Stochastic Processes

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1 Moment Generating Function

- Moment Generating Function: $\mathbb{E}[e^{tX}]$
  - Property:
    - $\mathbb{E}[e^{tX}] = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx$
    - $\mathbb{E}[e^{tX}] = \sum_{k=0}^{\infty} E[X^k] \frac{t^k}{k!}$
      - $e^{tx} = \sum_{k=0}^{\infty} \frac{(tx)^k}{k!}$
      - $E[e^{tX}] = E[\sum_{k=0}^{\infty} \frac{(tX)^k}{k!}] = \sum_{k=0}^{\infty} E[X^k] \frac{t^k}{k!}$
    - $\frac{d\mathbb{E}[e^{tX}]}{dt} = \mathbb{E}[X]$
    - $\mathbb{E}[e^{t(aX+b)}] = e^t b \mathbb{E}[e^{taX}]$
    - 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 funciton 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 $X_1, \ldots, X_i, \ldots, X_N$ are i.i.d random variables with mean μ and variance σ^2
  - $Y = \sum_{i=1}^{N} X_i$
  - $\mathbb{E}[Y] = \mathbb{E}[N]\mu$
    - $\mathbb{E}[Y] = \sum_{n=1}^{\infty} \mathbb{E}[\sum_{i=1}^{N} X_i | N = n] P[N = n]$
      $= \mu \times \sum_{n=1}^{\infty} n P[N = n] = \mathbb{E}[N]\mu$

- $\mathbb{E}[Y^2] = \mathbb{E}[N]\mathbb{E}[X^2] + \mathbb{E}[N^2]\mu^2 - \mathbb{E}[N]\mu^2$
  - $\mathbb{E}[Y^2] = \sum_{n=1}^{\infty} \mathbb{E}[(\sum_{i=1}^{N} X_i)^2 | N = n] P[N = n] = \sum_{n=1}^{\infty} (n\mathbb{E}[X_i^2] + n(n-1)\mu^2) P[N = n]$ $= \mathbb{E}[N]\mathbb{E}[X^2] + \mathbb{E}[N^2]\mu^2 - \mathbb{E}[N]\mu^2$
- $Var(Y) = \mathbb{E}[N]\sigma^2 + Var(N)\mu^2$

- 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
    - $\mathbb{E}[X] = \int_0^{\infty} x f_X(x)dx = \int_0^{\infty} \int_0^{x} f_X(x)dydx = \int_0^{\infty} \int_y^{\infty} f_X(x)dxdy = \int_0^{\infty} P[X > y]dy$

3 Inequality

- Markov Inequality

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

  Proof:
  1. $\mathbb{E}[X] = \int_0^{\infty} x f_X(x) \geq \int_{\epsilon}^{\infty} x f_X(x) \geq \epsilon \int_{\epsilon}^{\infty} f_X(x) = \epsilon P[X \geq \epsilon]$
  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 $m = \mathbb{E}[X], \sigma^2 = Var(X)$, 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, σ

- Chernoff Inequality

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

* Substitude t with $\log(1+\epsilon)$
* the last inequality is without proof

- $P[X \le \epsilon] \le \frac{(pe^t+1-p)^n}{e^{t\epsilon}} \le \frac{e^{np(e^t-1)}}{e^{t\epsilon}}$
  * $P[X \le \epsilon] = P[e^{-tX} \ge e^{-t\epsilon}] \le \frac{E[e^{-tX}]}{e^{-t\epsilon}} = \frac{(E[e^{-tX_i}])^n}{e^{-t\epsilon}} = \frac{(pe^{-t}+1-p)^n}{e^{-t\epsilon}} \le \frac{e^{np(e^{-t}-1)}}{e^{-t\epsilon}}$
- $P[X \le np(1-\epsilon)] \le (\frac{e^{-\epsilon}}{(1-\epsilon)^{1-\epsilon}})^{np} \le e^{\frac{-\epsilon^2 np}{2}}$
  * Substitude ϵ with $np(1-\epsilon)$
  * Substitude 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 $a_i \le X_i \le b_i$
  - Suppose $X = \sum_{i=1}^n X_i$ and $\mu = \mathbb{E}[X]$
  - $P[|X-\mu| \ge \epsilon] \le 2e^{\frac{-2\epsilon^2}{\sum_{i=1}^n (b_i-a_i)^2}}$ without proof

- Application:
  - Balls in Bins
    Definition: Throw n balls into n bins, find bounds for the maximum number of balls in all bins
    * $P[$ maximum number of balls in all bins $\ge \epsilon]$
      $= P[\cup_{i=1}^n$ number of balls in i-th bin $\ge \epsilon]$
      $\le n \times P[$ number of balls in one bin $\ge \epsilon]$
    * By Markov inequality:
      · $P[$ number of balls in one bin $\ge \epsilon] \le \frac{1}{\epsilon} \rightarrow$ useless
    * By Chebyshev inequality:
      · $P[$ number of balls in one bin $\ge \epsilon] \le \frac{(1-\frac{1}{n})}{\epsilon^2}$
      · $P[$ maximum number of balls in all bins $\ge n^{\frac{1}{2}+\epsilon}] \le \frac{(1-\frac{1}{n})}{n^{2\epsilon}}$
      · when $n \rightarrow \infty$, the maximum number of balls should less than $n^{\frac{1}{2}+\epsilon}$
    * By Chernoff inequality:
      · $P[$ number of balls in one bin $\ge 2\log n] \le \frac{e^{np(e^t-1)}}{n^{2t}}$
      · $P[$ maximum number of balls in all bins $\ge 2\log n] \le \frac{e^{np(e^t-1)}}{n^{2t-1}}$
      · when t is a constant ≥ 0.5 and $n \rightarrow \infty$, 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
  $\mathbb{E}[X_i] = m$, $Var(X_i) = \sigma_i^2$.
- $M_n = \frac{1}{n}\sum_{i=1}^n X_i$
- $M_n \rightarrow m$ almost surely, in mean square and in probability.

5 Memoryless

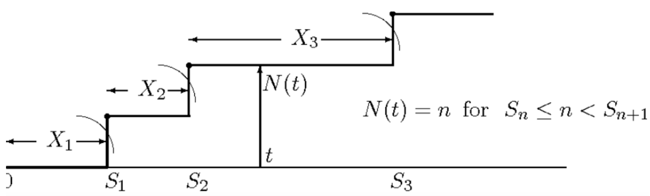
- Definition: $P[X > x_1 + x_2 | X > x_1] = P[X > x_2]$
- Property:
  - Exponential random variable is the only continuous memoryless random variable
  - Bernoulli random variable is the only discrete memoryless random variable

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, $n \to \infty, p \to \frac{\lambda}{n}$
  - $\to P[X=k] = \lim_{n\to\infty}\binom{n}{k}(\frac{\lambda}{n})^k(\frac{n-\lambda}{n})^{n-k} = \frac{\lambda^k}{k!}(1-\frac{\lambda}{n})^n = \frac{\lambda^k}{k!}\exp(-\lambda)$
- 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 $X_1, X_2, ..., X_n$ are i.i.d exponential random variable with λ.
  - $X = \sum_{i=1}^{n} X_i$
  - 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:
    * $N(t) < n \leftrightarrow S_{n+1} > t$
    * $N(t) \ge n \leftrightarrow S_n \le t$
    * $N(t) = n \leftrightarrow S_n \le t < S_{n+1}$
    * $N(t) = \max\{n : S_n \le t\}$
  - 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 $X_{i-1} \to$ not renewal process

    S_i Property
    * $P[\lim_{n\to\infty} S_n = \infty] = 1$
      Proof: $\lim_{n\to\infty} P[S_n = \infty] = \lim_{n\to\infty} P[\sum_{i=1}^{n} X_n = n \times \mathbb{E}[X_i]] = 1$
      Interpretation: infinite events do not take finite time

$N(t)$ Property

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

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
* $P[\lim_{t\to\infty} \frac{1}{t} \int_0^t (S_{N(t)+1} - s)ds = \frac{\mathbb{E}[X_i^2]}{2\mathbb{E}[X_i]}] = 1$
  Proof:
  $P[\lim_{t\to\infty} \frac{1}{t} \sum_{i=i}^{N(t)} \frac{\mathbb{E}[X_i^2]}{2} \leq \lim_{t\to\infty} \frac{1}{t} \int_0^t (S_{N(t)+1} - s)ds] = 1$ and $P[\lim_{t\to\infty} \frac{1}{t} \sum_{i=i}^{N(t)} \frac{\mathbb{E}[X_i^2]}{2} = \frac{\mathbb{E}[X_i^2]}{2\mathbb{E}[X_i]}] = 1$
  $P[\lim_{t\to\infty} \frac{1}{t} \int_0^t (S_{N(t)+1} - s)ds \leq \lim_{t\to\infty} \frac{1}{t} \sum_{i=i}^{N(t)+1} \frac{\mathbb{E}[X_i^2]}{2}] = 1$ and $P[\lim_{t\to\infty} \frac{1}{t} \sum_{i=i}^{N(t)+1} \frac{\mathbb{E}[X_i^2]}{2} = \frac{\mathbb{E}[X_i^2]}{2\mathbb{E}[X_i]}] = 1$
* $P[\lim_{t\to\infty} \frac{1}{t} \int_0^t (s - S_{N(t)})ds = \frac{\mathbb{E}[X_i^2]}{2\mathbb{E}[X_i]}] = 1$
  Proof: similar to above
* $P[\lim_{t\to\infty} \frac{1}{t} \int_0^t X_{N(t)} ds = \frac{\mathbb{E}[X_i^2]}{\mathbb{E}[X_i]}] = 1$
  Proof: $P[\lim_{t\to\infty} \frac{1}{t} \int_0^t X_{N(t)} ds = \lim_{t\to\infty} \frac{1}{t} \int_0^t (S_{N(t)+1} - S_{N(t)})ds] = 1$
* $\mathbb{E}[X_{N(t)+1}] = \frac{\mathbb{E}[X_i^2]}{\mathbb{E}[X_i]}$
  Proof: $P[\lim_{t\to\infty} \frac{1}{t} \int_0^t X_{N(t)} ds = \frac{\mathbb{E}[X_i^2]}{\mathbb{E}[X_i]}] = P[\mathbb{E}[X_{N(t)+1}] = \frac{\mathbb{E}[X_i^2]}{\mathbb{E}[X_i]}] = 1$

Central Limit Theorem

* $\mu = \mathbb{E}[X_i]$
* $\sigma = \sqrt{Var(X_i)}$
* $Z \sim$ Normal(0,1)
* $\lim_{t\to\infty} P[N(t) \leq \frac{t}{\mu} + k\frac{\sigma\sqrt{t}}{\sqrt{\mu}^3}] = P[Z \leq k]$
  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 $t \to \infty$, $\frac{t-n\mu}{\sigma\sqrt{n}} \to k$
  4. By law of large number, $\lim_{t\to\infty} P[\frac{S_{n(t)} - n\mu}{\sigma\sqrt{n}} \leq k] = P[Z \leq k]$

  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 μ, the ratio between t and $N(t)$ and changing n with $\frac{t}{\mu}$

Wald's Identity

* Stopping Times: a random variable τ s.t. $\{\tau = n\}$ is independent of $\{X_i\}_{i=n+1}^{\infty}$
* Stopping Condition: a condition to stop if we can consider $\tau = \min\{n : \text{ condition}(n) = \top\}$
* Example: $N(t) + 1$ is a stopping times and can be consider $N(t) + 1 = \min\{n : S_n > t\}$
* $\mathbb{E}[\sum_{i=1}^{\tau} X_i] = \mathbb{E}[\tau]\mathbb{E}[X_i]$
  Proof:
  1. $\mathbb{E}[\sum_{i=1}^{\tau} X_i] = \sum_{i=1}^{\infty} \mathbb{E}[X_i \times \mathbb{1}_{i\leq\tau}]$ (by Fubin's Theorem without proof)
  2. $\sum_{i=1}^{\infty} \mathbb{E}[X_i \times \mathbb{1}_{i\leq\tau}] = \mathbb{E}[X_i] \sum_{i=1}^{\infty} \mathbb{E}[\mathbb{1}_{i\leq\tau}]$ (by $P[\tau \geq i] = 1 - P[\tau < i]$ is independent of X_i)
  3. $\mathbb{E}[X_i] \sum_{i=1}^{\infty} \mathbb{E}[\mathbb{1}_{i\leq\tau}] = \mathbb{E}[\tau]\mathbb{E}[X_i]$

* $\lim_{t\to\infty} \frac{\mathbb{E}[N(t)]}{t} = \frac{1}{\mathbb{E}[X_i]}$
  Proof:
  · Suppose $\mu = \mathbb{E}[X_i]$
  · $\frac{\mathbb{E}[N(t)]}{t} = \frac{\mathbb{E}[S_{N(t)+1}]}{t\times\mu} - \frac{1}{t}$ (by considering $N(t)+1$ as the stopping time)
  · $\lim_{t\to\infty} \frac{\mathbb{E}[N(t)]}{t} \geq \frac{1}{\mu}$ (by $\mathbb{E}[S_{N(t)+1}] > t$)
  · Suppose $\hat{X}_n = \min\{X_n, T\}$, where T is a constant
  · $\frac{\mathbb{E}[N(t)]}{t} \leq \frac{\mathbb{E}[\hat{N}(t)]}{t} = \frac{\mathbb{E}[S_{\hat{N}(t)+1}]}{t\times\hat{\mu}} - \frac{1}{t} \leq \frac{t+T}{t\times\hat{\mu}} - \frac{1}{t}$
  · $\lim_{n=\sqrt{t},t\to\infty} \frac{\mathbb{E}[N(t)]}{t} \leq \frac{1}{\mu}$

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

– Poisson Process: a renewal process with $X_i \sim$ Exponential(λ)
  S_i Property
  * S_i is an Erlang random variable
    Erlang is the sum of the Exponential random variables
  * Joint Distribution $f_{S_1,\ldots,S_n}(s_1,\ldots,s_n) = \lambda^n e^{-\lambda s_n}$
    Prove by induction.
    Induce by $f_{S_1,\ldots,S_n}(s_1,\ldots,s_n) = f_{S_1,\ldots,S_{n-1}}(s_1,\ldots,s_{n-1}) \times f_{S_n|S_1,\ldots,S_{n-1}}(s_n, s_1,\ldots,s_{n-1})$

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

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

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

  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 λ_1, λ_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 λ_1, λ_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: $\frac{1}{t}\int_0^t P[T > t-x]dx = \frac{1}{t}\int_0^t P[T > x]dx$