

# Stochastic Processes

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## 1 Moment Generating Function

- Moment Generating Function:  $\mathbb{E}[e^{tX}]$ 
  - Property:
    - \*  $\mathbb{E}[e^{tX}] = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx$
    - \*  $\mathbb{E}[e^{tX}] = \sum_{k=0}^{\infty} \frac{E[X^k] t^k}{k!}$ 
      - $e^{tx} = \sum_{k=0}^{\infty} \frac{(tx)^k}{k!}$
      - $E[e^{tX}] = E[\sum_{k=0}^{\infty} \frac{(tX)^k}{k!}] = \sum_{k=0}^{\infty} E[X^k] \frac{t^k}{k!}$
    - \*  $\frac{d\mathbb{E}[e^{tX}]}{dt} = \mathbb{E}[X]$
    - \*  $\mathbb{E}[e^{t(aX+b)}] = e^{tb} \mathbb{E}[e^{taX}]$
    - \* Not all random variables have Moment generating function
  - Characteristic Function:  $\mathbb{E}[e^{itX}]$ 
    - Property:
      - \* All random variables have Moment generating function
  - Joint Moment Generating Function:  $G(x, y) = \mathbb{E}[e^{xX} e^{yY}]$
  - Property:
    - (Joint) moment generating function uniquely determines the (joint) CDF
  - Example
    - Trapped miner's random walk
      - \* Miner has probability of  $\frac{1}{3}$  to waste 3 hours in vain,  $\frac{1}{3}$  to waste 5 hours in vain, and  $\frac{1}{3}$  to spend 2 hours to go out of the mine.
      - \*  $X$  is the random variables of the hours to go out of the mine
      - \*  $Y_i$  is the random variables of the hours for the  $i$ -th action.
      - \*  $\mathbb{E}[e^{tX}] = \mathbb{E}[e^{tX} | Y_1 = 2] + \mathbb{E}[e^{tX} | Y_1 = 3] + \mathbb{E}[e^{tX} | Y_1 = 5]$   
 $= \mathbb{E}[e^{2t}] + \mathbb{E}[e^{t(X+3)}] + \mathbb{E}[e^{t(X+5)}]$
      - \* Find expectation and variance by joint moment generating function

## 2 Expectation

- $N$  i.i.d. events, when  $N$  is a random variable
  - Suppose  $N$  is a integer random variable
  - Suppose  $X_1, \dots, X_i, \dots, X_N$  are i.i.d random variables with mean  $\mu$  and variance  $\sigma^2$
  - $Y = \sum_{i=1}^N X_i$
  - $\mathbb{E}[Y] = \mathbb{E}[N]\mu$ 
    - \*  $\mathbb{E}[Y] = \sum_{n=1}^{\infty} \mathbb{E}[\sum_{i=1}^N X_i | N = n] P[N = n]$   
 $= \mu \times \sum_{n=1}^{\infty} n P[N = n] = \mathbb{E}[N]\mu$

- $\mathbb{E}[Y^2] = \mathbb{E}[N]\mathbb{E}[X^2] + \mathbb{E}[N^2]\mu^2 - \mathbb{E}[N]\mu^2$ 
  - \*  $\mathbb{E}[Y^2] = \sum_{n=1}^{\infty} \mathbb{E}[(\sum_{i=1}^N X_i)^2 | N=n] P[N=n] = \sum_{n=1}^{\infty} (n\mathbb{E}[X_i^2] + n(n-1)\mu^2) P[N=n]$   
 $= \mathbb{E}[N]\mathbb{E}[X^2] + \mathbb{E}[N^2]\mu^2 - \mathbb{E}[N]\mu^2$
- $\text{Var}(Y) = \mathbb{E}[N]\sigma^2 + \text{Var}(N)\mu^2$
- Expectation by  $P[X > x]$ 
  - $\mathbb{E}[X] = \sum_x P[X > x]$ , when  $X$  is a non-negative discrete random variable
    - \*  $\mathbb{E}[X] = \sum_{x=0}^{\infty} xP[X=x] = \sum_{x=0}^{\infty} \sum_{y=0}^{x-1} P[X=x] = \sum_{y=0}^{\infty} \sum_{x=y+1}^{\infty} P[X=x] = \sum_{y=0}^{\infty} P[X > y]$
  - $\mathbb{E}[X] = \int_0^{\infty} P[X > x] dx$ , when  $X$  is a non-negative continuous random variable
    - \*  $\mathbb{E}[X] = \int_0^{\infty} x f_X(x) dx = \int_0^{\infty} \int_0^x f_X(x) dy dx = \int_0^{\infty} \int_y^{\infty} f_X(x) dx dy = \int_0^{\infty} P[X > y] dy$

### 3 Inequality

- Markov Inequality

Definition:

- Suppose  $X \geq 0$ , then  $P[X \geq \epsilon] \leq \frac{\mathbb{E}[X]}{\epsilon}$

Proof:

1.  $\mathbb{E}[X] = \int_0^{\infty} x f_X(x) dx \geq \int_{\epsilon}^{\infty} x f_X(x) dx \geq \epsilon \int_{\epsilon}^{\infty} f_X(x) dx = \epsilon P[X \geq \epsilon]$
2.  $X(\omega) \geq \epsilon \mathbb{1}_{X(\omega) \geq \epsilon}, \forall \omega \in S$ 
  - Calculate expectation on both side.
  - $\mathbb{E}[X] \geq \epsilon P[X \geq \epsilon]$

Property:

- The equality happens when  $P[X = k] = 0, \forall k \notin \{0, \epsilon\}$ .

- Chebyshev Inequality

Definition:

- Suppose  $m = \mathbb{E}[X], \sigma^2 = \text{Var}(X)$ , then  $P[|X - m| \geq \epsilon] \leq \frac{\sigma^2}{\epsilon^2}$

Proof:

- $P[|X - m| \geq \epsilon] = P[(X - m)^2 \geq \epsilon^2]$
- $P[(X - m)^2 \geq \epsilon^2] \leq \frac{\mathbb{E}[(X - m)^2]}{\epsilon^2}$  (by Markov Inequality)

Property:

- The equality happens when  $P[X = k] = 0, \forall k \notin \{m - \epsilon, m, m + \epsilon\}$ .
- Might be tighter than Markov Inequality since it requires  $m, \sigma$

- Chernoff Inequality

Definition:

- Suppose  $X_1, \dots, X_n$  are independent identically distributed Bernoulli random variable with probability  $p$  and  $X = \sum_{i=1}^n X_i$
- $P[X \geq \epsilon] \leq \frac{(pe^t + 1 - p)^n}{e^{t\epsilon}} \leq \frac{e^{np(\epsilon^t - 1)}}{e^{t\epsilon}}$ 
  - \*  $P[X \geq \epsilon] = P[e^{tX} \geq e^{t\epsilon}] \leq \frac{E[e^{tX}]}{e^{t\epsilon}} = \frac{(E[e^{tX_i}])^n}{e^{t\epsilon}} = \frac{(pe^t + 1 - p)^n}{e^{t\epsilon}} \leq \frac{e^{np(\epsilon^t - 1)}}{e^{t\epsilon}}$
- $P[X \geq np(1 + \epsilon)] \leq (\frac{e^{\epsilon}}{(1 + \epsilon)^{1 + \epsilon}})^{np} \leq \begin{cases} e^{-\frac{\epsilon^2 np}{3}} & \text{if } 0 \leq \epsilon \leq 1 \\ e^{-\frac{\epsilon^2 np}{(2 + \epsilon)}} & \text{if } \epsilon \geq 1 \end{cases}$ 
  - \* Substitute  $\epsilon$  with  $np(1 + \epsilon)$

- \* Substitute  $t$  with  $\log(1 + \epsilon)$
- \* the last inequality is without proof
- $P[X \leq \epsilon] \leq \frac{(pe^t + 1 - p)^n}{e^{t\epsilon}} \leq \frac{e^{np(e^t - 1)}}{e^{t\epsilon}}$ 
  - \*  $P[X \leq \epsilon] = P[e^{-tX} \geq e^{-t\epsilon}] \leq \frac{E[e^{-tX}]}{e^{-t\epsilon}} = \frac{(E[e^{-tX_i}])^n}{e^{-t\epsilon}} = \frac{(pe^{-t} + 1 - p)^n}{e^{-t\epsilon}} \leq \frac{e^{np(e^{-t} - 1)}}{e^{-t\epsilon}}$
- $P[X \leq np(1 - \epsilon)] \leq (\frac{e^{-\epsilon}}{(1 - \epsilon)^{1 - \epsilon}})^{np} \leq e^{-\frac{\epsilon^2 np}{2}}$ 
  - \* Substitute  $\epsilon$  with  $np(1 - \epsilon)$
  - \* Substitute  $t$  with  $-\log(1 - \epsilon)$
  - \* the last inequality is without proof

#### • Chernoff/ Hoeffding Lemma

Definition:

- Suppose  $X_1, \dots, X_n$  are independent distributed random variable and  $a_i \leq X_i \leq b_i$
- Suppose  $X = \sum_{i=1}^n X_i$  and  $\mu = \mathbb{E}[X]$
- $P[|X - \mu| \geq \epsilon] \leq 2e^{\frac{-2\epsilon^2}{\sum_{i=1}^n (b_i - a_i)^2}}$  without proof

#### • Application:

- Balls in Bins

Definition: Throw  $n$  balls into  $n$  bins, find bounds for the maximum number of balls in all bins

- \*  $P[\text{maximum number of balls in all bins} \geq \epsilon]$ 
  - $= P[\cup_{i=1}^n \text{number of balls in } i\text{-th bin} \geq \epsilon]$
  - $\leq n \times P[\text{number of balls in one bin} \geq \epsilon]$
- \* By Markov inequality:
  - $\cdot P[\text{number of balls in one bin} \geq \epsilon] \leq \frac{1}{\epsilon} \rightarrow \text{useless}$
- \* By Chebyshev inequality:
  - $\cdot P[\text{number of balls in one bin} \geq \epsilon] \leq \frac{(1 - \frac{1}{n})}{\epsilon^2}$
  - $\cdot P[\text{maximum number of balls in all bins} \geq n^{\frac{1}{2} + \epsilon}] \leq \frac{(1 - \frac{1}{n})}{n^{2\epsilon}}$
  - $\cdot \text{when } n \rightarrow \infty, \text{ the maximum number of balls should less than } n^{\frac{1}{2} + \epsilon}$
- \* By Chernoff inequality:
  - $\cdot P[\text{number of balls in one bin} \geq 2 \log n] \leq \frac{e^{np(e^t - 1)}}{n^{2t}}$
  - $\cdot P[\text{maximum number of balls in all bins} \geq 2 \log n] \leq \frac{e^{np(e^t - 1)}}{n^{2t - 1}}$
  - $\cdot \text{when } t \text{ is a constant } \geq 0.5 \text{ and } n \rightarrow \infty, \text{ the maximum number of balls should less than } 2 \log n$

## 4 Law of Large Numbers

- $\{X_i\}_{i=1}^\infty$  is a sequence of pairwise uncorrelated random variable with  $\mathbb{E}[X_i] = m, \text{Var}(X_i) = \sigma_i^2$ .
- $M_n = \frac{1}{n} \sum_{i=1}^n X_i$
- $M_n \rightarrow m$  almost surely, in mean square and in probability.

## 5 Memoryless

- Definition:  $P[X > x_1 + x_2 | X > x_1] = P[X > x_2]$
- Property:
  - Exponential random variable is the only continuous memoryless random variable
  - Bernoulli random variable is the only discrete memoryless random variable

## 6 Famous Random Variable

- Poisson:

$$P[X = k] = \frac{\lambda^k}{k!} \exp(-\lambda)$$

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

Interpretation:

- Cut total time into infinite period in Binomial random variable,  $n \rightarrow \infty, p \rightarrow \frac{\lambda}{n}$
- $\rightarrow P[X = k] = \lim_{n \rightarrow \infty} \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k} = \frac{\lambda^k}{k!} \left(1 - \frac{\lambda}{n}\right)^n = \frac{\lambda^k}{k!} \exp(-\lambda)$

- Erlang:

$$f_X(x) = \frac{\lambda^n x^{n-1} e^{-\lambda x}}{(n-1)!}, \forall x \in \mathbb{R}$$

$$\mathbb{E}[X] = \frac{n}{\lambda}$$

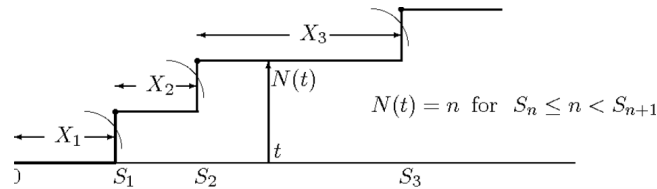
Interpretation:

- Suppose  $X_1, X_2, \dots, X_n$  are i.i.d exponential random variable with  $\lambda$ .
- $X = \sum_{i=1}^n X_i$
- Proof by induction:  
Suppose  $n = 2$ ,  $f_X(x) = \int_0^x \lambda e^{-\lambda t} \lambda e^{-\lambda(x-t)} dt = \lambda^2 x e^{-\lambda x}$

## 7 Stochastic Processes

- Stochastic Process: a collection of random variable

Arrival Process: a sequence of arriving event in continuous time



- $X_i$ : the time between the  $i$ -th event and the  $i - 1$ -th event
- $S_i$ : the time from start to  $i$ -th event
- $N(t)$ : the number of the arrived event at time  $t$
- $X$  and  $S$  Relation:

$$* X_1 = S_1, X_i = S_i - S_{i-1}$$

- $N$  and  $S$  Relation:

$$* N(t) < n \leftrightarrow S_{n+1} > t$$

$$* N(t) \geq n \leftrightarrow S_n \leq t$$

$$* N(t) = n \leftrightarrow S_n \leq t < S_{n+1}$$

$$* N(t) = \max\{n : S_n \leq t\}$$

- Renewal Process: an arrival process with i.i.d  $X_i$

Delayed Renewal Process: the process becomes a renewal process after several arrivals

$X_i$  Property

- \* if  $X_i$  is dependent on the interval states, then  $X_i$  might be dependent on  $X_{i-1} \rightarrow$  not renewal process

$S_i$  Property

$$* P[\lim_{n \rightarrow \infty} S_n = \infty] = 1$$

$$\text{Proof: } \lim_{n \rightarrow \infty} P[S_n = \infty] = \lim_{n \rightarrow \infty} P[\sum_{i=1}^n X_i = n \times \mathbb{E}[X_i]] = 1$$

Interpretation: infinite events do not take finite time

### $N(t)$ Property

- \* for any  $t, P[N(t) < \infty] = 1$   
 Proof:  $P[\lim_{n \rightarrow \infty} S_n = \infty] = 1 \rightarrow$  for any  $t, P[\lim_{n \rightarrow \infty} S_{n+1} > t] = 1$   
 Interpretation: infinite events do not take finite time
- \*  $P[\lim_{t \rightarrow \infty} N(t) \rightarrow \infty] = 1$   
 Proof: if  $P[\lim_{t \rightarrow \infty} N(t) = k] > 0 \rightarrow P[X_{k+1} = \infty] > 0$   
 Interpretation: finite events do not take infinite time
- \*  $P[\lim_{t \rightarrow \infty} \frac{N(t)}{t} = \frac{1}{\mathbb{E}[X_i]}] = 1$   
 Proof:  $P[\lim_{t \rightarrow \infty} \frac{N(t)}{S_{N(t)+1}} \leq \lim_{t \rightarrow \infty} \frac{N(t)}{t}] = 1$  and  $P[\lim_{t \rightarrow \infty} \frac{N(t)}{S_{N(t)+1}} = \frac{1}{\mathbb{E}[X_i]}] = 1$   
 $P[\lim_{t \rightarrow \infty} \frac{N(t)}{t} \leq \lim_{t \rightarrow \infty} \frac{N(t)}{S_{N(t)}}] = 1$  and  $P[\lim_{t \rightarrow \infty} \frac{N(t)}{S_{N(t)}} = \frac{1}{\mathbb{E}[X_i]}] = 1$

### Inspection Paradox

- \*  $\mathbb{E}[X_{N(t)+1}] \geq \mathbb{E}[X_i]$ : inspection paradox  
 Interpretation: when selecting  $t$  with equal probability, we tend to choose  $X_i$  with longer period
- \*  $P[\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t (S_{N(t)+1} - s) ds = \frac{\mathbb{E}[X_i^2]}{2\mathbb{E}[X_i]}] = 1$   
 Proof:  
 $P[\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{i=1}^{N(t)} \frac{\mathbb{E}[X_i^2]}{2} \leq \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t (S_{N(t)+1} - s) ds] = 1$  and  $P[\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{i=1}^{N(t)} \frac{\mathbb{E}[X_i^2]}{2} = \frac{\mathbb{E}[X_i^2]}{2\mathbb{E}[X_i]}] = 1$   
 $P[\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t (S_{N(t)+1} - s) ds \leq \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{i=1}^{N(t)+1} \frac{\mathbb{E}[X_i^2]}{2}] = 1$  and  $P[\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{i=1}^{N(t)+1} \frac{\mathbb{E}[X_i^2]}{2} = \frac{\mathbb{E}[X_i^2]}{2\mathbb{E}[X_i]}] = 1$
- \*  $P[\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t (s - S_{N(t)}) ds = \frac{\mathbb{E}[X_i^2]}{2\mathbb{E}[X_i]}] = 1$   
 Proof: similar to above
- \*  $P[\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t X_{N(t)} ds = \frac{\mathbb{E}[X_i^2]}{\mathbb{E}[X_i]}] = 1$   
 Proof:  $P[\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t X_{N(t)} ds = \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t (S_{N(t)+1} - S_{N(t)}) ds] = 1$
- \*  $\mathbb{E}[X_{N(t)+1}] = \frac{\mathbb{E}[X_i^2]}{\mathbb{E}[X_i]}$   
 Proof:  $P[\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t X_{N(t)} ds = \frac{\mathbb{E}[X_i^2]}{\mathbb{E}[X_i]}] = P[\mathbb{E}[X_{N(t)+1}] = \frac{\mathbb{E}[X_i^2]}{\mathbb{E}[X_i]}] = 1$

### Central Limit Theorem

- \*  $\mu = \mathbb{E}[X_i]$
- \*  $\sigma = \sqrt{\text{Var}(X_i)}$
- \*  $Z \sim \text{Normal}(0,1)$
- \*  $\lim_{t \rightarrow \infty} P[N(t) \leq \frac{t}{\mu} + k \frac{\sigma\sqrt{t}}{\sqrt{\mu^3}}] = P[Z \leq k]$   
 Proof:
  1. Suppose  $n(t) = \frac{t}{\mu} + k \frac{\sigma\sqrt{t}}{\sqrt{\mu^3}}$
  2.  $P[N(t) \geq n(t)] = P[S_{n(t)} \leq t] = P[\frac{S_{n(t)} - n\mu}{\sigma\sqrt{n}} \leq \frac{t - n\mu}{\sigma\sqrt{n}}]$
  3. When  $t \rightarrow \infty, \frac{t - n\mu}{\sigma\sqrt{n}} \rightarrow k$
  4. By law of large number,  $\lim_{t \rightarrow \infty} P[\frac{S_{n(t)} - n\mu}{\sigma\sqrt{n}} \leq k] = P[Z \leq k]$
 Interpretation:
  - $\frac{t}{\mu}$  is approximately the mean of  $N(t)$
  - $k \frac{\sigma\sqrt{t}}{\sqrt{\mu^3}}$  is  $k\sigma\sqrt{n}$  after dividing by  $\mu$ , the ratio between  $t$  and  $N(t)$  and changing  $n$  with  $\frac{t}{\mu}$

### – Renewal-Reward Process:

#### Definition

- \* A renewal process  $N(t)$  and  $\{R_i\}_{i=1}^{\infty}$  such that  $(X_i, R_i)$  are i.i.d.  
 $(X_i, R_j, i \neq j)$  are independent, but  $X_i, R_i$  might be dependent

#### Property

- \*  $P[\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{i=1}^{N(t)} R_i = \frac{\mathbb{E}[R_i]}{\mathbb{E}[X_i]}] = 1$   
 Proof:  $P[\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{i=1}^{N(t)} R_i = \lim_{t \rightarrow \infty} \sum_{i=1}^{N(t)} \frac{R_i}{N(t)} \times \lim_{t \rightarrow \infty} \frac{N(t)}{t}] = 1$

- Poisson Process: a renewal process with  $X_i \sim \text{Exponential}(\lambda)$

#### $S_i$ Property

- \*  $S_i$  is an Erlang random variable  
Erlang is the sum of the Exponential random variables
- \* Joint Distribution  $f_{S_1, \dots, S_n}(s_1, \dots, s_n) = \lambda^n e^{-\lambda s_n}$   
Prove by induction.  
Induce by  $f_{S_1, \dots, S_n}(s_1, \dots, s_n) = f_{S_1, \dots, S_{n-1}}(s_1, \dots, s_{n-1}) \times f_{S_n|S_1, \dots, S_{n-1}}(s_n, s_1, \dots, s_{n-1})$

#### $N(t)$ Property

- \*  $N(t) \sim \text{Poisson}(\lambda t)$ ,  $P[N(t) = n] = \frac{(\lambda t)^n}{n!} e^{-\lambda t}$   
Prove by  $P[N(t) = n] = P[S_n \leq t \text{ and } S_{n+1} > t]$
- \* Conditioned on  $N(t) = n$ , the set of arrival times  $\{s_1, \dots, s_n\}$  have the same distribution with a set of  $n$  sorted i.i.d.  $\text{Uniform}(0, t)$  random variables  
Prove by  $f_{S_1, \dots, S_n|N(t)}(s_1, \dots, s_n, n) = \frac{f_{S_1, \dots, S_n}(s_1, \dots, s_n) P[X_{n+1} > t - s_n]}{P[N(t) = n]} = \frac{n!}{t^n}$

#### Property

- \*  $Z$  is the interval from  $t$  to the first arrival  $\rightarrow Z$  is exponential random variable with same  $\lambda$  and independent of  $N(t)$  and the arrival time before  $t$   
Proof:  
$$P[Z > z] = \sum_{n=0}^{\infty} \int_0^{\infty} \dots \int_0^{\infty} P[Z > z | N(t) = n, S_1 = s_1, \dots, S_n = s_n] ds_1 \dots ds_n$$
$$= \sum_{n=0}^{\infty} \int_0^{\infty} \dots \int_0^{\infty} P[X_{n+1} > z + t - s_n | N(t) = n, S_1 = s_1, \dots, S_n = s_n] ds_1 \dots ds_n$$
$$= \sum_{n=0}^{\infty} \int_0^{\infty} \dots \int_0^{\infty} P[X_{n+1} > z + t - s_n | X_{n+1} > t - s_n] ds_1 \dots ds_n = e^{-\lambda z}$$
- \* Stationary Increments:  $N(t_1 + t_2) - N(t_1)$  and  $N(t_2)$  share the same distribution  
Without Proof
- \* Independent Increments:  $\forall 0 < t_1 < t_2 < \dots, t_k, N(t_1), N(t_2) - N(t_1), \dots$  are independent  
Without Proof
- \* Any arrival process with stationary and independent increments must be a Poisson process  
Without Proof

#### Exercise

- \*  $\mathbb{E}[S_i | N(t) = n] = \frac{t \times i}{n+1}$   
 $\cdot \mathbb{E}[S_i | N(t) = n] = i \times \mathbb{E}[X_1 | N(t) = n] = i \int_0^t \int_0^{s_n} \dots \int_0^{s_2} s_1 \times \frac{n!}{t^n} ds_1 \dots ds_{n-1} ds_n = \frac{t \times i}{n+1}$
- \*  $\mathbb{E}[\sum_{i=0}^{N(t)} S_i] = \frac{\lambda t^2}{2}$   
 $\cdot \mathbb{E}[\sum_{i=0}^{N(t)} S_i] = \sum_{n=0}^{\infty} \mathbb{E}[\sum_{i=0}^n S_i | N(t) = n] P[N(t) = n]$ 
$$= \sum_{n=0}^{\infty} \frac{n t}{2} P[N(t) = n] = \frac{\lambda t^2}{2}$$

#### 2D Poisson Process

- \* Definition:
  - For any region  $R$ : number of points in  $R$  is a Poisson random variable
  - number of points in the non-overlapping region is independent

#### Combining Poisson Process

- \*  $N^1(t), N^2(t)$  are two independent Poisson process with  $\lambda_1, \lambda_2$
- \*  $X_i$  is the first arrival of  $X_i^1, X_i^2$
- \* Property
  - $X_i$  is independent of  $\{X_i^1 < X_i^2\}$  and  $\{X_i^1 > X_i^2\}$   
Proof:  $P[X_1^1 < X_1^2] = \frac{\lambda_1}{\lambda_1 + \lambda_2}$   
 $P[X_1 > x] = P[X_1^1 > x, X_1^2 > x] = e^{-(\lambda_1 + \lambda_2)x}$   
 $P[X_1 > x, X_1^1 < X_1^2] = P[X_1 > x] P[X_1^1 < X_1^2]$
  - $X_i$  is a Poisson Process with  $\lambda = \lambda_1 + \lambda_2$

#### Splitting Poisson Process

- \*  $N^1(t), N^2(t)$  are two independent Poisson process with  $\lambda_1, \lambda_2$
- \*  $N(t)$  is a random process with  $\lambda = \lambda_1 + \lambda_2$ 
  - $N^{1*}(t)$  is the process of the first event  
when  $N(t)$  arrives consider it as first event with probability  $\frac{\lambda_1}{\lambda_1 + \lambda_2}$

- $N^{2*}(t)$  is the process of the second event  
when  $N(t)$  arrives consider it as second event with probability  $\frac{\lambda_2}{\lambda_1 + \lambda_2}$
- \*  $N^i(t)$  and  $N^{i*}(t)$  share the same distribution
- \* Proof:
  - $B_n(k)$  is a Binomial random variable with  $p = \frac{\lambda_1}{\lambda_1 + \lambda_2}$
  - $P[N^{1*}(t) = m, N^{2*}(t) = n] = P[N(t) = m + n, B_{m+n}(m)] = P[N^1(t) = m, N^2(t) = n]$

#### Compound Poisson Process

- \*  $N(t)$  is a Poisson Process
- \*  $A_n$  is a sequence of cost
- \*  $A(t) = \sum_{n=0}^{N(t)} A_n$  is the summation of cost over Poisson Process

#### Non-Homogeneous Poisson Process

- \*  $N(t) - N(s) \sim \text{Poisson}(\int_s^t \lambda(x) dx)$

#### Queuing Theory

- \* Definition: *Arrival\_Process/Service\_Process/number\_of\_services*
  - $M$ : memoryless (Poisson) process
  - $D$ : deterministic process
  - $G$ : general renewal process
- \*  $T$ : the random variable of the processing time for each customer
- \*  $Y(t)$ : number of cutomers in the service
  - $Y(t) \sim \text{Poisson}(\lambda \int_0^t P[T > x] dx)$
  - Proof:  
Consider  $Y(t)$  is a splitting Poisson Process. Since the distribution for the arrival given  $N(t)$  is universal, the probability the arrival is still in service:  $\frac{1}{t} \int_0^t P[T > t-x] dx = \frac{1}{t} \int_0^t P[T > x] dx$