu} \right)^s}{s! \left(1 - \frac{\lambda}{s\mu} \right)} \right\}$$

$$\pi_k = \begin{cases} \frac{1}{k!} \left(\frac{\lambda}{\mu} \right)^k \pi_0 & \text{for } k = 0, 1, \dots, s \\ \frac{1}{s!} \left(\frac{\lambda}{\mu} \right)^s \left(\frac{\lambda}{s\mu} \right)^{k-s} \pi_0 & \text{for } k \geq s \end{cases}$$



M/M/s System: Performance Measures

$$\begin{aligned}L_0 &= \sum_{j=s}^{\infty} (j-s)\pi_j \\&= \pi_0 \sum_{k=0}^{\infty} k \frac{\left(\frac{\lambda}{\mu}\right)^s}{s!} \left(\frac{\lambda}{s\mu}\right)^k \\&= \frac{\pi_0}{s!} \left(\frac{\lambda}{\mu}\right)^s \sum_{k=0}^{\infty} k \left(\frac{\lambda}{s\mu}\right)^k \\&= \frac{\pi_0}{s!} \left(\frac{\lambda}{\mu}\right)^s \frac{\left(\frac{\lambda}{s\mu}\right)}{\left(1 - \frac{\lambda}{s\mu}\right)^2} \\W_0 &= \frac{L_0}{\lambda} \quad W = W_0 + \frac{1}{\mu} \quad L = \lambda W = L_0 + \frac{\lambda}{\mu}\end{aligned}$$

M/G/1 System

Let Y_1, Y_2, \dots be a sequence of service times with cumulative distribution function $G(y)$, with mean $\nu = \mathbb{E}[Y_k]$

$$\lim_{t \rightarrow \infty} p_0(t) = \pi_0 = \frac{\mathbb{E}[l_1]}{\mathbb{E}[l_1] + \mathbb{E}[B_1]}$$

$\mathbb{E}[l_1] = \frac{1}{\lambda}$, A : number of arrivals during service time of first customer of the busy period

$$\mathbb{E}[B_1 | Y_1 = y, A = 0] = y, \quad \mathbb{E}[B_1 | Y_1 = y, A = 1] = y + \mathbb{E}[B_1]$$

$$\mathbb{E}[B_1 | Y_1 = y, A = 1] = y + n\mathbb{E}[B_1]$$

$$\mathbb{E}[B_1 | Y_1 = y] = \sum_{n=0}^{\infty} (y + n\mathbb{E}[B_1]) \frac{(\lambda y)^n}{n!} e^{-\lambda y} = y + \lambda y \mathbb{E}[B_1]$$

Finally $\mathbb{E}[B_1] = \mathbb{E}[\mathbb{E}[B_1 | Y]] = \nu + \nu \lambda \mathbb{E}[B_1]$ such that

$$\mathbb{E}[B_1] = \frac{\nu}{1 - \nu \lambda} \text{ and } \pi_0 = \frac{\frac{1}{\lambda}}{\frac{1}{\lambda} + \frac{\nu}{1 - \nu \lambda}} = 1 - \nu \lambda \text{ for } \lambda \nu < 1$$



M/G/1 Embedded Markov chain at departures

$$\begin{aligned}X_{n+1} &= \begin{cases} X_n - 1 + A_n & \text{for } X_n \geq 1 \\ A_n & \text{for } X_n = 0 \end{cases} \\&= (X_n - 1)^+ A_n \\ \alpha_k &= \mathbb{P}\{A_n = k\} = \int_0^\infty \frac{(\lambda y)^k}{k!} e^{-\lambda y} dG(y) \\ P_{ij} &= \begin{cases} \alpha_{j-i-1} & \text{for } j \geq i-1 \geq 0 \\ \alpha_j & \text{for } i = 0 \end{cases}\end{aligned}$$



Mean Queue Length in Equilibrium

$$\lim_{n \rightarrow \infty} \mathbb{P}\{X_n = k\} = \pi_k, \quad \lim_{n \rightarrow \infty} \mathbb{E}[X_n] = L$$

$$X_{n+1} = X_n - \delta + A_n, \quad \mathbb{E}[X_{n+1}] = \mathbb{E}[X_n] - \mathbb{E}[\delta] + \mathbb{E}[A_n]$$

Leading to $\mathbb{E}[A_n] = \mathbb{E}[\delta] = 1 - \pi_0 = \lambda\nu$

Now by Squaring

$$X_{n+1}^2 = X_n^2 + \delta^2 + A_n^2 - 2X_n\delta + 2A_n(X_n - \delta)$$

$$\mathbb{E}[X_{n+1}^2] = \mathbb{E}[X_n^2] + \mathbb{E}[\delta] + \mathbb{E}[A_n^2] - 2\mathbb{E}[X_n] + 2\mathbb{E}[A_n]\mathbb{E}[X_n - \delta]$$

$$0 = \lambda\nu + \mathbb{E}[A_n^2] - 2L + 2\lambda\nu(L - \lambda\nu)$$

$$L = \frac{\lambda\nu + \mathbb{E}[A_n^2] - 2(\lambda\nu)^2}{2(1 - \lambda\nu)}$$



M/G/1 Calculation of $\mathbb{E}[A_n^2]$

$$\mathbb{E}[A_n^2 | Y = y] = (\lambda y + (\lambda y)^2)$$

$$\mathbb{E}[A_n^2] = \int_0^\infty (\lambda y + (\lambda y)^2) dG(y) = \lambda\nu + \lambda^2(\nu^2 + \tau^2)$$

with $\tau^2 = \text{Var}(Y)$. Finally, inserting and rearranging

$$L = \frac{\lambda\nu + \lambda\nu + \lambda^2(\nu^2 + \tau^2) - 2(\lambda\nu)^2}{2(1 - \lambda\nu)} = \rho + \frac{\lambda^2\tau^2 + \rho^2}{2(1 - \lambda\nu)}$$

The distributions of $X(t)$ and X_n are identical

$$A_t = \{(w, v) : 0 \leq w \leq t \text{ and } v > t - w\}$$

$$\begin{aligned}\mu(A_t) &= \int_0^t \left\{ \int_{t-w}^{\infty} dG(y) \right\} dw \\ &= \lambda \int_0^t [1 - G(t-w)] dw \\ &= \lambda \int_0^t [1 - G(x)] dx\end{aligned}$$

$$\mathbb{P}\{X(t) = k\} = \frac{(\lambda \mu(A_t))^k}{k!} e^{-\lambda \mu(A_t)} \rightarrow \frac{(\lambda \nu)^k}{k!} e^{-\lambda \nu} \text{ as } t \rightarrow \infty$$