SSIE 660: Stochastic Systems Dr. Sung H. Chung Note 11 Chapter 4. Discrete Markov Chains

Time Reversible Markov Chains

- Consider an irreducible and ergodic Markov Chain with one-step transition probabilities, P_{ij} , that has reached steady state, with steady state probabilities π_i .
- Let us trace the sequence of states backward in time. That is, starting at time n, we consider the sequence of states, X_n , X_{n-1} , X_{n-2} , This sequence of states is itself a Markov Chain with transition probabilities Q_{ij} , given by

 $Q_{ij} =$

• What should we prove so that the reversed process is indeed a Markov Chain?

• If $Q_{ij} = P_{ij}$, then the Markov Chain is said to be Time Reversible.

Chapter 5. The Exponential Distribution and the Poisson Process

The Exponential Distribution

$$f_X(x) = \left\{ egin{array}{ll} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & otherwise \end{array}
ight. \ P(X \leq a) = F_X(a) = \int_0^a \lambda e^{-\lambda x} dx = \ P(X > a) = \left\{ egin{array}{ll} a > 0 \\ otherwise \end{array}
ight. \ E[X] = \end{array}
ight.$$

$$Var(X) =$$

<u>Properties</u> (I) Assume that the lifetime of a component follows exponential density function. Let us find the probability that the component lasts for at least (s + t) hours, given that it has survived t hours.

$$P[X > t + s | x > t] =$$

- That is, if the component is working at time *t*, then the distribution of the remaining amount of time that it survives is
- This is called the memoryless property of exponential distribution. (The component does not *remember* that it has already been in use for time *t*.)

Example 1. Suppose that the amount of time a customer spends in a bank is exponentially distributed with a mean of 5 minutes ($\lambda = 1/5$).

- 1. What is the probability that a customer spends more than 10 minutes in the bank?
- 2. What is the probability that a customer spends an additional 10 minutes in the bank, given that she/he is still in the bank after 5 minutes?

 $X \sim$ amount of time the customer spends in the bank.

1.
$$P[X > 10] =$$

2.
$$P[X > 10 + 5|X > 5] =$$

<u>Properties</u> (II) Let $X_1, X_2, ..., X_n$ be independent and identically distributed (iid) exponential random variables having mean $1/\lambda$. Let $S = \sum_{i=1}^{n} X_i$. Then S follows gamma distribution with parameters n and λ .

$$f_S(s) = \begin{cases} \lambda e^{-\lambda s} \frac{(\lambda s)^{n-1}}{(n-1)!}, & s > 0 \\ 0, & otherwise \end{cases}$$

<u>Properties</u> (III) Let X_1 and X_2 be two exponential random variables with means $1/\lambda_1$ and $1/\lambda_2$, respectively. X_1 and X_2 are independent to each other. What is $P[X_1 < X_2]$?

$$f_{X_1}(x_1) = \begin{cases} \lambda_1 e^{-\lambda_1 x_1}, & x_1 > 0\\ 0, & otherwise \end{cases}$$

$$f_{X_2}(x_2) = \begin{cases} \lambda_2 e^{-\lambda_2 x_2}, & x_2 > 0\\ 0, & otherwise \end{cases}$$

$$P[X_1 < X_2] =$$

$$F_{X_1}(x_2) =$$

Properties (IV) The failure rate (or hazard rate) function r(t) is

$$r(t) = \frac{f(t)}{1 - F(t)}$$

For exponential density function,

$$r(t) =$$

Let the density function of *X* be $f_X(x)$ and the density function of *Y* be $f_Y(y)$.

$$f_X(x) = \begin{cases} \lambda_1 e^{-\lambda_1 x}, & x > 0 \\ 0, & otherwise \end{cases}$$

$$f_Y(y) = \begin{cases} \lambda_2 e^{-\lambda_2 y}, & y > 0 \\ 0, & otherwise \end{cases}$$

Let $Z = \min\{X, Y\}$. What is the conditional density function of Z, given that Z = X?

In problems like this, it is easier to obtain the cumulative distribution function of Z, $F_Z(z)$ and derive $f_Z(z)$ by differentiating $F_Z(z)$ with respect to z.

$$P[z < x < y] = P[x > z, x < y] =$$

The Poisson Process

Counting Processes: A stochastic process $\{N(t), t \ge 0\}$ is said to be a counting process, if $\overline{N(t)}$ represents the *total number* of 'events' that have occurred up to time t.

Example 2. The number of customers entered a store up to time t.

$$N(2) = ; N(3) = ; N(7) = ; N(5.2) =$$

Requirements of a Counting Process

- 1. $N(t) \ge 0$.
- 2. N(t) is integer valued.
- 3. If s < t, $N(s) \le N(t)$.
- 4. For s < t, N(t) N(s) equals the number of events that have occurred in the interval (s,t).

Example 3. N(5.8) - N(2.2) =

Definition 4. A counting process is said to possess <u>independent increments</u>, if the number of events which occur in disjoint time intervals are independent.

Example 5. If $\{N(7) - N(5.5)\}$ is independent of $\{N(4.6) - N(1.9)\}$, then N(t) possesses independent increments.

Definition 6. A counting process is said to possess stationary increments, if the probability distribution of the number of events which occur in any interval of time depends only on the length of time interval.

Example 7. If P[N(7) - N(5.5) = n] = P[N(20) - N(18.5) = n] for all n, then N(t) possesses stationary increments.

Definition 8 (Poisson Process). A counting process $\{N(t), t \ge 0\}$ is said to be a Poisson process having rate $\lambda > 0$, if

- 1. N(0) = 0.
- 2. The process has independent increments, and
- 3. For all $s, t \geq 0$,

$$P[N(t+s) - N(s) = n] = P[N(t) = n] = \frac{e^{-\lambda t}(\lambda t)^n}{n!}, n = 0, 1, 2, ...$$

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 $E[N(t)] = \lambda t$. (Mean of Poisson process)

Definition 9 (Alternative Definition). *A counting process* $\{N(t), t \geq 0\}$ *is said to be a Poisson process having rate* $\lambda > 0$, *if*

- 1. N(0) = 0.
- 2. The process has stationary and independent increments, and
- 3. $P[N(h) = 1] = \lambda h + o(h)$, and

4.
$$P[N(h) \ge 2] = o(h)$$
.

Note that
$$f(\cdot)$$
 is $o(h)$ if $\lim_{h\to 0} = \frac{f(h)}{h} = 0$.

Example 10. Let $\{N(t), t \ge 0\}$ be a Poisson process with rate $\lambda = 15$. Compute:

1.
$$P[N(6) = 9] =$$

2.
$$P[N(6) = 9, N(20) = 13, N(56) = 27] =$$

3.
$$P[N(20) = 13|N(6) = 9] =$$