

## 1. Moment Generating Function

$$M_X(t) = E(e^{tx})$$

$$\text{continuous: } M_X(t) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx$$

$$\text{discrete: } M_X(t) = \sum e^{tx} P(x)$$

$$e^{tx} \text{ expansion: } \sum_{n=0}^{\infty} \frac{(tx)^n}{n!}$$

property:

$$M_X^{(n)}(0) = E(X^n)$$

$$VAR[X] = E[X^2] - E^2[X] = M_X''(0) - [M_X'(0)]^2$$

$$M_X(t) = M_Y(t) \rightarrow XY \text{ has same distribution}$$

$$M_{a+bX}(t) = e^{at} M_X(bt)$$

$$M_{X+Y}(bt) = M_X(t) M_Y(t) \quad (X, Y \text{ independent})$$

## 2. Chi-Square

- (a) Goodness of fit test problem: Outcome vs Expected  
df = t-1. If expected is not clear, use maximum likelihood to maximize and df = Unknown - 1

- (b) Two way chi square test: (2 r.v indep. ?)  
calculate the probability from raw data  
assume two r.v. are independent, get the expected number to fill out the expected table

$$D = \sum \frac{(x_i - np_i)^2}{np_i}, \text{ df} = (\text{row}-1)(\text{col}-1)$$

Compare with  $\chi^2_{df, \alpha}$  or Use *P-value*

Calculator:  $\chi^2$ -test, input 2 matrices

## 3. ANOVA: test whether means are the same When ANOVA fails:

- (a) Contrast - split to two groups:

$$c = a_1 u_1 + a_2 u_2 + \dots (\sum a_i = 0)$$

$$H_0: c = 0, \hat{c} = a_1 \bar{x}_1 + a_2 \bar{x}_2 + \dots$$

$$\text{MSE} = \text{ANOVA Error} \rightarrow \text{MS}$$

$$t = \frac{\hat{c}}{\text{Sxp} \sqrt{\sum \frac{a_i^2}{n_i}}} \text{ or } \frac{\hat{c}}{\sqrt{\text{MSE} \sum \frac{a_i^2}{n_i}}} \quad df = n - k$$

n: total # of data, k: total # of groups

compare with  $t_{\frac{\alpha}{2}, df}$

- (b) Bonferroni method

comparing two group:  $\alpha' = \frac{2\alpha}{k(k-1)}, df = n - k$

$$t_{a,b} = \frac{\bar{x}_a - \bar{x}_b}{\text{Sxp} \sqrt{\frac{1}{n_a} + \frac{1}{n_b}}} \quad t_{\frac{\alpha'}{2}, df}$$

## 4. Find Regression Curve for Y on X

known:  $f_{x,y}(x, y)$

$$f_X(x) = \int f_{x,y}(x, y) dy$$

$$f_Y(y|x) = \frac{f_{x,y}(x, y)}{f_X(x)}$$

$$\text{Regression Equation} = E(Y|X = x) = \int y f(y|x) dy$$

## 5. Linear Regression

- (a) LinRegTTest:  $y = \hat{\beta}_0 + \hat{\beta}_1 x$   
→  $r^2$  bigger is better fitting linear model

- (b) slope confidence Interval:

$$\hat{\beta}_0 \pm t_{n-2, \frac{\alpha}{2}} \frac{S}{\sqrt{\sum (x_i - \bar{x})^2}} \text{ or } \text{LinRegTInt}$$

- (c) Test at the  $\alpha\%$  to see slope is  $t_0$  (usually 0)

$$t = \frac{\hat{\beta}_1 - t_0}{\frac{S}{\sqrt{\sum (x_i - \bar{x})^2}}} \quad t_{n-2, \frac{\alpha}{2}} \text{ or } \text{LinRegTTest}$$

- (d) Forecasting, Find  $\alpha\%$  confidence Interval:  
Estimated mean:

$$\bar{y} = \hat{y}(x = k) \pm S t_{n-2, \frac{\alpha}{2}} \sqrt{\frac{1}{n} + \frac{(x - \bar{x})^2}{\sum (x_i - \bar{x})^2}}$$

Expected Value:

$$\hat{y} = \hat{y}(x = k) \pm S t_{n-2, \frac{\alpha}{2}} \sqrt{1 + \frac{1}{n} + \frac{(x - \bar{x})^2}{\sum (x_i - \bar{x})^2}}$$

- (e) exponential model:

$$y = ab^x \rightarrow \ln y = \ln a + x \ln b, \hat{\beta}_0 \rightarrow \ln a, \hat{\beta}_1 \rightarrow \ln b$$

- (f)  $\sum (x_i - \bar{x})^2 = (n-1) VAR_x^2$   
Use LIST → variance or STAT → Test → T-test

- (g) r estimates correlation coefficient of (x, y)

$$\rho = \frac{COV[X, Y]}{STD[X] STD[Y]}$$

$$STD[X] = \sqrt{E(X^2) - E^2(X)}$$

$$E(X) = \int x f_X(x) dx, f_X(x) = \int f_{X,Y} dy$$

$$COV[X, Y] = E[XY] - E[X]E[Y]$$

$$E(XY) = \int \int xy f_{X,Y} dx dy$$

## 6. Markov chains

- (a) Properties of Transition Matrix **P**

Sum of Rows are 1, all terms  $\in [0, 1]$

$P^n$  → go through  $n$  transitions

$P^n \vec{v}$  → the probability of getting each state given starting vector  $\vec{v}$  after  $n$  transitions

- (b) Absorbing Markov Chains rewrite the Transition Matrix **P** to:

$$\tilde{P} = \begin{pmatrix} \mathbf{Q} & \mathbf{R} \\ \mathbf{0} & \mathbf{I} \end{pmatrix}$$

Fundamental Matrix **N** =  $(\mathbf{I} - \mathbf{Q})^{-1}$ , ( $\mathbf{N} > 0$ )

Time to absorption:

add up the corresponding row in **N**

Absorption Probabilities: **B** = **NR**, find  $P_{ij} = \mathbf{B}_{ij}$

- (c) Ergodic and Regular Markov Chains

- i. Ergodic:

It is possible to go from every state to every state (not necessarily in one move)

- ii. Regular:

It is possible to go to every state to every state after  $n$  transitions. →  $\exists k, s.t. \forall$  terms in  $P^k$  are non-zero

- (d) Stationary / Equilibrium vector

For Regular Markov Chains, exists

$$\mathbf{wP} = \mathbf{w}, \quad \lim_{n \rightarrow \infty} P^n = \mathbf{W}$$

where **W**'s rows are all equal to **w**

Calculate **w**: simply calculate  $\mathbf{wP} = \mathbf{w}$ ,  $\sum w_i = 1$  →  $n+1$  equations for  $n$  unknowns.

- (e) Meaning of **w<sub>j</sub>**

- i.  $w_j$ : Probability/fraction of time spent in  $j$
- ii.  $\frac{1}{w_j}$ : first return time/revisit steps to state  $j$
- (f) Tricks:
  - i. mean time of state  $i \rightarrow$  state  $j$ :  
set state  $j$  to absorbing state, calculate  $\mathbf{N}$  and find the time to get absorbed
  - ii. probability move from  $i$  to  $j$  in  $k$  steps:  $\mathbf{P}_{ij}^k$
- (g) Reversible Markov Chain:  $\Leftrightarrow \mathbf{w}_i \mathbf{P}_{ij} = \mathbf{w}_j \mathbf{P}_{ji}$

## 7. Poisson Process: simple Poisson $\rightarrow$ poissonpdf

- (a) Basic Properties:  $\lambda$  = Rate of Arrivals  
 $N(t)$  = numbers of arrivals up to time  $t$   
 $P(N(t) = k) = \frac{(\lambda t)^k}{k!} e^{-\lambda t}$   
 $E(N(t)) = \lambda t$   
 $P(N(s) - N(e) = k) = P(N(s - t) = k)$   
 $E(N(s) - N(e)) = E(N(s - e)) = \lambda(s - e)$
- (b) First arrival time(equal to next arrival time)  $T_1$  is an Exponential Distribution  
 $f_{T_1}(t) = \lambda e^{-\lambda t} (t \geq 0)$   
 $F_{T_1}(t) = 1 - e^{-\lambda t} (t \geq 0)$   
 $\Leftrightarrow P(T_1 < t) = 1 - e^{-\lambda t} \Leftrightarrow P(T_1 > t) = e^{-\lambda t}$   
 $E(T_n) = nE(T_1)$
- (c) Prob. that more than  $n$  arrivals comes in  $T$  time:  
 $\rightarrow n^{th}$  arrival is less than  $T$  time:  
 $P(T_n < T) \rightarrow \text{CLT: } P(Z_n < \frac{T - \mu n}{\sigma \sqrt{n}})$   
 Since  $T_n$  is Exponential Distribution,  $\mu = \sigma = \frac{1}{\lambda}$
- (d) Merging of Poisson  
 If  $N_1(t) \sim P.P$  rate  $= \lambda_1$ ,  $N_2(t) \sim P.P$  rate  $= \lambda_2$   
 then  $N(t) \sim P.P$  rate  $= \lambda_1 + \lambda_2$   
 $P(\text{first/next arrival is type 1})$   
 $= P(N_1(t) = 1, N_2(t) = 0 | N(t) = 1) = \frac{\lambda_1}{\lambda_1 + \lambda_2}$   
 $P(\text{first/next arrival is type 2})$   
 $= P(N_2(t) = 1, N_1(t) = 0 | N(t) = 1) = \frac{\lambda_2}{\lambda_1 + \lambda_2}$   
 Prob. that  $k$  of  $n$  arrivals are of type 1:  
 Binomial Distribution.  
 $P(\text{type 1}) = \frac{\lambda_1}{\lambda_1 + \lambda_2}$

## 8. Discrete Finite Queues

Draw the chain; steady state prob.: each pair of arrows carry the same -  $w_i \lambda = w_{i+1} \mu$   
 Little's Law:  
 $\lambda T = N \Rightarrow (\text{Arrival Rate}) E(T) = E(N)$   
 $E(T) \rightarrow$  mean time;  $E(N) \rightarrow$  mean number  
 In discrete, arrival rate:  $\sum_{i=0}^{n-1} \lambda W_i$

## 9. M/M/1

$\lambda$  = arrival rate of customer  
 $\mu$  = service rate per customer  
 $\rho = \frac{\lambda}{\mu}$ ,  $\lambda P_k = \mu P_{k+1} \rightarrow P_{k+1} = \rho P_k$   
 $P_k = \rho^k (1 - \rho)$   
 number in system:  $E(N) = \frac{\rho}{1 - \rho} = \frac{\lambda}{\mu - \lambda}$   
 number in queue:  $E(N_q) = \frac{\rho^2}{1 - \rho} = \frac{\lambda^2}{\mu(\mu - \lambda)}$   
 Mean time in system:  $E(T) = \frac{E(N)}{\lambda} = \frac{1}{\mu - \lambda} = \frac{1}{\mu} + E(T_q)$   
 Mean time in queue:  $E(T_q) = \frac{E(N_q)}{\lambda} = \frac{\lambda}{\mu(\mu - \lambda)}$

Mean service time:  $E(T) - E(T_q) = \frac{1}{\mu}$

Distribution of Time in System is equivalent to an Exponential Distribution where mean:  $\frac{1}{\lambda^*} = \frac{1}{\mu - \lambda}$

$T$ : time in system

PDF:  $P(T < t) = F(X = x) = 1 - e^{-\lambda^* x}, (x > 0)$

## 10. M/M/C single queue, C servers

$\lambda$  = arrival rate of customer  
 $\mu$  = single server's service rate per customer  
 $\rho = \frac{\lambda}{c\mu}$

$$P_0 = (1 + \rho + \frac{\rho^2}{2} + \frac{\rho^3}{3!} + \dots + \frac{\rho^{c-1}}{(c-1)!} + \frac{\rho^c}{c!(1 - \frac{\rho}{c})})^{-1}$$

$$P_1 = \rho P_0, P_2 = \frac{\rho^2}{2} P_0, P_3 = \frac{\rho^3}{3!} P_0 \dots$$

$$P_c = \frac{\rho^c}{c!} P_0, P_{c+k} = (\frac{\rho}{c})^k P_c$$

Traffic density:  $\frac{\rho}{c} = \frac{\lambda}{c\mu}$ , stable if  $\frac{\rho}{c} < 1$

number in system:  $E(N) = \rho + P_c \frac{\frac{\rho}{c}}{(1 - \frac{\rho}{c})^2} = \rho + E(N_q)$

number in queue:  $E(N_q) = P_c \frac{\frac{\rho}{c}}{(1 - \frac{\rho}{c})^2} =$

Mean time in system:  $E(T) = \frac{1}{\lambda} E(N)$

Mean time in queue:  $E(T_q) = \frac{1}{\lambda} E(N_q)$

Mean service time:  $E(T) - E(T_q) = \frac{1}{\mu}$

## 11. M/M/C/k C servers, max customer in system k

$\lambda$  = arrival rate of customer  
 $\mu$  = single server's service rate per customer

$$P_i = \frac{\rho^i}{i!} P_0, i = 0, 1, \dots, c$$

$$P_{c+p} = \frac{\rho^p}{c^p} P_c, p = 0, 1, \dots, k - c$$

$$\sum P_i = 1, E(N) = \sum i P_i, E(N_q) = \sum (i - c) P_i (i > c)$$

Effective arrive rate  $\lambda_a = \lambda(1 - P_k)$

$$E(T) = \frac{E(N)}{\lambda_a}, E(T_q) = \frac{E(N_q)}{\lambda_a}$$

## 12. Stochastic Process

mean:  $m(t) = E[X(t)]$ , autocorrelation:  $R(t, s) =$

$E[X(t)X(s)]$ , autocovariance:  $C(t, s) = R(t, s) - m(t)m(s)$

Stock and Option problem: (I outcomes, J wagers):

list outcome, cost, future value, return for each wager.

$$E(R_j) = \sum_{i=1}^I r_{ji} p_i, R_i = \sum_{j=1}^J x_i r_{ji}$$

No arbi. price:  $E(R_i) = 0, \sum p_i = 1 \rightarrow c$  (option price)

Find arbi. return:  $\forall R_i > 0$  (usually sell stock buy option)

## 13. Brownian Motion

$B(t) \Leftrightarrow$  normal dist. with  $\mu = 0, \text{VAR} = t$ ;  $B(t) = \sqrt{t} Z$

Process start over at every time:  $B(t_2) - B(t_1) = B(t_2 - t_1)$

$B(t_2) - B(t_1), B(t_3) - B(t_2)$  are independent if no overlap.

BM with drift:

$X(t) = x_0 + \mu t + \sigma B(t)$ ,  $x_0$ : starting value,  $\mu t$ : drift term.

## 14. Geometric Brownian Motion

$X(t) = x_0 e^{\mu t + \sigma B(t)} \rightarrow$  convert to normal.  $E(e^{aZ}) = e^{\frac{a^2}{2}}$

Black-Scholes Formula:

$\alpha$  = interest rate (risk-free interest),  $x(0)$  = current price (start price),  $K$  = Threshold of option (strike price),  $T$  = time to experience option (maturity),  $\sigma$  = (annualized) volatility,  $\sigma^2$  = variance para.  $c$  = cost of option.

No arbitrage option:  $\alpha = \mu + \frac{\sigma^2}{2}$ ,  $F$ : std. normal cdf

$$C = X(0)F(b + \sigma\sqrt{T}) - Ke^{-\alpha T}F(b), b = \frac{(\alpha - \frac{\sigma^2}{2})T + \ln(\frac{x(0)}{K})}{\sigma\sqrt{T}}$$