

balls into k urns. What's the probability the last urn contains j balls?
 telephone with seven total digits; 732 are the first three digits.
 four digits remain with 10 potential digits each.

 $\binom{n}{k}$
 $k!(n-k)!$
 $n-1$

$$= \frac{k!(n-k)!}{n!(j-1)!}$$

2. 26-letter English Alphabet
 into 8-bit binary words.

$$\begin{aligned} \binom{26}{8} &= \frac{26!}{26!(26-8)!} \\ &= \frac{26 \cdot 25 \cdot 24 \cdot 23 \cdot 22 \cdot 21 \cdot 20 \cdot 19}{8!} \\ &= 2.74 \times 10^8 \end{aligned}$$

Total possibilities are $10^8 = 10^4$.

Chances of four more distinct digits are

$$\frac{7 \cdot 6 \cdot 5 \cdot 4}{10^4} = \frac{840}{10000} = 8.4\%$$

13. a) Straight five cards in unbroken sequence: $4 \text{ suits} / \binom{5}{5} = 4 / [3!/(5-3)!] = 4 \cdot (\frac{1}{3})(\frac{1}{2})(\frac{1}{1})(\frac{1}{0})$

b) Four of a kind: $\binom{13}{1} \binom{4}{1} \binom{12}{1} \binom{4}{1} = \frac{13!}{1! 12!} \cdot \frac{4 \cdot 4!}{1! 3!} \cdot \frac{12!}{1! 11!} \cdot \frac{4!}{2! 2!} = 13 \cdot 4 \cdot 12 \cdot 4 \cdot 3/2 = 3744$

$$\frac{3744}{\binom{52}{5}} = \frac{3744}{2598960} = 0.05\%$$

c) A full house (three cards of one value and two of another)

(Probability of three cards of fifty-two) \times (Probability of two cards of fifty-two)

14. Prove $P(A|E) \geq P(B|E)$ and $P(A|E^c) \geq P(B|E^c)$
 then $P(A) \geq P(B)$

$$P(A|E) \geq P(B|E) \quad \text{and} \quad P(A|E^c) \geq P(B|E^c)$$



15. 4 meats, 6 vegetables, three starches

$$\binom{11}{4} \cdot 6 \cdot 3 = 172 \text{ meals}$$

16. Simpson's Paradox:

Black Urn: {3 red and 6 green balls} } Set #1
 White Urn: {5 red and 4 green balls} }

First trial: Black Urn $\left(\frac{3}{9}\right)$, White Urn $\left(\frac{5}{9}\right)$

Black Urn: {2 red and 6 green balls} } Set #2
 White Urn: {5 red and 4 green balls} }

Second Trial: Black Urn $\left(\frac{2}{9}\right)$, White Urn $\left(\frac{15}{16}\right)$

Black Urn: {5 red and 12 green balls} } Set #3
 White Urn: {20 red and 5 green balls} }

1: Black Urn $\left(\frac{5}{12}\right)$, White Urn $\left(\frac{20}{25}\right)$



17. Accepts: 4 items of 100

Rejects: 1 item is defective

$$P(A) = \frac{\binom{100-K}{4} \binom{K}{0}}{\binom{100}{4}} = \frac{(100-K)!}{4! (96!)!}$$

$$= \frac{(100-K)(100-K-1)(100-K-2)(100-K-3)(100-K-4)}{(100-K-4)!}$$

$$(100 \times 99 \times 98 \times 97)^{-1}$$

$$= \frac{(100-K)(99-K)(98-K)(97-K)}{100 \times 99 \times 98 \times 97} = \left(1 - \frac{K}{100}\right) \left(1 - \frac{K}{99}\right) \left(1 - \frac{K}{98}\right) \left(1 - \frac{K}{97}\right)$$

$$\frac{\text{Major out choice}}{\text{Total choices}} = \frac{\left(\frac{1}{6}\right)\left(\frac{1}{6}\right)\left(\frac{1}{6}\right)\left(\frac{1}{6}\right)}{\left(\frac{1}{6}\right)^4} = \frac{1}{1296}$$

19. Five Chicanos, two Asians, three African

Total choices

20. Arrangements : Statistically

$$S^2 = 2; E^2 = 3; A^2 = 2; \\ L^2 = 2; C^2 = 1; O^2 = 1; B^2 = 2$$

$$\text{Total Amount} = 13 ; \quad y' = 1$$

$$\text{Total Amount} = 13 ; \quad y's = 1$$

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$$\frac{\binom{2}{1} \binom{3}{1} \binom{2}{1} \binom{2}{1} \binom{1}{1} \binom{1}{1} \binom{2}{1} \binom{1}{1}}{\binom{13}{13}} = \frac{2 \cdot 3 \cdot 2 \cdot 2 \cdot 1 \cdot 1 \cdot 2 \cdot 1}{1} = 48$$

$$\begin{aligned}
 b. & \quad \left(\begin{array}{c} 5 \\ 1 \end{array} \right) \circ \left(\begin{array}{c} 2 \\ 1 \end{array} \right) \circ \left(\begin{array}{c} 3 \\ 1 \end{array} \right) = \frac{5 \cdot 2 \cdot 3 \cdot 5!}{10 \cdot 9 \cdot 8 \cdot 7 \cdot 6!} \\
 & \quad \left(\begin{array}{c} 10 \\ 5 \end{array} \right) = \frac{35 \cdot 2 \cdot 3 \cdot (4!)^2}{10 \cdot 9 \cdot 8 \cdot 7} \\
 & \quad = \boxed{140}
 \end{aligned}$$

$$21. \quad \frac{2^2 + 2^2 + 2^2}{2^5} = \boxed{\frac{12}{32}}$$

$$22. \quad \left(\frac{1}{4}\right)\left(\frac{1}{3}\right)\left(\frac{1}{2}\right)\left(\frac{1}{1}\right) = \boxed{\frac{1}{24}}$$

$$23. \quad \binom{n}{1} \binom{n}{2} \binom{n-1}{1} (n-2)!$$

1st layer 2nd layer 3rd layer
inner inner inner
outer outer outer

$$24. \text{ 52 cards; } \frac{\text{Probability Aces next to each other}}{\text{Total Arrangements}} = \frac{\binom{13}{4}}{\binom{52}{4}}$$

$$\frac{n!}{1!(n-1)!} \cdot \frac{n!}{2!(n-2)!} \cdot \frac{(n-1)!}{1!(n-2)!} = (n)_2 \cdot (n)_3$$

$$\binom{n}{2} \cdot n! = \binom{n}{2} (n^n)$$

26. n items with K defects in are selected.

26. n items with K defects; m are selected and inspected.

$$= \frac{13 \cdot 12 \cdot 11 \cdot 10}{4! \cdot 52 \cdot 51 \cdot 50 \cdot 49} = \frac{41}{4165} = 1\%$$

value of m to be below a probability

$$a) n=1000; \frac{\text{Probability of defect}}{\text{Total outcomes}} = \frac{\binom{0.90}{n-k} \binom{K}{m}}{\binom{n}{m}} = \frac{\binom{n-m}{n} \binom{m}{k}}{\binom{n}{k}} = \frac{(n-m)!}{k!(n-m-k)!} \cdot \frac{n!}{m!(n-k)!} = \frac{(1000-m)!}{1000!} \cdot \frac{(n-k)!}{(n-m-k)!}$$

$$b) n=1000 \wedge 0.9 \frac{(1000)!}{(900)!} = \frac{(1000-m)!}{(900-m)!}$$

$$27. \text{Probability of no letters occurring} = \frac{26^5}{26^5} = \frac{5!}{26^5} = \frac{5!(21)!}{26^5} = \frac{5 \cdot 4 \cdot 3 \cdot 2 \cdot 1}{26^5}$$

$$20. \text{ 5 players with } \underline{\text{five}} \text{ cards from 52-card deck.} = \frac{52!}{25!(27!)} = 5.53 \times 10^{-5} = 0.55\%$$

29.0 Three Spades and Two Hearts:

④ Discards two hearts and draws two more cards

$$= \left(\frac{11}{47}\right)\left(\frac{10}{46}\right) = \frac{110}{2162} = \frac{55}{1081} = 5.10\%$$

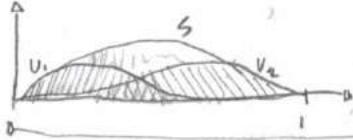
$$= 4.775 \times 10^{14} \text{ W/m}^2$$

30. 60% 2nd graders into two classes of 30 each. Probability of five chosen into same class

$$\frac{\binom{2}{4}}{\binom{60}{5}} = \frac{2!}{60!} = \frac{2 \cdot 5!}{60 \cdot 59 \cdot 58 \cdot 57 \cdot 56}$$

$$-0.00004\% = \left(\frac{60}{30}\right) \cdot \left(\frac{160}{50}\right) = \frac{0.00004}{1}$$

43. V_1 & V_2 from $[0,1]$; $S = V_1 + V_2$ 44. $X \& Y \in \{0, 1, 2\}$ $P(0) = \frac{1}{3}; P(1) = \frac{1}{3}; P(2) = \frac{1}{3}$; Frequency function of $X+Y$.



X	0	0	0	1	1	1	2	2	2
Y	0	1	2	0	1	2	0	1	2
$X+Y$	0	1	2	1	2	3	2	3	4
$P(X+Y)$	$\frac{1}{9}$	$\frac{2}{9}$	$\frac{3}{9}$	$\frac{2}{9}$	$\frac{3}{9}$	$\frac{2}{9}$	$\frac{1}{9}$	$\frac{2}{9}$	$\frac{1}{9}$
$X+Y$	0	1	2	3	4				
N	1	2	3	2	1				
$P(X+Y)$	$\frac{1}{9}$	$\frac{2}{9}$	$\frac{3}{9}$	$\frac{2}{9}$	$\frac{1}{9}$				

45 Poisson Distribution:

$$P(X) = \frac{\lambda^k e^{-\lambda}}{k!}$$

$$P_A + P_B = 1$$

Prove N_A is a poisson with

$$\text{parameter } P_A \lambda : P(N_A = n) = \sum_{i=n}^{\infty} P[N_A = n | X_i = i] P[X = i] = \sum_{i=n}^{\infty} \binom{i}{n} P_A^n (1-P_A)^{i-n} \cdot \frac{\lambda^i}{i!} e^{-\lambda}$$

Law of Total Probability

$$= \frac{e^{-\lambda} \cdot \lambda^n P_A^n}{n!} \sum_{i=n}^{\infty} \frac{[(1-P_A)\lambda]^{i-n}}{(i-n)!} = \frac{e^{-\lambda} \lambda^n P_A^n}{n!} \sum_{j=0}^{\infty} \frac{[(1-P_A)\lambda]^j}{j!} = \frac{e^{-\lambda} \lambda^n P_A^n (1-P_A)\lambda}{n!} e^{-\lambda}$$

46. Let T_1 and T_2 be independent

exponentials with λ_1 and λ_2 . Find $T_1 + T_2$.

$$P(T_1) = \lambda_1 e^{-\lambda_1}; P(T_2) = \lambda_2 e^{-\lambda_2}; T_1 + T_2 = \lambda_1 e^{-\lambda_1} + \lambda_2 e^{-\lambda_2};$$

$$\begin{aligned} J &= \left| \begin{array}{cc} \frac{\partial T_1}{\partial r} & \frac{\partial T_1}{\partial s} \\ \frac{\partial T_2}{\partial r} & \frac{\partial T_2}{\partial s} \end{array} \right| = \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} = 1 \\ F(T_1, T_2) &= \lambda_1 \lambda_2 e^{-\lambda_1 - \lambda_2} \end{aligned}$$

$$= e^{-\frac{\lambda_1 + \lambda_2}{n}} \frac{(\lambda_1 \lambda_2)^n}{n!}$$

$$47. f(x) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}}; f(y) = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(y-\mu_2)^2}{2\sigma_2^2}}; Z = X+Y = \frac{1}{2\pi\sigma_1\sigma_2} e^{-\frac{(X-\mu_1)^2}{2\sigma_1^2} - \frac{(Y-\mu_2)^2}{2\sigma_2^2}}$$

Sums and Differences: $X, Y, Z = X+Y$, then $Y = Z-X$; $P(Z) = \sum_{x=-\infty}^{\infty} P(X, Z-x); P(x, y) = P_x(x) \cdot P_y(y)$

$$f(z) = \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-x^2/2} \cdot e^{-\frac{(z-x)^2}{2}} dx$$

$$= \sum_{x=-\infty}^{\infty} P_x(x) P_y(z-x) \quad \text{[Convolution]} \quad \text{[Discrete]}$$

$$\begin{aligned} &= \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-x^2/2} \cdot e^{-\frac{(z-x)^2}{2}} dx = \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-\frac{2x^2-2xz+x^2}{2}} dx \\ &= \frac{e^{-z^2/2}}{2\pi} \times \sqrt{\pi} e^{-\frac{z^2}{4}} = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{z}{\sqrt{2}} \right)^2} \end{aligned}$$

$$\begin{aligned} F(z) &= \iint f(x, y) dx dy = \int_{-\infty}^{\infty} \int_{-\infty}^z f(x, y) dy dx = \\ f(z) &= \int_{-\infty}^z f(x, z-x) dx = \int_{-\infty}^z f_x(x) f_y(z-x) dx \end{aligned}$$

$$48. F(N_1) = \frac{\lambda^k}{k!} e^{-\lambda N_1}; F(N_2) = \frac{\lambda^k}{k!} e^{-\lambda N_2}; F(N) = \int_{-\infty}^{\infty} f(N_1, N-N_1) dN_1 = \int_{-\infty}^{\infty} F_1(N_1) \cdot F(N-N_1) dN_1 = \int_{-\infty}^{\infty} \frac{\lambda_1^k}{k!} e^{-\lambda_1 N_1} \cdot \frac{\lambda_2^k}{k!} e^{-\lambda_2 (N-N_1)} dN_1$$

$$49. f(x, y) = \begin{cases} \lambda_1^2 e^{-\lambda_1 y}; & 0 \leq x \leq y, \lambda > 0 \\ 0 & \text{elsewhere} \end{cases}$$

$$= \frac{(\lambda_1 \lambda_2)^k}{(k!)^2} e^{-\lambda_1 N_1 - \lambda_2 N_2 + \lambda_2 N_1}$$

$$dN_1 = \frac{(\lambda_1 \lambda_2)^k}{k!^2} e^{-\lambda_2 N_1} \frac{1}{(\lambda_1 - \lambda_2)} dN_1$$

$$f(z) = \int_{-\infty}^z \lambda_1^2 e^{-\lambda_1 y} dy = \boxed{\lambda_1 e^{-\lambda_1 z} - \lambda_1^2 z}$$

$$= \frac{(\lambda_1 \lambda_2)^k}{(k!)^2} e^{-\lambda_2 N} \frac{1}{(\lambda_1 - \lambda_2)}$$

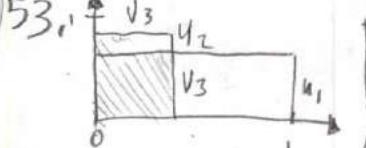
$$51. Z = XY; f(x, y) = f(x) \frac{1}{y} = f(\frac{z}{y}, y)$$

$$F(z) = \int_{-\infty}^{\infty} f(\frac{z}{y}, y) \frac{1}{y} dy = \int_{-\infty}^{\infty} f(\frac{z}{y}, y) \frac{1}{y} dz dy$$

50. X & Y are jointly continuous variables. Find $Z = X-Y$

$$P(z) = \int_{-\infty}^{\infty} f(x, x-z) dx = \int_{-\infty}^{\infty} f(x) \cdot f(x-z) dx$$

$$Z = X/Y$$



$$f(z) = \int_{-\infty}^{\infty} f(\frac{z}{y}, y) \frac{1}{y} dy$$

$$1 \geq \sum_{i=1}^m \sum_{j=1}^{n_i} P(v_i) P(u_{ij})$$

$$f(z) = \int f(x, y) dx dy = \int f(xz, y) y dz dy; f(z) = \int f(yz, y) y dy$$

$$\text{Area}_{12} = v_1 \cdot v_2; P(v_1, v_2) = P(v_1) \cdot P(v_2);$$

$$\text{Area}_{33} = v_3^2; P(v_3, v_3) = P(v_3)^2;$$

25. $f(x) = p(Y=x) = \frac{1}{2}$; $p(Y=-x) = \frac{1}{2}$; Show Y is symmetric about zero. Bernoulli Distribution: $P(R) = p^x(1-p)^{1-x}$

Conditional Density of a random variable is expressed as:

$$f_{Y|X}(y|x) = F_{Y|X}(x|x) = Y_2; f_{Y|X}(y|x) = f_{Y|X}(-x|x) = Y_2$$

$$f_{Y|X}(y|x) = \frac{f_{YX}(x,y)}{f_X(x)}; f(x,y) = f_{Y|X}(y|x)F(x) = \frac{1}{2}f(x)$$

$$f(x,x) = \frac{1}{2}f(x);$$

$$F_{Y|X}(y|x) = \frac{F(x,y)}{f_X(x)}; f(x,y) = f_{Y|X}(y|x)f_X(x) = \frac{1}{2}f_X(-x)$$

$$f_Y(y) = \frac{1}{2}f(x) + \frac{1}{2}f(x) + f_Y(-y).$$

$$P(0) = \int_0^1 p^0(1-p)^1 dp = 1 - p^1 = Y_2$$

$$P(1) = \int_0^1 p^1(1-p)^0 dp = \frac{1}{2}$$

27. Prove X and Y are independent if $f_{X,Y}(x,y) = f_X(x) \frac{f(x,y)}{f(y)} = \frac{f(x)f(y)}{f(y)} = f(x)$

28. Show if $C(u,v) = uv$ is a copula. Why is it called "the independence copula?"

Copula: a joint cumulative distribution of random variables that have uniform marginal distributions. The function $C(u,v) = uv$ is known by the independence copula because independent variables, and margins, are separable.

29. Marginal Density: $\lambda e^{-\lambda x}$ Fisher-Morgenstern Copula:
 $H(x,y) = F(x)G(y)\{1 + \alpha[1-F(x)][1-G(y)]\} = \lambda_1 e^{-\lambda_1 x} \lambda_2 e^{-\lambda_2 y} \{1 + \alpha[1-\lambda_1 e^{-\lambda_1 x}][1-\lambda_2 e^{-\lambda_2 y}]\}$
 $h(x,y) = \frac{\partial^2}{\partial x \partial y} H(x,y) = \frac{\partial^2}{\partial x \partial y} \lambda_1 e^{-\lambda_1 x} \lambda_2 e^{-\lambda_2 y} \{1 + \alpha[1-\lambda_1 e^{-\lambda_1 x}][1-\lambda_2 e^{-\lambda_2 y}]\}$
 $+ \lambda_1 e^{-\lambda_1 x} \lambda_2 e^{-\lambda_2 y} \{1 + \alpha[1-\lambda_1 e^{-\lambda_1 x}][1+\lambda_2 e^{-\lambda_2 y}]\}$

30. For $0 \leq \lambda \leq 1$ and $0 \leq \beta \leq 1$

$$\text{Show } C(u,v) = \min(u^{1-\lambda}, v^{1-\beta})$$

is a copula (Marshall-Olkin)

$$\lim_{\lambda \rightarrow 1} \lim_{\beta \rightarrow 1} C(u,v) = \min(u, v) = 1$$

Joint Density:

$$h(x,y) = \frac{\partial^2}{\partial u \partial v} H(x,y) = \min\left[\left(1-\lambda\right)u^\lambda, \left(1-\beta\right)v^\beta\right]$$

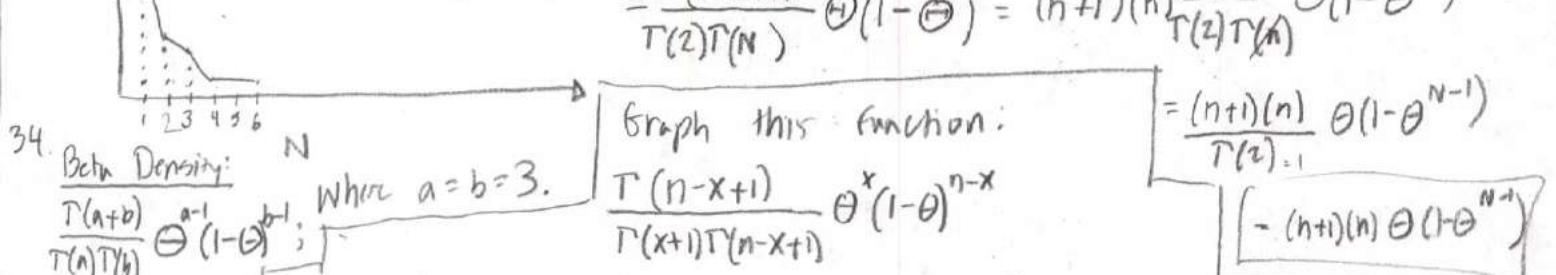
$$= \lambda^2 e^{-\lambda x} \lambda_2^2 e^{-\lambda_2 y} \{1 + \alpha[1-\lambda_1 e^{-\lambda_1 x}][1-\lambda_2 e^{-\lambda_2 y}]\}$$
 $+ \lambda_1 e^{-\lambda_1 x} \lambda_2^2 e^{-\lambda_2 y} \{1 + \alpha[1+\lambda_1^2 e^{-\lambda_1 x}][1-\lambda_2 e^{-\lambda_2 y}]\}$
 $+ \lambda_1^2 e^{-\lambda_1 x} \lambda_2 e^{-\lambda_2 y} \{1 + \alpha[1-\lambda_1 e^{-\lambda_1 x}][1+\lambda_2 e^{-\lambda_2 y}]\}$
 $+ \lambda_1 e^{-\lambda_1 x} \lambda_2 e^{-\lambda_2 y} \{1 + \alpha[1+\lambda_1 e^{-\lambda_1 x}][1+\lambda_2 e^{-\lambda_2 y}]\}$

31. (X, Y) is a uniform disc of radius of 1. $f(x,y) = \begin{cases} \frac{1}{\pi} x^2 + y^2 \leq 1 \\ 0, \text{ otherwise} \end{cases}$ X and Y are not independent because of the constraint $x^2 + y^2 = 1$.

32. $F_R(r)$: Probability of passing per mesh: Probability Passing. Aren Square $= \frac{\pi r^2}{(nW + (n+1)d)^2}$

33a) Posterior Density [Beta Density]: $f(\theta) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1} (1-\theta)^{b-1}$ Area mesh $= \frac{\Gamma(n+2)}{\Gamma(2)\Gamma(n)} \theta^{(n+1)-1} (1-\theta)^{(n+1)-1}$

$$= \frac{\Gamma(n+2)}{\Gamma(2)\Gamma(n)} \theta^{(n+1)-1} (1-\theta)^{(n+1)-1} = (n+1)(n) \frac{\Gamma(n)}{\Gamma(2)\Gamma(n)} \theta^{(n+1)-1} (1-\theta)^{(n+1)-1}$$

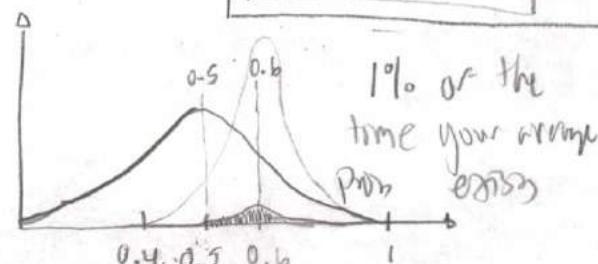
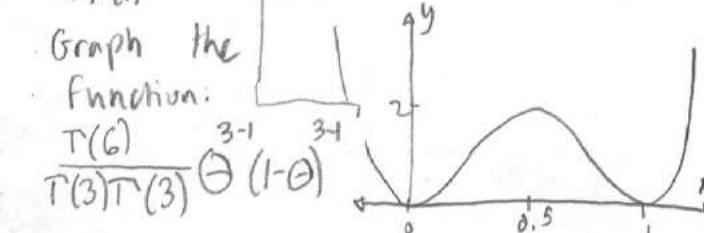


34. Beta Density: $\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1} (1-\theta)^{b-1}$; Where $a=b=3$.

$$\frac{\Gamma(n+1)}{\Gamma(x+1)\Gamma(n-x+1)} \theta^x (1-\theta)^{n-x}$$

$$= \frac{(n+1)(n)}{\Gamma(2)} \theta^{(n+1)-1}$$

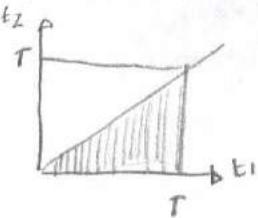
$$= (n+1)(n) \theta^{(n+1)-1}$$



$$P(T_1 > 2T_2) = \int_0^{\infty} \int_{2T_2}^{\infty} \kappa e^{-\kappa t_1} \beta e^{-\beta t_2} dT_1 dT_2 = \frac{\beta}{(2\kappa + \beta)}$$

20. Probability of packet collision: $f(t_1, t_2) = \frac{1}{T^2}$ [Joint Density] From $[0, T]$

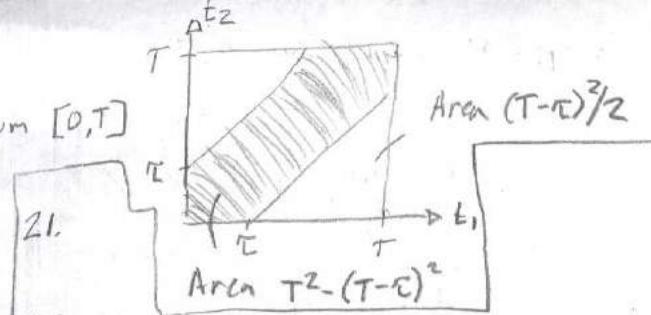
Time between arrivals:



Integral is $F(T_1, t_2) \times \text{Area}$

$$= \frac{1}{T^2} (T^2 - (T-t)^2)$$

$$= 1 - (1-t/T)^2$$



$$f(x) = \text{Present chemical}$$

$$R(x) = \text{Probability Detected}$$

y = concentration of a chemical in soil.

Integral is: $f(t_1, t_2) \times \frac{1}{2} T \cdot T = \boxed{\frac{T}{2}}$ If $g(y)$ is uniform, then $g(y) = \frac{\text{Probability of Detection} \times \text{Density function}}{\text{Total outcomes of concentration}}$

$$= R(y) \cdot f(y) / \int_0^{\infty} R(x) f(x) dx$$

22. Poisson Distribution: $\frac{\lambda^k e^{-\lambda}}{k!} = p(x); N(t_1, t_2) = \text{Number of events.}$

If $t_0 < t_1 < t_2$; find the conditional distribution of $N(t_0, t_1)$ given $N(t_0, t_2) = n$

$$N(t_0|t_1) = \frac{N(t_0, t_1)}{N(t_1)}; N(t_0|t_2) = \frac{N(t_0, t_2)}{N(t_2)} = \frac{n}{N(t_2)}; N(t_1, t_2) \circ p = \lambda; p(x) = \frac{[N(t_1, t_2)p]^x}{k!} \circ e^{-N(t_1, t_2)p}$$

$$P(N(t_0, t_1)) = e^{-\lambda(t_1-t_0)} \frac{[\lambda(t_1-t_0)]^x}{x!}$$

$$P(N(t_0, t_1) = x | N(t_0, t_2) = n) = P(N(t_0, t_1) = x, N(t_0, t_1) + N(t_1, t_2) = n)$$

$$= \frac{[N(t_1) N(t_2) \cdot p_1 \cdot p_2]^k}{k!} e^{-N(t_1) N(t_2) \cdot p_1 \cdot p_2}$$

23. $p(N|X) = \frac{p(N, X)}{p(X)}$

Binomial Distribution:

$$P(k) = \binom{n}{k} p^k (1-p)^{n-k}$$

N = Trials, p = probability of success.

= Binomial random variable with n trials and probability p .

$$p(x) = \frac{p(N, X)}{p(N|X)} = \frac{\binom{n}{k} p^k (1-p)^{n-k}}{\binom{m}{r} r^r (1-r)^{m-r}}$$

$$= \binom{m}{r} (pr)^r (1-p)^{m-r}$$

$$= \frac{P(N(t_0, t_1) = x, N(t_1, t_2) = n-x)}{P(N(t_0, t_2) = n)} = \frac{P(N(t_0, t_1) = x, N(t_1, t_2) = n-x)}{P(N(t_0, t_2) = n)}$$

$$= e^{-\lambda(t_1-t_0)} \frac{[\lambda(t_1-t_0)]^x}{x!} \times e^{-\lambda(t_2-t_1)} \frac{[\lambda(t_2-t_1)]^{n-x}}{(n-x)!}$$

$$= \frac{n!}{x(n-x)!} \frac{(t_1-t_0)^x (t_2-t_1)^{n-x}}{(t_2-t_0)^n}$$

Joint Density: $f_{\theta, X}(0, x) = f_{X|\theta}(x|\theta) \cdot f(\theta)$

$$= \binom{n}{x} \theta^x (1-\theta)^{n-x} \quad x = 0, 1, \dots, n; 0 \leq \theta \leq 1$$

24. Section 3.5.2
Bayesian Inference: Conditional: $f_{X|\theta}(x|\theta) = \binom{n}{x} \theta^x (1-\theta)^{n-x} \quad x = 0, 1, \dots, n$

$$\text{Marginal Density: } f_{\theta}(\theta) = \int_0^1 \binom{n}{x} \theta^x (1-\theta)^{n-x} d\theta = \int_0^1 \frac{\Gamma(n+1)}{\Gamma(x+1)\Gamma(n-x+1)} \theta^x (1-\theta)^{n-x} d\theta \quad \text{by the fact } \Gamma(r) = (r-1)!$$

$$\dots \text{becomes the beta density} \quad = \int_0^1 \frac{\Gamma(n+1)}{\Gamma(x+1)\Gamma(n-x+1)} \theta^x (1-\theta)^{n-x} d\theta = \frac{\Gamma(n+1)}{\Gamma(x+1)\Gamma(n-x+1)} \frac{\Gamma(x+1)\Gamma(n-x+1)}{\Gamma(n+2)} = \frac{1}{n+1} \frac{\Gamma(n+1)}{\Gamma(x+1)} = \frac{1}{n+1}$$

$$\text{Conditional: } f_{\theta|X}(\theta|x) = \frac{f_{\theta, X}(0, x)}{f_X(x)} = \frac{(n+1) \binom{n}{x} \theta^x (1-\theta)^{n-x}}{(n+1) \frac{\Gamma(n+1)}{\Gamma(x+1)\Gamma(n-x+1)} \theta^x (1-\theta)^{n-x}} = \frac{\Gamma(n+2)}{\Gamma(x+1)\Gamma(n-x+1)} \theta^x (1-\theta)^{n-x}$$

Posterior Density is a β -density with $a = x+1, b = n-x+1; g(a) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} u^{a-1} (1-u)^{b-1}; g'(b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \left[(a-1) u^{a-2} (1-u)^{b-1} + (b-1) u^{a-1} (1-u)^{b-2} \right] = 0$

25. P is uniform from $[0, 1]$, and conditional on $P=p$. Let X be a Bernoulli Distribution with parameter p .

Find the conditional distribution of P given X .

Bernoulli Distribution. Find $P(P|X) = \frac{f(p, x)}{f(x)} = \frac{p^x (1-p)^{1-x}}{\int_0^1 p^x (1-p)^{1-x} dp} = \frac{1}{2} p^x (1-p)^{1-x}$

$$\begin{aligned} \frac{(a-1)}{(b-1)} (1-a) &\approx u \\ \frac{(a-1)}{(b-1)} &= u \left[1 + \frac{(a-1)}{(b-1)} \right] \\ \theta &= \frac{(a-1)(b-1)}{(b-1)[(b-1)+(a-1)]} \end{aligned}$$

15. Suppose the joint density $f(x,y) = c\sqrt{1-x^2-y^2}$, $x^2+y^2 \leq 1$

a) Find c : $x=r\cos\theta$; $y=r\sin\theta$; $\iint f(x,y) dA = \int_0^{2\pi} \int_0^1 c\sqrt{1-r^2} r dr d\theta = c\left(\frac{2}{3}\right)\pi = 1 \Rightarrow c = \left(\frac{3}{2\pi}\right)$

$P(X^2+Y^2 \leq 1) \leq 1/2$ is a half of the disk,

$$\iint f(x,y) dA; x^2+y^2 \leq 1/2 = \int_0^{\pi/4} \int_0^1 \left(\frac{3}{2\pi}\right) \sqrt{1-r^2} r dr d\theta = \int_0^{\pi/4} \left(\frac{3}{2\pi}\right) \sqrt{1-r^2} r dr d\theta = \left[\frac{3}{2\pi}\right] \int_0^{\pi/4} (\frac{1}{2}r^2) d\theta = \boxed{\frac{1}{8}}$$

b) The joint density is an area of decreasing size.

c) $f(x) = \int_{-1}^1 \sqrt{1-x^2-y^2} \left(\frac{3}{2\pi}\right) dy = \left(\frac{3}{4}\right)x^2$; $f(y) = \int_{-1}^1 \sqrt{1-x^2-y^2} \left(\frac{3}{2\pi}\right) dx = \left(\frac{3}{4}\right)y^2$

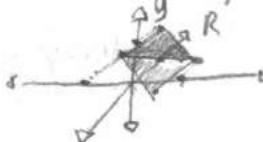
To check independence, $f(x,y) = f_x(x)f_y(y) = \left(\frac{9}{16}\right)x^2y^2 \neq \text{independence.}$

d) Conditional Densities: $f(y|x) = f(x,y)/f_x(x)$; $f(x|y) = f(x,y)/f_y(y)$

16. X_1 is uniform on $[0,1]$, and, conditional on X_1, X_2 , from $[0, X_1]$

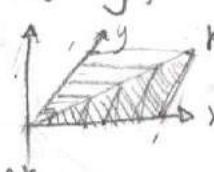
Find the joint Distributions: $f(x_1, x_2) = \int_0^1 \int_0^{x_1} dx_2 dx_1$ = Marginal Distributions: $f(x_1) = \int_0^1 dx_2$

17. (X,Y) is a random point of the region $R = \{(x,y) : |x| + |y| \leq 1\}$

a)  b) $f_x(x) = R = 2$; $f_y(y) = R = 2$
c) $f_{Y|X}(Y|X) = \frac{f(y,x)}{f(x)} = \frac{|x|+|y|}{R} = \boxed{1}$

$$f(x_2) = \int_0^1 dx_1$$

18 $f(x,y) = k(x-y)$, $0 \leq y \leq x \leq 1$ and zero elsewhere.

a)  b) $I = \int_0^1 \int_0^x k(x-y) dy dx = \int_0^1 k\left(x - \frac{y^2}{2}\right) \Big|_0^x dx = \int_0^1 k\left(x - \frac{x^2}{2}\right) - k(x) dx = \int_0^1 k\frac{x^2}{2} dx = -k\frac{1}{6} = 1$

b) $f_x(x) = \int_0^x k(x-y) dy = \boxed{k(-\frac{x^2}{2})} ; f_y(y) = \int_0^1 k(x-y) dx = k(\frac{1}{2}-y) + ky = 6(\frac{1}{2}) = \boxed{3}$

d) $f_{Y|X}(Y|X) = \frac{f(x,y)}{f(x)} = \frac{k(x-y)}{-3x^2} ; f_{X|Y}(X|Y) = \frac{f(x,y)}{f(y)} = \boxed{\frac{k(x-y)}{3}}$

19. a) Exponentially Distributed lifetimes means: $A e^{-\lambda x} = f(x)$; $f(T_1) = \alpha e^{-\kappa T_1}$; $f(T_2) = \beta e^{-\beta T_2}$

Find $P(T_1 > T_2) = \int_0^{T_1} \beta e^{-\beta t_2} dt_2 = -e^{-\beta t_2} \Big|_0^{T_1} = -[e^{-\beta T_1} - 1] = \boxed{\frac{1-e^{-\beta T_1}}{1+e^{-\beta T_1}}} \quad \text{Let } S = T_1 + T_2$

b) $P(T_2 > 2T_1) = \boxed{\frac{1+e^{-\kappa(2T_1)}}{2}}$ $P(T_1 > T_2) = \int_0^{T_1} \kappa e^{-\kappa t_1} \cdot \beta e^{-\beta t_2} dt_2 = -\kappa e^{-\kappa t_1} \cdot e^{-\beta t_2} \Big|_0^{T_1} = -\kappa e^{-\kappa T_1} \cdot e^{-(\kappa+\beta)T_1} = -\kappa e^{-(\kappa+\beta)T_1}$
 $P(T_1 > T_2) = \int_{T_2}^{\infty} \int_{T_1}^{\infty} \kappa e^{-\kappa t_1} \beta e^{-\beta t_2} dt_2 dt_1 = \int_0^{\infty} \beta e^{-\beta t_2} - [e^{-\kappa t_1} - e^{-\kappa t_1}] dt_2 = \int_0^{\infty} \beta e^{-(\kappa+\beta)t_2} dt_2 = \boxed{\frac{\beta}{\kappa+\beta}}$

12. $f(x,y) = C(x^2 - y^2)e^{-x}$, $0 \leq x < \infty$, $-x \leq y < x$

a) Find C . $P(x,y) = 1 = \int_0^\infty \int_{-x}^x C(x^2 - y^2)e^{-x} dy dx$

b) $f(x) = \int_{-x}^x C(x^2 - y^2)e^{-x} dy = \frac{2}{3}x^3 e^{-x}$; $f(y) = \int_0^\infty 2(x^2 - y^2)e^{-x} dx = 2(2 - y^2)e^{-x}$

c) $f_{XY}(Y|X) = \frac{f(x,y)}{f(x)} = \frac{-2(x^2 - y^2)e^{-x}}{\frac{4}{3}x^3 e^{-x}} = \frac{-3(x^2 - y^2)}{2x^3}$; $f_{XY}(X|Y) = \frac{f(x,y)}{f(y)}$

B. Sample Space: Throws

	1	2
0	H	H
1	H	T
2	T	H
	T	T

$P(0) = \frac{1}{2}$; $P(2) = \frac{1}{4}$; $P(1) = \frac{1}{2}$

14 Point in a unit sphere (\mathbb{R}_3)

$$V = \frac{4}{3}\pi r^3 = \frac{4}{3}\pi \sqrt{x^2 + y^2 + z^2}$$

Density Function of a unit Sphere:

$$f(x,y,z) = \begin{cases} k & 0 \leq x^2 + y^2 + z^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

To find the value of k , such that:

$$\iiint k dx dy dz = 1 ; \text{ let } x = p \sin\phi \cos\theta, y = p \sin\phi \sin\theta, z = p \cos\phi ; p^2 = x^2 + y^2 + z^2 = 1$$

$$0 \leq x^2 + y^2 + z^2 \leq 1$$

$$0 < p < 1 ; 0 < \phi < \pi ; 0 < \theta < 2\pi$$

$$\text{Volume} = \int_0^{2\pi} \int_0^\pi \int_0^1 p^2 \sin\phi dp d\phi d\theta = \frac{4\pi}{3} ; k \frac{4\pi}{3} = 1 ; k = \frac{3}{4}\pi$$

$$\text{The density function becomes: } f(x,y,z) = \begin{cases} \frac{3}{4}\pi & 0 < x^2 + y^2 + z^2 \leq 1 \\ 0 & \text{otherwise.} \end{cases}$$

Marginal Densities: 1) Joint Densities:

$$f_{XY}(x,y) = \int_{-\infty}^{\infty} f(x,y,z) dz = \int_{-\sqrt{1-x^2-y^2}}^{\sqrt{1-x^2-y^2}} \frac{3}{4}\pi dz = \frac{3}{4}\pi \sqrt{1-x^2-y^2} ; f_{XY}(x,y) = \begin{cases} \frac{3}{2\pi} \sqrt{1-x^2-y^2} & 0 < x^2 + y^2 < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$2) f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x,y) dy = \int_{-\sqrt{1-x^2}}^{\sqrt{1-x^2}} \frac{3}{2\pi} \sqrt{1-x^2-y^2} dy ; y = \sqrt{1-x^2} \sin u$$

$$dy = \sqrt{1-x^2} \cos u du$$

$$f_Y(y) = \begin{cases} \frac{3}{4}(1-y^2) & -1 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases} ; f_Z(z) = \begin{cases} \frac{3}{4}(1-z^2) & -1 \leq z \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\boxed{\frac{1}{\pi}}$$

$$\textcircled{2} Z=0 \quad f_{XY|Z}(x,y|z) = \frac{f_{XYZ}(x,y,z)}{f_Z(z=0)} = \frac{\frac{3}{4}\pi}{\frac{3}{4}(1-(0)^2)} = \boxed{\frac{1}{\pi}}$$

C. Conditional Density: $f_{Y|X}(y|x) = \frac{f_{XY}(x,y)}{f_X(x)} = \begin{cases} \frac{6}{7}(x^2 + xy) \\ x^2 + \frac{x}{2} \end{cases}$; $f_{X|Y}(x|y) = \frac{f_{XY}(x,y)}{f_Y(y)} = \begin{cases} \frac{6}{7}(x^2 + xy) \\ \frac{1}{3} + \frac{y}{2} \end{cases}$

9. (X, Y) uniformly distributed over: $0 \leq y \leq 1-x^2; -1 \leq x \leq 1$ Assuming Bivariate Normal Density:

a) Find the marginal distribution: $F_X(x) = \int_0^{1-x^2} \frac{1}{2\pi\sigma_X\sigma_Y} \exp\left(\frac{(x-\mu_x)^2}{\sigma_x^2} + \frac{(y-\mu_y)^2}{\sigma_y^2}\right) f(x,y) = \frac{1}{2\pi\sigma_X\sigma_Y} \exp\left(\frac{(x-\mu_x)^2}{\sigma_x^2} + \frac{(y-\mu_y)^2}{\sigma_y^2}\right)$

b) Find the two conditional densities:

$$f_{Y|X}(y|x) = \frac{f_{XY}(x,y)}{f_X(x)}$$

$$= \frac{1}{2\pi\sigma_X\sigma_Y} \exp\left(\frac{(x-\mu_x)^2}{\sigma_x^2} + \frac{(y-\mu_y)^2}{\sigma_y^2}\right) \left[\frac{1}{\sqrt{2\sigma_Y}} T\left(\frac{1}{2}\right) \right] \left[\frac{1}{\sqrt{2\sigma_Y}} T\left(\frac{1}{2}\right) \right] \left[\frac{1}{\sqrt{2\sigma_Y}} T\left(\frac{1}{2}\right) \right] \left[\frac{1}{\sqrt{2\sigma_Y}} T\left(\frac{1}{2}\right) \right]$$

$$= \frac{\mu_y}{\sqrt{2\sigma_Y} T\left(\frac{1}{2}\right)} \exp\left[\frac{-1}{2} \left(\frac{(y-\mu_y)^2}{\sigma_y^2} - \frac{(1-x^2)^2}{\sigma_y^2} + \mu_y^2 \right)\right]$$

$$f_{Y|X}(y|x) = \frac{\mu_y}{\sqrt{2\pi\sigma_Y/\mu_y}} \exp\left(\frac{(x-\mu_x)^2}{\sigma_x^2} + \frac{(1-x^2)^2}{\sigma_y^2} - \frac{\mu_y^2}{\sigma_y^2} - \frac{1}{2}\right) = \frac{-1}{2\sigma_Y^2}$$

$$f_{X|Y}(x|y) = \frac{f_{XY}(x,y)}{f_Y(y)}$$

$$f_Y(y) = \int_{-1}^1 \frac{1}{2\pi\sigma_X\sigma_Y} \exp\left(\frac{-1}{2} \left(\frac{(x-\mu_x)^2}{\sigma_x^2} + \frac{(y-\mu_y)^2}{\sigma_y^2} \right)\right) dx$$

$$= \frac{2T\left(\frac{1}{2}\right)}{\sqrt{2\pi\sigma_X\mu_X}} \exp\left(\frac{(x-\mu_x)^2 - \mu_x^2}{\sigma_x^2} + \frac{(y-\mu_y)^2}{\sigma_y^2}\right)$$

$$10. \text{ Suppose } f(x,y) = xe^{-x(y+1)}$$

$$0 \leq x \leq \infty; 0 \leq y < \infty$$

a) Find the marginal density of X and Y .

b) Find the conditional densities.

$$f_{Y|X}(y|x) = \frac{f_{XY}(x,y)}{f_X(x)} = \frac{xe^{-x(y+1)}}{e^x} = x e^{-xy - x - 1}$$

$$f_{X|Y}(x|y) = \frac{f_{XY}(x,y)}{f_Y(y)} = \frac{xe^{-x(y+1)}}{(y+1)^2} = x(y+1)^2 e^{-xy - x - 1}$$

$$F(x) = \int_0^\infty xe^{-x(y+1)} dy = \frac{xe^{-x(y+1)}}{-x} \Big|_0^\infty = -e^{-x(0+1)} + e^{-x(1)} = e^{-x}$$

$$f(y) = \int_0^\infty xe^{-x(y+1)} dx; \int u du = uv - \int v du \quad u = x, dv = e^{-x(y+1)} \\ du = dx, v = -e^{-x(y+1)} \quad \boxed{\text{Independent}}$$

$$= \frac{-xe^{-x(y+1)}}{y+1} \Big|_0^\infty + \int_0^\infty \frac{e^{-x(y+1)}}{y+1} dx = -\frac{e^{-x(y+1)}}{y+1} \Big|_0^\infty = \frac{1}{(y+1)^2}$$

11. $U_1, U_2, \text{ and } U_3$ independent from $[0,1]$

Find the probability the roots of the quadratic

$$0 = U_1x^2 + U_2x + U_3; x_1, x_2 = \frac{-U_2 \pm \sqrt{U_2^2 - 4(U_1)(U_3)}}{2(U_1)}$$

$U_1x^2 + U_2x + U_3$ are real.

$$P(U_1) = \int_0^1 \int_0^1 \int_0^1 U_1x^2 + U_2x + U_3 dU_2 dU_3 = \int_0^1 U_1x^2 + U_2x + \frac{U_3^2}{2} dU_2$$

$$= U_1x^2 + \frac{x}{2} + \frac{1}{2}$$

Extrema and Order Statistics

$$f(U_{(1)}, U_{(2)}, U_{(3)}, \dots) = n! \prod_{i=1}^n f(U_i); \text{ for } i=3; f(U_1, U_2, U_3) = 3! \prod_{i=1}^3 f(U_i) : 6f(U_1)f(U_2)f(U_3)$$

$$P(U_2^2 > 4U_1U_3) = P(|U_2| \geq 2\sqrt{U_1U_3}) = \int_0^1 \int_0^1 \int_{2\sqrt{U_1U_3}}^1 f(U_1, U_2, U_3) dU_2 dU_3 dU_1 = \int_0^1 \int_0^1 (1 - 2\sqrt{U_1U_3}) dU_2 dU_1$$

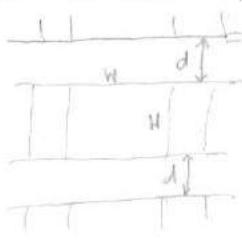
$$= 1 - \frac{4}{3} \frac{1^{3/2}}{3/2} = \boxed{\frac{1}{9}}$$

3. Three Players play 10 independent rounds of a game. $P(\text{Player } i \text{ winning}) = \frac{1}{3}$

$$P(\text{Player A, B, C winning}) = \left(\frac{1}{3} \right)^3 \left(\frac{1}{3} \right)^3 \left(\frac{1}{3} \right)^3$$

Multinomial Distribution: $P(X, Y, Z) = \binom{n}{X, Y, Z} P_1^X P_2^Y P_3^Z$

4. Wire diameter = d , holes side length = W , spherical particle radius = r . What is probability of passing?



$$\text{Area} = \pi r^2$$

$$\text{Probability passing per hole} = \frac{\text{Area particle}}{\text{Area square}} = \frac{\pi r^2}{W^2}$$

$$\text{Area} = W^2$$

$$\text{Probability passing per mesh} =$$

$$\text{Probability passing} \times \frac{\text{Area square}}{\text{Area mesh}}$$

$$= \frac{\pi r^2}{W^2} \frac{W^2}{(nW + (n+1)d)^2} = \frac{\pi r^2}{(nW + (n+1)d)^2}$$

Fails to pass through if dropped n -times:

$$P(\text{Failing to pass through}) = \left(1 - \frac{\pi r^2}{(nW + (n+1)d)^2}\right)^n$$

5. $L \geq r$

$$\text{Probability needle crosses line} = 2 \left(\frac{\text{Length of Needle}}{\text{Distance of lines}} \right) \times \frac{1}{\pi r^2} = \frac{2L}{\pi r^2}$$

$\leftarrow a \rightarrow k \rightarrow a \rightarrow$ Area of ellipse: $\text{Area} = \pi \cdot a \cdot b$

6. $\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1$: Marginal Density of X and y coordinates inside an ellipse: $\text{Area} = \pi \cdot a \cdot b$

$$f_y(y) = \int_{-\infty}^{\infty} f(x, y) dx = \frac{1}{\pi a b} \int_{-\sqrt{a^2(1-y^2/b^2)}}^{\sqrt{a^2(1-y^2/b^2)}} dx = \frac{1}{\pi b} 2\sqrt{a^2(1-y^2/b^2)} = \frac{2\sqrt{1-y^2/b^2}}{\pi b}$$

7. CDF: $F(x, y) = (1 - e^{-\alpha x})(1 - e^{-\beta y})$; $x \geq 0, y \geq 0, \alpha > 0, \beta > 0$

Joint Density: $f(x, y) = \frac{\partial^2}{\partial x \partial y} (1 - e^{-\alpha x})(1 - e^{-\beta y}) = (1 + \alpha e^{-\alpha x})(1 + \beta e^{-\beta y})$

Marginal Density: $F_x(x) = \int_{-\infty}^{\infty} (1 - e^{-\alpha x})(1 - e^{-\beta y}) dy = (1 - e^{-\alpha x})(1 + \beta e^{-\beta y}) \Big|_{-\infty}^{\infty} = \frac{2(1 - e^{-\alpha x})}{\alpha}$

8. $f(x, y) = \frac{6}{7}(x+y)^2, 0 \leq x \leq 1, 0 \leq y \leq 1$

i) Find $P(X > Y) = \frac{6}{7} \int_0^1 \int_0^x (x^2 + xy) dy dx = \frac{6}{7} \int_0^1 \left(x^2 y + \frac{x^2 y^2}{2} \right) \Big|_0^x dx = \frac{6}{7} \left(\frac{x^4}{4} + \frac{x^4}{8} \right) \Big|_0^1 = \frac{6}{7} \left(\frac{1}{4} + \frac{1}{8} \right) = \frac{6}{25} + \frac{6}{49} = \boxed{\frac{11}{56}}$

ii) Find $P(X+Y \leq 1) = \frac{6}{7} \int_0^1 \int_0^{1-y} (x^2 + xy) dx dy = \frac{6}{7} \int_0^1 \left(\frac{x^3}{3} + \frac{x^2 y}{2} \right) \Big|_0^{1-y} dy = \frac{6}{7} \int_0^1 \left(\frac{(1-y)^3}{3} + \frac{(1-y)^2 y}{2} \right) dy = \frac{6}{7} \left[\frac{-(1-y)^4}{12} + \frac{1}{4} - \frac{1}{3} + \frac{11}{12} \right] \Big|_0^1 = \boxed{10}$

iii) $P(X \leq \frac{1}{2}) = \frac{6}{7} \int_0^{\frac{1}{2}} \int_0^{1-x} (x^2 + xy) dy dx = \frac{6}{7} \int_0^{\frac{1}{2}} \left(\frac{x^3}{3} + \frac{x^2 y}{2} \right) \Big|_0^{1-x} dx = \frac{6}{7} \int_0^{\frac{1}{2}} \left(\frac{1}{18} + \frac{1}{16} \right) dx = \boxed{17/168}$

b) Marginal Densities of X & Y :

$$f_x(x) = F'_x(x) = \int_0^1 (x^2 + yx) dy = \frac{x^2 + x}{2}$$

$$f_y(y) = F'_y(y) = \int_0^1 (x^2 + yx) dx = \frac{1}{3} + \frac{y}{2}$$

$$69. P(X) = \lambda e^{-\lambda x}; V = \frac{4}{3} \pi R^3; R = \sqrt[3]{\frac{3V}{4\pi}} = \lambda \Rightarrow P(R) = \lambda e^{-\lambda \sqrt[3]{\frac{3V}{4\pi}}} \cdot \frac{d}{dV} \left| \lambda e^{-\lambda \sqrt[3]{\frac{3V}{4\pi}}} \right|$$

$$= \lambda e^{-\lambda \sqrt[3]{\frac{3V}{4\pi}}} \cdot \lambda \left(-\lambda \frac{1}{3} \left(\frac{3V}{4\pi} \right)^{-\frac{2}{3}} \cdot \frac{3}{4\pi} \right) e^{-\lambda \sqrt[3]{\frac{3V}{4\pi}}}$$

"Density Function"

$$70. P(X) = \lambda e^{-\lambda r}; A = \pi r^2; r = \sqrt{\frac{A}{\pi}}$$

$$f(y) = f_x(g^{-1}(y)) \left| \frac{dy}{dy} g^{-1}(y) \right|; f(y) = \lambda e^{-\lambda r} = \lambda e^{-\lambda \sqrt{\frac{A}{\pi}}} \left| \frac{d}{dA} \lambda e^{-\lambda \sqrt{\frac{A}{\pi}}} \right|$$

71. $F = \text{CDF of random variable.}$

V is uniform from $[0,1]$.

Define, $Y = k$ if $F(k-1) < V \leq F(k)$.

$$\int_{k=1}^{k=1} F(k) dk = \int_0^1 P(dX=F(k)) F$$

$$= \lambda e^{-\lambda \sqrt{\frac{A}{\pi}}} \left| -\frac{1}{2} \left(\frac{A}{\pi} \right)^{-\frac{1}{2}} e^{-\lambda \sqrt{\frac{A}{\pi}}} \right|$$

"Density Function"

$m=3$:	X 0 1 2 1 1 0 1 2 1 1
---------	-------------------------------------------

$$72. X_n = (ax_{n-1} + c) \bmod m \quad a) a=1 \quad b) \quad x | 69069 | 2 | 13813 | 944 | \dots$$

Chapter 3: Joint Distributions:

1. Joint Frequency Function:

	X	1	2	3	4	$P_y(y)$
y		0.10	0.05	0.02	0.02	0.19
		0.05	0.20	0.05	0.02	0.32
		0.02	0.05	0.20	0.04	0.31
		0.02	0.02	0.04	0.10	0.18
x		0.19	0.32	0.31	0.18	

Marginal Frequencies

= Joint Frequencies

a) Find the marginal frequency functions of X and Y , i.e. $P(x)$, and $P(y)$.

b) Find the conditional frequency of X given $Y=1$ and Y given $X=1$.

$$P(X|Y=1) = P(X, Y=1) = \frac{0.10}{0.19} = \frac{10}{19}; \quad P(Y|X=1) = \frac{P(Y, X=1)}{P(X)} = \frac{0.10}{0.19} = \frac{10}{19}$$

$$P(1|1) = \frac{10}{19}; \quad P(2|1) = \frac{5}{19}; \quad P(3|1) = \frac{2}{19} \Rightarrow P(4|1) = \frac{2}{19}$$

2. p -black balls n chosen
 q -white balls
 r -red balls

a) Find the joint distribution of black, white and red balls.
 Multinomial Distribution: $P(n_1, n_2, \dots, n_r) = \frac{n!}{n_1! n_2! \dots n_r!} p_1^{n_1} p_2^{n_2} \dots p_r^{n_r}$

b) Joint Distribution of black and white balls.

$$P(\text{red}, \text{white}, \text{black}) = \frac{p}{x} \binom{p}{x} \binom{q}{y} \binom{r}{z}$$

where $n = x + y + z$

Total Selection Options

Sample Size

$$P(\text{black}(X), \text{white}(Y)) = \frac{(x)(y)(n-x-y)}{\binom{p+q+r}{n}}$$

Outcomes
Black + White

$$C) P(Y) = \frac{\binom{q}{y} \binom{p+r}{n-y}}{\binom{p+q+r}{n}}$$

Outcomes, P(WINning)

61. Density of cX when X follows gamma distribution; Gamma Distribution: $g(t) = \frac{\lambda^x}{T(x)} t^{x-1} e^{-\lambda t}$

$$g(cX \leq \lambda) = g(t \leq \frac{\lambda}{c}) = \frac{(\frac{\lambda}{c})^x}{T(x)} t^{x-1} e^{-\lambda t/c}$$

$$\text{Normally Distributed: } p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}}$$

$$= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{E^2/20^2}{2\sigma^2}} = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\frac{1}{2}mv^2)^2/20^2}{2\sigma^2}}$$

$$T(x) = \int_0^\infty u^{x-1} e^{-u} du$$

62. m=mass; V=random velocity; $\mu=0$ and σ . Find the density function of Kinetic Energy: $E = \frac{1}{2}mv^2$

$$f(v) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(v-\mu)^2}{2\sigma^2}}$$

63. Suppose Θ is a uniform distribution; Interval or domain $[-\pi/2, \pi/2]$: Find the cdf and density of $\tan\theta = X$; $\theta = \arctan(X)$; $P(\arctan(-X) \leq \Theta \leq \arctan(X)) = \Phi(\arctan(X)) - \Phi(\arctan(-X))$

64. f_x = "Density Function" and $Y = aX + b$, then.

$$f_y(y) = \frac{1}{|a|} f_x\left(\frac{y-b}{a}\right)$$

$$F_y(y) = P(Y \leq y) = P(aX + b \leq y) = P(X \leq \frac{y-b}{a}) = f_x\left(\frac{y-b}{a}\right) \cdot F(x) = \left|f_x\left(\frac{y-b}{a}\right)\right| \frac{1}{|a|}$$

65. $f(x) = \frac{1+\kappa x}{2}$ from $-1 \leq x \leq 1$ and $-1 \leq \kappa \leq 1$.

$$F_x(x) = \int_{-1}^x \frac{1+\kappa t}{2} dt = \int_{-1}^x \frac{1}{2} + \frac{\kappa t}{2} dt$$

66 $f(x) = \kappa x^{-\kappa-1}$ for $x \geq 1$ and $f(x) = 0$

$$\int_1^\infty \kappa x^{-\kappa-1} dx = \frac{x^{-\kappa}}{(-\kappa)} \Big|_1^\infty = -\frac{1}{\kappa} \Big|_1^\infty = -\frac{1}{\kappa} + \frac{1}{\kappa} = 1 = f(x)$$

$F^{-1}(1) = X$ "Cumulative Distribution Functions are pseudo random number generators"

67. Weibull Cumulative Distribution Function:

$$F(x) = 1 - e^{-\frac{(x/\alpha)^\beta}{\beta}}, x \geq 0, \alpha > 0, \beta > 0$$

a) Find the density function. $p(x) = F'(x) = \frac{d}{dx} \left[\frac{-(x/\alpha)^\beta}{\beta} \right] e^{-\frac{(x/\alpha)^\beta}{\beta}} = \frac{1}{\beta} \alpha^{-\beta} x^{\beta-1} e^{-\frac{(x/\alpha)^\beta}{\beta}}$

b) If Weibull is W , then $X = (W/\alpha)^\beta$ is an exponential

$$W = \alpha^{\frac{1}{\beta}} X^{\frac{1}{\beta}}; \frac{dW}{dx} = \frac{1}{\beta} \alpha^{\frac{1}{\beta}} X^{\frac{1}{\beta}-1}$$

$$F_X(w) = F_X(x \cdot \alpha^{\frac{1}{\beta}}) \cdot \left| \frac{dW}{dx} \right| = \frac{1}{\beta} e^{-w} \cdot \left(\frac{X^{\frac{1}{\beta}}}{\alpha} \right)^{\beta-1} \cdot \frac{1}{\beta} X^{\frac{1}{\beta}-1} = \frac{1}{\beta} e^{-w} = c$$

c). $V = e^{-W}; \ln V = -W; W = -\ln V;$

68. U = Uniform Random Variable. Find $V = U^{-\kappa}$ for $\kappa > 0$

$$P(U^{\frac{1}{\kappa}}) = P(V^{\frac{1}{\kappa}}) \cdot \left| \frac{d}{dy} V^{\frac{1}{\kappa}} \right| = P(V^{\frac{1}{\kappa}}) \cdot \left(\frac{1}{\kappa} \right) \cdot V^{\frac{(1-\kappa)/\kappa}{\kappa}}$$

The rates of decrease for the density function is described as of greater rates.

$$U = V^{\frac{1}{\kappa}}, V = U^{\frac{\kappa}{\kappa}}$$

Proposition B

52. $\mu=70$ and $\sigma=3$ in. a) What proportion of the population is over 6 ft tall?

$$P(Z>2) = \frac{1}{3\sqrt{2\pi}} e^{-(78-70)^2/2\cdot 3^2} = 0.1065 ; \boxed{0.35\% \text{ over the height of 6ft tall.}}$$

$$P(Z>2) = \frac{1}{3\sqrt{2\pi}} \int_{78}^{\infty} e^{-(x-70)^2/18} dx = 0.00038 = \boxed{0.35\%}$$

$$b) \text{ CM: } 70 \text{ in} \times \frac{2.54 \text{ cm}}{1 \text{ inch}} = 175 \text{ cm} ; 3 \text{ in} \times \frac{2.54 \text{ cm}}{1 \text{ inch}} = 7.5 \text{ cm} ; \text{ m3: } 70 \text{ inches} \times \frac{2.54 \text{ in}}{\text{inch}} \times \frac{1 \text{ m}}{100 \text{ cm}} = 1.75 \text{ m} ; 7.5 \text{ in} \times \frac{1 \text{ m}}{100 \text{ cm}} = 0.075 \text{ m}$$

53. $\mu=5$, and $\sigma=10$. a) Find $P(X>10) = \frac{1}{10\sqrt{2\pi}} \int_{10}^{\infty} e^{-(x-5)^2/2\cdot 10^2} dx = 0.3085 = \boxed{30.85\%}$

Z-table:

$$\frac{10-5}{10} = \frac{1}{2} = Z(30.85\%)$$

b) Find $P(-20 < X < 15) = \frac{1}{10\sqrt{2\pi}} \int_{-20}^{15} e^{-(x-5)^2/2\cdot 10^2} dx = 0.8351 = \boxed{83.51\%} (Z(\frac{15-5}{10}) - Z(\frac{-20-5}{10}))$

$$Z(0.9938) - Z(0.8413) = \boxed{84.75\%}$$

54. $X \sim N(0, \sigma^2)$; $Y=|X|$

$$= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-x^2/2\sigma^2} dx = \frac{\sqrt{\pi \cdot 2\sigma^2}}{2\sigma\sqrt{2\pi}} = \boxed{}$$

55. $X \sim N(\mu, \sigma^2)$ find c in terms of σ , such that, $P(\mu-c \leq X \leq \mu+c) = 0.95$

$$0.95 = \frac{1}{\sigma\sqrt{2\pi}} \int_{\mu-c}^{\mu+c} e^{-(x-\mu)^2/2\sigma^2} dx ; \int_{\mu-c}^{\mu+c} e^{-ax^2} dx = \sqrt{\frac{\pi}{a}} ; \boxed{c \approx 1.95996\sigma}$$

56. $X \sim N(\mu, \sigma^2)$; $P(|X-\mu| \leq 0.675\sigma) = 0.5 = 0.5 - \frac{1}{0.675\sqrt{2\pi}} \int_{0}^{0.675\sigma} e^{-x^2/2\sigma^2} dx = \boxed{0.5}$

57. $X \sim N(\mu, \sigma^2)$; $Y=aX+b$, where $a < 0$, show $Y \sim N(a\mu+b, a^2\sigma^2)$

$$P(Y) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(y-a\mu)^2/2\sigma^2} dy = P\left(\frac{y-b}{a}\right) = \frac{1}{a\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y-b-a\mu}{a\sigma}\right)^2} = \frac{1}{a\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{y-a\mu+b}{a\sigma}\right)^2\right]$$

$$\boxed{Y \sim N(a\mu+b, a^2\sigma^2)}$$

58. $Y = e^Z$, where $Z \sim N(\mu, \sigma^2)$; Lognormal Density

$$Y = e^Z = e^{N(\mu, \sigma^2)} ; \log Y = N(\mu, \sigma^2) = 1.5 \boxed{Y = e^Z}$$

59. $U[-1, 1]$; Find density function of U^2 ; $F_U = P(-\sqrt{x} \leq z \leq \sqrt{x})$

$$= \Phi(\sqrt{x}) - \Phi(-\sqrt{x})$$

$$= \frac{1}{2} \int_{-\sqrt{x}}^{\sqrt{x}} \phi(z) dz + \frac{1}{2} \int_{-\sqrt{x}}^{\sqrt{x}} \phi(-z) dz$$

$$= \int_{-\sqrt{x}}^{\sqrt{x}} \phi(z) dz ; f_U(x) = \frac{x^{-1/2} e^{-x/2}}{\sqrt{2\pi}}$$

$$F_U = P(X^2 \leq z \leq x^2) = \phi(x^2) + \phi(0)$$

$$= 2x \phi(x^2) ; f(x) = 2x e^{-x^2/2}$$

$$\boxed{\frac{2x e^{-x^2/2}}{\sqrt{2\pi}}}$$

$\lambda e^{-\lambda t} = e^{-\lambda t}$

45. Exponential Distribution: $p(x) = \lambda e^{-\lambda x}$; $\lambda = 0.1$ a) Probability lifetime < 10 years.

b) $\frac{e^{-t/10}}{10} - \frac{e^{-0}}{10}$ c) $0.01 = \frac{e^{-t/10}}{10}$; $-1 = -\frac{t}{10}$; $t = 10$

$P(\text{lifetime}) + P(\text{death}) = P(\text{lifetime}) + \frac{e^{-10}}{10} = 1$

$$P(\text{lifetime}) = 1 - \frac{e^{-1}}{10}$$

46. Gamma Density: $g(t) = \frac{\lambda^x}{T(x)} t^{x-1} e^{-\lambda t}$, $t \geq 0$

where $T(x) = \int_0^\infty u^{x-1} e^{-u} du$; $x > 0$

$$\int_0^\infty g(t) dt = \int_0^\infty \frac{\lambda^x t^{x-1} e^{-\lambda t}}{T(x)} dt = \frac{\lambda^x}{T(x)} \int_0^\infty t^{x-1} e^{-\lambda t} dt; t = x/\lambda; -\frac{\lambda^x}{T(x)} \int_0^\infty (\frac{x}{\lambda})^{x-1} e^{-\frac{x}{\lambda}} \frac{dx}{\lambda}$$

$$= \frac{1}{T(x)} \int_0^\infty x^{x-1} e^{-x} dx = \frac{T(x+1)}{T(x) \lambda} = \frac{x T(x)}{T(x) \lambda} = \left[\frac{x}{\lambda} \right]; \lambda = 1 \text{ and } x = 1.$$

47. $x > 1$, Show maximum of Gamma Density: $(x-1)/\lambda$; $\frac{d}{dt} g(t) = 0$

$$= \frac{\lambda^x}{T(x)} [(x-1)t^{x-2} - \lambda t^{x-1}] e^{-\lambda t} = 0; (x-1)t^{x-2} = \lambda t^{x-1}; \frac{(x-1)}{\lambda} = t = t$$

48. T is an exponential Random variable: $p(x) = \lambda e^{-\lambda x}$, and $P(T < 1) = 0.05$.

What is λ ? $0.05 = \lambda e^{-\lambda} = \lambda (1 - \lambda + \frac{\lambda^2}{2!} - \dots) = \lambda - \lambda^2 + \frac{\lambda^3}{2!}$; $\lambda = 0.0527$

49. a) $T(1) = 1$; Gamma Density: $g(t) = \frac{\lambda^x}{T(x)} t^{x-1} e^{-\lambda t}$ "Third order Quadrant"

Gamma Function: $T(x) = \int_0^\infty u^{x-1} e^{-u} du$; $T(1) = \int_0^\infty u^{1-1} e^{-u} du = \int_0^\infty e^{-u} du = [-e^{-u}]_0^\infty = [0 - (-1)] = 1$

b) $T(x+1) = xT(x)$; $T(x+1) = \int_0^\infty u^{x-1} e^{-u} du$; Integration by Parts: $= -u e^{-u} \Big|_0^\infty + \int_0^\infty (x) u^{x-1} e^{-u} du = xT(x)$

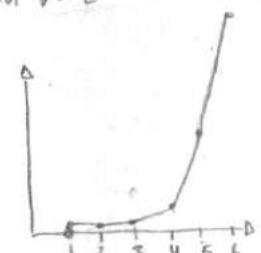
$u = u^x$
 $du = (x)u^{x-1} du$
 $dv = e^{-u}$
 $v = -e^{-u}$

c) Conclude $T(n) = (n-1)!$; $n = 1, 2, 3, \dots$

Table:

n	$T(n)$	$(n-1)!$
1	0.9	0
2	1	1
3	2	2
4	6	6
5	24	24
6	120	120

Graph:



51. Normal Distribution

$$p(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Standard Normal: $\mu = 0, \sigma = 1$

$$p(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

50. $T(x) = 2 \int_0^\infty t^{2x-1} e^{-t^2} dt = \int_{-\infty}^\infty e^{xt} e^{-t^2} dt$

$$= \int_{-\infty}^\infty t^{2x-1} e^{-t^2} dt = \int_{-\infty}^\infty (e^{tx})^{2x-1} e^{-t^2} dt$$

$$= \int_{-\infty}^\infty e^{2xt} - t^{2x-2} dt = \int_{-\infty}^\infty e^{2xt} dt - \int_{-\infty}^\infty t^{2x-2} dt$$

$$= \int_{-\infty}^\infty e^{2xt} dt = \int_{-\infty}^\infty e^{2x} e^{-t^2} dt$$

$$= e^{2x} \int_{-\infty}^\infty e^{-t^2} dt = e^{2x} \cdot \frac{\sqrt{\pi}}{2}$$

$$2 \int_{-\infty}^\infty e^{-x^2/2} dx = 2 \sqrt{\frac{\pi}{2}} = \sqrt{2\pi}$$

$$\int_{-\infty}^\infty e^{-x^2/2} dx \cdot \int_{-\infty}^\infty e^{-y^2/2} dy = 2\pi$$

$$\int_{-\infty}^\infty \int_{-\infty}^\infty e^{-(x^2+y^2)/2} dx dy = \int_0^\infty r e^{-r^2/2} dr$$

39. Cauchy Cumulative Distribution:

$$F(x) = \frac{1}{2} + \frac{1}{\pi} \tan^{-1}(x), -\infty < x < \infty$$

a. Cumulative Distribution Requirements: $\lim_{x \rightarrow -\infty} F(x) = 0$; $\lim_{x \rightarrow \infty} F(x) = 1$.

$$\lim_{x \rightarrow -\infty} F(x) = \lim_{x \rightarrow -\infty} \frac{1}{2} + \frac{1}{\pi} \tan^{-1}(x) = \frac{1}{2} - \frac{1}{2} = 0; \lim_{x \rightarrow \infty} \frac{1}{2} + \frac{1}{\pi} \tan^{-1}(x) = \frac{1}{2} + \frac{1}{2} = 1$$

b. $f(x) = F'(x) = \frac{d}{dx} \left[\frac{1}{\pi} \tan^{-1}\left(\frac{x}{1}\right) \right] = \frac{1}{(1+x^2)\pi}$

c. $P(X > x) = 0.1$; $0.1 \cdot \frac{1}{\pi} (1+x^2) \pi x = 1$

$$(1+x^2) = \frac{10}{\pi}$$

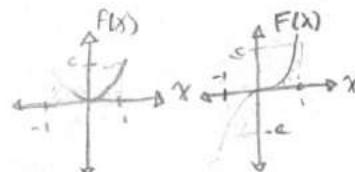
$$x^2 = \frac{10-\pi}{\pi}$$

$$x = \sqrt{\frac{10-\pi}{\pi}}$$

40. $f(x) = cx^2$ for $0 \leq x \leq 1$ and $f(x) = 0$ otherwise

a) $f(1) = c$; $f(0) = 0$; $C = f(0) + f(1) = 4f(x)$

b) $F(x) = \frac{cx^3}{3}$ c) $P(0.1 \leq X < 0.5) = \frac{[F(0.5) - F(0.1)] / (0.5 - 0.1)}{F(1) - F(0) / (1-0)} = \frac{[c(\frac{1}{4}) - c(\frac{1}{8})]}{c} / 0.4$



41. Find the upper and lower quantiles

at an exponential distribution.

Exponential Distribution: $f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$

Lower quantile: $P(X) = \frac{1}{4} = \lambda e^{-\lambda x} \Rightarrow -\lambda x = -\ln 4 \lambda \Rightarrow x = -\frac{\ln 4 \lambda}{\lambda}$

$$x = \frac{-\ln 4 \lambda}{\lambda}$$

42.

Event: $(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4)$

$$P(X) = \sqrt{\left(\frac{x_2-x_1}{x_2!} - \frac{x_1-x_2}{x_1!}\right)^2 + (y_2-y_1)^2}$$

$$f(x) = 2\pi\lambda x e^{-\pi\lambda x^2}$$

Upper quantile: $P(X) = \frac{3}{4} = \lambda e^{-\lambda x} \Rightarrow x = \log\left(\frac{4}{3}\right)/\lambda$

$$x = \log\left(\frac{4}{3}\right)/\lambda$$

43.

Event: $(x_1, y_1, z_1), (x_2, y_2, z_2)$

$$f(x) = \frac{d}{dx} e^{-4\pi x^3/3} = 4\pi x^2 e^{-4\pi x^3/3}$$

Multivariate Poisson Distribution:

$$P(X) = \exp(-\sum_{i=1}^m \theta_i) \prod_{i=1}^m \frac{\theta_i^{x_i}}{x_i!} \sum_{k=0}^{\infty} \prod_{i=1}^m \binom{x_i}{k} \frac{\theta_i^k}{k!} \left(\frac{\theta_i}{\pi}\right)^{x_i}$$

44. T: Exponential Random Variable with λ , $T = \lambda e^{-\lambda X}$

$$k = \lambda e^{-\lambda X}; k+1 = \lambda e^{-\lambda X}$$

$$x = \log\left(\frac{k}{T}\right)/\lambda$$

$$P(X) = \lambda e^{-\lambda X}$$

X: Discrete Random variable; $X = k$; $k < T < k+1$

for $k = 0, 1, \dots$

30. Poisson Frequency Function : $p(k) = \frac{\lambda^k \exp(-\lambda)}{k!}$; $p'(k) = \frac{k \cdot \lambda^{k-1} (-\lambda) \exp(-\lambda)}{k!} = 0$

Sources rate ratio: $\frac{P(X=k+1)}{P(X=k)} = \frac{\lambda^{k+1} \exp(-\lambda) / (k+1)!}{\lambda^k \exp(-\lambda) / k!}$

$$\begin{aligned} &= \lambda / (k+1) \\ &\lambda = 1 \\ &\boxed{\lambda = 1} \end{aligned}$$

$$= \lambda / (k+1)$$

"Not logical because mass at Poisson changes basis n changes."

There are maximum and minimum to that
Probability Decreases

Problem set. $\lambda < 1$, $\lambda > 1$ (int), $\lambda > 1$ (Rational) $\lambda = np = 1$

31. $\lambda = 2$ per hour a) 10-min shower; $p(\text{phone rings}) = \frac{2^6 \exp(-2)}{6!} = 0.27$

$$\text{b) } p(\text{phone rings}) = 0.5 = \frac{2^0 e^{-2}}{0!} = e^{-2}; \frac{2^0}{0!} \approx 0.693$$

Fractions and Factorial approx to one

32. $\lambda = 0.33$ per month

$$\text{a) } k=0; p(0) = \frac{(1/3)^0 \exp(-1/3)}{0!} = \exp(-1/3) = 0.716$$

$$\text{Time} = \frac{60 \text{ min}}{2 \text{ phone calls}} = 0.693$$

$$k=1; p(1) = \frac{(1/3)^1 \exp(-1/3)}{1!} = 0.239$$

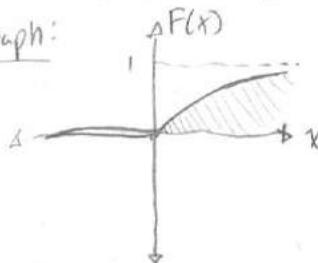
$$= 20.79 \text{ min}$$

$$k=2; p(2) = \frac{(1/3)^2 \exp(-1/3)}{2!} = 0.004$$

The most probable number of suicides would be at $k=0$
because $\lambda < 1$ and demonstrates a decreasing probability.

33. $F(x) = 1 - \exp(-\alpha x^\beta)$ for $x \geq 0, \alpha > 0, \beta > 0$, $F(x) = 0$ for $x < 0$.

Graph:



$$P(x) = \frac{d}{dx} F(x) = \alpha \beta x^{\beta-1} \exp(-\alpha x^\beta)$$

Cumulative Density Function

$$\lim_{x \rightarrow -\infty} F(x) = 0; \lim_{x \rightarrow +\infty} F(x) = 1$$

34. $f(x) = (1 + \alpha x)/2$ for $-1 \leq x \leq 1$ and $f(x) = 0$

Probability Density Function Requirements

$$P(X=x_i) = p(x_i); \sum p(x_i) = 1$$

$$F(x) = \int_{-1}^x (1 + \alpha x)/2 dx = \frac{x}{2} + \frac{\alpha x^2}{4} \Big|_{-1}^1 = \frac{1}{2} + \frac{1}{2} + \frac{\alpha \cdot 1^2}{4} - \frac{\alpha \cdot (-1)^2}{4} = 1$$

$$F(x) = \frac{x}{2} + \frac{\alpha x^2}{4}$$

$$P(x) = \begin{cases} 1 & -1 \leq x \leq 0 \\ 2 & 0 < x < 1 \end{cases}$$

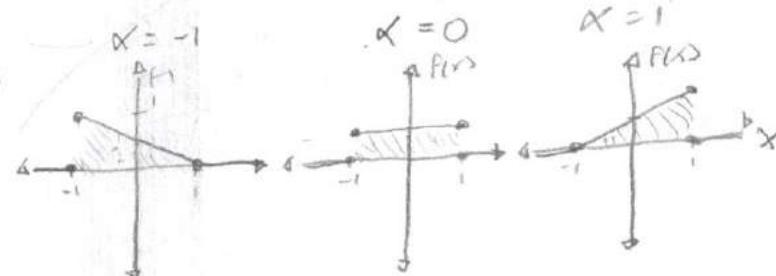
$$F(x) = \int_{-1}^0 1 dx + \int_0^1 2 dx = 1$$

36. U is uniform $[0, 1]$. 37. $P(X \leq 1/3) = \frac{1}{3}$

$$X = [n]U, \text{ where } [t]$$

$$P(X \geq 2/3) = \frac{1}{3}$$

Probability Mass Function



Probability Mass Function

$$F(x) = \int_{-1}^0 1 dx + \int_0^1 2 dx = 1$$

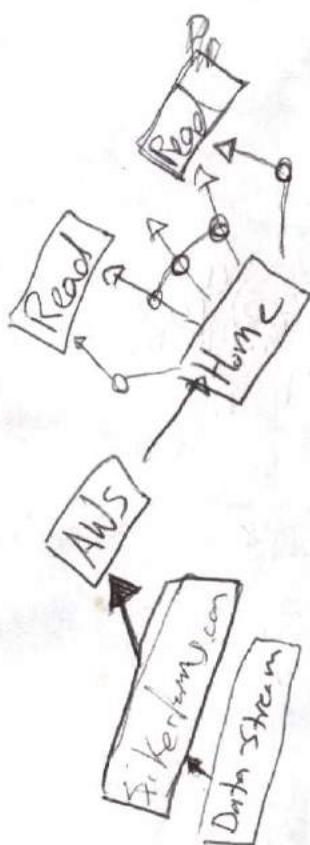
$$1 - 2x = 1$$

38. $Kf + (1-K)g \quad \sum P(x) = 1 = Kf + (1-K)g$
while $0 \leq K \leq 1$

$$\max_{\frac{d}{dx} Kf + (1-K)g = f - g$$

$$F(x) = \frac{x^2}{2} + (K - \frac{x^2}{2})$$

- Randomize Router [IP] ✓
- Randomize Mac Address ✓
- Randomize external IP. ✓
- VPN through AWS
- Tor for browsing
↳ IP Scan - ping
- Tor guard -



27. $P(\text{Disease}) = \frac{1}{10,000}$; $n = 100,000$ people

$R=0$ cases: Poisson Distribution

$$P(k) = \frac{\lambda^k e^{-\lambda}}{k!}; P(0) = \frac{\lambda^0 e^{-\lambda}}{0!} = 4.54 \times 10^{-10}$$

$R=1$ cases: $P(1) = \frac{\lambda^1 e^{-\lambda}}{1!} = \frac{(10)^1 e^{-10}}{1!} = 4.54 \times 10^{-4}$

$R=2$ cases: $P(2) = \frac{\lambda^2 e^{-\lambda}}{2!} = \frac{(10)^2 e^{-10}}{2!} = 2.26 \times 10^{-2}$

28. $CDF = F(k) = p_0, p_1, \dots, p_n$; n , and $p. q = 1-p$

Prove the binomial probability by $p_0 = q^n$.

$$p_k = \frac{(n-k+1)p}{kq} p_{k-1}; k = 1, 2, \dots, n.$$

$$\boxed{p_0 = (1-p)^n; p_1 = n \frac{p}{(n-1)(1-p)} (1-p)^{n-1}; p_2 = \frac{(n-1)p}{(n-2)(1-p)} p_1 = \frac{(n-1)p^2}{2!(1-p)(1-p)} (1-p)^{n-2}}$$

$$\boxed{= n(p(1-p))^{n-1} p_0 = \frac{1}{2} (n-1)p^2 (1-p)^{n-2}}$$

Recursive Binomial Distribution: $\frac{n}{k} p(1-p)^{n-1}$

$$= \prod \frac{(n-k+1)p}{k} (1-p)^{n-k}$$

$P(X \leq 4)$ for $n = 9000$ and $p = 0.0005$

$$= \frac{(9000-3)(9000-2)(9000-1)(9000)}{4!} (0.0005)^4 (1-0.0005)^{8996} = 1.89 \times 10^{-1} \approx 0.00$$

As a Poisson

$$n = 9000; p = 0.0005; np = 9/2$$

$$P(4) = \frac{(9/2)^4}{4!} e^{-9/2} = 1.89 \times 10^{-1}$$

$$p_k = \frac{\lambda^k}{k!} p_{k-1}; k = 1, 2, \dots$$

$$p_0 = \exp(-\lambda); p_1 = \lambda \cdot p_0 = \lambda \exp(-\lambda); p_2 = \frac{\lambda^2}{2} \exp(-\lambda); p_k = \frac{\lambda^k}{k!} \exp(-\lambda)$$

$$P(X \leq 4); \lambda = 4.5; p_k = \frac{(4.5)^k}{k!} \exp(-4.5) = 1.89 \times 10^{-1}$$

(20) Minimum Trials: $n+1$ Maximum Trials: $2n+1$

$$P(\text{Left}) = \frac{1}{2} \quad P(\text{Right}) = 1 - p = \frac{1}{2}$$

$$P(\text{K in other box}) = \binom{n+1}{n+1} p^{n+1} q^0 + \binom{n+1}{n+1} p^0 q^{n+1} = p^{n+1} + q^{n+1} = 2\left(\frac{1}{2}\right)^{n+1} = \left(\frac{1}{2}\right)^{n+2}$$

$$P(\text{K-1 in other box}) = \binom{n+1}{n} p^n q^1 + \binom{n+1}{n} p^0 q^n = 2\left(\frac{n+1}{n}\right)\left(\frac{1}{2}\right)^n = \left(\frac{n+1}{n}\right)\left(\frac{1}{2}\right)^{n+1}$$

21. X : Geometric Random Variable

$$P(X > n+k-1 | X > n-1) = P(X > k) = \left(\frac{n+1}{n}\right)\left(\frac{1}{2}\right)^{n+1}$$

$$P(\text{Hypergeometric Function}) = \frac{\binom{r}{k} \binom{n-r}{m-k}}{\binom{n}{m}}$$

22. X : Geometric random variable

$$P = 0.5 ; P(X \leq k) \approx 0.99 = 1 - (1-p)^k$$

$$(0.5)^k \approx 0.01 \quad | \quad k \log(0.5) \approx \log(0.01) ; k = 6.6435 \quad | \quad k = 7.$$

$$P(X > n+k-1 | X > n-1) = P(X > k) = \left(\frac{n+1}{n}\right)\left(\frac{1}{2}\right)^{n+1}$$

$$= P(X + t - n > k | X + 1 > n) P(k = n - r) = \binom{n+r}{n} \left(\frac{1}{2}\right)^{n+r}$$

$$= P(X - n > k | X - n > 0) P = \binom{n+n-k}{n} \left(\frac{1}{2}\right)^{n+n-k}$$

$$= P(X > K | X > 0) = P(X > k).$$

23. $p(\text{success})$; r successes before k th failure; Binomial

$$p(k) = \binom{k+r-1}{r} p^r (1-p)^{k+r-1}$$

Total Number of trials $\approx (k+r)$

Last trial probability $\approx (1-p)$

Binomial: $\binom{k+r-1}{r-1} p^r (1-p)^{k-1}$

$$p(\text{success}) = \binom{k+r-1}{k-1} p^r (1-p)^{k-1}$$

$$= \binom{k+r-1}{k-1} p^r (1-p)^k$$

24. $H=2$; $P(\text{Same}) = P(HHH) + P(TTT) = \frac{1}{8} + \frac{1}{8} = \frac{1}{4}$

$$P(K) = \sum_{k=1}^{\infty} (0.75)^{k-1} (0.25)^{n-k} = (0.75) \frac{(1+0.75)^{n-1}}{1-0.75} = (0.75) \frac{(1+0.75)^{n-1}}{0.25} = 3(0.75)^{n-1}$$

$$P(X > 3) = 1 - P(X \leq 3) = 1 - \{P(X=1) + P(X=2) + P(X=3)\} = 1 - \{(0.75)(0.25) + (0.75)^2(0.25) + (0.75)^3(0.25)\} = 1 - \{0.25 + 0.1975 + 0.140625\} \approx 0.4219$$

25. $P(\text{Royal Straight Flush}) = 1.3 \times 10^{-8}$

$n = 100$ hands/week; $52 \text{ weeks/year} ; 20 \text{ years} = 1.04 \times 10^5$

$$\lambda = n \cdot p = 1.04 \times 10^5 \cdot 1.3 \times 10^{-8} = 1.35 \times 10^{-3}$$

$$P(K) = \frac{\lambda^K e^{-\lambda}}{K!} \Rightarrow P(0) = \frac{\lambda^0 e^{-\lambda}}{0!} = e^{-1.35 \times 10^{-3}} = 9.986 \times 10^{-1}$$

- ① State Space
- ② Frequency Function
- ③ $1 - p(1)p(2)p(3)$

b). $Z = \prod_{i=1}^n p(1-p)^{n-i} = P(Z) = \frac{\lambda^Z e^{-\lambda}}{Z!} = \frac{(1.35 \times 10^{-3})^2 e^{-1.35 \times 10^{-3}}}{2!} = 9.10 \times 10^{-7}$

26. $\frac{1}{10,000}$ chance of being trapped. $n = 5 \text{ days} \cdot 52 \text{ weeks} \cdot \frac{1}{4} \text{ year} = 1,300$; $\lambda = np = \frac{13}{50}$

$$P(0) = \frac{\lambda^0 e^{-\lambda}}{0!} = e^{-13/50} = 7.71 \times 10^{-1} ; P(1) = \frac{(13)}{50} e^{-13/50} = 2.0 \times 10^{-1} ; P(2) = 0.026$$

10. Player A: $p_1 = P(\text{success})$; Player B: $p_2 = P(\text{success})$ a) $P(X) \neq \text{Even}$ & $P(X) = (1-p_1)^{\frac{k-1}{2}} \cdot (1-p_2)^{\frac{k-1}{2}} \cdot p_1^k$

$$b. P(\text{Player A Wins}) = \frac{p_1}{1-(1-p_1)(1-p_2)} = p_1 \cdot \boxed{[(1-p_1)(1-p_2)]^k} \quad \text{odd: } p(X) = (1-p_1)^{\frac{k+1}{2}} \cdot (1-p_2)^{\frac{k+1}{2}} \cdot p_1^k$$

11. Binomial Distribution: $P(X) = \sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k}$; Mode $\hat{x} = p'(X) = 0 = k p^{k-1} (1-p)^{n-k} + (n-k) p^k (1-p)^{n-k-1}$

$$\begin{aligned} 12. \text{Prove } P(X) &= \sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} = 1 \\ &= \binom{1}{0} p^0 (1-p)^1 + \binom{1}{1} p^1 (1-p)^0 \\ &\vdash (1-p) - p = 1 \end{aligned}$$

13. 20 items [4-chances] - Elimination of one, remainder of three
- Passing is 12 or more, correct.

$$a. P(\text{Pass}) = \frac{P(\text{correct})}{\text{Total Outcomes}} = \frac{\binom{1}{20}}{\binom{7}{20}} = \frac{1}{3 \cdot 20} = \boxed{\frac{1}{60}}$$

$$b. P(\text{Pass}) = \frac{P(\text{correct})}{\text{Total Outcomes}} = \frac{3}{\binom{7}{20}} = \frac{1}{2 \cdot 20} = \boxed{\frac{1}{40}}$$

$$\frac{1}{p} + \left(\frac{n}{k}\right) - 2 = 0$$

$$\left(\frac{1}{p}\right) - 2 = \left(\frac{n}{k}\right) + 2$$

$$\frac{1-2p}{p} = \frac{n-k}{k}$$

$$P = \frac{k}{n} = \frac{p}{1-2p}$$

14.  $P(\text{change}) = 0.05$; Mutually Independent.

$$P(\text{change} | 7 \text{ bits}) = \prod_{i=1}^7 p(\text{change}_i) = p(\text{change})^7 = \boxed{0.05^7}$$

$$P(\text{change} | 4 \text{ bits}) = \prod_{i=1}^4 p(\text{change}_i) = p(\text{change})^4 = \boxed{0.05^4}$$

$$P(\text{correct}) = \frac{1 - P(\text{change})}{1 - 0.05^7}$$

15. $P(\text{Winning Game A}) = 0.4$; Better advantage of 3 or 5 games
or 4 or 7 games. 0.6

$$P(3 \text{ or } 5) = \prod_{i=1}^3 p(\text{winning game}_i) = (0.4)^3; P(4 \text{ or } 7) = \prod_{i=1}^4 p(\text{winning game}_i) = (0.4)^4$$

16. $n \rightarrow \infty$ and $r/n \rightarrow p$ and $m = \text{constant}$. Hypergeometric Function: $P(X=k) = \frac{\binom{r}{k} \binom{n-r}{m-k}}{\binom{n}{m}}$

$$\lim_{n \rightarrow \infty} \lim_{r/n \rightarrow p} P(X=k) = \lim_{n \rightarrow \infty} \lim_{r/n \rightarrow p} \frac{\frac{r!}{k!(r-k)!} \frac{(n-r)!}{(m-k)!(n-r-m+k)!}}{\frac{n!}{m!(n-m)!}} = \frac{(m) \left[r(r-1)\dots(r-k+1) \right] \left[(n-r)\dots(n-r-m+k+1) \right]}{\left[n(n-1)\dots(n-m+1) \right]} \binom{n}{m}$$

$$= \binom{m}{k} \left(\frac{1}{q} \right)^k \left(\frac{q-1}{q} \right)^{m-k}; \text{ where } q = \frac{1}{p} = \frac{n}{r}$$

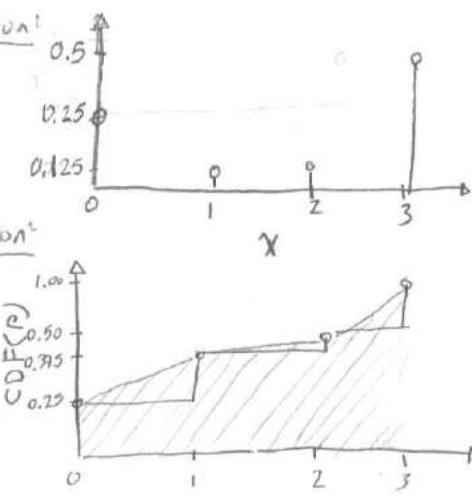
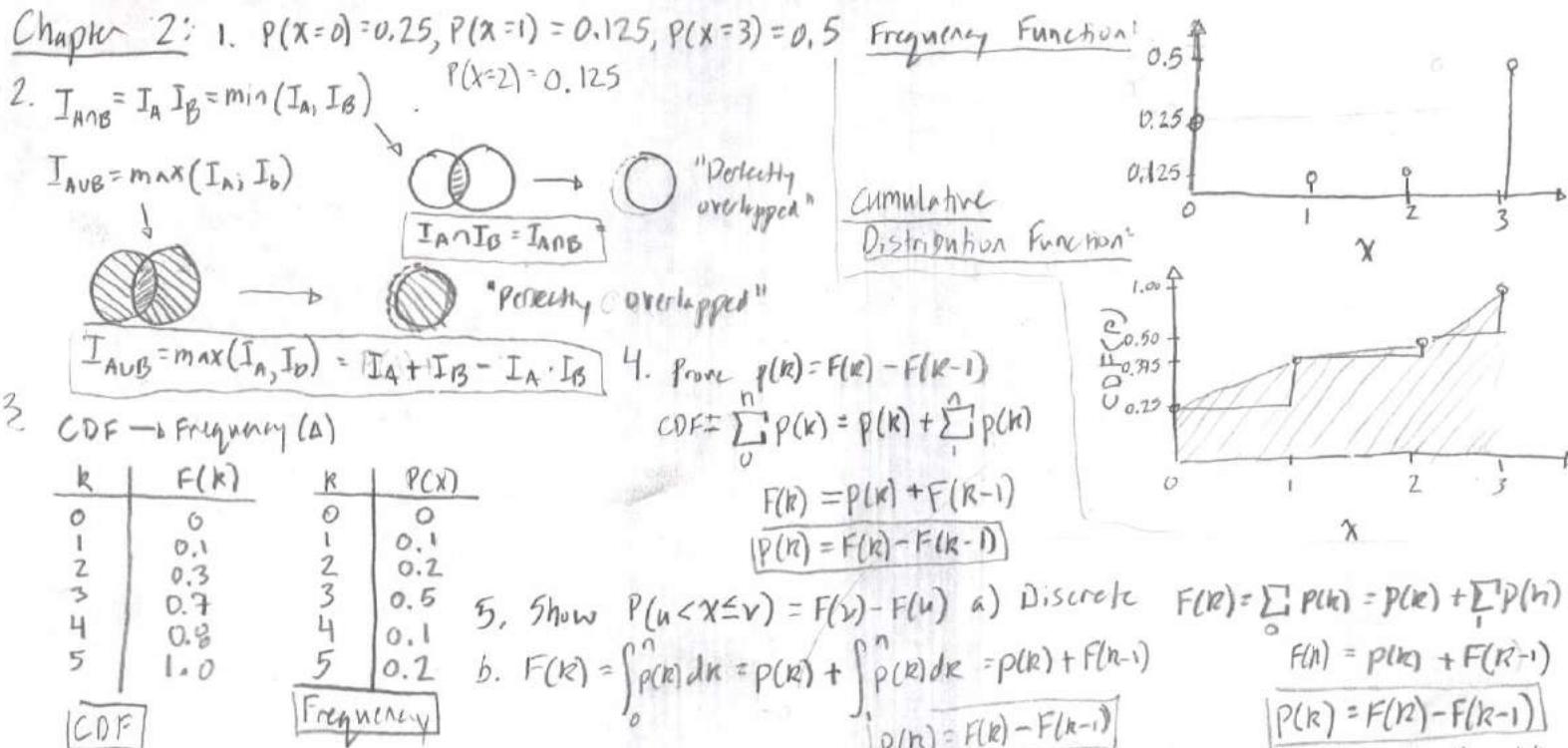
$$\vdash \binom{m}{k} p^k (1-p)^{m-k}$$

17. Bernoulli Trials; $p(\text{success}) = p$; Failures in first round are counted.

$$\text{Frequency Function: } P(\text{Failure}) = p \prod_{i=0}^n (1-p)^i$$

18. Frequency Function $P(\text{Failure}) = p \prod_{i=0}^n (1-p)^i = p(1-p)^n$

19. CDF $\sum_{x=0}^{\infty} P(X=x) = 1$; $P(\{t \leq X \leq t+1\}) = \text{CDF}_{t+1} - \text{CDF}_t$



b) the number of Heads following first tails

c) (the number of heads) - (number of tails)

② Frequency Function

X	0	1	2	3	4
$n(x)$	1	1	2	4	0
$P(x) = \frac{n(x)}{16}$	$\frac{1}{16}$	$\frac{1}{16}$	$\frac{1}{8}$	$\frac{1}{4}$	$\frac{1}{2}$
$F(x)$	$\frac{1}{16}$	$\frac{2}{16}$	$\frac{4}{16}$	$\frac{8}{16}$	$\frac{16}{16}$

d) Frequency Function = (c)

7. Bernoulli Random Variable: $P(1) = p$; $P(0) = 1-p$; $P(X) = \begin{cases} p^x (1-p)^{1-x}; & x=0 \text{ or } x=1 \\ 0 & \text{otherwise.} \end{cases}$

CDF of Bernoulli Random Variable: $F(x) = \sum_{k=0}^{x+1} P(k) = \sum_0^x P(0) + \sum_0^y P(1) + \sum_0^z P(2)$

$$8. P(9 \text{ Heads in 10 Tosses}) = \frac{\text{chance}}{\text{outcomes}} = \frac{10}{2^{10}} = \frac{10}{1024} = \frac{5}{512} \quad = \sum_0^x P + \sum_0^y 1-P + \sum_0^z 0 = \left| \sum_0^x P + \sum_0^y 1-P \right|$$

$$P(10 \text{ Heads in 20 Tosses}) = \frac{\binom{20}{10}}{2^{20}} = \frac{105}{1048576} = \frac{1}{524288}$$

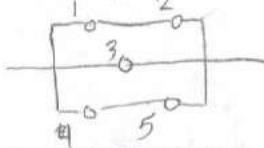
$$9. n=3sp = \sum_0^3 \binom{n}{k} p^k (1-p)^{n-k} = \binom{3}{0} p^0 (1-p)^3 + \binom{3}{1} p^1 (1-p)^2 + \binom{3}{2} p^2 (1-p)^1 + \binom{3}{3} p^3 (1-p)^0 = (1-p)^3 + 3p(1-p)^2 + 3p^2(1-p)^1 + 6p^3 = 1; p = \frac{n}{m} = \frac{3}{10}$$

$$n=3; p = \sum_0^3 \binom{3}{k} p^k (1-p)^{3-k} = \binom{3}{0} p^0 (1-p)^3 + \binom{3}{1} p^1 (1-p)^2 + \binom{3}{2} p^2 (1-p)^1 + \binom{3}{3} p^3 (1-p)^0 = (1-p)^3 + 3p(1-p)^2 + 3p^2(1-p)^1 + 6p^3 > 1-p$$

$$p < 0.5$$

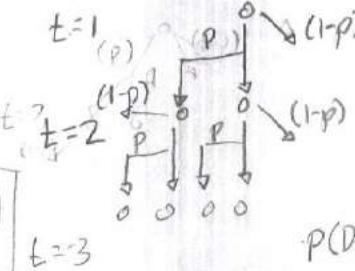
73. n independent units, each with probability p of failure; $P(F) = \text{System failure}$. $P(\text{System}) = (1-p)^n$; $P(\text{Fail}) = \text{System failure} = 1 - (1-p)^n$

74. Probability of failure



$$P(F) = P(A_1 \cap A_2) + P(A_3) + P(A_4 \cap A_4) \\ + P(A_1 \cap A_2 \cap A_3 \cap A_4 \cap A_5)$$

$$= p + 2p^2 - p^5$$



$$0.5 = -3p + 2p^2$$

$$2p^2 - 3p - 0.5 = 0$$

$$p_1 = 1.65 \Rightarrow p_2 = -6.15$$

$$= 1 - (1-p)^5$$

$$P(\text{Dead}) = 1 - (1-p)^3 = 1 - a^3 - 3a^2b + 3ab^2 - b^3 = 1 - (a-b)^3 \\ = 1 - 1 - 3p + 3p^2 - p^3 = -3p + 2p^2$$

$$76. -o-n-a-n-o \quad p(\text{Success}) = (1-p_1 p_2)^n \quad ; \quad p(\text{Success}) = (1-0.05^2)^{10} = 0.9975 = 99.75\%$$

$$77. 5\% = P(\text{Bulls-Eye}) \quad 0.5 = (1-0.05)^n \quad ; \quad \log \frac{1}{2} = n \log(1-0.05) \quad ; \quad n = 13.51$$

$$78. \text{Pairs of (A or a); AA, Aa, aa, or (Aa or aA). a) Parent \#1: AA; Parent \#2: Aa; Offspring: AA, AA, Aa, Aa} \\ \text{b) AA (p); Aa (2q); aa (r); } 1 = (p+2q+r)^n \quad ; \quad n=2 \quad ; \quad 1 = (p+2q+r)^2 \quad ; \quad n=3 \quad ; \quad 1 = (p+2q+r)^3 \\ \text{c) } 1 = (V+V+W)^4 \quad ; \quad 1 = (V+V+W)^3$$

Hardy-Weinberg Law

$$79. \text{a. } aa = \text{deaf}; \quad Aa = \text{carrier, alive}, \quad AA = \text{not carrier, not deaf}. \quad AA \times AA = AA + 2Aa + aa \\ \text{b. } P(\text{Not Deaf} \cap \text{Carrier}) = 50\%$$

$$AA \times AA = AA + 2Aa + aa$$

$$AA(25\%) ; Aa(50\%) ; aa(25\%)$$

		Genotypes of Parents			
		AA-AA	AA-Aa	Aa-AA	Aa-Aa
P(Offspring)	AA	$\frac{1}{3}(1-p)$	$\frac{1}{2}\left(\frac{1}{3}\right)p$	$\frac{1}{2}\left(\frac{2}{3}\right)(1-p)$	$\frac{1}{4}\times\frac{2}{3}\times p$
	Aa	0	$\frac{1}{2}\left(\frac{1}{3}\right)\times p$	$\frac{1}{2}\left(\frac{2}{3}\right)(1-p)$	$\frac{1}{2}\times\frac{2}{3}\times p$
AA	0	0	0	$\frac{1}{4}\times\frac{2}{3}\times p$	

$$P(AA) = \frac{1}{3}(1-p) + \frac{1}{2}\left(\frac{1}{3}\right)p + \frac{1}{2}\left(\frac{2}{3}\right)(1-p) + \frac{p}{6}(1-p) = \frac{1}{2}$$

$$P(Aa) = \frac{2}{3} - \frac{p}{3}$$

$$P(Aa) = \frac{p}{6} + \frac{2}{6}(1-p) + \frac{2}{6}p \\ = \frac{p}{6}$$

$$\frac{P(AA)}{P(Aa)} = \frac{(2-p)/3}{1-p/6}$$

80. Parent Aa (50%) ; A = child #1 & #2 have the same gene

B = child #1 and #3 have the same gene

C = child #2 & #3 have same gene.

Mutually Independence: $P(A_{i1} \cap \dots \cap A_{im}) = P(A_{i1}) \dots P(A_{im})$

Pairwise Independence: $P(A \cap B \cap C) = 0 \neq P(A)P(B)P(C)$.

$$P(\#1 \cap \#2 \cap \#3) = P(\#1 \cap \#2) P(\#3) \Rightarrow P(\#1)P(\#2)P(\#3)$$

$$P(B) = P(\text{child \#1} \cap \text{child \#3})$$

$$P(A) = P(\text{child \#1} \cap \text{child \#2})$$

$$P(C) = P(\text{child \#2} \cap \text{child \#3})$$

$$P(A \cap B \cap C) \neq P(A)P(B)P(C) = P(\#1 \cap \#3)P(\#1 \cap \#2)P(\#2 \cap \#3)$$

56. a) A survey of household expenditures in a city. [Stratification of expenditure type or district]
 b) Examination of lead concentration in a large plot of land [concentration ranges]
 c) Surveying the number of people who use elevators in a large building [Time of day]
 d) Surveying television by time of day [Stratification or seasons]
57. Sample Pool: $\{1, 2, 2, 4, \text{ and } 8\} \rightarrow (1, 2, 2) \text{ and } (4, 8)$: $\bar{X}_{S1} = \frac{1}{3}(1) + \frac{1}{3}(2) + \frac{1}{3}(2) = \frac{5}{3}$; $\bar{X}_{S2} = \frac{3}{5}(\frac{5}{3}) + \frac{2}{5}(6) = 1 + \frac{12}{5} = 1+2.4 = 3.4$
58. $[n_1, n_2, \dots, n_m] \quad \left[\begin{array}{c} n_1, n_2, \dots, n_k \\ \vdots \\ n_1, n_2, \dots, n_{l_2} \end{array} \right] \quad \left\{ \begin{array}{c} n_1, n_2, \dots, n_{l_2} \\ \vdots \\ n_1, n_2, \dots, n_{l_2} \end{array} \right\} \times 100$
- 59.
60. $n_H = 100,000, \sigma_H = 20$
 $n_L = 500,000, \sigma_L = 12$
 Sample size = 100
- a) Optimal Allocation
 Population Mean:
 $\bar{X}_{S0} = \sum_{L=1}^L W_L \bar{X}_L =$
- b) $\mu_H - \mu_L = W_H \bar{X}_H - W_L \bar{X}_L$
 $= \frac{100}{100,000} \bar{X}_H - \frac{100}{500,000} \bar{X}_L$
61. $\mu(t) = \alpha + \beta t$
 Sample size = 11
 @ time = 1, 2 and 3
 $\hat{\beta} = w_1 \bar{X}_1 + w_2 \bar{X}_2 + w_3 \bar{X}_3$
 a) Find w_1, w_2 and w_3 , such that $\hat{\beta} = w_1 \bar{X}_1 + w_2 \bar{X}_2 + w_3 \bar{X}_3$ is unbiased estimate of β . X_i denotes sample mean.
- $\frac{d\hat{\beta}}{dX} = w_1 + w_2 + w_3 = 0$
 and
 XX time: $w_1 + w_2(2) + w_3(3) = 1$
- b) $w_1 = -w_2 - w_3; w_1 = 1 - 2w_2 - 3w_3 - w_2 - w_3 = 1 - 2w_2 - 3w_3$
 $w_1 + 1 - 2w_2 - 3w_3 = 0$
 $w_1 + 1 - w_3 = 0; w_1 - w_3 = -1; w_1 = -\frac{1}{2}; w_3 = \frac{1}{2} \Rightarrow w_2 = 0$
62. Example B: Section 7.5.2
- $\bar{X}_1 = 240.6 \quad S_1^2 = 6827.6$
 $\bar{X}_2 = 507.4 \quad S_2^2 = 23790.7$
 $\bar{X}_3 = 865.1 \quad S_3^2 = 42573.0$
 $\bar{X}_4 = 1716.5 \quad S_4^2 = 152,099.6$
- $\bar{X}_S = 332.5$
 $S_X^2 = \frac{1}{10} \sum_{i=1}^4 W_i^2 \left(1 - \frac{n-1}{N-1}\right) S_i^2 = 1282.0$
- The estimate of $S_X = 35.8$
 has a standard error of $S_{T_S} = 393 \bar{X}_S = 327,192$.
- $S_X^2 = \sqrt{\frac{S_X^2}{10} \left(1 - \frac{10}{393}\right)} = 11.2$
 which demonstrates the sample size of $n=10$ is small compared to the population size of $N=393$.
- $S_X = \sqrt{\frac{S_X^2}{n} \left(1 - \frac{n}{N}\right)} = \sqrt{\frac{1}{1000^2} \left(\frac{1}{2\pi}\right) \left[2\pi \sum_{i=1}^{1000} e^{-x_i^2/2} - \left(\sum_i e^{-x_i^2/2}\right)^2\right] \left(1 - \frac{n}{N}\right)}$ where $n=1000$

The population stratification would be best exemplified as or-intervals of separation.

Stratum	Ne	ne	σ_e
\$1000+	70	3000	1250
\$200-1000	500	500	100
\$1-200	10,000	90	30

a) Mean: S. D.

Proportional Allocation: $\bar{X} = \sum_{e=1}^L W_e X_e$ $\text{Var}(\bar{X}_S) = \frac{1}{n} \sum_{e=1}^L W_e (1 - \frac{n_e-1}{N-1}) \sigma_e^2$

Optimal Allocation: $\mu = \frac{1}{N} \sum_{e=1}^L N_e \mu_e$ $\text{Var}(\bar{X}_S) = \sum_{e=1}^L W_e^2 \left(\frac{1}{n_e} (1 - \frac{n_e-1}{N-1}) \sigma_e^2 \right)$

Relative Sampling: $\frac{n_e}{N_e} = \frac{n}{N}$; $n_e = N_e \frac{n}{N} = n W_e$; $\$1-200: n_e = n \left(\frac{10000}{10570} \right) = 0.95 n$

b) Two methods exist
to compare the differences
of population mean based
upon proportional allocation

and optimal allocation.

$\text{Var}(\bar{X}_{SP}) - \text{Var}(\bar{X}_{SO}) = \frac{1}{n} \sum_{e=1}^L W_e (\sigma_e - \bar{\sigma})^2$ Optimal Allocation

$= \frac{1}{n} \left[\sum_{e=1}^L W_e \sigma_e^2 - \left(\sum_{e=1}^L W_e \sigma_e \right)^2 \right]$ and

$\frac{\text{Var}(\bar{X}_{SP})}{\text{Var}(\bar{X}_{SO})} = 1 + \frac{\sum_{e=1}^L W_e (\sigma_e - \bar{\sigma})^2}{(\sum_{e=1}^L W_e \sigma_e)^2}$

65.

Time: 1950-1960

Adult White Female Population (160,341 counties, North Carolina, South Carolina, Georgia).

a) Histogram: Bins by year b) Mean: $\bar{x} = \frac{1}{N} \sum x_i$; Total cancer Mortality: $T = N$.

c) $N = 25$

Variance: $\sqrt{\frac{\sum (x_i - \bar{x})^2}{N}}$; SD: $\sqrt{\frac{\sum (x_i - \bar{x})^2}{N}}$

d) Mean: $\bar{x} = \frac{1}{n} \sum x_i$; $T = N \bar{x}$ e) $\text{Var}(\bar{x}) = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n}}$

f) $\bar{x} \pm 1.96 s_x$, $T = N s_x$ g) See (d-f) h) Ratio estimator (r) = $\frac{\sum_{i=1}^n \bar{x}_i}{\sum_{i=1}^n \bar{x}_i}$ would be effective to
i) See c) j) See d) k) -- l) Separate and stratify by compare counts.

66. The sampling procedure $n_e = n \frac{W_e \sigma_e}{\sum W_e \sigma_e}$ or $n_e = n W_e$

Would be regions of
the beach vs # of people.

Proportional Allocation

Optimal Allocation

n) Further strata may
resolve or represent
the data better.

Stratified means would be calculated with proportional allocation for variance.

67. a) i) Proportion of female-headed Families [$n = 500$]: $\bar{x} = \sum_{e=1}^L W_e X_e$; $\text{Var}(\bar{X}_S) = \frac{1}{500} \sum_{e=1}^L (W_e) \left(1 - \frac{500-1}{43086-1} \right) \sigma_e^2$

ii) The average number of children per family $s_x = \sqrt{\frac{\sigma_{xs}^2}{n}} (1 - \frac{n}{N})$; $\bar{x} \pm 1.96 s_x$

representation would be best demonstrated by region of Cyberville. $\bar{x}_R = \sum_{e=1}^L W_e X_e$

$\text{Var}(\bar{X}_{SR}) = \frac{1}{500} \sum_{e=1}^L (W_e) \left(1 - \frac{500-1}{43086-1} \right) \sigma_e^2$

$\bar{x} \pm 1.96 s_x$

iii) The proportion of heads of household who did not receive a high school diploma $\bar{x} \pm 1.96 \sqrt{\frac{\sigma^2}{n} (1 - \frac{n}{N})}$

62. Four players EB cards each] $\therefore 52! = 10 \times 10^{67}$

63. $P(Age > 70) = 0.6$; $P(Age > 80) = 0.2$. $P(Age > 80 | Age > 70) = \frac{P(Age > 80 \cap Age > 70)}{P(Age > 70)} = \frac{0.2}{0.6} = \frac{1}{3} 0.2$

64. Three Shifts. 1% of shift 1 are defective; 2% of shift 2 are defective; 5% of shift 3 are defective;

$$P(\text{Defective}) = P(\text{Defective} | \text{Shift } \#1)P(\text{Shift } \#1) + P(\text{Defective} | \text{Shift } \#2)P(\text{Shift } \#2) + P(\text{Defective} | \text{Shift } \#3)P(\text{Shift } \#3)$$

$$= 1\% \left(\frac{1}{3}\right) + 2\% \left(\frac{1}{3}\right) + 5\% \left(\frac{1}{3}\right) = 2.667\%$$

65. A and B are independent; A^c and B^c , A^c and B are too.

$$P(A \cap B) = P(A)P(B); P(A \cap B^c) = P(A)P(B^c); P(A^c \cap B^c) = P(A^c)P(B^c)$$

$$\sum P(\text{Defective} | \text{Shift } \#i) = \frac{5\% \left(\frac{1}{3}\right)}{2.667\%} = 62\%$$

66. \emptyset independent of A for any A . $P(A \cap \emptyset) = P(A) \cdot P(\emptyset) = 0$

67. If $P(A \cap B) = P(A)P(B)$; then $P(A \cup B) = P(A) + P(B) - P(A \cap B) = P(A) + P(B) - P(A)P(B)$

Addition Law

Law of Independence

68. If $P(A \cap B) = P(A)P(B)$ and $P(B \cap C) = P(B)P(C)$; $P(A \cap C) = P(A \cap B \cap C) = P(A \cap B)P(C)$

$$P(A \cap B) = P(A) \frac{P(B \cap C)}{P(C)} \Rightarrow \frac{P(A \cap B)}{P(B \cap C)} = P(A \cap C) = \frac{P(A)}{P(C)} = P(A)P(B \cap C) = P(A)P(B)P(C)$$

69. If $A \cap C = \emptyset$ "Disjoint", $P(A) = 0 \vee P(C) = 0$; thus independent.



70. If $A \cap B$; then they are not independent.

71. If A, B, C are mutually independent, then $A \cap B$ and C are independent along with $A \cup B$ and C .

$$P(A \cap (B \cap C)) = P(A)P(B \cap C) = P(A)P(B)P(C)$$

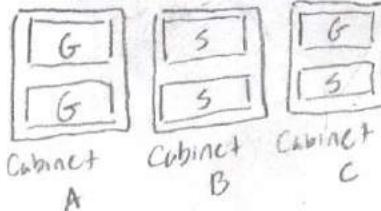
$$P(A \cup (B \cap C)) = P(A) + P(B \cap C) - P(A \cap B \cap C)$$

$$= P(A) + P(B)P(C) - P(A \cap B \cap C)$$

72. ($t = 0, 1, 2, \dots$) $\rightarrow p$, then q . @ $t=0, n=1$:

probability of 0, 1, 2, 3 people at $t=2$.

57. Cabinet A, B, C with two drawers each, inside a win. [Multiplicative Law] $P(S) = P(S_1|S_1)P(S_2) + P(S_2|G_1)P(G_1)$



$$P(\text{Draw } \#1 | B) \cdot P(B)$$

$$\left(\frac{2}{3}\right)\left(\frac{1}{2}\right) = P(\text{Draw } \#1 | B) \cdot P(B) + P(\text{Draw } \#1 | A) \cdot P(A)$$

$$= \left(\frac{2}{3}\right)\left(\frac{1}{2}\right) + P(\text{Draw } \#1 | C) \cdot P(C)$$

$$= \frac{1}{3} \cdot \frac{1}{3} = \frac{1}{3} \cdot \frac{1}{3} + \left(\frac{1}{3}\right)\left(\frac{1}{2}\right) = \frac{1}{3} \cdot \frac{1}{3} = \boxed{\frac{2}{3}}$$

58. Drew, Chris, Jason; Two must stay home; one leaves.

Drew, Chris, Jason

3 ways

2 remain

The possibilities following Drew asking the teacher contain a relationship known as the multiplicative law. If Chris is chosen to remain ($\frac{1}{3}$), then there are ($\frac{1}{2}$) possible outcomes. If Jason is chosen ($\frac{1}{3}$), then there is ($\frac{1}{2}$)-outcomes. While if Drew is chosen 1 outcome. Thus,

$$P(\text{Drew Asking}) = P(\text{Outcomes} | \text{Drew})P(\text{Drew}) + P(\text{Outcomes} | \text{Chris}) \\ \times P(\text{Chris}) + P(\text{Outcomes} | \text{Jason})P(\text{Jason})$$

$$= \frac{1}{3}(1) + \left(\frac{1}{2}\right)\left(\frac{1}{3}\right) + \left(\frac{1}{2}\right)\left(\frac{1}{3}\right) = \frac{1}{3}.$$

$P(HH|HH)P(H) + P(HT|HT)P(HT)$ Tasking is no better than waiting

$$P(HH|H) = \frac{P(H|HH)P(HH)}{P(H|HH)P(HH) + P(H|HT)P(HT) + P(H|TT)P(TT)} = \frac{1 \cdot \frac{1}{3}}{1 \cdot \frac{1}{3} + \frac{1}{2}\left(\frac{1}{3}\right) + 0\left(\frac{1}{3}\right)} = \frac{1}{3} = \frac{\frac{2}{6}}{\frac{2}{6} + \frac{1}{6}} = \boxed{\frac{2}{3}}$$

$$b) P(H) = P(H|HH)P(HH) + P(H|HT)P(HT) + P(H|TT)P(TT) = \frac{3}{6} = \boxed{\frac{1}{2}}; P(T) = P(T|HT)P(HT) + P(T|TT)P(TT)$$

$$= \left(\frac{1}{2}\right)\left(\frac{1}{2}\right) + 1 \cdot \frac{1}{3} = \frac{3}{6} = \boxed{\frac{1}{2}}$$

$$c) P(H_2) = P(H|HH_1)P(HH_1) + P(H|HH_1)P(HT_1)$$

$$= 1 \cdot \left(\frac{2}{3}\right) + \frac{1}{2}\left(\frac{1}{3}\right) = \frac{2}{3} + \frac{1}{6} = \boxed{\frac{5}{6}}$$

$$60. P(B) > 0; Q(A) = P(A|B); \boxed{\text{Addition Law}} \quad P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

$$61. \text{Defect} = 0.95 \quad \text{Sound} = 0.97$$

Accuracy Accuracy

If 0.5% are faulty, what is the probability faulty if sound?

$$P(F|\text{Defect}) = \frac{P(F|\text{Defect})P(\text{Defect})}{P(F|\text{Defect})P(\text{Defect}) + P(F|\text{Sound})P(\text{Sound})}$$

$$= \frac{0.05(0.95)}{0.05(0.95) + 0.03(0.97)} = \boxed{0.5}$$

$$P(F|\text{Defect}) = \frac{P(F \cap \text{Defect})}{P(\text{Defect})} = \frac{P(F|\text{Sound})P(\text{Sound})}{P(F|\text{Sound})P(\text{Sound}) + P(F|\text{Defect})P(\text{Defect})}$$

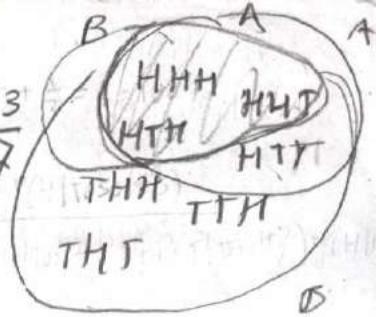
$$= \frac{0.03 \cdot 0.95}{0.03 \cdot 0.95 + 0.97 \cdot 0.05} = \boxed{0.06\%} \quad P(\text{Defect})$$

49. 3 tosses of a coin

$$a) P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(HHH + HHT + HTT + TTH + THH)}{P(HHH + HHT + HTT + TTH + THH + THT + THT)} = \frac{3}{7}$$

$$b) P(TIH) = \frac{HHT + HTT + THH + THT + THT}{HHH + HHT + HTT + TTH + THH + THT} = \frac{6}{21}$$

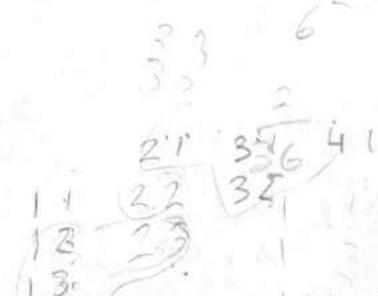
$$P(T) = (Prob\ T) \cdot (Prob\ T) \cdot (Prob\ T) = \frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{8}$$



$$50. \text{Two dice; sum total } = 6: P(6) = \frac{P(6 \cap 3)}{P(6)} = \frac{1/36}{25/36} = \frac{1}{25} = \frac{1}{5}$$

Law of Independent Events

$$51. \text{Two dice; sum total } = 6: P(<6) = \frac{P(<6 \cap 3)}{P(<6)} = \frac{15}{36} = \frac{4}{10} = \frac{2}{5}$$



$$52. P(G|G) = \frac{P(G \cap G)}{P(G)} = \frac{1}{4}; P(G|G) = \frac{P(G \cap G)}{P(G)} = \frac{1}{4}$$

$$53. \begin{array}{ll} \text{High-Risk [0.02]} & [0.10] 2 \times 10^{-3} \\ \text{Medium Risk [0.01]} & [0.20] 2 \times 10^{-3} \\ \text{Low Risk [0.0025]} & [0.70] 1.75 \times 10^{-3} \\ (\text{Filing}) & (\text{People}) \end{array}$$

$$P(\text{High Risk} | \text{People}) = \frac{P(\text{High Risk} \cap \text{People})}{P(\text{Risk} \cap \text{People})} = \frac{8}{23}$$

54. R_i = event of rain on day i

$$P(R_i | R_{i-1}) = \alpha; P(R_i^c | R_{i-1}^c) = \beta$$

$$P(R_i | R_{i-1} \cap R_{i-2} \cap \dots \cap R_0) = P(R_i | R_{i-1})$$

a) p=probability of rain, w/out looking tomorrow?

$$P(R_i | R_0) = P(R_i | R_{i-1}) = P = \alpha$$

$$b) P(R_2 | R_1 \cap R_0) = P(R_2 | R_{11}) = \alpha$$

$$c) P(R_i | R_{i-1} \cap R_{i-2} \cap \dots \cap R_0) = P(R_i | R_{i-1})$$

$$\lim_{n \rightarrow \infty} P \cdot \prod_{i=1}^n \alpha_i$$

56 5 cards of 52 card Deck

1st = King. Law of Independent Events

$$\begin{aligned} 3 \binom{51}{3} &= \frac{3 \cdot 51!}{11 \cdot 49!} = \frac{51 \cdot 50 \cdot 49 \cdot 48 \cdot 47}{11} \\ \binom{51}{4} &= \frac{51!}{51 \cdot 50 \cdot 49 \cdot 48} \\ &= \frac{1}{2} = 50! \end{aligned}$$

$$P(V_2) = P(V_2 | V_1)P(V_1) + P(V_2 | M_1)P(M_1) + P(V_2 | L_1)P(L_1) = 0.037$$

$$P(M_2) = 0.578 \quad P(V_3) = 0.064$$

$$P(L_2) = 0.352 \quad P(M_3) = 0.614$$

$$P(L_3) = 0.322$$

	V_2	M_2	L_2	
V_1	0.45	0.48	0.07	$P(V_2 V_1) = 0.45$
M_1	0.05	0.70	0.25	
L_1	0.01	0.50	0.49	

$$a) P(M_1 | M_2) = 0.70; P(L_1 | L_2) = 0.49.$$

	V_3	M_3	L_3	
V_2	$P(V_3 V_2)P(V_2)$	$P(M_3 V_2)P(V_2)$	$P(L_3 V_2)P(V_2)$	
M_2	$P(V_3 M_2)P(M_2)$	$P(M_3 M_2)P(M_2)$	$P(L_3 M_2)P(M_2)$	
L_2	$P(V_3 L_2)P(L_2)$	$P(M_3 L_2)P(L_2)$	$P(L_3 L_2)P(L_2)$	
V_2		$42/25$	$81/100$	
U_3		M_3	L_3	

	V_2	M_2	L_2	
V_2	0.225	0.3064	0.0367	
M_2	0.025	1.176	0.2025	
L_2	0.005	0.94	0.3969	

$$P(V_2) = P(V_2 | V_1)P(V_1) + P(V_2 | M_1)P(M_1) + P(V_2 | L_1)P(L_1) = 0.037$$

$$P(M_2) = 0.578 \quad P(V_3) = 0.064$$

$$P(L_2) = 0.352 \quad P(M_3) = 0.614$$

$$P(L_3) = 0.322$$

$$45. \text{ Prove } P(A_1 \cap A_2 \cap \dots \cap A_n) = P(A_1) \cdot P(A_2 | A_1) P(A_3 | A_1 \cap A_2) \dots P(A_n | A_1 \cap A_2 \cap \dots \cap A_{n-1})$$

Multiplication Law: If A & B be events and assume $P(B) \neq 0$, then $P(A \cap B) = P(A|B)P(B)$

$$\begin{aligned} P(A_n | A_{n-1} \cap \dots \cap A_2 \cap A_1) &= P(A_n | A_1 \cap A_2 \cap \dots \cap A_{n-1}) \cdot P(A_1 \cap A_2 \cap \dots \cap A_{n-1}) \\ &= P(A_n | A_1 \cap A_2 \cap \dots \cap A_{n-1}) P(A_{n-1} | A_1 \cap A_2 \cap A_3 \dots) P(A_1 \cap A_2 \cap A_3 \dots) \end{aligned}$$

$$= P(A_n | A_1 \cap A_2 \cap \dots \cap A_{n-1}) \cdot \dots \cdot P(A_3 | A_1 \cap A_2) \cdot P(A_2 | A_1) \cdot P(A_1)$$

46. cont. from w210
 Urn A: $\begin{cases} 3 \times R \\ 2 \times W \end{cases}$ Urn B: $\begin{cases} 2 \times R \\ 5 \times W \end{cases}$ A ball is drawn from Urn A into Urn B, then a ball is drawn from Urn B.
 A) Probability of a red ball: $\frac{\binom{3}{1}}{\binom{5}{1}} \cdot \frac{\binom{3}{1}}{\binom{6}{1}} = \frac{(3!)}{(2!)(5!)} \cdot \frac{(3!)}{(2!)(6!)} = \frac{3}{10}$

46. a) Urn A: $\begin{cases} 3 \times R \\ 2 \times W \end{cases}$ Urn B: $\begin{cases} 2 \times R \\ 5 \times W \end{cases}$ coin [50/50]:
 Heads = Urn A
 Tails = Urn B.

$$\begin{aligned} P(\text{Red} \cap \text{Urn A}) &= P(\text{Red} | \text{Urn A}) \cdot P(\text{Urn A}) = \frac{1}{2} \left(\frac{3}{5} \right)^2 = \frac{9}{25} \\ P(\text{Red} \cap \text{Urn B}) &= P(\text{Red} | \text{Urn B}) \cdot P(\text{Urn B}) = \frac{1}{2} \left(\frac{2}{5} \right) = \frac{1}{5} \\ P(R) &= P(\text{Red} \cap \text{Urn A}) + P(\text{Red} \cap \text{Urn B}) = \frac{9}{25} + \frac{1}{5} = \frac{14}{25} \end{aligned}$$

b) $P(R) = P(\text{Heads}) P(\text{Urn A}) + P(\text{Tails}) P(\text{Urn B}) = 1 = P(\text{Heads}) \left(\frac{3}{5} \right) + (1 - P(\text{Heads})) \left(\frac{2}{5} \right)$
 $1 = P(\text{Heads}) \left[\left(\frac{3}{5} \right) - \left(\frac{2}{5} \right) \right] + \frac{2}{5}; \quad P(\text{Heads}) = \frac{3}{5}$

47. Urn A: $\begin{cases} 4 \times R \\ 3 \times B \\ 2 \times G \end{cases}$ Urn B: $\begin{cases} 2 \times R \\ 3 \times B \\ 4 \times G \end{cases}$ a) $P(R) = P(R | \text{Urn B} \cap R) P(\text{Urn A} \cap R) + P(R | \text{Urn B} \cap \bar{R}) P(\text{Urn A} \cap \bar{R}) + P(R | \text{Urn B} \cap \bar{G}) P(\text{Urn A} \cap \bar{G})$
 $= \left(\frac{3}{10} \right) \left(\frac{4}{9} \right) + \left(\frac{2}{10} \right) \left(\frac{3}{9} \right) + \left(\frac{2}{10} \right) \left(\frac{2}{9} \right) = \frac{12}{90} + \frac{6}{90} + \frac{4}{90} = \frac{22}{90} = \frac{11}{45}$

b) $1 = P(R | \text{Urn B} \cap R) P(\text{Urn A} \cap R) + P(R | \text{Urn B} \cap \bar{R}) P(\text{Urn A} \cap \bar{R}) + P(R | \text{Urn B} \cap \bar{G}) P(\text{Urn A} \cap \bar{G})$
 $1 = \left(\frac{3}{10} \right) \left(\frac{4}{9} \right) + \left(\frac{2}{10} \right) \left(\frac{3}{9} \right) + \left(\frac{2}{10} \right) \left(\frac{2}{9} \right); \quad \frac{10}{3} \left(1 - \left(\frac{2}{10} \right) \left(\frac{2}{9} \right) - \left(\frac{2}{10} \right) \left(\frac{2}{9} \right) \right) = X$

b) Bayes Formula: $P[\text{Urn A}(R_{\text{ca}}) | \text{Urn B}(R)] = P[\text{Urn A}(R), \text{Urn B}(R_{\text{ca}})] = P[\text{Urn B}(R_{\text{ca}}) | \text{Urn A}(R)] P[\text{Urn A}(R)]$

48. Urn A: $\begin{cases} 3 \times R \\ 2 \times W \end{cases}$ Urn B: $\begin{cases} 2 \times R \\ 3 \times B \\ 4 \times G \end{cases}$
 1 Draw + 1 Return + Same color Ball. 2nd Draw
 Multiplication Law: $P[\text{Urn B}(R_{\text{ca}})] = P(R_{\text{ca}} | \text{Urn A}) P(\text{Urn A})$
 $P(R_{\text{ca}} | \text{Urn A}) = P(R | \text{Urn B} \cap R) P(\text{Urn A} \cap R) + P(R | \text{Urn B} \cap \bar{R}) P(\text{Urn A} \cap \bar{R}) + P(R | \text{Urn B} \cap \bar{G}) P(G)$

a) Probability of white? $P(W | \text{Draw #2}) = P(W | \text{Draw #2} \cap W) P(W \cap \text{Draw #1})$

$$\begin{aligned} &+ P(W | \text{Draw #2} \cap \bar{R}) P(\bar{R} \cap \text{Draw #1}) \\ &= \left(\frac{3}{6} \right) \left(\frac{2}{5} \right) + \left(\frac{2}{6} \right) \left(\frac{3}{5} \right) = \left(\frac{6}{30} \right) + \left(\frac{6}{30} \right) = \frac{12}{30} = \frac{4}{10} = \frac{2}{5} \end{aligned}$$

D. Bayes Theorem:

$$P(\text{Draw #1} \cap W | \text{Draw #2} \cap W)$$

$$= P(\text{Draw #2} \cap W | \text{Draw #1} \cap W) P(\text{Draw #1} \cap W)$$

$$P(W | \text{Draw #2} \cap W) P(W \cap \text{Draw #1}) + P(W | \text{Draw #2} \cap \bar{R}) P(\bar{R} \cap \text{Draw #1})$$

$$= \left(\frac{2}{5} \right) \left(\frac{2}{5} \right) / \left[\left(\frac{3}{6} \right) \left(\frac{2}{5} \right) + \left(\frac{2}{6} \right) \left(\frac{3}{5} \right) \right] = \boxed{\frac{1}{2}}$$

$$= \frac{6}{11}$$

36.

R	R	R	G	G	G
---	---	---	---	---	---

 Arrangements: Combinations per type - $\binom{6}{3}\binom{3}{3} = \frac{6!}{3!3!} \cdot \frac{(3!)^3}{3!0!} = \frac{6 \cdot 5 \cdot 4}{3 \cdot 2} = \frac{120}{6} = 20$

6 Blocks

R	R	R	W	W	W	G	G	G
---	---	---	---	---	---	---	---	---

9 blocks

Combinations per type - $\binom{9}{3}\binom{6}{3}\binom{3}{3}$

$$= \frac{9!}{3!6!} \cdot \frac{6!}{3!3!} = \frac{9!}{3!3!0!} = 16800$$

37. Coefficient of $x^2y^2z^3$ in $(x+y+z)^7$:

Multinomial: $(x_1+x_2+x_3)^7 = \sum \binom{n}{n_1 n_2 n_3} x_1^{n_1} x_2^{n_2} x_3^{n_3}$; $(x+y+z)^7 = \sum \binom{7}{223} x^2 y^2 z^3$
Coefficient: $\binom{7}{223} = \frac{7!}{2!2!3!} = \frac{7 \cdot 6 \cdot 5 \cdot 4}{2 \cdot 2 \cdot 3} = 210$

38. coefficient of x^3y^4 for $(x+y)^7$:

$$(x+y)^7 = \sum \binom{n}{k} x^k y^{7-k} = \binom{7}{07} x^7 y^0 + \binom{7}{61} x^6 y^1 + \dots$$

39. a. 26 letters choose 6.

Probability Hunter = $\frac{\binom{6}{1}}{\binom{26}{6}} = \frac{6!}{5!} \cdot \frac{(6!(20)!)}{26!}$ coefficient: $\binom{7}{34} = \frac{7!}{3!4!} = \frac{7 \cdot 6 \cdot 5}{3 \cdot 2} = \frac{210}{6} = 35$

b. $0.90 = n \left(\frac{3}{115115} \right) = \frac{3}{115115} = 0.0026\%$

$n = 34534$ monkeys

40. 12 people into three groups: $\binom{12}{4}\binom{8}{4}\binom{4}{4} = \frac{12!}{4!(8)!} \cdot \frac{8!}{4!4!} \cdot \frac{4!}{4!1!} = \frac{12!}{4!4!4!} = 34650$.

6 pairs of partners: $\binom{6}{2}\binom{4}{2}\binom{2}{2} = \frac{6!}{2!4!} \cdot \frac{4!}{2!2!} \cdot \frac{2!}{2!0!} = \frac{6!}{2!2!2!} = 90$.

41. Seven black socks, eight blue socks, and nine green socks. Total: 24.
 a) Probability of Matching: $\frac{\binom{7}{2}}{\binom{24}{2}} + \frac{\binom{8}{2}}{\binom{24}{2}} + \frac{\binom{9}{2}}{\binom{24}{2}} = \frac{7!}{5!} \cdot \frac{21!22!}{24!} + \frac{8!}{6!} \cdot \frac{2!22!}{24!} + \frac{9!}{7!} \cdot \frac{2!21!}{24!} = \frac{7}{92} + \frac{7}{69} + \frac{3}{32} = 27\%$

b. $7/92 = 7.61\%$

42. Number of ways to choose 11 boys grouped into 4 forwards, 3 midfielders, 3 defenders, 1 goalie.

$$\binom{11}{4}\binom{7}{3}\binom{4}{3}\binom{3}{3} = \frac{11!}{4!(7!)!} \cdot \frac{7!}{3!3!} \cdot \frac{4!}{3!2!} \cdot \frac{3!}{3!0!} = \frac{11!}{4!7!3!3!2!3!0!} = 46,200$$

43. Three Jobs: Two Jobs require 3 programmers, the third requires four.

Total of ten programmers. $\binom{10}{3}\binom{7}{3}\binom{4}{4} = 4,200$

44. Combinations in Tentacles x Shaking Hands: $\sum_{i=1}^{n+3} 8 \binom{8-i}{i+1} =$: Matrix

$$= 8 \cdot 7 \binom{8}{2} + 8 \cdot 6 \binom{8}{3} + 8 \cdot 5 \binom{8}{4} + 8 \cdot 4 \binom{8}{5} + 8 \cdot 3 \binom{8}{6} + 8 \cdot 2 \binom{8}{7} + 8 \cdot 1 \binom{8}{8}$$

$$= 1568 + 2688 + 2800 + 1792 + 672 + 128 + 8 = 9656$$

$$\text{four students: } \frac{\binom{2}{1}}{\binom{60}{4}} = \frac{2}{\frac{60!}{4!(56!)}} = \frac{2 \cdot 4 \cdot 3 \cdot 2}{60 \cdot 59 \cdot 58 \cdot 57} = 0.0004\%$$

Marcelle in one class and her friends in another: $\frac{\binom{2}{1}\binom{55}{29}}{\binom{60}{30}} = \frac{2 \cdot 29! \cdot (26)!}{60! \cdot 30!} = 6\%$

31. Six Male and Six Female Donors: $6P_6 \cdot 6P_6$

$$\frac{\binom{2}{1}\binom{55}{29}}{\binom{60}{30}} = \frac{2 \cdot 29! \cdot (26)!}{60! \cdot 30!} = 6\%$$

$$32. \frac{40 \binom{13}{n}}{\binom{52}{n}} = \frac{40 \cdot 13!}{n!(13-n)!} \cdot \frac{52!}{(13-n)!52!} = \frac{6!}{0!} \cdot \frac{6!}{0!} = 720^2$$

When is the value 0.5?

$$= \frac{40 \cdot 13!}{(13-n)!52!} \cdot \frac{1.85 \times 10^{-57} (52-n)!}{(13-n)!} = \frac{3.7 \times 10^{-57} \cdot T(53-n)}{T(14-n)} = 1; n=3.$$

Gamma Identity: $T(n) = (n-1)!$

33. Five people and five floors. Probability of a person floor choosing fire.

Probability of choosing fire.

34. Prove the following

identity:

$$\sum_{k=0}^n \binom{n}{k} \binom{m-n}{n-k} = \binom{m}{n}$$

$$= \frac{\binom{5}{1}}{\binom{7}{5}} = \frac{5!}{1!(5-1)!} = \frac{5!}{7!} = \frac{5! \cdot 2!}{7!} = \frac{5! \cdot 5! \cdot 2!}{4! \cdot 7!} = 23.8\%$$

$$\begin{aligned} & \sum_{k=0}^n \frac{n!}{k!(n-k)!} \frac{(m-n)!}{(n-k)!(m-n-n+k)!} = \sum_{k=0}^n \frac{n \cdot (n-1)(n-2)(n-3) \cdots (n-k)! (m-n)!}{k! (n-k)! (n-k)! (m+k)!} \\ &= \sum_{k=0}^n \frac{n(n-1)(n-2)(n-3) \cdots (m-n)!}{k! \left(\frac{n!}{n(n-1)(n-2)(n-3) \cdots} \right) (m+k)!} = \sum_{k=0}^n \frac{[n \cdot (n-1)(n-2)(n-3) \cdots] (m-n)!}{k! n! (m+k)!} \end{aligned}$$

Two methods: 1. Pascal's Identity: $\binom{n+r}{r} = \binom{n}{r} + \binom{n}{r-1}$ or $\binom{n}{k} = \binom{n-1}{k-1} + \binom{n-1}{k}$

$$\begin{aligned} & \sum_{k=0}^n \binom{n}{k} = \sum \left[\binom{n+1}{k+1} - \binom{n}{k+1} \right] = \sum_{k=1}^n \binom{n+1}{k+1} - \sum_{k=1}^n \binom{n}{k+1} \\ & r! = r(r-1)(r-2) \dots \end{aligned}$$

$$= \sum_{k=1}^{n+1} \binom{n}{k+1} - \sum_{k=1}^n \binom{n}{k+1} = \binom{n+1}{k+1} - \binom{n}{k+1} = \binom{n+1}{k+1} - \dots$$

$$2. \text{ Binomial Theorem: } \sum_{k=0}^n \binom{n}{k} \binom{m-n}{n-k} = \sum_{k=0}^n \binom{n}{k} (1+n-k)^{n-k} (1+n-k)^{m-n} = \binom{n}{0} C_0 R^{n-1} + \binom{n}{1} C_1 R^{n-2} + \binom{n}{2} C_2 R^{n-3} + \dots$$

$$= \binom{m-n}{0} C_0 (n-k)^{m-n-1} + \binom{m-n}{1} C_1 (n-k)^{m-n-2} + \binom{m-n}{2} C_2 (n-k)^{m-n-3} + \dots$$

$$\begin{aligned} & (1+x)^n = (1+nk + \frac{n(n-1)}{2!} k^2 + \frac{n(n-1)(n-2)}{3!} k^3 + \dots) (1+(m-n)(n-k) + \frac{(m-n)(m-n-1)}{2!} (n-k)^2 + \dots) \\ &= (1+mn + \frac{m(m-1)}{2!} n^2 + \dots) = \binom{m}{n} \end{aligned}$$

35. Prove the following identities.

$$a) \binom{n}{r} = \binom{n}{n-r} = \frac{n!}{r!(n-r)!} = \frac{n!}{(n-n+r)!(n-r)!} = \binom{n}{n-r}$$

; An expansion of a binomial is equivalent to telescoping

$$b) \binom{n}{r} = \frac{n!}{r!(n-r)!} = \frac{(n-1)!n}{r!(n-r)!} = \frac{(n-1)!\left[n-r + \frac{r}{(n-r)} \right]}{r!(n-1-r)!} = \frac{(n-1)!}{r!(n-1-r)!} + \frac{(n-1)!(n-1+r)}{(r-1)!(n+k)!} = \binom{n-1}{r-1} + \binom{n-1}{r}$$

$P(U_3^2 > V_1, V_2) ; F(u_1, u_2, u_3) = \begin{cases} 1 & 0 \leq u_i \leq 1, i=1,2,3 \\ 0 & \text{Otherwise} \end{cases}$ To find the required probability consider,

$$P(U_3^2 \geq V_1, V_2) = \int_0^1 \int_0^1 \int_{\sqrt{u_1 u_2}}^1 f(u_1, u_2, u_3) du_3 du_2 du_1$$

54. $X, Y, \text{ and } Z$ be independent $N(0, \sigma^2)$. Let Θ, Φ, R be

Spherical coordinates.

$$X = r \sin \phi \cos \theta ; Y = r \sin \phi \sin \theta ; Z = r \cos \phi ; 0 \leq \phi \leq \pi ; 0 \leq \theta \leq 2\pi$$

$$f(u_1, u_2, u_3) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y, z) dx dy dz = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x) f(y) f(z) dx dy dz$$

$$f(u_1, u_2, u_3) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x) f(y) f(z) dx dy dz = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (1 - \sqrt{u_1} \sqrt{u_2}) du_3 du_2 du_1 = \int_0^1 (1 - \frac{2}{3} \sqrt{u_1}) du_1 = \boxed{\frac{5}{9}}$$

$$f(u_1, u_2, u_3) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{3/2} \sigma^3} e^{-(x^2+y^2+z^2)/2} dx dy dz = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{3/2} \sigma^3} e^{-r^2/2\sigma^2} r^2 \sin \phi dr d\theta d\phi$$

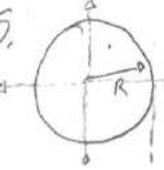
$$f(u_1, u_2, u_3) = \int_0^{2\pi} \int_0^{\pi} \int_0^{\infty} \frac{1}{(2\pi)^{3/2} \sigma^3} e^{-r^2/2\sigma^2} r^2 \sin \phi dr d\theta d\phi = \frac{\pi \sigma^2}{2^2 (2\pi)^{3/2} \sigma^3} \sqrt{\pi/2\sigma^2} \int_0^{\pi} \int_0^{\pi} \sin \phi d\theta d\phi$$

$$f(u_1, u_2, u_3) = \frac{2\pi}{2(2\pi)^3} [-\cos(2\pi) + \cos(0)] = \frac{4\pi}{16\pi^2} = \boxed{\frac{1}{4\pi}}$$

$$f(\theta) = \int_0^{\pi} \int_0^{\infty} \frac{1}{(2\pi)^{3/2} \sigma^3} e^{-r^2/2\sigma^2} r^2 \sin \phi dr d\phi = \int_0^{\pi} \frac{1}{2(2\pi)} \sin \phi d\phi = \boxed{\frac{1}{2\pi}}$$

$$f(r) = \int_0^{\pi} \int_0^{\infty} \frac{1}{(2\pi)^{3/2} \sigma^3} e^{-r^2/2\sigma^2} r^2 \sin \phi dr d\phi = \frac{4\pi}{(2\pi)^{3/2} \sigma^3} e^{-r^2/2\sigma^2} \cdot r^2$$

$$f(\phi) = \int_0^{2\pi} \int_0^{\infty} \frac{1}{(2\pi)^{3/2} \sigma^3} e^{-r^2/2\sigma^2} r^2 \sin \phi dr d\phi = \frac{2\pi \cdot 2\sigma^2}{(2\pi)^{3/2} \sigma^3} \sqrt{2\pi/2\sigma^2} \sin \phi = \boxed{\frac{1}{2\pi^2} \sin \phi}$$

55.  a) $X = R \cos \Theta, Y = R \sin \Theta$ a) Find $f(R, \Theta) F(R) f(R \cos \Theta, R \sin \Theta)$

$$\Theta [0, 2\pi] \quad b) f(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-x^2/2} dx dy = \frac{\sqrt{2\pi}}{2\pi} e^{-x^2/2} = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} = \boxed{\frac{r}{2\pi} e^{-r^2/2}}$$

$$A = \pi R^2 ; A = \pi \sqrt{x^2 + y^2}^2$$

c) PDF density is uniform over the disk.

$$f(y) = \frac{1}{\sqrt{2\pi}} e^{-y^2/2}$$

$$\frac{A}{x^2 + y^2} ; x^2 + y^2 \leq 1$$

56. Exponential Random Variables: $\lambda e^{-\lambda}; X = \lambda_x e^{-\lambda x}; Y = \lambda_y e^{-\lambda y}$

$$f(x, y) = \lambda e^{-\lambda x} \cdot \lambda e^{-\lambda y} = \lambda^2 e^{-\lambda(x+y)}$$

$$= \lambda^2 e^{-\lambda r(\cos \theta + \sin \theta)}$$

r and θ are not independent.

57. $Y_1 = N(0, 1); Y_2 = N(0, 2); \rho = 1/\sqrt{2}$; Find $X_1 = a_{11}Y_1 + a_{12}Y_2$ and $X_2 = a_{21}Y_1 + a_{22}Y_2$

$$J(Y_1, Y_2) = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$= a_{11} \cdot a_{22} - a_{12} \cdot a_{21} = 1$$

$$X_1 = y_1 ; X_2 = y_2 - y_1$$

58. If X_1, X_2 are $N(\mu, \sigma^2)$

then $f_{X_1, X_2}(y_1, y_2)$ is bivariate normal.

$$Y_1 = a_1 X_1 + b_1 ; Y_2 = a_2 X_2 + b_2$$

Example C: (Section 3.6.2)

$$Y_1 = X_1 ; Y_2 = X_1 + X_2 ; J(X, Y) = \det \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} = 1$$

$$X_2 = a_{21}Y_1 + a_{22}Y_2$$

$$f_{Y_1, Y_2}(y_1, y_2) = \frac{1}{2\pi} \exp \left[-\frac{1}{2} [y_1^2 + (y_2 - y_1)^2] \right]$$

$$= \frac{1}{2\pi} \exp \left[-\frac{1}{2} (2y_1^2 + y_2^2 - 2y_1 y_2) \right]$$

$$a_{11} a_{22} \sqrt{1 - \rho^2} = 1$$

$$1 \cdot (2) \sqrt{1 - \rho^2} = 1 \Rightarrow 1 - \frac{1}{4} = \rho^2$$

$$58. J(x,y) = \det \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = 1 \therefore f_{Y_1 Y_2}(y_1, y_2) = \frac{1}{2\pi} e^{-\frac{1}{2} \left(\left[\frac{(y_1 - b_1)}{a_{11}} \right]^2 + \left[\frac{(y_2 - b_2)}{a_{12}} \right]^2 \right)} = \frac{1}{2\pi} e^{-\frac{1}{2} \left(\frac{(y_1 - b_1)^2}{a_{11}^2} + \frac{(y_2 - b_2)^2}{a_{12}^2} \right)}$$

$$59. Y_1 = a_{11} X_1 + a_{12} X_2 + b_1; Y_2 = a_{21} X_1 + a_{22} X_2 + b_2$$

$$\textcircled{1} f(x_1, x_2) = \frac{1}{2\pi} e^{-\frac{1}{2}(x_1^2 + x_2^2)}$$

$$\textcircled{2} \text{Linear Transformation: } \left(\frac{-a_{12}}{a_{12}} \right) Y_1 = \left(\frac{-a_{22}}{a_{12}} \right) a_{11} X_1 + \left(\frac{-a_{22}}{a_{12}} \right) a_{12} X_2 + \left(\frac{-a_{22}}{a_{12}} \right) b_1 \quad \boxed{X \left(\frac{-a_{22}}{a_{11}} \right)}$$

$$\left(\frac{-a_{12}}{a_{12}} \right) Y_1 + Y_2 = \left[\frac{-a_{12}}{a_{12}} \right] a_{11} + \left[\frac{-a_{12}}{a_{12}} \right] a_{12} X_2 + \left(\frac{-a_{22}}{a_{12}} \right) b_1 + b_2 \quad \boxed{\textcircled{1} + \textcircled{2}}$$

Solve for X_1

$$X_1 = \frac{\left(\frac{-a_{12}}{a_{12}} \right) Y_1 + Y_2 + \left(\frac{a_{22}}{a_{12}} \right) b_1 - b_2}{\left[\left(\frac{-a_{12}}{a_{12}} \right) a_{11} + a_{21} \right]} = \frac{a_{22}(Y_1 - b_1) - a_{12}(Y_2 - b_2)}{(a_{22}a_{11} - a_{21}a_{12})}$$

\textcircled{3} Solve the Jacobian:

$$|J| = \begin{vmatrix} \frac{\partial X_1}{\partial y_1} & \frac{\partial X_1}{\partial y_2} \\ \frac{\partial X_2}{\partial y_1} & \frac{\partial X_2}{\partial y_2} \end{vmatrix} = \begin{vmatrix} \frac{a_{22}}{(a_{22}a_{11} - a_{21}a_{12})} & \frac{-a_{12}}{(a_{22}a_{11} - a_{21}a_{12})} \\ \frac{a_{21}}{(a_{22}a_{11} - a_{21}a_{12})} & \frac{a_{11}}{(a_{22}a_{11} - a_{21}a_{12})} \end{vmatrix} = \frac{1}{(a_{22}a_{11} - a_{21}a_{12})}$$

\textcircled{4} Solve for the new bivariate density:

$$f(y_1, y_2) = \frac{1}{2\pi\sigma_{y_1}\sigma_{y_2}\sqrt{1-\rho^2}} \exp \left[-\frac{1}{2(1-\rho^2)} \left[\left(\frac{y_1 - \mu_{y_1}}{\sigma_{y_1}} \right)^2 - 2\rho \frac{(y_1 - \mu_{y_1})(y_2 - \mu_{y_2})}{\sigma_{y_1}\sigma_{y_2}} + \left(\frac{y_2 - \mu_{y_2}}{\sigma_{y_2}} \right)^2 \right] \right]$$

\textcircled{5} Evaluate $x_1^2 + x_2^2$

$$x_1^2 + x_2^2 = \frac{\{(y_1 - b_1)^2(a_{11}^2 + a_{12}^2) + (y_2 - b_2)^2(a_{21}^2 + a_{22}^2) - 2(y_1 - b_1)(y_2 - b_2)(a_{12}a_{11} + a_{11}a_{21})\}}{(a_{22}a_{11} - a_{21}a_{12})^2}$$

$$\textcircled{6} \text{ Since } X_1, X_2 \sim N(0, 1), \text{ then } a_{11}X_1 + a_{12}X_2 + b_1 \sim N(b_1, a_{11}^2 + a_{12}^2) \quad \boxed{H_{Y_1} = b_1; \sigma_{Y_1}^2 = a_{11}^2 + a_{12}^2} \\ a_{21}X_1 + a_{22}X_2 + b_2 \sim N(b_2, a_{21}^2 + a_{22}^2) \quad \boxed{H_{Y_2} = b_2; \sigma_{Y_2}^2 = a_{21}^2 + a_{22}^2}$$

$$\textcircled{7} \text{ Rewriting } x_1^2 + x_2^2, \dots \text{ first term } \frac{(\frac{(y_1 - \mu_{y_1})}{\sigma_{y_1}})^2}{(a_{22}a_{11} - a_{21}a_{12})^2} = \frac{(y_1 - b_1)^2}{(a_{11}^2 + a_{12}^2)}$$

$$\textcircled{8} \text{ Solving for } \frac{1}{1-\rho^2} = \frac{\sigma_{y_1}\sigma_{y_2}}{(a_{22}a_{11} - a_{21}a_{12})^2}; \rho = \frac{(a_{11}^2 + a_{12}^2)}{\sqrt{(a_{11}^2 + a_{12}^2)(a_{21}^2 + a_{22}^2)}}$$

$$\textcircled{9} \sigma_{y_1}\sigma_{y_2}\sqrt{1-\rho^2} = |(a_{22}a_{11} - a_{21}a_{12})| = J^{-1}$$

60. Pseudorandom variables occur from the previous bivariate normal by a cumulative sum distribution from $-\infty$ to X .

$$61. X \& Y \text{ are continuous random variables. } V = a + bX; W = c + dY. f(v, w) = f(x, y) \cdot J^{-1}$$

$$62. X \& Y \text{ are } N(0, 1); P(X^2 + Y^2 \leq 1) = \frac{-(x^2+y^2)/2}{2\pi} = \frac{1}{2\pi} e^{-\frac{1}{2}}$$

Proposition A

$$= f\left(\frac{v-a}{b}, \frac{w-c}{d}\right) \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix}$$

$$63. a) X+Y=Z; f(u, v) = f_{XY}\left(\frac{v-y}{2}, \frac{v-z}{2}\right) \cdot \frac{1}{2} \quad \boxed{X-Y=V}$$

$$\frac{1}{2\pi} \leq P(X^2 + Y^2 \leq 1) \leq \frac{1}{2\pi} e^{-\frac{1}{2}}$$

$$= f\left(\frac{v-a}{b}, \frac{w-c}{d}\right) \frac{1}{bd}$$

$$b) XY=Z; f(u, v) = f_{XY}\left(\sqrt{2}v, \sqrt{2}z\right) \frac{1}{2|v|}$$

$$64. X+Y=Z, X|Y=V; f_{XY}\left(\frac{v-z}{\sqrt{v+1}}, \frac{z}{\sqrt{v+1}}\right) \cdot \frac{1}{\sqrt{v+1}} = f_{XY}\left(\frac{v-z}{\sqrt{v+1}}, \frac{z}{\sqrt{v+1}}\right) \frac{-Y^2}{\sqrt{v+1}}$$

$$c) X \sim N(0, 1), Y \sim N(0, 1)$$

$$= f_{XY}\left(\frac{v-z}{\sqrt{v+1}}, \frac{z}{\sqrt{v+1}}\right) \frac{-Z^2/(v+1)}{\sqrt{v+1}} + f_{XY}\left(\frac{v-z}{\sqrt{v+1}}, \frac{z}{\sqrt{v+1}}\right) \frac{-Z}{(v+1)^2}$$

65. Exponential random variable: $\lambda e^{-\lambda x}$; $f_{X_1+X_2}(x)$

67. n -chips; $P(\text{failure} \mid \text{chips} \geq 2)$; Exponential Dist.
 $P(x) = \lambda e^{-\lambda x}$

$$f_u(u) = n [F(u)]^{n-1} f(u); u \leq U \leq u + du$$

k^{th} -order statistic?

$$f_k(x) = \frac{n!}{(k-1)!(n-k)!} f(x) F^{k-1}(x) [1 - F(x)]^{n-k}$$

$$f(x) = \lambda e^{-\lambda x} \quad F(x) = \int_0^x f(t) dt = 1 - e^{-\lambda x}$$

$$f_R(x) = \frac{n!}{(2-1)!(n-2)!} [\lambda e^{-\lambda x}] [1 - e^{-\lambda x}]^{2-1} [1 - 1 + e^{-\lambda x}]^{n-2}$$

$$= \frac{n!}{(n-2)!} [\lambda e^{-\lambda x}] [1 - e^{-\lambda x}] [e^{-\lambda x}]^{n-2}$$

$$= n(n-1) \lambda e^{-(n-1)\lambda x} [1 - e^{-\lambda x}]$$

$$= n(n-1) \lambda [e^{-(n-1)\lambda x} - e^{-n\lambda x}]$$

65. Exponential Random Variable: $p(x) = \lambda e^{-\lambda x}$;

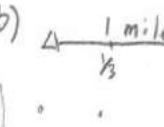
$$P(X_1, \dots, X_n) = \prod_{i=1}^n \lambda_i e^{-\lambda_i} = (\lambda_1 \lambda_2 \dots \lambda_n)^{-\sum \lambda_i}$$

66. 
 $F(A) = P(1A)P(1B) + P(2A)P(2B) + P(3A)P(3B)$
 $= 3\lambda^2 - 2\lambda^3$
 $f(t) = \frac{d}{dt} F(t) = -6\lambda^3 - 2\lambda^2$

Notes about order statistics: Multinomial + Differential Argument.

68. U_1, U_2 , and U_3 be independent uniform random variables.

a) Find $f(U_1, U_2, U_3) = n! \prod_{i=1}^3 f(U_i) = 3 \cdot 2 \cdot 1 f(U_1) \cdot f(U_2) \cdot f(U_3)$

b) 
 $\int \int f(u) du = \int_0^{1/3} u du = \frac{(1/3)^2}{2} = \frac{1}{18}$

70. $P(\text{no stations } k \text{ apart}) = 1 - P(\text{any two stations } k \text{ apart})$

Joint Distribution of Order Statistics

$$x \leq X_{(1)} \leq x + dx; y \leq X_{(n)} \leq y + dy$$

$$V = X_{(1)} : V = X_{(n)}$$

$$f(u, v) = n(n-1) f(v) f(u) [F(u) - F(v)]^{n-2} \quad u \geq v$$

$$\text{Uniform case: } f(u, v) = n(n-1)(n-v)^{n-2}, \quad 1 \geq u \geq v \geq 0$$

$$F(x, y) = \int_{F(y)}^{F(y)} F(y)^n = [F(y)^n - [F(y) - F(x)]^n]$$

$$= 1 - \frac{1}{18} = 0.94. \quad f_R(t) = \frac{n!}{(1-1)!(n-1)!} f(t) \cdot F(t) \cdot [1 - F(t)]^{n-1}$$

$$F(t) = \int_0^t \lambda^{-\beta} t^{\beta-1} e^{-(t/\kappa)} dt \Big| \left(\frac{t}{\kappa}\right)^\beta = u$$

$$= \int_0^{\left(\frac{t}{\kappa}\right)^\beta} \lambda^{-\beta} \left(\frac{u}{\kappa}\right)^{\beta-1} e^{-u} du$$

$$= \frac{\lambda^{-\beta}}{\kappa^\beta} \int_0^{\left(\frac{t}{\kappa}\right)^\beta} u^{\beta-1} e^{-u} du$$

$$= \frac{\lambda^{-\beta}}{\kappa^\beta} t^{\beta-1} dt = \frac{\lambda^\beta}{\kappa^\beta} t^{\beta-1}$$

$$71. X_1, \dots, X_n: f_1, \dots, f_n: f(r) = \int_{-\infty}^{X_m} f(v+r, v) dv = \int_{-\infty}^{X_m} f(r+v, v) dv \quad | \quad f_k(t) = \frac{n \beta}{\kappa^\beta} t^{\beta-1} e^{-\frac{(t/\kappa)^\beta}{\kappa^\beta} - (n-1)(t/\kappa)^\beta}$$

$$\int_{-\infty}^r f(v+r, v) dv = \int_{-\infty}^r f(v+r, v) dv = f(X_m) - f(-\infty)$$

$$= \frac{n \beta}{\kappa^\beta} t^{\beta-1} e^{-n(t/\kappa)^\beta}$$

$$72. \text{Five numbers } [0, 1]; \text{ probability } \left[\frac{1}{4} \leq X_1, X_2 \leq X_3, X_4, X_5 \leq \frac{3}{4} \right] = \iiint \int f(u) = \iiint \int u du = \int \int \int \frac{u^2}{2} du = \int \int \frac{u^3}{6} du = \int \frac{u^4}{24} du = \frac{3/4^4}{24} = \frac{3/4^5}{120}$$

$$73. \text{Definition of } n^{\text{th}} \text{ independent random variable: } \boxed{\text{Definition } k^{\text{th}} \text{ order statistic}}$$

$$f_k(x) = n! f(x_1) f(x_2) f(x_3) \dots f(x_n)$$

$$= \frac{272/4!}{120} = \frac{272}{120} = \frac{272}{120}$$

74. n -servers; $T = \lambda e^{-\lambda t}$; $P(\text{Service Time} \geq t) = P(\text{No departure during } t) = P_N(t)$; $P_n(t) = e^{-\lambda t}$
 $S(t) = P(T \leq t) = 1 - P(T \geq t) = 1 - e^{-\lambda t}$
 Distribution of waiting time $\frac{1}{\lambda}$ with a variance $\frac{1}{\lambda^2}$.

75. $\frac{d}{dt} S(t) = \mu e^{-\lambda t}; s(t) = \begin{cases} \lambda e^{-\lambda t}, & t \geq 0 \\ 0, & t < 0 \end{cases}$
 Find the joint density of $X_{(i)}$ and $X_{(j)}, i < j$.
 $f_{W,U,V}(u,v) = \frac{n!}{(i-1)!(j-i-1)!(n-j)!} \times F(u)^{i-1} \times f(u) [F(v) - F(u)]^{j-i-1} \times f(v) [1 - F(v)]^{n-j}$ continued...

76. Prove Theorem A:

$$f_K(x) = \frac{n!}{(k-1)!(n-k)!} f(x) F^{k-1}(x) [1 - F(x)]^{n-k}$$
 is derived from
 Multinomial Probability Law:

$$\frac{n!}{(i-1)!(j-i-1)!(n-j)!} P_1 P_2 P_3 P_4 \cdots = F(x); P_2 = P(x \leq X_i \leq x+dx) = F(x+dx) \cdot F(x)$$

$f(x,y) = \lim_{dx \rightarrow 0} \lim_{dy \rightarrow 0} \frac{P(E)}{dx dy}$
 $P_1 = P(x \leq X_i \leq x+dx)$
 $P_3 = P(x+dx < X_i \leq y) = F(y) \cdot F(x+dx)$
 $P_4 = P(y < X_i \leq y+dy) = F(y+dy) \cdot F(y)$
 $P_5 = P(X_i > y+dy) = 1 - P(X_i \leq y+dy) = 1 - F(y+dy)$

77. $V_{(n)} - V_{(n-1)} = V_{i=1, \dots, n}$.
 $F(V_k) = \prod_{i=1}^n F(V_i); f(V_{k-1}) = n! \prod_{i=1}^{k-1} f(V_i)$
 $F(V_R) - F(V_{R-1}) = n! f(V_1) \cdot f(V_2) \cdots f(V_{k-1}) (f(V_k) - 1)$

78. Show $\int_0^1 \int_0^y (y-x)^n dx dy = \frac{1}{(n+1)(n+2)}$; $\int_0^y \int_{y-1}^y (y-x)^{n+1} dx dy = \frac{-1}{(n+1)} \int_0^1 [(y-1) - y^{n+1}] dy = \frac{-1}{(n+1)(n+2)} (y-1) - y^{n+2} \Big|_0^1$

79. T_1, T_2 are exponential random variables; $R = T_{(2)} - T_{(1)}$
 $F(R_{T_2}) = \iint f(T_1, T_2) dT_1 dT_2 = \iint f(T_1, R-T_1) dT_1 dR = \iint \lambda e^{-\lambda T_1} \lambda e^{-\lambda(R-T_1)} dT_1 dR$
 $f(z) = \int_0^\infty \int_0^\infty \lambda^2 e^{-(\lambda_1 + \lambda_2)T_1} \lambda^2 e^{-\lambda R} dT_1 dR$
 $= \frac{\lambda_1 \lambda_2}{(\lambda_1 - \lambda_2)} e^{-\lambda_2 R}$
 a) Find $P(V \leq V_{(n)}) = \int_0^V n! \prod_{i=1}^n f(V_i) dV$

80. U_1, \dots, U_n , V uniform, U_i independent.
 $P(V \leq V_{(n)}) = \int_0^{U_{(n)}} n! \prod_{i=1}^n f(U_i) dV = n! \prod_{i=1}^n f(V_i)^2 / 2$
 $P(V \leq V_{(n)}) = \int_0^{U_{(n)}} n! \prod_{i=1}^n f(V_i) dV + n! \prod_{i=1}^n f(V_i)^2 / 2$, $P(V_{(n)} \leq V < V_{(n)}) = \int_{V_{(n)}}^{U_{(n)}} n! \prod_{i=1}^n f(V_i) dV = n! \prod_{i=1}^n f(V_i)^2 / 2$

Chapter 4: 1) Prove if $|X| < M < \infty$, then $E(X)$ exists. $M = \sum_{i=1}^{\infty} m_i p(x_i) \leq M_1 + M_2 + \dots + M_{50}$

2) $F(x) = 1 - e^{-\lambda x}$, $x \geq 0$; a) $E(X) = \int_0^\infty x f(x) dx = \int_0^\infty x \frac{d}{dx} (1 - e^{-\lambda x}) dx = x e^{-\lambda x} \Big|_0^\infty + \int_0^\infty e^{-\lambda x} dx = \lambda^{-1}$; b) $\text{Var}(X) = E[(X - E(X))^2] = \int_0^\infty x^2 e^{-\lambda x} dx = \frac{-x e^{-\lambda x}}{\lambda} \Big|_0^\infty + \frac{1}{\lambda^2} \int_0^\infty e^{-\lambda x} dx = \frac{1}{\lambda^2}$

$= \int_0^\infty \left[x - \frac{\lambda}{\lambda+1} \right]^2 dx = \int_0^\infty \left[x^2 - 2x \frac{\lambda}{\lambda+1} + \left(\frac{\lambda}{\lambda+1} \right)^2 \right] dx = \left[\frac{x^3}{3} - x^2 \left(\frac{\lambda}{\lambda+1} \right) + \left(\frac{\lambda}{\lambda+1} \right)^2 x \right] \Big|_0^\infty = \infty$

$= E(X^2) - \mu^2 = \int_0^\infty x^2 e^{-\lambda x} dx = \int_0^\infty \lambda x e^{-\lambda x} dx = \lambda x e^{-\lambda x} \Big|_0^\infty + \int_0^\infty \lambda e^{-\lambda x} dx = \frac{\lambda}{\lambda+2} + \left(\frac{\lambda}{\lambda+1} \right)^2 = \frac{\lambda}{(\lambda+2)} + \left(\frac{\lambda}{\lambda+1} \right)^2$

3. Find $E(x)$ and $\text{Var}(x)$

for Chapter 2: Problem #3

R	F(R)
0	0
1	0.1
2	0.3
3	0.7
4	0.8
5	1.0

$$E(X) = \sum_{i=1}^n i p(x_i) = \sum_i X_i f(x_i) = \sum_i X_i [F(x_i) - F(x_{i-1})] = 5[1.0 - 0.0] + 4[0.8 - 0.7] + 3[0.7 - 0.3] + 2[0.3 - 0.1] + 1[0.1 - 0]$$

$$\text{Var}(X) = (0.2 - 3.1)^2(0.2) + (0.1 - 3.1)^2(0.1) + (0.4 - 3.1)^2(0.4) + (0.2 - 3.1)^2 \cdot 0.2 + (0.1 - 3.1)^2 \cdot 0.1 = 1.62$$

$$= \frac{5 \cdot 2}{10} + \frac{4 \cdot 1}{10} + \frac{3 \cdot 4}{10} + \frac{2 \cdot 2}{10} + \frac{1 \cdot 1}{10} = \frac{10 + 4 + 12 + 4 + 1}{10} = \frac{31}{10} = 3.1$$

4. $P(X=k) = 1/n$ for $k=1, 2, \dots, n$: Find $E(X)$ and $\text{Var}(X)$; $E(X) = 1 \cdot \left(\frac{1}{n}\right) + 2 \cdot \left(\frac{1}{n}\right) + 3 \cdot \left(\frac{1}{n}\right) + \dots + n \cdot \left(\frac{1}{n}\right) = \frac{n(n+1)}{2} \cdot \frac{1}{n}$

5. $f(x) = \frac{1+\lambda x}{2}$; $-1 \leq x \leq 1$; $-1 \leq \lambda \leq 1$

$$\text{Var}(X) = \left[\left(1 - \frac{(n+1)}{2} \right)^2 + \left(2 - \frac{(n+1)}{2} \right)^2 + \dots + \left(n - \frac{(n+1)}{2} \right)^2 \right] \frac{(n+1)n}{2}$$

$$E(X) = \int_{-1}^1 \frac{(1+\lambda x)x}{2} dx = \left[\frac{x^2}{4} + \frac{\lambda x^3}{6} \right] \Big|_{-1}^1 = \frac{1}{4} + \frac{\lambda}{6} + \frac{1}{4} + \frac{\lambda}{6} = \left(\frac{\lambda}{3} \right), E(X^2) = \int_{-1}^1 x^2 \frac{(1+\lambda x)}{2} dx = \frac{1}{2} \left[\frac{x^3}{3} + \frac{\lambda x^4}{4} \right] \Big|_{-1}^1 = \left(\frac{1}{3} \right)$$

6. $f(x) = 2x$; $0 \leq x \leq 1$

$$\text{a) } E(X) = \int_0^1 2x dx = \frac{2}{3}, \text{ b) } Y = X^2; \text{ Find } E(Y) = E(X^2) = \int_0^1 2x^3 dx = \frac{1}{2}, \text{ c) } \text{Var}(X) = E(X^2) - [E(X)]^2 = \frac{1}{3} - \frac{4}{9} = \frac{3-\lambda^2}{9}$$

$$\text{c) } E(X^2) = \int_0^1 2x^3 dx = \frac{2}{3}, \text{ d) } \text{Var}(X) = E[(X - E(X))^2] = \int_0^1 (x - \frac{2}{3})^2 2x dx = \frac{1}{18}$$

$$\text{Theorem B: } \text{Var}(X) = E(X^2) - E(X)^2 = \frac{2}{3} - \left(\frac{2}{3} \right)^2 = \frac{1}{18}$$

$$\text{a) } E(X) = \sum x f(x) = 0 \left(\frac{1}{2} \right) + 1 \left(\frac{3}{8} \right) + 2 \left(\frac{1}{8} \right) = \frac{5}{8}$$

$$\text{b) } Y = X^2, E(Y) = 0^2 \left(\frac{1}{2} \right) + 1^2 \left(\frac{3}{8} \right) + 2^2 \left(\frac{1}{8} \right) = \frac{7}{8}$$

$$\text{c) Theorem A: a) } E(Y) = \sum g(x) p(x) = 0^2 \left(\frac{1}{2} \right) + 1^2 \left(\frac{3}{8} \right) + 2^2 \left(\frac{1}{8} \right) = \frac{7}{8}$$

$$\text{b) } E(Y) = \int_{-\infty}^{\infty} g(x) f(x) dx;$$

$p(k) = \text{Number of items by customer.}$

$$\sum_{R=1}^{\infty} p(k) > C \sum_{k=1}^{n-1} p(k) \text{ and } \sum_{R=n+1}^{\infty} p(k) < C \sum_{k=n+1}^{\infty} p(k)$$

selling should be greater than cost?

Future sales should be cheaper than cost.

$$\text{d) } \text{Var}(X) = E[(X - E(X))^2] = \frac{1}{2} (0 - \frac{5}{8})^2 + \frac{3}{8} (1 - \frac{5}{8})^2 + \frac{1}{8} (2 - \frac{5}{8})^2 = \frac{31}{64}$$

$$\text{Var}(X) = E(X^2) - E(X)^2 = \frac{7}{8} - \left(\frac{5}{8} \right)^2 = \frac{31}{64}$$

n+1

10. n-items "Random" numbers
Let $E(X) = \sum_{i=1}^n p(x_i)x_i = \sum_{i=1}^n \left(\frac{1}{n}\right)x_i = \frac{\sum x_i}{n}$ " " $E(X) = \sum p_i x_i$; $E(X) = \prod X_i(1-p_1)(1-p_2)\cdots(1-p_{n-1})p_n$
 $P_1 + 2(1-p_1)p_2 + 3(1-p_1)(1-p_2)p_3 + \cdots + n(1-p_1)(1-p_2)\cdots(1-p_{n-1})p_n$

12. Suppose $E(X)=\mu$ and $\text{Var}(X)=\sigma^2$. Let $Z=(X-\mu)/\sigma$. Show $E(Z)=0$ and $\text{Var}(Z)=1$

$$E(Z) = E\left(\frac{X-\mu}{\sigma}\right) = \frac{E(X)-E(\mu)}{\sigma} = \frac{\mu-\mu}{\sigma} = 0; \text{Var}(Z) = \text{Var}\left(\frac{X-\mu}{\sigma}\right) = \frac{1}{\sigma^2}[\text{Var}(X)-\text{Var}(\mu)] = \frac{\sigma^2}{\sigma^2} = 1$$

13. $E(X) = \int_0^\infty x f(x) dx$; Product Rule: $[H = [X F(x)]]' = F(x) + x f(x)$; $1 - F(x) = x f(x)$; $E(X) = \int_0^\infty [1 - F(x)] dx$
 $E(X) = \frac{E(X)}{n!} = \int_0^\infty [1 + \frac{x}{n!}] dx = x + \frac{e^x}{n!} \Big|_0^\infty = \frac{1}{n!}$

14. $f(x) = 2x$; $0 \leq x \leq 1$; $E(X) = \int_0^1 2x^2 dx = \frac{2}{3}x^3 \Big|_0^1 = \frac{2}{3}$ $\Rightarrow E(X^2) = \int_0^1 2x^3 dx = \frac{1}{2}$

15. Lottery A Lottery B
n-possible #'s n-possible #'s $E(X) = \sum_{j=1}^n \frac{1}{n!} \cdot X$ $E(A+B) = \frac{E(A)+E(B)}{2}$ $\text{Var}(X) = E(X^2) - E(X)^2 = E[(X-E(X))^2]$
Payoff A = Payoff B $F(X) = \sum_{j=1}^n \frac{1}{n!} \cdot X$ $= E(A) = E(B)$ $\frac{1}{2} - \left(\frac{2}{3}\right)^2 = \frac{5}{9}$

16. $\text{Var}(+x) = \text{Var}(-x)$; $f_X(s+t) = f_X(s-s)$; $y = x - s$; $f_y(y) = f_x(y+s)$; $f_y(y) = f_x(-y)$

$Y = X - S$; $E(Y) = E(X) - E(S)$; $f_Y(y) = f_X(y)$

17. Rth-order Statistic:
 $\frac{n!}{(k-1)!(n-k)!} x^{k-1} (1-x)^{n-k}; 0 \leq x \leq 1$; $E(X) = \int_0^1 \frac{n!}{(k-1)!(n-k)!} x^k (1-x)^{n-k} dx = \frac{n!}{(k-1)!(n-k)!} \frac{\frac{n!}{(k-1)!(n-k)!}}{(n+1)!} \frac{k!(n-k)!}{(n+1)!} = \frac{k!}{(k-1)!(n+1)!} = \frac{k}{(n+1)}$

$$E(X^2) = \frac{n!}{(k-1)!(n-k)!} \int_0^1 x^{k+1} (1-x)^{n-k} dx = \frac{n!}{(k-1)!(n-k)!} \frac{(k+1)!(n-k+1)}{(n+2)!} = \frac{k(k+1)}{(n+1)(n+2)} = k(k+1); \text{Var}(X) = \frac{k(k+1)}{(n+1)(n+2)} - \frac{k^2}{(n+1)^2} = \frac{k(k+1)(n+1) - k^2(n+2)}{(n+1)^2(n+2)}$$

18. U_1, \dots, U_n ; $E(U_{(n)} - U_{(1)})$; $E(U_{(n)} - U_{(1)}) = \sum_{i=1}^n (U_{(n)} - U_{(1)}) f(U)$ $= \frac{(k^2+k)(n+1) - k^2 n + k^2(2)}{(n+1)^2(n+2)}$

19. $E(U_{(k)} - U_{(k-1)}) = \sum_{i=1}^n (U_{(k)} - U_{(k-1)}) f(U)$ $= \frac{k^3 n + k^2 + k n + k - k n - k^2 z}{(n+1)^2(n+2)}$

20. $E[1/(X+1)]$; $X = \frac{\lambda^k}{k!} e^{-\lambda x}$; $E\left[\frac{1}{(x+1)}\right] = \int_0^\infty \frac{1}{k!} \frac{1}{(x+1)} e^{-\lambda x} dx$
 $= \frac{\lambda^k}{k!} \int_0^\infty \frac{e^{-\lambda x}}{(1+x)} dx$; $u = 1+x$; $du = dx$; $x = u-1$; $\frac{1}{k!} \int_0^\infty \frac{e^{-\lambda(u-1)}}{u} du = \frac{\lambda^k}{k!} e^{-\lambda u} \Big|_0^\infty = \frac{\lambda^k}{k!} e^{-\lambda} E_1(k)$

$$= \frac{k(k+1-k)}{(n+1)^2(n+2)}$$

21. Expected $(\bar{X}) = \int_0^1 x^2 dx = \frac{1}{3}$ 22. Expected $(\bar{X}^2) = \int_0^1 x^2 dx = \frac{1}{3}$ 23. Expected $(X^2) = \int_0^\infty x^2 e^{-\lambda x} dx$
Area $\left(\frac{1}{2}\right)^2 + 1^2$ $E(X)E(Y) = \int_0^\infty x e^{-\lambda x} dx \cdot \int_0^\infty y e^{-\lambda y} dy = \frac{1}{12}$

24. Prove Theorem A of Section 4.1.2; $Y = a + \sum_{i=1}^n b_i X_i$; $E(Y) = a + \sum_{i=1}^n b_i E(X_i)$

$$\text{Proof: } E(Y) = \iint (a + b_1 X_1 + b_2 X_2) f(X_1, X_2) dX_1 dX_2 = a \iint f(X_1, X_2) dX_1 dX_2 + b_1 \iint X_1 f(X_1, X_2) dX_1 dX_2 \\ + b_2 \iint X_2 f(X_1, X_2) dX_1 dX_2 = \int X_1 \left[\int f(X_1, X_2) dX_2 \right] dX_1 = \int X_1 f(X_1) dX_1 = E(X_1)$$

$$E(Y) = a + b_1 E(X_1) + b_2 E(X_2); \quad \iint |a + b_1 X_1 + b_2 X_2| f(X_1, X_2) dX_1 dX_2 < \infty$$

25. Gamma Distribution: $|a + b_1 X_1 + b_2 X_2| \leq |a| + |b_1| |X_1| + |b_2| |X_2|$

$$F(x) = \frac{\lambda^a}{\Gamma(a)} x^{a-1} e^{-\lambda x} \quad \text{Find } R^2 = X_1^2 + X_2^2; \quad E(R^2) = \int (X_1^2 + X_2^2) T(x) dX_1 dX_2 = \int_{X_1=0}^{\infty} \int_{X_2=0}^{\infty} X_1^2 \frac{\lambda^x}{\Gamma(x)} x^{x-1} e^{-\lambda x} dx + \int_{X_2=0}^{\infty} \int_{X_1=0}^{\infty} X_2^2 \frac{\lambda^x}{\Gamma(x)} x^{x-1} e^{-\lambda x} dx$$

26. Expectation Long Price $= \frac{E(L)}{E(S)}$
Expectation Shorter Price $= \frac{\sum L \cdot f(x)}{\sum S \cdot f(x)}$

$$27. N-\text{men} \rightsquigarrow P(\text{IL}) \quad E(\# \text{ of men}) = \sum \frac{x}{n} = \frac{n}{n} = 1$$

$$28. X_i = \begin{cases} 1 & \text{if Aircrew i is hit} \\ 0 & \text{otherwise} \end{cases}; Z_{ij} = \begin{cases} 1 & \text{if gunner hits i} \\ 0 & \text{otherwise} \end{cases}$$

$$P(Z_{ij}=1|B_i) = p; \quad P(Z_{ij}=1|B_i) = 0; \quad P(B_i) = \frac{1}{n}$$

$$P(B) = 1 - P(B) = 1 - \frac{1}{n} \quad \text{"Even gunners survive"}$$

Addition Rule:

$$P(Z_{ij}=1) = P(Z_{ij}=1|B_i)P(B_i) + P(Z_{ij}=1|\bar{B}_i)P(\bar{B}) \\ = P\left(\frac{1}{n}\right) + 0\left(\frac{1}{n}\right) = \frac{p}{n}$$

Since the total probability is equal to 1, this implies:

$$P(Z_{ij}=0) = 1 - P(Z_{ij}=1) = 1 - \frac{p}{n}$$

$$E(X) = \sum X_i P(X_i) = 0(P(X=0)) + 1(P(X=1))$$

$$= 1 - P(X=1) = 1 - \left(1 - \frac{p}{n}\right)$$

$$= 1 - \{P(Z_{i1}=0)P(Z_{i2}=0)\cdots P(Z_{im}=0)\}$$

$$= 1 - \left(1 - \frac{p}{n}\right)^m$$

31. $X[1, 2]$

$$E[1/X] = \int x \left(\frac{1}{x}\right) dx$$

$$= \int dx = 1$$

$$\frac{1}{E(X)} = \frac{1}{\int x^2 dx} = \frac{3}{8-1} = \frac{3}{7}; \quad \text{They are not equal.}$$

30. Coupon Collection: n -distinct types of coupons.

$P(\text{coupon})$ are equivalent.

$$X_1=1, X_2=2, X_3=3 \cdots X_n=n; \quad P(\text{success}) = (n-r+1)/n$$

$$E(X_r) = n/(n-r+1)$$

$$E(X) = \sum_{r=1}^n E(X_r) = \frac{n}{n} + \frac{n}{n-1} + \frac{n}{n-2} + \dots + \frac{n}{1} = n \sum_{r=1}^n \frac{1}{r}$$

$$r = 2r \sum_{r=1}^{\infty} \frac{1}{r} = r$$

32. Gamma Distribution:

$$f(x) = \frac{\lambda^a}{\Gamma(a)} x^{a-1} e^{-\lambda x}$$

$$E\left(\frac{1}{x}\right) = \int_0^{\infty} \left(\frac{1}{x}\right) \frac{\lambda^a}{\Gamma(a)} x^{a-1} e^{-\lambda x} dx = \frac{\lambda^a}{\Gamma(a)} \int_0^{\infty} x^{(a-1)-1} e^{-\lambda x} dx$$

$$= \frac{\lambda^a}{\Gamma(a)} \frac{T(a-1)}{\lambda^{a-1}} = \frac{\lambda T(a-1)}{\Gamma(a)} = \frac{\lambda}{a}$$

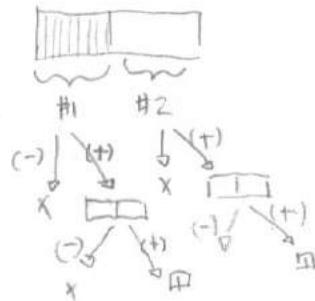
33. Prove Chebyshev's Inequality:

X, μ, σ^2 . For $t > 0$,

$$P(|X-\mu| > t) \leq \frac{\sigma^2}{t^2}$$

$$E(y) = E[(X-\mu)^2] = \int_{-\infty}^{\infty} (x-\mu)^2 f(x) dx \geq \int_{-\infty}^{\mu-E} (x-\mu)^2 f(x) dx + \int_{\mu+E}^{\infty} (x-\mu)^2 f(x) dx = \int_{-\infty}^{\mu-E} f(x) dx + \int_{\mu+E}^{\infty} (x^2 f(x)) dx = E^2 P(|X-\mu| \geq G)$$

34.

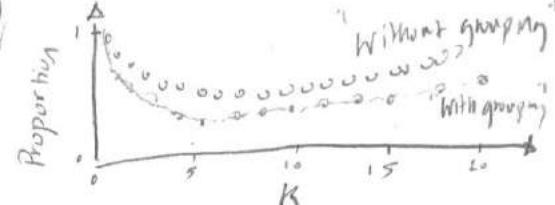
 $n = \text{Group Samples}$ $M = \text{Groups}$ $K = \text{Samples}$ $n = MK$ $"\text{With no grouping}"$

$$E(X) = \sum_{k=1}^m k p^k + (K+1)(1-p^K) = \sum_{k=1}^m K - Kp^K + 1$$

$$= m(K+1) - MKp^K = n(1 + \frac{1}{K} - p^K)$$

 $"\text{Average number of tests performed}"$

$$F(X) = K + 1 - Kp^K = K(1 + \frac{1}{K} - p^K)$$



35. Mean of Negative Binomial Random Variable.

$$E(R) = \sum_{r=1}^{\infty} r \binom{K-1}{r-1} p^r (1-p)^{K-r} = \sum_{r=1}^{\infty} \frac{K(r-1)!}{(r-1)!(K-r)!} p^r (1-p)^{K-r}$$

$$= \frac{K T(K)}{T(r) T(K-r+1)} \frac{T(r+1) T(K-r+1)}{T(K+2)} = \frac{KT(K) r T(r)}{T(K) (K+1) K T(K)} = \frac{r}{K+1}$$

$$36. X[0,1], Y=\sqrt{X}; E(Y) \text{ a. } E(Y) = E(\sqrt{X}) = \sum_0^1 \sqrt{x} f(x) + \sqrt{x} \cdot p + \sqrt{X}(1-p)^{1-x} = \sqrt{1} = 1$$

$$37. \text{Example C: Section 4.1.2- } E(N) = n(1 + \frac{1}{K} - p^K); E(X) = n \text{ b. } E(X) = E(N) \\ n = n(1 + \frac{1}{K} - p^K)$$

$$38. E(Y) = \sum_{R=0}^n \binom{n}{R} K p^R (1-p)^{n-R} = np$$

$$\text{a) } Y = \sum_{i=1}^n X_i; \text{ Length of DNA} = G, \text{ Fragments} = N \text{ of length} = L. \\ G > 10,000 \quad L > 500$$

Probability of left end is $1, 2, \dots, G-L+1$.

$$\frac{1}{K} = p^L \quad | \quad p = \left(\frac{1}{K}\right)^{1/L}$$

What is the probability a particular location $X \in \{L, L+1, \dots, G\}$ How many fragments are expected to cover a particular location, $\{1, 2, \dots, L-1\}$ What is the chance of covering the left end of L locations $\{x-L+1, x-L, \dots, x\}$

$$p = \frac{L}{G-L+1} \approx \frac{L}{G}; \text{ The binomial probability formula, } P(N \geq 0) = 1 - (1 - \frac{L}{G})^N \quad \lambda = Np = NL/G$$

a. Probability that a fragment is the leftmost member of a cutting $\frac{L}{G-L+1}$ b. Expected number of fragments left of cutting: $E(K) = \sum_{n=0}^N k P(k=0) = [1 - (1 - \frac{L}{G})^N] L$ c. Expected number of cuttings: $E(L) = L e^{-NL/G} = \frac{N}{L}$ 39. DNA Length = 10^6 , fragment length = 100

$$\text{a. } P(W > 0) = 0.79 = 1 - \left(1 - \frac{100^2}{10^6}\right)^N; \left(1 - \frac{1}{10}\right)^4 = 0.01; N \approx \frac{10^2}{\log(0.9999)} = 4.60 \times 10^4 \text{ fragments.}$$

$$\text{b) The expected misses } E(I) = e^{-4.60 \times 10^4 \cdot 100/10^6} = 0.01 \quad 0.999$$

$$40. Q, W, E, R, T, F \text{ produces 1000 letters in all. } E(QQQQQ) = \sum_{n=1}^{N-q+1} E(I_n) = (N-q+1) \left(\frac{1}{5}\right)^q$$

$$41. E(TWY) = \sum_{n=1}^{N-q+1} E(I_n) = (1000-3+1) \left(\frac{1}{5}\right)^3 = 998 \left(\frac{1}{5}\right)^3 = 79.84 \text{ times.}$$

$$n = 1000, q = 4 = (997) \left(\frac{1}{5}\right)^4 = 15.95 \text{ times}$$

Markov's Inequality:

$\frac{79.84}{1000} \approx 0.08$; Yes, the author would be surprised by the answer to occur.

42. Exponential Random Variable:
 $p(x) = \lambda e^{-\lambda x}$; $P(|X - E(X)| > k\sigma)$ | compare results to the bounds from Chebyshev's inequality

Chebyshev's Inequality: $P(|X - \mu| > t) \leq \frac{\sigma^2}{t^2}$

43. Show $\text{Var}(X-Y) = \text{Var}(X) + \text{Var}(Y) - 2\text{Cov}(X, Y)$ | $P(|X - E(X)| > k\sigma) \leq \frac{\sigma^2}{k^2\sigma^2} = \frac{1}{k^2}$ for $k=2, 3, 4 \dots$

$= E[(X-Y)^2] - E(X-Y)^2 = E(X^2) - 2E(XY) + E(Y^2) - E(X)^2 - E(Y)^2$ | covariance:

44. $= \text{Var}(X) + \text{Var}(Y) - 2\text{Cov}(X, Y)$ | $\text{Cov}(X, Y) = E[(X-\mu_X)(Y-\mu_Y)]$ provided the expectation exists

$X \& Y$ have equal variance. Find $\text{Cov}(X+Y, X-Y)$

$\text{Cov}(X+Y, X-Y) = E[(X+Y - E(X+Y))(X-Y - E(X-Y))] = E[(X-E(X) + Y-E(Y))(X-E(X) - Y+E(Y))]$

45. Find the covariance of N_1 and N_2 :
 $= E[(X-E(X))^2] - E[(X-E(X))(Y+E(Y))] + E[(Y-E(Y))(X-E(X))] - E[(Y-E(Y))^2]$
 $= E[(X-E(X))^2] - 2E[(X-E(X))(Y+E(Y))] - E[(X-E(Y))^2]$

where N_1, N_2, \dots, N_r are multinomial random variables. Multinomial Random Variable:

$\text{Cor}(N_i, N_j) = E[(N_i - E(N_i))(N_j - E(N_j))]$ | $P(n_1, n_2, \dots, n_r) = \binom{n}{n_1, n_2, \dots, n_r} p_1^{n_1} p_2^{n_2} \dots p_r^{n_r}$

$= E(N_i N_j) - E(N_i) E(N_j)$
 $= Pr(N_i = N_j) - Pr(N_i = 1) Pr(N_j = 1) = 0 - np_i p_j$ | $P(N_i = 1)$
 $= Pr(N_i = N_j) - Pr(N_i = 1) Pr(N_j = 1) = 0 - np_i p_j$ | $E(Z)$ and $P(Z=1)$.

46. $U \& V \geq \mu$ and σ^2 : $Z = \alpha U + \sqrt{1-\alpha^2} V$ | find $E(Z)$ and $P(Z=1)$

$E(Z) = E(\alpha U + \sqrt{1-\alpha^2} V) = E(\alpha U) + E(\sqrt{1-\alpha^2} V) = \alpha E(U) + \sqrt{1-\alpha^2} E(V) = (\alpha + \sqrt{1-\alpha^2}) \mu$

Correlation coefficient: If X and Y are jointly distributed random variables and the variances and covariances of both X and Y are nonzero, then the correlation of X and Y , denoted by ρ_{XY} , is

$\rho = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = \frac{E(VU) - E(V)E(U)}{\sqrt{\text{Var}(V)\text{Var}(U)}} = \frac{\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} b^{-\frac{1}{2}}(x-\mu_x)(y-\mu_y) e^{-\frac{(x-\mu_x)^2}{2\sigma_x^2} - \frac{(y-\mu_y)^2}{2\sigma_y^2}} uv du dv}{\sqrt{\sigma_x^2 \cdot \sigma_y^2}}$

$= \frac{(\frac{1}{2})^2 - (\frac{1}{2})^2}{\sigma_x^2 \cdot \sigma_y^2} = \phi$

$\therefore E[(X-E(X))(Z-E(Z))] = E[XZ] - E(X)E(Z) = E(X(Y-\phi)) - E(X)E(Y-\phi)$

$= E(XY) - E(XZ) - E(X)(E(Y) - E(Z)) =$

47. $Z = Y-X$; σ_Z^2 | find $\text{Cov}(X, Z) = \text{Cov}(X, Y-X) = 0$

$\text{corr}(X, Z) = \rho_{XZ} = \frac{\text{Cov}(X, Z)}{\sqrt{\text{Var}(X)\text{Var}(Z)}} = \frac{E(XY) - E(XZ) - E(X)(E(Y) - E(Z))}{\sqrt{\text{Var}(X)\text{Var}(Z)}} = \frac{E(XY) - E(X)(E(Y) - E(Z))}{\sqrt{\text{Var}(X)\text{Var}(Z)}}$

48. $U = a+bX$; $V = c+dY$ | show that $|P_{UV}| = |\rho_{XY}|$; $\rho = \frac{\text{Cov}(U, V)}{\sqrt{\text{Var}(U)\text{Var}(V)}} = \frac{\text{Cov}(a+bX, c+dY)}{\sqrt{\text{Var}(a+bX)\text{Var}(c+dY)}} = \frac{E[(a+bX)(c+dY)] - E(a+bX)E(c+dY)}{\sqrt{[E(a+bX)^2] - E(a+bX)^2} \sqrt{[E(c+dY)^2] - E(c+dY)^2}}$

$= E(ac) + E(adY) + E(bcX) + E(bdX) - (E(a) + E(bX))(E(c) + E(dY))$

$= \sqrt{[E(a^2) + 2E(abX) + E(b^2X^2)] - [E(a) - E(bX)]^2} \sqrt{[E(c^2) + 2E(cdY) + E(d^2Y^2)] - [E(c) + E(dY)]^2}$

$= \boxed{|\rho_{XY}|}$

49. $E(X) = E(Y) = \mu$, but $\sigma_X \neq \sigma_Y$; $Z = \alpha X + (1-\alpha)Y$; where $0 \leq \alpha \leq 1$

a) Show $E(Z) = \mu$; $E(Z) = E(\alpha X + (1-\alpha)Y) = \alpha E(X) + (1-\alpha)E(Y) = \alpha\mu + (1-\alpha)\mu = \mu$

b) Find α in terms of σ_X^2, σ_Y^2 to minimize $\text{Var}(Z)$

$$\text{Var}(Z) = \text{Var}(\alpha X + (1-\alpha)Y) = \alpha^2 E[X^2] - \alpha^2 E[X]^2 + (1-\alpha)^2 E[Y^2] - (1-\alpha)^2 E[Y]^2 = \alpha^2 [\text{Var}(X)] + (1-\alpha)^2 [\text{Var}(Y)]$$

$$\frac{d}{d\alpha} \text{Var}(Z) = 0 \Leftrightarrow (\alpha^2 \text{Var}(X) - (1-\alpha)^2 \text{Var}(Y)) = (2\alpha \text{Var}(X) + 2(1-\alpha)(-1)\text{Var}(Y)) = 0$$

$$\left[\alpha = \frac{2\text{Var}(Y)}{\text{Var}(X) + \text{Var}(Y)} \right] \Leftrightarrow \text{Var}\left(\frac{X+Y}{2}\right) \leq \text{Var}(X) \quad \left[\frac{1}{4}[\text{Var}(X) + \text{Var}(Y)] \leq \text{Var}(X) \right] \Leftrightarrow \text{Var}(Y) \leq 3\text{Var}(X)$$

c) When is the average $(X+Y)/2$ better to use than X or Y alone?

When the variance of the average is less than variance of X or Y alone.

50 $X_i; i=1 \dots n$; $E(X_i) = \mu$ and $\text{Var}(X_i) = \sigma_i^2$; $\bar{X} = n^{-1} \sum_{i=1}^n X_i \Rightarrow E(\bar{X}) = \mu$ and $\text{Var}(\bar{X}) = \sigma^2/n$

$$E(\bar{X}) = E\left(n^{-1} \sum_{i=1}^n X_i\right) = E\left(\frac{X_1 + X_2 + \dots + X_n}{n}\right) = \mu; \text{Var}(\bar{X}) = E(\bar{X}^2) - E(\bar{X})^2 = \frac{1}{n} E\left(\sum_{i=1}^n X_i^2\right) - \frac{1}{n^2} E\left(\sum_{i=1}^n X_i\right)^2 = \sigma^2/n$$

51. Example E: Section 4.3; $\mu_1 = \mu_2 = \mu$; $\sigma_{ij} = \text{Cov}(R_i, R_j) = 0$; Portfolio $(\pi, 1-\pi)$

Expected Return: $E(R(\pi)) = \pi\mu + (1-\pi)\mu = \mu$; Risk or Return: $\text{Var}(R(\pi)) = \pi^2 \sigma_1^2 + (1-\pi)^2 \sigma_2^2$

Minimizing Risk with respect to π : $\pi_{\text{opt}} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$; $\text{Var}(R(\frac{1}{2})) = \frac{\sigma^2}{2}$

When considering unique returns: $E(R(\pi)) = \pi\mu_1 + (1-\pi)\mu_2$

$$\text{Var}(R(\pi)) = \pi^2 \sigma_1^2 + 2\pi(1-\pi)\rho\sigma_1\sigma_2 + (1-\pi)^2 \sigma_2^2$$

When considering n-total investments: $E(R(\pi)) = \sum \pi_i \mu_i$; $\text{Var}(R(\pi)) = \sum_{i=1}^n \sum_{j=1}^n \pi_i \pi_j \sigma_{ij}$

Problem: n-securities (μ_i, σ_i)

Uncorrelated: $E(R(\pi)) = \sum_{i=1}^n \pi_i \mu_i$; $\text{Var}(R(\pi)) = \sum_{i=1}^n \sum_{j=1}^n \pi_i \pi_j \sigma_{ij}$
 $\mu = n\pi_i \mu_i$; $1 = n\pi_i \Rightarrow \frac{1}{n} = \pi_i$; $\text{Var} = \frac{1}{n^2} \sigma^2$; S.D. = $\frac{1}{\sqrt{n}} \sigma$

Risk of one security = $\frac{\sigma}{1}$ b) 50% into each stock

$$E(R(\pi)) = 0.5 \cdot 1 + 0.5 \cdot 0.5 = 0.9$$

$$\text{Var}(R(\pi)) = 0.5^2 (0.1)^2 + 2 \cdot 0.5 (1-0.5) (-0.5) (0.1) (0.1) + (1-0.5)^2 (0.1)^2$$

$$\sigma_{\pi_2} = 0.074$$

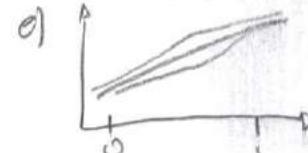
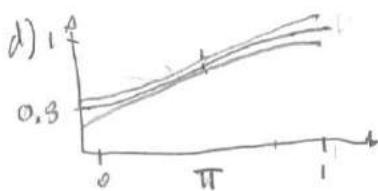
52. Two securities ($\mu_1 = 1, \sigma_1 = 0.1$)

$$(\mu_2 = 0.8, \sigma_2 = 0.12); \rho = -0.8;$$

a) Return #1 = $\mu_1 \pm \sigma_1 = 0.1 \pm 0.1$; $\frac{(\mu_2 - \mu_1)}{\sigma_1} = 10$ greater return per risk.

$$\text{Return } \#2 = \mu_2 \pm \sigma_2 = 0.8 \pm 0.12 \quad (\mu_2 / \sigma_2 = 6.75)$$

c) $E(R(\pi_1 = 80\%, \pi_2 = 20\%)) = 0.8 \cdot 1 + 0.2 \cdot 0.8 = 0.96$; $\text{Var}(R(\pi_1 = 80\%, \pi_2 = 20\%)) = 0.8^2 (0.1)^2 + 2 \cdot 0.8 (0.2) (-0.8) \cdot 0.1 \cdot 0.12 + (0.2)^2 (0.12)^2$



53. $\text{Cov}(X, Y) \leq \sqrt{\text{Var}(X)\text{Var}(Y)}$

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y) \leq \sqrt{E(X^2) - E(X)^2} \sqrt{E(Y^2) - E(Y)^2}$$

$$\leq \sqrt{E(X^2)E(Y^2) - E(X^2)E(Y)^2 - E(Y^2)E(X)^2 + E(X)^2E(Y)^2}$$

54. X, Y, Z with $\sigma_x^2, \sigma_y^2, \sigma_z^2$ $\neq 0.06$

$$\text{Let } U = Z + X; V = Z + Y$$

$$\text{Cov}(U, V) = E(UV) - E(U)E(V) = E[(Z+X)(Z+Y)] - E[Z+X]E[Z+Y]$$

$$= E[Z^2] + E[XZ] + E[ZY] + E[XY] - E[Z^2] - E[XZ] - E[ZY] - E[XY]$$

$$\Leftrightarrow 0$$

$$\text{Corr}(U, V) = \rho_{UV} = 0$$

55. $T = \sum_{k=1}^n k X_k$; X_k are independent random variables with μ, σ^2 . Find $E(T)$ and $\text{Var}(T)$

$$E(T) = E\left(\sum_{k=1}^n k X_k\right) = \frac{n(n+1)}{2} \mu; \quad \text{Var}(T) = \text{Var}\left(\sum_{k=1}^n k X_k\right) = E\left[\left(\sum_{k=1}^n k X_k\right)^2\right] - E\left[\sum_{k=1}^n k X_k\right]^2 = \frac{n(n+1)(2n+1)}{6} \sigma^2$$

56. $S = \sum_{k=1}^n X_k$; $\text{Cov}(S, T) = E(ST) - E(S)E(T) = E(\sum_{k=1}^n k X_k \sum_{k=1}^n k X_k) - E(\sum_{k=1}^n k X_k)E(\sum_{k=1}^n k X_k)$

$$= \frac{n(n+1)(2n+1)}{6} \mu^2 - \frac{n(n+1)}{2} \mu \cdot \mu = \left[\frac{n(n+1)(2n+1)}{6} - \frac{n(n+1)}{2} \right] \mu^2$$

$$\text{Corr}(S, T) = \rho_{ST} = \frac{\text{Cov}(S, T)}{\sqrt{\text{Var}(S)\text{Var}(T)}} = \frac{\left[\frac{n(n+1)(2n+1)}{6} - \frac{n(n+1)}{2} \right] \mu^2}{\sqrt{\sigma^2 \cdot \frac{n(n+1)(2n+1)}{6} \sigma^2}} = \frac{\left[\frac{n(n+1)(2n+1)}{6} - \frac{n(n+1)}{2} \right] \mu^2}{\sqrt{\frac{n(n+1)(2n+1)}{6} \sigma^2}}$$

57. $\text{Var}(XY) = E[(XY - E(XY))^2]$

$$= E(X^2Y^2 - 2XYE(XY) + E(XY)^2) = E(X^2Y^2) - 2E(X)E(Y)E(XY) + E(XY)^2$$

$$= E(X^2Y^2) - 2E(XY)^2 + E(XY)^2 = E(X^2Y^2) - E(XY)^2$$

$$= E(X^2)E(Y^2) - \mu_X \mu_Y = [\text{Var}(X) + E(X)^2][\text{Var}(Y) + E(Y)^2] - \mu_X^2 \mu_Y^2$$

$$= \text{Var}(X)\text{Var}(Y) + \text{Var}(X)E(Y)^2 + E(X)^2\text{Var}(Y) + E(X)^2E(Y)^2 - \mu_X^2 \mu_Y^2$$

$$= \sigma_X^2 \sigma_Y^2 + \mu_X^2 \mu_Y^2 + \mu_X^2 \sigma_Y^2 + \mu_X^2 \mu_Y^2 - \mu_X^2 \mu_Y^2$$

58. $X_1 = f(x) + \epsilon_1$; $X_2 = f(x+h) + \epsilon_2$; $\epsilon_1, \epsilon_2 \sim N(0, \sigma^2)$; $Z = \frac{f(x+h) - f(x)}{h}$

a) Find $E(Z) = E\left(\frac{X_2 - X_1}{h}\right) = E\left(\frac{f(x+h) + \epsilon_2 - f(x) - \epsilon_1}{h}\right) = \frac{1}{h} [E(f(x+h)) + E(\epsilon_2) - E(f(x)) - E(\epsilon_1)]$

$$= \frac{f(x+h) - f(x)}{h} \quad \boxed{= \frac{1}{h^2} [\text{Var}(f(x+h)) + \text{Var}(\epsilon_2) - \text{Var}(f(x)) - \text{Var}(\epsilon_1)]} \quad \begin{array}{l} \text{Mean} \\ \text{Squared} \\ \text{Error} \end{array}$$

Find $\text{Var}(Z) = \text{Var}\left(\frac{f(x+h) + \epsilon_2 - f(x) - \epsilon_1}{h}\right) = \frac{h^2}{h^2} \sigma^2 + \frac{\sigma^2}{h^2} = \frac{2\sigma^2}{h^2}$

In the limit of $E(Z) = \lim_{h \rightarrow 0} E(Z) = f'(x)$; $\lim_{h \rightarrow 0} \text{Var}(Z) = \lim_{h \rightarrow 0} \frac{2\sigma^2}{h^2} = 0$

b) Mean Squared Error of Z :

$$\text{MSE}(Z) = E[(Z - E(Z))^2] = \text{Var}(Z - Z_0) + E[(Z - Z_0)]^2 = \frac{2\sigma^2}{h^2} + \frac{f(x+h) - f(x)}{h}$$

$\lim_{h \rightarrow 0} \text{MSE}(Z) = f'(x)$; $X_3 = f(x+h+k) + \epsilon_3$; $E(\epsilon_1) = E(\epsilon_2) = E(\epsilon_3) = 0$; $\text{Var}(\epsilon_1) = \text{Var}(\epsilon_2) = \text{Var}(\epsilon_3) = \sigma^2$

c) $X_1 = f(x) + \epsilon_1$; $X_2 = f(x+h) + \epsilon_2$; $Z_1 = \frac{1}{h}[X_2 - X_1]$; $Z_2 = \frac{1}{h}[X_3 - X_2]$; $Z_3 = \frac{1}{h}[Z_2 - Z_1] = \frac{1}{h}\left(\frac{X_3 - X_2}{h} - \frac{X_2 - X_1}{h}\right)$

$$Z_3 = \frac{1}{h^2} X_1 - \left(\frac{1}{hk} + \frac{1}{h^2}\right) X_2 + \frac{1}{h^2} X_3; \quad E(Z_3) = \frac{1}{h^2} f(x) - \left(\frac{1}{hk} + \frac{1}{h^2}\right) f(x+h) + \frac{1}{h^2} f(x+h+k)$$

$$\text{Var}(Z_3) = 2\sigma^2 \left(\frac{1}{h^4} + \frac{1}{h^2 k^2} + \frac{1}{h^3 k}\right)$$

Show that $\text{Cov}(X, Y) = 0$: $E(XY) - E(X)E(Y)$

$$= \frac{4}{\pi^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x \sqrt{1-x^2} y \sqrt{1-y^2} dx dy - \frac{2}{\pi} \int_{-\infty}^{\infty} x \sqrt{1-x^2} \int_{-\infty}^{\infty} y \sqrt{1-y^2} dy = 0$$

59. (X, Y) is a random point on a disk.

$$f(x, y) = \begin{cases} \frac{1}{\pi r^2} x^2 + y^2 \leq r \\ 0 \text{ otherwise} \end{cases}$$

$$\text{Cov}(X, Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_x)(y - \mu_y) f(x, y) dx dy$$

60. Y is symmetric about $z=0$, $X = SY$

$$S = \pm 1; P(S=1) = P(S=-1) = \frac{1}{2}; \text{Show } \text{Cov}(X, Y) = 0$$

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y) = E(SY^2) - E(SY)E(Y) = S E(Y^2) - S E(Y^2) = 0$$

$$E(X) = E(SY) = SE(Y); \quad \frac{E(X)}{E(Y)} = S; \quad = 2 \int_{-\infty}^{\infty} \left(\frac{x^2}{2}\right) (y - \mu_y) dy = 0$$

61.
 $f(x, y) = z$

$0 \leq x \leq y$

a)

$\text{Cov}(X, Y)$

$\text{Corr}(X, Y)$

$\text{Var}(X, Y)$

$\text{MSE}(X, Y)$

$\text{MSE}(X, Y)$

$$X \& Y \text{ from } [0,1] ; f(x,y) = 2 ; 0 \leq x \leq y \leq 1$$

a) $\text{Cov}(X,Y) = E(XY) - E(X)E(Y)$

$$\begin{aligned} &= \frac{1}{4} - \left(\frac{1}{3}\right)\left(\frac{2}{3}\right) = \frac{1}{4} - \frac{2}{9} \\ &= \frac{9}{36} - \frac{8}{36} = \boxed{\frac{1}{36}} \end{aligned}$$

$E(X) = \int_0^1 x \left[\int_x^1 f(x,y) dy \right] dx = \int_0^1 x \left[\int_x^1 2 dy \right] dx = \int_0^1 x [2x] dx = 2 \int_0^1 x^2 dx = 2 \left[\frac{x^3}{3} \right] = \boxed{\frac{2}{3}}$

$E(Y) = \int_0^1 y \left[\int_0^y f(x,y) dx \right] dy = \int_0^1 y \left[\int_0^y 2 dx \right] dy = \int_0^1 y [2y] dy = \int_0^1 2y^2 dy$

b. $\text{Corr}(X,Y) = \frac{\text{Cov}(X,Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}$

$$\begin{aligned} &= \frac{(1/36)}{\sqrt{(E[X^2]-E[X]^2)(E[Y^2]-E[Y]^2)}} \\ &= \frac{1/36}{\sqrt{(\frac{1}{12}-\frac{1}{9})(\frac{1}{2}-\frac{4}{9})}} = \frac{1/36}{\sqrt{1/18}} = \boxed{\frac{1}{12}} \end{aligned}$$

$$\begin{aligned} &\quad \boxed{\frac{2}{3}[2-2x]} \\ &\quad \boxed{2[x^2-x^3]} \\ &\quad \boxed{2[\frac{x^3}{3}-\frac{x^4}{4}]} \\ &\quad \boxed{\frac{2}{3}-\frac{2}{9}=\frac{8}{12}-\frac{4}{12}=\frac{4}{12}} \end{aligned}$$

Find $E(X|Y=y)$ and $E(Y|X=x)$

Conditional Expectations:

if $P_{Y|X}(y|x)$, then $E(Y|X=x) = \sum_y y P_{Y|X}(y|x)$

$$= \int y f_{Y|X}(y|x) dy$$

More Generally,

$$E[h(Y)|X=x] = \int h(y) f_{Y|X}(y|x) dy$$

c) Find $E(X|Y)$ and $E(Y|X)$

$$\begin{aligned} &= y/2 & &= (x+1)/2 \end{aligned}$$

$$\begin{aligned} f_{W_1}(W_1) &= 2f_Y(2W_1) & f_{W_2}(W_2) &= 2(2W_2-1) \\ &= 2(2(2W_1)) & &= 8(1-W_2) \end{aligned}$$

F_{W_1}

$$\begin{aligned} E(Y|X=x) &= \int y \frac{f(x,y)}{F(X)} = \int y \left(\frac{2}{2-2x} \right) dy = \frac{y^2}{4} \Big|_0^1 = \frac{1}{4}(x+1)^2 \\ &= \int y \cdot 2 \left(\frac{1}{1-x} \right) dy = \frac{1}{2} [1-x^2] \left(\frac{1}{1-x} \right) \Big|_0^1 = \frac{1}{2} \\ E(X|Y=y) &= \int_x^y x \cdot P_{X|Y}(x|y) dx = \int_x^y \frac{f(x,y)}{F(y)} dx = \int_x^y \frac{2}{2y} dx \\ &= \frac{y^2}{2y} = \boxed{\frac{y}{2}} \end{aligned}$$

d) $\hat{Y} = a + bX$; $\min(E((Y-\hat{Y})^2))$ Predictor

$$E(\hat{Y}) = a + bE(X); \mu_Y = a + b\mu_X$$

$$a = \mu_Y - b\mu_X = \frac{2}{3} - \frac{1}{2} \left(\frac{1}{3} \right) = \frac{2}{3} - \frac{1}{6} = \frac{1}{2}$$

$$= \frac{12}{18} - \frac{3}{18} = \boxed{\frac{9}{18}}$$

Mean Squared Error: $E(Y - \frac{1}{2} - \frac{1}{2}X)^2 = \sigma_Y^2(1-p^2)$

$$= \frac{1}{18} \left(1 - \frac{1}{4} \right) = \boxed{1/24}$$

$$= E(Y^2) - E(E(Y|X))^2 = \frac{1}{2} - E\left(\frac{(x+1)^2}{2}\right) = \frac{1}{2} - \int_0^1 \frac{(x+1)^2}{4} (1-x) dx$$

$$= \boxed{1/24}$$

$$\text{Cov}(\bar{X}, \bar{Y}) = E((\bar{X}-\bar{X})(\bar{Y}-\bar{Y}))$$

$$= E(\bar{X}\bar{Y}) - E(\bar{X}\bar{Y}) - E(\bar{Y}\bar{X}) + E(\bar{X})E(\bar{Y})$$

$$= E(\bar{X}\bar{Y}) - E(\bar{X})E(\bar{Y})$$

$$= E\left(\frac{X-E(X)}{\sqrt{\text{Var}(X)}} \frac{Y-E(Y)}{\sqrt{\text{Var}(Y)}}\right) - \frac{E(X)-E(E(X))}{\sqrt{\text{Var}(X)}} \frac{E(Y)-E(E(Y))}{\sqrt{\text{Var}(Y)}} + p_{XY}$$

a) $\text{Cov}(X,Y) = E[(X-\mu_X)(Y-\mu_Y)] = E[XY] - E[X]E[Y]$

$$= \int_0^1 \int_0^1 xy f(x,y) dx dy - \int_0^1 x f(x) dx \int_0^1 y f(y) dy$$

$$= \int_0^1 \int_0^1 xy \frac{6}{7}(x+y)^2 dx dy - \int_0^1 x \left[\int_0^1 \frac{6}{7}(x+y)^2 dy \right] dx \int_0^1 y \left[\int_0^1 \frac{6}{7}(x+y)^2 dx \right] dy$$

62. $E(Y|X=x) = \frac{1}{2} - E\left(\frac{(x+1)^2}{4}\right)$

$$= \frac{1}{2} - \int_0^1 \frac{(x+1)^2}{4} (1-x) dx$$

X & Y joint

$$= \boxed{1/24}$$

random variables with Define the Standardized correlation p_{XY} , random variables \tilde{X} and \tilde{Y}

$$\tilde{X} = (X - E(X)) / \sqrt{\text{Var}(X)}$$

$$\tilde{Y} = (Y - E(Y)) / \sqrt{\text{Var}(Y)}$$

Show that $\text{Cov}(\tilde{X}, \tilde{Y}) = p_{XY}$

$$f(x,y) = \frac{6}{7}(x+y)^2$$

$$0 \leq x \leq 1 ; 0 \leq y \leq 1$$

$$= \int_0^1 \int_0^1 xy \frac{6}{7}(x^2 + 2xy + y^2) dx dy - \int_0^1 x \frac{6}{7}(x^2 + x + \frac{1}{3}) dx \int_0^1 y \frac{6}{7}(\frac{1}{3} + y + y^2) dy$$

$$= \int_0^1 y \frac{6}{7}(\frac{1}{3} + y + y^2) dy - \frac{6}{7} \left[\frac{1}{4} + \frac{1}{3} + \frac{1}{6} \right] \frac{6}{7} \left[\frac{1}{6} + \frac{1}{3} + \frac{1}{4} \right] = \frac{6}{7} \left[\frac{1}{6} + \frac{1}{3} + \frac{1}{4} \right] - \frac{36}{49} \left(\frac{3}{4} \right) = -0.0085$$

$$\text{Corr}(X, Y) = \rho_{XY} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = \frac{-19/34}{\sqrt{(E[X^2] - E[X]^2)(E[Y^2] - E[Y]^2)}} = \frac{-19/34}{\sqrt{\left(\int_0^1 \frac{6}{7}[x^4 + x^3 + \frac{x^2}{3}] dx - \frac{81}{196}\right) \left(\int_0^1 \frac{6}{7}[\frac{y^2}{3} + y^3 + y^4] dy - \frac{81}{196}\right)}}$$

$$= \frac{-19/34}{\sqrt{\left(\frac{6}{7}\left[\frac{1}{5} + \frac{1}{4} + \frac{1}{9}\right]\right)^2}} = 0.1256 \quad \text{Miscalculation}$$

b.

$$\text{Find } E(Y|X=x) \text{ for } 0 \leq x \leq 1$$

$$\text{Conditional Expectation: } E(Y|X=x) = \sum y P_{Y|X}(y|x)$$

$$= \int_0^1 y \frac{f(x,y)}{F(x)} dx$$

	x				
	1	2	3	4	
y	1	0.12	0.05	0.02	0.02
	2	0.05	0.20	0.85	0.02
	3	0.02	0.05	0.20	0.04
	4	0.02	0.02	0.04	0.10
F(x)	0.19	0.32	0.31	0.18	

$$= \int_0^1 y \frac{f(x,y)}{F(x)} dx$$

$$= \int_0^1 y \frac{6}{7}(x^2 + 2xy + y^2) dy$$

$$= \frac{6}{4} \frac{x^2 + 3x + 3}{(3x^2 + 3x + 1)}$$

$$E(X) = 1 \cdot 0.19 + 2 \cdot 0.32 + 3 \cdot 0.31 + 4 \cdot 0.18 = 2.48 = E(Y)$$

$$E(X^2) = 1^2 \cdot 0.19 + 2^2 \cdot 0.32 + 3^2 \cdot 0.31 + 4^2 \cdot 0.18 = 7.14 = E(Y^2)$$

$$\text{Cov} = 0.5046; \text{Corr} = 0.514455$$

$$\text{a. Cov}(X, Y) = E(XY) - E(X)E(Y) = \sum xy f(x,y) - \sum x f(x) \sum y f(y)$$

$$= 1^2 \cdot 0.1 + 2 \cdot 1 \cdot 0.05 + 3 \cdot 1 \cdot 0.02 + 4 \cdot 1 \cdot 0.02 + 2 \cdot 1 \cdot 0.05 + 4^2 \cdot 0.2 + 6 \cdot 1 \cdot 0.05 + 8 \cdot 1 \cdot 0.02 + 3 \cdot 1 \cdot 0.02 + 6 \cdot 1 \cdot 0.05 + 5^2 \cdot 0.2 + 12 \cdot 1 \cdot 0.04 + 4 \cdot 1 \cdot 0.02 + 8 \cdot 1 \cdot 0.02 + 3 \cdot 4 \cdot 0.04 + 4^2 \cdot 0.10 = 6.66$$

$$\text{Var}(X) = E(X^2) - E(X)^2 = 7.14 - 2.48^2 = 0.9896$$

$$\text{Var}(Y) = 0.9896$$

b)

$$\text{Find } E(Y|X=x) \text{ for } x=1, 2, 3, 4 : E(Y|X=1) = \sum y f(y|x) = \sum y \frac{f(x,y)}{f(x)} = \frac{1 \cdot 0.1}{0.19} + \frac{2 \cdot 0.05}{0.19} + \frac{3 \cdot 0.02}{0.19} + \frac{4 \cdot 0.02}{0.19} = 1.78$$

$$E(Y|X=2) = \sum y f(y|x) = \sum y \frac{f(x,y)}{f(x)} = \frac{1 \cdot 0.05 + 2 \cdot 0.2 + 3 \cdot 0.85 + 4 \cdot 0.02}{0.32} = 1.78$$

$$E(Y|X=3) = \sum y f(y|x) = \frac{1 \cdot 0.02 + 2 \cdot 0.15 + 3 \cdot 0.2 + 4 \cdot 0.14}{0.31} = 2.13$$

$$E(Y|X=4) = \frac{1 \cdot 0.02 + 2 \cdot 0.02 + 3 \cdot 0.04 + 4 \cdot 0.1}{0.18} = 0.87$$

65. Random Sums:

$$T = \sum_{i=1}^N X_i$$

$$E(T) = E[E(T|N)] = E[N E(X)] = E(N) E(X) \leftarrow \text{Independence}$$

$$66. \begin{array}{|c|c|} \hline \text{Fast} & \text{Slow} \\ \hline 1 \text{ min} & 3 \text{ min} \\ \hline \end{array}; E(T) = \sum E(T|P_i) P(c_i) = 1 \min \left(\frac{2}{3} \right) + 3 \min \left(\frac{1}{3} \right) = \frac{5}{3} \text{ min}$$

$$P(F) = \frac{2}{3}, P(S) = \frac{1}{3} \quad | \quad E(XH) = E[E(XH|X)] = E[X E(H|X)] = E(X) E(H|X)$$

$$E(2(X+H)) = E[E(2(X+H)|X)] = E[2X + 2E(H|X)] = \frac{1}{2} E(X^2) = \frac{1}{2} \int_0^1 x^2 dx = \frac{1}{6}$$

$$\text{Note: } E[2X] + E[2E(H|X)] = 2 \left(\frac{a+b}{2} \right) + \left(\frac{a+b}{2} \right) = 1 + \frac{1}{2} = \frac{3}{2}$$

$$E(Z) = \int_a^b z f(z) dz = \frac{1}{b-a} \int_a^b z dz = \frac{b^2 - a^2}{2(b-a)} = \frac{b+a}{2}$$

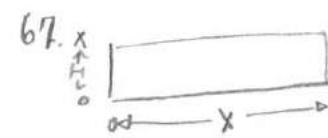
$$E(Y|X) = \mu_y + \rho \frac{\sigma_y}{\sigma_x} (X - \mu_x)$$

$$@P=0 \quad = \emptyset + \emptyset = 0$$

$$@P=0.5 \quad = \emptyset + \frac{1}{2} \left(\frac{1}{2} \right) (X - \mu_x) = \frac{1}{2} (X - \mu_x) = \frac{X - \mu_x}{2}$$

$$@P=0.9 \quad = \emptyset + \frac{1}{2} (X - \mu_x) = \frac{X - \mu_x}{2}$$

$$@P=0.1 \quad = \emptyset + \frac{1}{2} (X - \mu_x) = \frac{X - \mu_x}{2}$$



$$E_{\text{Arm}} = \sum \sum E(Y|X=x) P_X(x) = \sum \sum y P_{Y|X}(y|x) P_X(x)$$

$$67. \text{ Show } E[\text{Var}(Y|X)] \leq \text{Var}(Y)$$

$$E[E(Y^2|X)] - E[E(Y|X)]^2 \leq [E[Y^2] - E[Y]^2]$$

$$E(X|Y) = \mu_X + \rho \frac{\sigma_X}{\sigma_Y} (Y - \mu_Y)$$

$$@P=0 \quad E(X|Y) = 0$$

$$@P=0.5 \quad E(X|Y) = Y/2$$

$$@P=0.9 \quad E(X|Y) = Y/9$$

$$70. \text{ Show } E(X|Y=y) = E(X); E(X|Y=y) = \sum x P_{X|Y}(x|y) = \sum x \frac{f(x,y)}{P(y)} = \sum \frac{x}{P(y)} f(x) = \sum x f(x) = E[X]$$

H. Binomial Random Variables n -trials, Y -successes for m -trials $\Rightarrow m$ men

$$P(1) = p; P(0) = 1-p; P(x) = 0$$

$$P(x) = \begin{cases} p^x (1-p)^{n-x}, & \text{if } x \geq 0 \text{ or } x=1 \\ 0 & \text{otherwise} \end{cases}$$

Conditional Mean:

$$\frac{(K)(N-K)}{k(n-k)} = \frac{nK}{N}$$

$\binom{n}{k}$ Hypergeometric Fm

$$72. = m \frac{X}{n} = E[Y|X=x]$$

Distribution of a Hypergeometric Fm

$$\frac{\binom{X}{K} \binom{h-X}{x-k}}{\binom{n}{m}}$$

74.

$$\xrightarrow{n} p(n)$$

First n -tosses:

$$E[\text{Heads}] = E[\text{Hypergeom}] + E[\text{Short} | E[\text{Heads}]]$$

$$= np + np \cdot p = np(1+p)$$

$$E[X] = \sum_{x=1}^n x p(x) = \frac{n(n+1)}{2} p(x)$$

$$73. \text{ Var}(X) = \mu^2; E[X] = \mu; E[X^2] = \mu^2; E[X^3] = \mu^3$$

$$\text{Var}(X) = \sigma^2; \text{Var}(\mu^2) = \sigma^4; \text{Var}(\mu^3) = \sigma^6$$

$$75. P(T) = \lambda e^{-\lambda T}; E[V \cdot E[T]] = E[V] \cdot E[T] = \left[\frac{1}{2} \cdot \frac{1}{\lambda} \right]; \text{Var}(V \cdot E[T]) = \text{Var}(V) \cdot \text{Var}(T) = \left[\frac{1}{12} \left(\frac{1}{\lambda^2} \right) \right]$$

$$76. (X, Y): x^2 + y^2 \leq 1; y \geq 0.$$

$$f_{XY}(x, y) = \frac{|A|}{|R|} = \frac{1}{\pi/2} = \frac{2}{\pi}$$

$$f_X(x) = \int_{-\sqrt{1-x^2}}^{\sqrt{1-x^2}} f_{XY}(x, y) dy = \frac{2}{\pi} \sqrt{1-x^2}$$

$$f_Y(y) = \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} f_{XY}(x, y) dx = \frac{4}{\pi} \sqrt{1-y^2}$$

$$f_{Y|X}(y|x) = \frac{f(x, y)}{f_X(x)} = \frac{\frac{2}{\pi}}{\frac{2}{\pi} \sqrt{1-x^2}} = \frac{1}{\sqrt{1-x^2}}$$

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)} = \frac{1}{2\sqrt{1-x^2}}$$

$$E_{Y|X}(y|x) = \int_0^{\sqrt{1-x^2}} y f_{Y|X}(y|x) dy = \frac{\sqrt{1-x^2}}{2}$$

$$E_{X|Y}(x|y) = \frac{1}{\frac{1}{3} - \frac{1}{3} \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} f(x|y) dx} \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} x f(x|y) dx$$

= 0

$$77. f(x, y) = e^{-y}; 0 \leq x \leq y$$

$$b) E(X|Y=y) = \int x f_{X|Y}(x|y) dx = \int_0^y \frac{f(x,y)}{f(y)} dx$$

$$= \int_0^y x \frac{e^{-y}}{y} dy = \frac{y}{2}$$

$$E(Y|X=x) = \int_y y f_{Y|X}(y|x) dy = \int_x^y \frac{e^{-y}}{1} dy = \boxed{x+1}$$

c) Density Function $E(X|Y)$ and $E(Y|X)$

$$E[X] = E[E[X|Y]] = E[Y/2] = E[Y]/2$$

$$E[Y] = E[E[Y|X]] = E[X+1] = E[X] + 1$$

Skewness - third central moment - asymmetry of a density of frequency shows a min.

$$\begin{aligned} a) \text{Find } \text{cov}(X, Y) &= E[XY] - E[X]E[Y] = \iint_{\mathbb{R}^2} xy f(x, y) dx dy - \int_{\mathbb{R}} x [\int_{\mathbb{R}} y f(x, y) dy] dx - \int_{\mathbb{R}} y [\int_{\mathbb{R}} x f(x, y) dx] dy \\ &= \left[\int_0^\infty x^2 \right] \int_0^y y e^{-y} dy - \int_0^y x \left[\int_0^x y e^{-y} dy \right] \int_0^\infty y \left[\int_0^y x e^{-y} dx \right] dy \\ &= \int_0^\infty \frac{y^3}{2} e^{-y} dy + \int_0^y x e^y \int_0^y y^2 e^{-y} dy = 3 \end{aligned}$$

$$\text{Corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sqrt{\text{Var}(X) \text{Var}(Y)}} = \frac{3}{\sqrt{(2-1)(6-2)}} = \frac{1}{\sqrt{2}}$$

$$78. M(t) = \sum e^{tx} P(x) = e^{tr/t} \quad \text{1st Moment}$$

$$M'(t) = E[X] = \frac{e^{tx}}{t} \quad \text{2nd Moment}$$

$$M''(t) = E[X^2] = t e^{tx} \quad \text{3rd Moment}$$

$$M'''(t) = e^{tx} + t^2 e^{2tx} = (1+t^2)e^{tx} \quad \text{3rd Moment}$$

$$\delta = \lim_{t \rightarrow -\infty} M'''(t) - \lim_{t \rightarrow \infty} M'''(t)$$

79. $p(0) = \frac{1}{2}; p(1) = \frac{3}{8}; p(2) = \frac{1}{8}$; Find $M(t)$; $M(t) = \sum_x e^{tx} p(x) = e^{tx} \left[\frac{1}{2} + \frac{3}{8} + \frac{1}{8} \right] = e^{tx}$

$f(x) = 2x; 0 \leq x \leq 1$

$M(t) = \int_0^t e^{tx} \cdot 2x dx = \frac{2e^{tx}(tx-1)}{t^2} \Big|_0^t = \frac{2e^t(t-1)}{t^2} + \frac{2}{t^2}$

$M'(0) = X e^{tx} = E(X); M''(0) = X^2 e^{tx} = E(X^2)$

$M'(0) = 0$

$Bernoulli Random Variable.$

$$p(1) = p \\ p(0) = 1-p \\ p(x) = \begin{cases} p^x (1-p)^{1-x} & x=1 \\ 0 & x \neq 1 \end{cases}$$

$$M'(0) = \frac{d}{dt} \left[1+t+\frac{t^2}{2!}+\frac{t^3}{3!}+\dots \right] \left[\frac{2}{t}-\frac{2}{t^2} \right] + \frac{2}{t^2} \\ = 2(1)\left(\frac{1}{2!}-\frac{1}{3!}\right) + 2(2)(0)\left(\frac{1}{3!}-\frac{1}{4!}\right) + 2(3)(0)\left(\frac{1}{4!}-\frac{1}{5!}\right) + \dots$$

$\boxed{\frac{2}{3}}$ Binomial Random Variable:

MGF of a Binomial is \sum Bernoulli

$$M(t) = \prod_{i=1}^n M_x(t) = (1-p+pe^t)^n$$

$$M(t) = \sum_0^t e^{tx} p(x) = 1-p+e^t p$$

$$M'(0) = p = E(X) \\ M''(0) = p = E(X^2)$$

$$Var(X) = M'(0) - M''(0)^2 = p - p^2$$

$$M'(0) = n(1-p+p) \sum_{i=1}^{n-1} p^i = n \cdot p = E[X] \\ M''(0) = n(n-1)(1-p+p) \sum_{i=1}^{n-2} p^i + n(1-p+p) \cdot p = n(n-1)p^2 + np = (n^2-n)p^2 + np = np^2 - np^2 + np = np(1-p) \\ Var(X) = E[X^2] - E[X]^2 = n^2 p^2 - np^2 + np - n^2 p^2 = np(1-p)$$

$$\sum_{k=1}^n \binom{n}{k} p^k (1-p)^{n-k}$$

83. Binomial Distribution:

$$P(X) = \binom{n}{X} p^X (1-p)^{n-X}; P(X) = \sum_{i=1}^n X_i = X_1 + X_2 + \dots + X_n = \binom{n}{1} p^1 (1-p)^{n-1} + \binom{n}{2} p^2 (1-p)^{n-2} + \dots + \binom{n}{n} p^n (1-p)^{n-n}$$

84. $= \binom{n}{1} p_1 (1-p_1)^{n-1} + \binom{n}{2} p_2 (1-p_2)^{n-2} + \dots + \binom{n}{n} p_n (1-p_n)^{n-n} \neq \text{Binomial Distribution}$

85. Moment Generating Function: Geometric Random Variable - $p(k) = p(1-p)^{k-1}$

$$M(t) = \sum_0^{\infty} e^{tk} \cdot p(1-p)^{n-k} = \frac{e^{tp}}{1-(1-p)e^t} \cdot \text{Binomial Relationship} = e^{tp} (1-p)^{n-1} - \frac{1}{1-qe^t}$$

$$M'(t) = \frac{t}{(1-(1-p)e^t)^2} e^{tp} - \frac{(1-p)e^t}{(1-(1-p)e^t)^2} = \frac{te^{tp} - qe^t p(1-p)e^t + e^t p(1-p)e^{2t}}{(1-(1-p)e^t)^2} = \frac{qe^t(1-qe^t) + 2pe^t(1-qe^t)qe^t}{(1-qe^t)^2} = \frac{pe^t}{(1-qe^t)^2}$$

$$M''(0) = \frac{P}{P^2} = \frac{1}{P}; M''(t) = \frac{pe^t(1-qe^t)^2 - pe^t(2(1-qe^t)(-q)e^t)}{(1-qe^t)^4} = \frac{pe^t(1-qe^t) + 2pe^t(1-qe^t)qe^t}{(1-qe^t)^4} = \frac{2+q-2(1+2p+pq^2)}{P^3} = \frac{3-(1-p)-2(1-p)^2}{P^3}$$

$$Var(X) = E[X^2] - E[X]^2$$

$$= \frac{2+q-2(1+2p+pq^2)}{P^3} = \frac{2+q-2(1+2p+pq^2)}{P^3}$$

86. MGF of a Negative Binomial

$$p(X=r) = \binom{r-1}{r-1} p^r (1-p)^{r-r}$$

$$M(t) = \prod_{i=1}^n M_x(t) = p^n (1-qe^t)^{-n}$$

$$M'(t) = -np^n (1-qe^t)^{-(n-1)} (-qe^t); M'(0) = +np^n (1-q)^{-n} q$$

$$= np^n \cdot p^{n-n} \cdot q = np^{n-r+1} \cdot q = np^{r-1} \cdot q$$

$$M''(t) = \frac{d}{dt} \left[\frac{np^n q e^t}{(1-qe^t)^{n-1}} \right] = \frac{n nq}{P} + \frac{n^2 q^2}{P^2} + \frac{n q^2}{P^2} = \frac{n^2 q^2}{P^2} + \frac{n^2 q^2}{P^2}$$

$$Var(X) = E[X^2] - E[X]^2 = \frac{nq}{P}$$

87. When is the sum of independent random variables of a binomial also a negative binomial?

Binomial Distribution:

$$P(k) = \binom{n}{k} p^k (1-p)^{n-k}$$

Negative Binomial Distribution

$$P(R) = \binom{R-1}{r-1} p^r (1-p)^{R-r}$$

When $k-1=n$, and $r-1=k$.

When the total trials is the n

and successes is R

$X \sim N(0, \sigma^2)$; Prove odd moments of $M_X(t)$ are zero
and even moments are

Even Moments:

$$M_e(t) = \int_{-\infty}^{\infty} e^{tx} N(0, \sigma^2)$$

$$\mu_{2n} = \frac{(2n)! \sigma^{2n}}{2^n (n!)}$$

$$-\frac{x^2}{2\sigma^2} + tx = \frac{-1}{2\sigma^2} (x^2 - 2\sigma^2 t x)$$

$$= \frac{-1}{2\sigma^2} (x^2 - 2\sigma^2 t x + (\frac{\sigma^2 t}{2})^2) - (\sigma^2 t)^2$$

$$= \frac{-1}{2\sigma^2} (x - \sigma^2 t)^2 - (\sigma^2 t)^2$$

$$= \frac{e^t}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} e^{-\frac{1}{2\sigma^2}(x - \sigma^2 t)^2} dx ; u = x - \sigma^2 t, \frac{du}{dt} = -1$$

$$+ \frac{1}{2}\sigma^2 t^2$$

$$= \frac{e^t}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} e^{-\frac{u^2}{2\sigma^2}} du = \frac{e^t}{\sqrt{2\pi\sigma^2}} \sqrt{2\pi\sigma^2} = \frac{e^t}{\sigma^2}$$

$$\mu_{2n} = \frac{(2n)! \sigma^{2n}}{2^n (n!)}$$

$$M'(t) = +\sigma^2 t e$$

$$M''(t) = +\sigma^2 e^{-\sigma^2 t^2/2} + \sigma^2 t (-\sigma^2 t) e^{-\sigma^2 t^2/2} = -\sigma^2 t [1 - \sigma^2 t e^{-\sigma^2 t^2/2}] = +\sigma^2 @ n=0$$

89. $X_1, X_2, \dots, X_n = N(\mu_i, \sigma_i^2)$; Prove $Y = \sum_{i=1}^n X_i$ (where X_i are scalar). Find μ_Y, σ_Y^2

$$Y = \sum_{i=1}^n X_i; X_i \sim N(\mu_i, \sigma_i^2) \Rightarrow MGF of Y: M(t) = \prod_{i=1}^n e^{tX_i}$$

Completing the Square:

$$tx - \frac{(x-\mu)^2}{2\sigma^2} = tx - \frac{x^2 - 2\mu x + \mu^2}{2\sigma^2}$$

$$- \frac{x^2}{2\sigma^2} + \frac{(2\mu + 2\sigma^2 t)x}{2\sigma^2} + \frac{\mu^2}{2\sigma^2}$$

$$- \frac{1}{2\sigma^2} (x + (\mu + \sigma^2 t))^2 - \frac{(\mu + \sigma^2 t)^2}{2\sigma^2} + \frac{\mu^2}{2\sigma^2}$$

$$- \frac{1}{2\sigma^2} (x - (\mu + \sigma^2 t))^2 - \frac{(2\mu + \sigma^2 t)^2}{2\sigma^2} + \frac{\mu^2}{2\sigma^2} + \sigma^2 t^2$$

$$90. Z = \alpha X + \beta Y; M_Z(t) = E(e^{tZ}) = e^{t\alpha X + t\beta Y}$$

$$= E(e^{t\alpha X + t\beta Y}) = E(e^{t\alpha X} \cdot e^{t\beta Y}) \mu_1 + \mu_2 t^2$$

$$= E(e^{t\alpha X}) E(e^{t\beta Y})$$

$$= M_X(t) M_Y(t)$$

91. Exponential Distribution:

$$p(x) = \lambda e^{-\lambda x}$$

$$M_X(t) = \lambda e^{(t-\lambda)x}$$

$$M_{CX}(t) = \lambda e^{(t-\lambda)x}$$

92. Gamma Distribution: Poisson Distribution With Example

$$g(t) = \frac{\lambda^k}{T(k)} t^{k-1} e^{-\lambda t}$$
 $p(x=k) = \frac{\lambda^k}{k!} e^{-\lambda}$ $f(\theta) = \frac{\lambda^k}{T(k)} \theta^{k-1} e^{-\lambda \theta}$; $X|\theta = \frac{\theta^k}{x!} e^{-\theta}$

$$P(X=x) = \int_0^\infty P(X|\theta) f(\theta) d\theta = \int_0^\infty e^{-\theta} \frac{\lambda^k}{x!} \frac{\theta^{k-1} e^{-\lambda \theta}}{T(k)} d\theta = \int_0^\infty \frac{\lambda^k \theta^{x+k-1} e^{-(\lambda+1)\theta}}{x! (k-1)!} d\theta$$

$$= \frac{(x+k-1)!}{x! (k-1)!} \frac{\lambda^k}{(\lambda+1)^{x+k}} \int_0^\infty \frac{(\lambda+1)^{x+k} \theta^{x+k-1} e^{-(\lambda+1)\theta}}{T(x+\theta)} d\theta$$
; Rate = $(\lambda+1)$

$$\text{Shape} = k+x$$

$$M_{X|\theta}(t) = E[e^{tx}|\theta] = \exp((e^t - 1)\theta)$$
 and $M_\theta(m) = E[e^{m\theta}] = (1 - m/\lambda)^{-\lambda}$

$$M_X(t) = E[e^{tx}] = E[E[e^{tx}|\theta]] = E[M_{X|\theta}(t)] = E[\exp((e^t - 1)\theta)] = M_\theta(e^t - 1) = (1 - \frac{e^t - 1}{\lambda})^{-\lambda}$$

93. Geometric Sum: Exponential Random Variable: $M_X(t) = \left(\frac{1/(1+\lambda)}{1 - e^t(1-\lambda/(1+\lambda))} \right)^k \approx \frac{1}{\lambda + t}$

$$X_1 = X_2 + \dots + X_n$$
 $P(X) = \lambda e^{-\lambda x}$

$$M(t) = \sum_{k=0}^{\infty} \sum_{x_1, x_2, \dots, x_k} X(x) ; e^{tx} = \sum_{x_1, x_2, \dots, x_k} \lambda e^{-(\lambda+t)x} = \frac{-\lambda}{\lambda+t} e^{-(\lambda+t)x}$$

 negative binomial

94. Probability-Generating Function: $G(s) = \sum_{k=0}^{\infty} s^k p_k$; where $p_k = P(X=k)$
 a) Show $p_k = \frac{1}{k!} \frac{d^k}{ds^k} G(s) \Big|_{s=0}$; Fundamental theorem of calculus: $\int_a^b f(x) dx = F(b) - F(a) = \frac{d}{dx} F(x)$
 b). Show $\frac{dG}{ds} = E(X)$ $\frac{dG}{ds} = K s^{(k-1)} p(k) = E(X) = [K \cdot p(k)]$

$$\frac{d^2G}{ds^2} \Big|_{s=1} = E[X(X-1)]$$
 $\frac{d^2G}{ds^2} = K(K-1)s^{(k-2)} p(k) = [K(K-1) \cdot p(k)]$
 c) $M(t) = \sum_{s=0}^{\infty} \sum_{k=0}^{\infty} e^{tk} G(s) = \sum_{s=0}^{\infty} \sum_{k=0}^{\infty} e^{tk} \frac{s^k}{k!} p_k = \sum_{s=0}^{\infty} \frac{e^{ts}}{s!} \sum_{k=0}^{\infty} \frac{s^k}{k!} p_k = \frac{e^{ts}}{s!} \sum_{k=0}^{\infty} \frac{s^k}{k!} p_k = \frac{e^{ts}}{s!} \sum_{k=0}^{\infty} \frac{s^k}{k!} \frac{1}{k+1} \frac{k!}{k!} p_k = \frac{e^{ts}}{s!} \sum_{k=0}^{\infty} \frac{s^k}{(k+1)!} p_k = \frac{e^{ts}}{s!} \sum_{k=0}^{\infty} \frac{s^k}{(k+1)!} \frac{1}{k+1} \frac{(k+1)!}{k!} p_k = \frac{e^{ts}}{s!} \sum_{k=0}^{\infty} \frac{s^k}{k!} p_{k+1} = \frac{e^{ts}}{s!} \sum_{k=0}^{\infty} \frac{s^k}{k!} p_k = e^{ts} G(s)$
 d) $G(s) = \sum_{k=0}^{\infty} \frac{s^k}{k!} \lambda^{k-1} e^{-\lambda} d\lambda = e^{-\lambda} \sum_{k=0}^{\infty} \frac{(s\lambda)^k}{k!} = e^{-\lambda} e^{s\lambda} = \frac{e^{(s-\lambda)\lambda}}{\lambda!}$

95. Joint Moment Generating Function: $M(t) = \sum_{x,y} e^{tx+ty} xy = \sum_{x,y} e^{tx+ty} x y = M_X(t) M_Y(t)$
 96. $E(XY) = M'(0) = \frac{d}{dt} \left[\sum e^{tx} x e^{ty} \right] = XY p(x, y)$ $M(t) = \sum e^{tx+ty} p(x, y)$; $M'(t) = \sum (x+y) e^{tx+ty} p(x, y)$
 97. $\text{Var}(ax+by) = a^2 \text{Var}(X) + b^2 \text{Var}(Y)$; $M''(t) = \sum (x+y)^2 e^{tx+ty} p(x, y)$

$$M''(0) = (x+y)^2 p(x, y) = E[X^2]; M'(0) = (x+y) p(x, y) = E[X]$$

$$= E[X^2] - E[X]^2 = (x+y)^2 p(x, y) - (x+y)^2 p(x, y)^2 = (x^2 + 2xy + y^2)(p(x, y) - p(x, y)^2)$$

98. Compound Poisson Distribution: $M_2(t) = \exp[\mu(e^{\lambda(e^t-1)} - 1)]$

$$M'_2(0) = [\mu(e^{\lambda(e^t-1)} - 1)]' \exp[\mu(e^{\lambda(e^t-1)} - 1)]$$

$$= [\lambda(e^t-1)] [\mu(e^{\lambda(e^t-1)} - 1)] \exp[\mu(e^{\lambda(e^t-1)} - 1)]$$

$$= \lambda e^t [\mu(e^{\lambda(e^t-1)} - 1)] \exp[\mu(e^{\lambda(e^t-1)} - 1)] = \lambda e^t E[X]$$

99. $Y = g(X)$ a) $g(X) = \sqrt{X}$

$$E[Y] = \int_0^\infty x \sqrt{x} dx = x \left(\frac{2}{3}\right) x^{3/2} \Big|_0^\infty - \int_0^\infty \sqrt{x} dx = \infty$$

$$\text{Var}[Y] = 0$$

b) $E[X] = \int_0^{\infty} x \log x dx = x\left(\frac{1}{x}\right) \Big|_0^{\infty} - \int_0^{\infty} \log(x) dx = 1 - \frac{1}{x} \Big|_0^{\infty} = \text{undefined}$ $(x=1) + (x \rightarrow \infty)$

Var(X) = undefined

c) $g(x) = \sin^{-1}(x) \Rightarrow E[X] = \int_{-1}^{1/2} x \sin^{-1}(x) dx = \frac{\ln x - 1}{x} \Big|_{-1}^{1/2} = \text{Does not converge}$ $\text{Var}(X) = \text{Does not converge}$

100. $X \sim U[1, 20] \Rightarrow Y = \sqrt{X} \Rightarrow E[Y] = \int_{1/2}^{20} \frac{1}{10} \left(\frac{1}{x}\right) dx = \frac{\ln 20 - \ln 10}{10} = 0.0643$; $E[Y^2] = \int_{1/2}^{20} \frac{1}{10} \left(\frac{1}{x}\right)^2 dx = \left[\frac{1}{10x^2} x\right]_{1/2}^{20} = \frac{-1}{10x^2} \Big|_{1/2}^{20} = 0.005$

Exact Method ~~Approximate Method~~ $\text{Var}(Y) = E[Y^2] - E[Y]^2 = 0.0005 - 0.0643^2 = 0.000196$

101. $Y = \sqrt{X}; X \sim \text{Poisson Distribution}$

$E(Y) \sim g(\mu_x) + \left(\frac{1}{2}\right) \sigma_x^2 g''(\mu_x) = \frac{1}{2} + \left(\frac{1}{2}\right) 0.33 = 0.53$ (0.0006)

$\sigma_x^2 = \frac{(b-a)^2}{12} = 0.33$ $E[0.0244]$

$\sigma_x = 0.0127$

$E(Y) \sim g(\mu_x) + \frac{1}{2} (\sigma_x^2) g''(\mu_x)$ $\text{Var}(Y) \approx \sigma_x^2 [g'(\mu_x)]^2 = 0.000161$

$\sim \lambda^{\frac{1}{2}} - \frac{1}{2} \lambda - \frac{1}{4} \lambda^{-\frac{3}{2}}$ $\approx \lambda \left[\frac{1}{2} (\lambda)^{-\frac{1}{2}} \right]^2$

$\sim \sqrt{\lambda} - \frac{1}{8\sqrt{\lambda}}$ $\neq \frac{1}{4}$

102.

$y_0 = Y; E(Y) = y_0; \text{Var}(X) = \text{Var}(Y) = \sigma^2$ $E(\theta) \sim \tan^{-1}\left(\frac{E(Y)}{E(X)}\right) = \tan^{-1}\left(\frac{y_0}{x_0}\right)$

$\theta = \tan^{-1}\left(\frac{Y}{X}\right); E(\theta) \sim$ $\text{Var}(\theta) \sim \tan^{-1}\left(\frac{\text{Var}(Y)}{\text{Var}(X)}\right) = \tan^{-1}(1) = 45^\circ$

$X_0 = X$

103. $V = \frac{\pi}{6} D^3; D = 2 \text{ mm} \Rightarrow \sigma_V = 0.01 \text{ mm}; V = \frac{\pi}{2} D^2; \sigma_V^2 \approx \sigma_X^2 [g'(\mu_X)]^2; \sigma_V \approx \sigma_X g'(\mu_X)$

$\approx 0.01 \text{ mm} \cdot \frac{\pi}{2} 2^2 \text{ mm}^2 \approx 6.28 \times 10^{-3} \text{ mm}$

104. $r = R \cos \theta; Y = R \sin \theta$ a) $\text{Var}(Y) \sim \sigma_x^2 [g'(\mu_X)]^2 \approx \sigma_x^2 [R \cos \theta]^2 \approx R^2 \sigma_x^2$

b) $\frac{d \text{Var}(Y)}{d \theta} = R \sin \theta = 0 \Rightarrow 90^\circ = \theta$

Chapter 5: i) $X_1, X_2, \dots; E(X_i) = \mu; \text{Var}(X_i) = \sigma_i^2$, Show $n^{-2} \sum_{i=1}^n \sigma_i^2 \rightarrow 0; \bar{X} \rightarrow \mu$

Law of Large Numbers: $P(|\bar{X} - \mu| > \epsilon) \leq \frac{\text{Var}(\bar{X}_n)}{\epsilon^2} = \frac{\sigma^2}{n \epsilon^2} \rightarrow 0$

2. $E(X_i) = \mu_i$; if $E(\bar{X}) = \frac{1}{n} \sum_i^n E(X_i) = \mu$ $P(|\bar{X} - \mu| > \epsilon) \leq \epsilon \sigma^2 = E[\bar{X}^2] - E[\bar{X}]^2; \bar{X}^2 = \mu^2; |\bar{X} - \mu|$

3. Number of Insurance Claims, N , is a Poisson Distribution: $p(x) = \frac{\lambda^x}{x!} e^{-\lambda}$ $E(N) = 10,000$.

Standardizing Random Variables: $Z_n = \frac{X_n - E(X_n)}{\sqrt{\text{Var}(X_n)}} = \frac{10,200 - 10,000}{\sqrt{10,000}} = 102 - 100 = 2$

$P(Z_n) = 1 - 0.1772 = 0.0228$

4. Number of Traffic Accidents (N) is $E(N) = 100$. Find Δ if $\epsilon = p$, then $P(100 - \Delta < N < 100 + \Delta) \approx 0.9$

$Z_n = \frac{X_n - E(X_n)}{\sqrt{\text{Var}(X)}}; P(100 - \Delta < N < 100 + \Delta) = \frac{100 - \Delta - 100}{\sqrt{100}} = 10 - 10 - \Delta \approx -\Delta$

$P(N) = \frac{X_n - 100 + \Delta}{\sqrt{100}} = \Delta = \frac{100 - 100 + \Delta}{\sqrt{100}} = \frac{\Delta}{10} = 1.3$

Mems 1.3 cars more or less for probability of 90%.

5. $n \rightarrow \infty$, $p \rightarrow 0$, and $np = \lambda \rightarrow \infty$ Binomial Distribution: $P(X) = \binom{n}{k} p^k (1-p)^{n-k}$; n and p fixed parameter

Moment Generating Function: $M(t) = \int_0^\infty e^{tk} \binom{n}{k} p^k (1-p)^{n-k} dk$; if $np = \lambda$

$$P(k) = \frac{\lambda^k}{k!} e^{-\lambda}$$

Continuity Theorem: $\lim_{n \rightarrow \infty} M_n(t) \rightarrow M(t)$; $\lim_{n \rightarrow \infty} F_n(x) = F(x)$ [Law of Large Number]

$$= \binom{n}{k} \int_0^\infty e^{tk} \cdot \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k} dk$$

$$\lim_{n \rightarrow \infty} M_n(t) = \lim_{n \rightarrow \infty} \int_0^\infty \binom{n}{k} \cdot e^{tk} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k} dk = \lim_{n \rightarrow \infty} \int_0^\infty \frac{n!}{k!(n-k)!} \underbrace{\frac{1}{n^k}}_1 \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-k} dk = \int_0^\infty e^{tk} \frac{\lambda^k}{k!} e^{-\lambda} dk$$

$$= \int_0^\infty e^{tk} \frac{\lambda^k}{k!} e^{-\lambda} dk = \int_0^\infty \frac{(\lambda e^t)^k}{k!} e^{-\lambda} dk = e^{\lambda(e^t-1)}$$

b.

Poisson Distribution

$$\lambda \rightarrow \infty \text{ Gamma Distribution: } \frac{\lambda^x}{T(x)} t^{x-1} e^{-\lambda t}$$

$$\rightarrow M_\lambda(t) = \int_0^\infty e^{tx} \frac{\lambda^x}{T(x)} x^{x-1} e^{-\lambda x} dx; \lim_{x \rightarrow \infty} M_x(t) = \lim_{x \rightarrow \infty} \int_0^\infty e^{tx} \frac{\lambda^x}{T(x)} x^{x-1} e^{-\lambda x} dx$$

$$= \lim_{x \rightarrow \infty} \frac{\lambda^x}{T(x)} \int_0^\infty x^{x-1} e^{t(x-\lambda)} dx = \lim_{x \rightarrow \infty} \frac{\lambda^x}{T(x)} \left(\frac{T(x)}{(x-t)^\lambda} \right) = \left(\frac{\lambda}{\lambda-t} \right)^\lambda = \infty$$

7. $X_n \rightarrow c$; g is continuous, then $g(X_n) \rightarrow g(c)$

Continuity Theorem $\boxed{\lim_{X_n \rightarrow c} g(X_n) = g(c)}$

8. Poisson Cumulative Distribution: a) $\lambda = 10$; CDF_{Poisson} = $\int_0^x \frac{\lambda^k}{k!} e^{-\lambda} dk = e^\lambda \cdot e^{-\lambda}$; b) i) c) $\lambda \approx \text{Normal Standard}$

9. Binomial Cumulative Distribution: a) $n=20$, $p=0.2$. CDF_{Binomial} = $\int_0^x \binom{n}{k} p^k (1-p)^{n-k} dk = \int_0^x \frac{20!}{k!(20-k)!} 0.2^k (0.8)^{20-k} dk = 20! 0.8^x \int_0^x \frac{1}{4^k k! (20k)!}$

$$= 8.89 \times 10^{-1}$$

The binomial converges to the normal standard when current ratio $p = 0.5$

$$\text{Normal Approximation} \quad \left(\frac{\lambda - E(\lambda)}{\sqrt{\lambda}} \right) = \frac{0.2 - 20 \cdot 0.2}{\sqrt{20 \cdot 0.2 \cdot (1-0.2)}} = 0$$

10. Six-sided die, $n=100$; $\left(\frac{X - E(X)}{\sqrt{Var(X)}} \right) = P(Z)$; $P(15 < X < 20) = \left(\frac{15 - 100/16}{\sqrt{100/16(1-1/16)}} < Z < \frac{20 - 100/16}{\sqrt{100/16(1-1/16)}} \right) = 35\% \text{ to } 23\%$

$$\approx P(15.5 < X < 19.5) = P\left(\frac{15.5 - 100/16}{\sqrt{100/16(1-1/16)}} < Z < \frac{19.5 - 100/16}{\sqrt{100/16(1-1/16)}}\right)$$

$$\approx P(-0.31 < Z < 0.76) = P(Z < 0.76) - P(Z < -0.31)$$

$$= P(Z < 0.76) - 1 + P(Z < 0.31) = 0.774 - 1 + 0.6217 = 0.4$$

$$E[X] = \frac{6+1}{2} = 3.5; Var(X) = \frac{1}{12}(6^2 - 1) = 2.917$$

$$E[S] = 100 E[X] = 100(3.5) = 350; Var(S) = 100(2.917) = 291.67$$

$$P(S < 300) \approx P(S < 219.5) = P\left(Z < \frac{219.5 - 350}{\sqrt{291.67}}\right)$$

$$= P(Z < -2.96) = 1 - P(Z < 2.96) = 0.00154$$

$$\text{As } n \rightarrow \infty, t/(5\sqrt{n}) \rightarrow 0 \quad M''(0) = 0^2$$

$$M\left(\frac{t}{\sigma\sqrt{n}}\right) = 1 + \frac{1}{2}\sigma^2 \left(\frac{t}{\sigma\sqrt{n}}\right)^2 + E_n$$

$$M_Z(t) = \left(1 + \frac{t^2}{2n} + E_n\right)^n; \lim_{n \rightarrow \infty} \left(1 + \frac{an}{n}\right)^n = e^a$$

11. The argument suffices to say $\lambda = np = 100 \cdot p \Rightarrow \frac{1}{p} = 100$; the probability must approach 0 as $n \rightarrow \infty$.
12. Uniform Random Variable $[-\frac{1}{2}, \frac{1}{2}]$. $n=100$; $P(X > 1) = \text{Prob}\left(\frac{X - E[X]}{\sqrt{\text{Var}(X)}} > \frac{1 - 0}{\sqrt{100/12}}\right) = P\left(\frac{X - 0}{\sqrt{100/12}} > \frac{1 - 0}{\sqrt{100/12}}\right) = P\left(\frac{Y}{\sqrt{25}} > \frac{\sqrt{3}}{5}\right)$
 $E[X] = \frac{a+b}{2}; \text{Var}(X) = \frac{(b-a)^2}{12} = \frac{(\frac{1}{2} - (-\frac{1}{2}))^2}{12} \cdot \frac{1}{12}$
 $= 1 - \Phi\left(\frac{\sqrt{3}}{5}\right)$
 $b) P(Y > 2) = P\left(\frac{Y - 0}{\sqrt{25}} > \frac{2 - 0}{\sqrt{25}}\right) = 1 - \Phi\left(\frac{2\sqrt{3}}{5}\right) = 0.2442$
 $c) P(Y > 5) = P\left(\frac{Y - 0}{\sqrt{25}} > \frac{5 - 0}{\sqrt{25}}\right) = 1 - \Phi\left(\frac{5\sqrt{3}}{5}\right) = 0.0416$
13. $P(\text{North}) = \frac{1}{2}$; Step Length = 50cm $E(X) = \sum X \cdot P(X)$; $\text{Var}(X) = E[X^2] - E[X]^2$
 $P(\text{South}) = \frac{1}{2}$; Approximate probability after 1h.
 $\underbrace{= 50(\frac{1}{2}) + (-50)(\frac{1}{2})}_{\text{per minute}} = \emptyset$
 $= 50^2(\frac{1}{2}) + (-50)^2(\frac{1}{2})$
 $= 2500$
 $E(S) = \sum_{i=1}^{60} E(X) = 60 \cdot 0 = 0$; $\text{Var}(S) = \sum_{i=1}^{60} \text{Var}(X) = 60 \cdot 2500 = 150,000$
 $P(S > 150) = \Phi\left(\frac{150 - 0}{\sqrt{150,000}}\right) = \Phi(0.173) = 0.567$
14. $P(\text{North}) = \frac{2}{3}$; $P(\text{South}) = \frac{1}{3}$
 $E[X] = \frac{1}{3}(50) + \frac{2}{3}(-50) = \frac{50}{3}; E[X^2] = \frac{1}{3}(-50)^2 + \frac{2}{3}(50)^2 = 2500$
 $E(S) = \sum_{i=1}^{60} E[X] = \frac{60}{3} \cdot 1000 = 20000$; $\text{Var}[X] = E[X^2] - E[X]^2 = 2500 - 1000 = 1500$
 $n = 60$; Amount = \$5
 $P(\text{Loss} > 75) = P(S < -75) = P\left(\frac{S - E[S]}{\sqrt{\text{Var}(S)}} < \frac{-75 - 0}{\sqrt{1500}}\right) = P(Z < -2.12) = 0.171$
 $E(S^2) = \sum_{i=1}^{60} E[X^2] = 60 \cdot 2500 = 150,000$
 $\text{Var}(S) = \sum_{i=1}^{60} \text{Var}[X] = 60 \cdot 1500 = 90,000$
15. $P(W_n) = \frac{1}{2}; P(\text{Loss}) = \frac{1}{2}$
 $\sum_{i=1}^{50} X_i < -75; \bar{X} < \frac{-75}{50} = -1.5; E(X) = 0; \text{Var}(X) = E(X^2) - E(X)^2 = 0$
 $P(\bar{X} < -1.5) = P\left(Z < \frac{-1.5 - 0}{\sqrt{1/2}}\right) = P(Z < -2.12) = 0.171$
 $P(S \leq 10); E[X] = \int_0^1 x f(x) dx = \int_0^1 x \cdot 2x dx = \frac{2x^3}{3} \Big|_0^1 = \frac{2}{3}$
 $P(S \leq 10) = P\left(\frac{S - E[S]}{\sqrt{\text{Var}(S)}} < \frac{10 - 0}{\sqrt{1/2}}\right) = P\left(\frac{S - 0}{\sqrt{1/2}} < \frac{10 - 0}{\sqrt{1/2}}\right)$
 $F[5] = \sum_{i=1}^{20} \frac{2}{3} = \frac{40}{3}; E[X^2] = \int_0^1 x^2 \cdot 2x dx = \frac{2x^4}{4} \Big|_0^1 = \frac{1}{2}$
 $\text{Var}(X) = E[X^2] - E[X]^2 = \frac{1}{2} - \frac{4}{9} = \frac{1}{18}$
 $P(S \leq 10) = P\left(\frac{S - 0}{\sqrt{1/2}} < \frac{10 - 0}{\sqrt{1/2}}\right) = 1 - \Phi(3.16) = 0.9997$
 $\text{Var}(S) = \sum_{i=1}^{20} \text{Var}[X] = \frac{20}{18} = 1.11$
16. $\mu, \sigma^2 = 25; P(|\bar{X} - \mu| < 1) = P(-1 < \bar{X} - \mu < 1) = P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} < \frac{1 - 0}{\sigma/\sqrt{n}}\right) = P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} < \sqrt{n}/\sigma\right) = 0.95$
 $P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} < \sqrt{n}/\sigma\right) = \frac{1 - 0.95}{2} = 0.025; -\frac{\sqrt{n}}{\sigma} = -1.97; n = 97$
17. "Descriptive size of range"
 $P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} < \sqrt{n}/\sigma\right) = P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} < \frac{1700 - 1500}{\sigma/\sqrt{n}}\right) = P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} < \frac{200}{\sigma/\sqrt{n}}\right) = P(2) = 0.9772$
18. $\mu = 150 \text{ lbs}; P(S < 1700 \text{ lbs}) = P\left(\frac{S - E[S]}{\sigma/\sqrt{n}} < \frac{1700 - 1500}{\sigma/\sqrt{n}}\right) = P\left(\frac{S - E[S]}{\sigma/\sqrt{n}} < \frac{200}{\sigma/\sqrt{n}}\right) = P(2) = 0.9772$

$$19. a) n=100, n=1000; f(x) = \int_0^1 \cos(2\pi x) dx = \frac{\sin(2\pi x)}{2\pi} \Big|_0^1 = \emptyset; \hat{I}(f) = \frac{1}{n} \sum_{i=0}^n f(X_i) = \frac{1}{100} \sum_{i=0}^{100} \cos(2\pi x) = \frac{1}{100} + \frac{1}{100} = \frac{2}{100}$$

$$b) I(f) = E[X] = \int_0^1 x \cos(2\pi x^2) dx = \int_0^1 x \cos(u) du; u = 2\pi x^2 \quad \hat{I}(f) = \frac{1}{1000} \sum_{i=0}^{1000} f(X_i) = \frac{1}{1000} \sum_{i=0}^{1000} \cos(2\pi x^2) = 1 > 0$$

Exact Solution: cosine integral: $\int \cos(u) dx; u = 2\pi x^2 \quad \int \frac{\cos(u)}{2\pi x} dx = \int \frac{\cos(u)}{2\pi \sqrt{u}} du = \int \frac{\cos(u)}{\sqrt{u}} du = \int \frac{\cos(2\pi x^2)}{x} dx = \frac{C(2)}{2} = 0.24$

$$20. E(\hat{I}^2(f)) = \left[\frac{1}{1000} \left(\frac{1}{\sqrt{2\pi}} \right) \sum_{i=1}^{1000} e^{-x_i^2/2} \right]^2 = \frac{1}{1000^2} \sum_{i=1}^{1000} (e^{-x_i^2/2})^2 = \frac{0.386}{2\pi \times 10^3} = 6.14 \times 10^{-5}$$

$$\text{Var}(\hat{I}(f)) = E[\hat{I}^2(f)] - E[\hat{I}(f)]^2 = \left(\frac{1}{1000^2} \sum_{i=1}^{1000} (e^{-x_i^2/2})^2 \right) - \left(\frac{1}{1000} \sum_{i=1}^{1000} e^{-x_i^2/2} \right)^2$$

$$21. I(f) = \int_a^b f(x) dx; \hat{I}(f) = \frac{1}{n} \sum_{i=1}^n \frac{f(X_i)}{g(X_i)} \quad a) \text{Show } E(\hat{I}(f)) = I(f) = \int_a^b f(x)/g(x) dx + \frac{1}{n} \sum_{i=1}^n f(x)/g(x)$$

$$b) \text{Var}(\hat{I}(f)) = E[\hat{I}(f)^2] - E[\hat{I}(f)]^2; n=100; n \rightarrow \infty$$

$$c) E(\hat{I}(f)) = \hat{I}(f) = \int_0^1 \frac{f(x)}{g(x)} dx = \int_0^1 e^{-x^2/2} dx \rightarrow \text{Example A: Section 5.2.}$$

22. Find Δ ; $P(|\hat{I}(f) - I(f)| \leq \Delta) = 0.05$, where $\hat{I}(f)$ is the Monte Carlo Estimate of $\int_0^1 \cos(2\pi x) dx$ based upon $n=1000$

$$P\left(\left|\frac{1}{1000} \sum_{i=1}^{1000} \cos(2\pi x_i) - \int_0^1 \cos(2\pi x) dx\right| \leq \Delta\right) = 0.05$$

$$P(|I| \leq \Delta) = 0.05; P(\Delta) = 0.05 - P(I) = 0.05 - 0.84 = -0.79 \Rightarrow \boxed{\Delta = 0.81}$$

$$23. P(\Delta) - P(I) = 0.05$$

$0 \leq x \leq 1; 0 \leq y \leq 1$; Random (x, y) ; $Z=1$ if $sy \geq x$ otherwise. Prove $E(Z) = A = \sum_{i=1}^1 \sum_{j=1}^1 xy \cdot Z(i,j)$

$$24. \hat{A}; E(s) = \sum_{i=1}^n E[z_i] = nE[z]; \hat{A} = nE[z] = nA; P(|\hat{A} - A| < 0.1) \approx 0.99$$

$$+ \sum_{i=1}^n \sum_{j=1}^n xy Z(i,j) \quad \boxed{= 1.174}$$

$$P(|nA - A| < 0.1) \approx 0.99 \Rightarrow P(|n-1|0.2 < 0.1) \approx 0.99; P(|n| < 3/2) \approx 0.99$$

$$25. f(x) = \begin{cases} \frac{3}{2}x^2 - 1 & -1 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases} \quad E[x] = \int x \frac{3}{2}x^2 dx = \frac{1}{2} \quad P(3/2) - P(1/2) \approx 0.99 \\ P(1/2) \approx P(3/2) - 0.99 \approx 0.4332 - 0.99 = -0.566 \quad P(n) = 0.0566 \quad n = 1.58$$

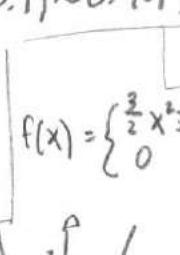
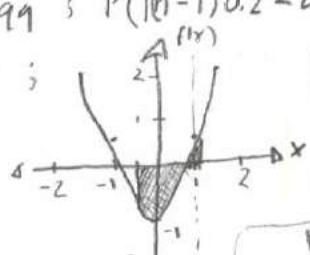
$$S = X_1 + \dots + X_{50}$$

$$F[S] = \sum_{i=1}^{50} S = \sum_{i=1}^{50} X_i$$

$$= 50 \cdot E[X] = 50 \cdot \int_{-1}^1 x dx = 0$$

$$= 50 \left[\frac{x^2}{2} - \left(\frac{3}{2}x^2 - 1 \right)^2 \right]$$

$$= 50 \left[\frac{x^2}{2} - \frac{9}{8}x^4 + \frac{3}{2}x^2 - \frac{1}{2} \right] = 50 \left[-\frac{1}{8}x^4 + 2x^2 - \frac{1}{2} \right] =$$

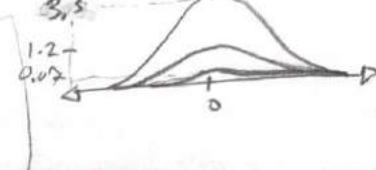


$$E[X] = \int x \frac{3}{2}x^2 dx = \frac{1}{2}$$

$$E[X^2] = \int x^2 \frac{3}{2}x^2 dx = 3/5 \Rightarrow \sigma^2 = \frac{3}{5}$$

$$F[S] F \sum_{i=1}^{50} X_i = 50 E[X] = 0$$

$$\text{Var}[S] = \sum_{i=1}^{50} \text{Var}[X_i] = 50 \text{Var}[X] = 30$$



26. $P(\text{shot}) = 0.3$; $E[S] = \sum_{i=1}^{25} i P(\text{success}_i | \text{shot}) = 25 \cdot p(x) = 25 \left(\frac{3}{10} \right)$; $\frac{5}{25} \geq p(x) > \frac{7}{25} \geq p(x) \quad \frac{9}{25} \geq p(x) \quad \frac{11}{25} \geq p(x)$

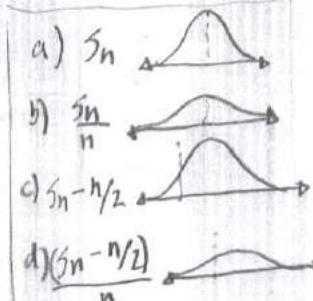
27. Prove $a_n \rightarrow a$, then $(1+a_n/n)^n \rightarrow e^a$; $\lim_{n \rightarrow \infty} (1+a_n/n)^n = \underbrace{\left[1 + \frac{1}{2} \left(\frac{a}{2} \right) + \frac{1}{2!} \left(\frac{a}{2} \right)^2 \right]}_e^a$

28. $f_n(x) = \begin{cases} \frac{1}{2} & x = \pm \left(\frac{1}{2} \right)^n \\ 0 & \text{otherwise} \end{cases}$; $E[x] = \sum_{x=-\infty}^{\infty} x f_n(x) = -\frac{1}{2} - \frac{1}{4} - 0 + \frac{1}{4} + \frac{1}{2}$

$F_n(x) = \begin{cases} 0 & (y_2)^{n+1} \\ y_2 & (y_2)/n \\ 0 & \text{otherwise} \end{cases}$; $\lim_{n \rightarrow \infty} F_n(x) = F(x)$

29. V_1, \dots, V_n from $[0, 1]$; $V_{(n)}$ = maximum.

$\int_0^1 V_{(n)} du = 0 = \frac{U - E[U]}{\sqrt{\text{Var}(U)}} = U_{(n)}$



V_1, V_2, \dots, V_{100} ; $S_n = \sum_{i=1}^n V_i$ for $n = 1, \dots, 100$

e) $(S_n - n/2)/\sqrt{n}$

Chapter 6: Distributions derived from Normal Distribution

$$\chi^2 = \text{Chi-squared } V = Z^2$$

$$X \sim N(\mu, \sigma^2); (X-\mu)/\sigma \sim N(0, 1); \left[\frac{X-\mu}{\sigma} \right]^2 \sim \chi^2$$

Chi-squared Distribution $[\chi^2]$ "n-degrees of freedom" || sum of independent Gamma $\text{cr} = \frac{n}{2} \Rightarrow \lambda = \frac{1}{2}$

$$f(v) = \frac{1}{2^{n/2} \Gamma(n/2)} v^{(n/2)-1} e^{-v/2}; v \geq 0$$

Moment Generating Function $M(t) = (1-2t)^{-n/2}$

$$E(V) = n; \text{Var}(V) = 2n$$

Sample Mean and Variance

Sample: independent random variables, which are normally distributed.

$$\bar{X} = \frac{1}{n} \sum_i X_i; S^2 = \frac{1}{n-1} \sum_i (X_i - \bar{X})^2$$

Sample Mean
 $E(\bar{X}) = \mu$

Sample Variance
 $\text{Var}(\bar{X}) = \frac{\sigma^2}{n}$

1. Prove Proposition A of Section 6.2

$$\frac{Z}{\sqrt{V/n}} = \frac{N(0, 1)}{\sqrt{X^2/n}} = \frac{N(0, 1)}{\sqrt{\frac{1}{2^{n/2} \Gamma(n/2)} v^{(n/2)-1} e^{-v/2}/n}}$$

$$f(t^2) = \int \sqrt{\frac{1}{n}} N(\sqrt{V/n} \cdot t) f(\chi^2_n) dy$$

$$= \frac{1}{\sqrt{2\pi n} 2^{n/2} \Gamma(n/2)} \int_{-\infty}^{\infty} v^{(n-1)/2} e^{-(1+t^2/n)v/2} dv$$

$$= \frac{(1+t^2/n)^{-(n+1)/2}}{\sqrt{\pi n} \Gamma(n/2)} \int_0^{\infty} x^{(n+1)/2-1} e^{-x} dx \left| \frac{-(1+t^2/n)^{-(n+1)/2}}{\sqrt{\pi n} \Gamma(n/2)} \Gamma((n+1)/2) \right.$$

F-distribution | $W = \frac{U/m}{V/m}$

Density Function: $f(W) = \frac{\Gamma[(m+n)/2]}{\Gamma(m/2) \Gamma(n/2)} \left(\frac{m}{n} \right)^{m/2} W^{m/2-1} \cdot \left(1 + \frac{m}{n} W \right)^{-(m+n)/2}$

$$E(W) = \frac{n}{(n-2)}$$

If $(X_1 - \bar{X}, X_2 - \bar{X}, \dots, X_n - \bar{X})$ are independent,

$$M(s, t_1, \dots, t_n) = E \left\{ \exp [s\bar{X} + t_1(X_1 - \bar{X}) + \dots + t_n(X_n - \bar{X})] \right\}$$

$$\sum_{i=1}^n t_i (X_i - \bar{X}) = \sum_{i=1}^n t_i X_i - n \bar{X} \bar{t}$$

$$s\bar{X} + \sum_{i=1}^n t_i (X_i - \bar{X}) = \sum_{i=1}^n \left[\frac{s}{n} + (t_i - \bar{t}) \right] X_i = \sum_{i=1}^n a_i X_i$$

$$M(s, t_1, \dots, t_n) = \exp(\mu s + \frac{\sigma^2}{2n} s^2) \exp \left[\frac{\sigma^2}{2} \sum_{i=1}^n (t_i - \bar{t})^2 \right]$$

$$x = (1+t^2/n)V/2$$

2. Prove Proposition B of Section 6.2

$$W = \frac{U/m}{V/n}$$

$$f(W) = \frac{\Gamma[(m+n)/2]}{\Gamma(m/2) \Gamma(n/2)} \left(\frac{m}{n} \right)^{m/2} W^{m/2-1} \left(1 + \frac{m}{n} W \right)^{-(m+n)/2}$$

$$f(w) = \int_0^\infty \frac{1}{2^{n/2} \Gamma(n/2)} w^{(n/2)-1} e^{-w/2} \cdot \frac{z^{m/2}}{2^{m/2} \Gamma(m/2)} (xz)^{m/2-1} e^{-xz/2} dx = \frac{z^{m/2-1}}{\Gamma(\frac{m}{2}) \Gamma(\frac{n}{2}) 2^{(m+n)/2}} \int_0^\infty x^{(m+n)/2-1} e^{-x(z+1)/2} dx$$

"similar to $T(t) = \int_0^t x^{t-1} e^{-x} dt$
where $t = x(\frac{z+1}{2})$

3. $n=16 \Rightarrow \bar{X} = \mu = 0 = \frac{1}{16} \sum_{i=1}^{16} X_i$

$$\begin{aligned} P(|\bar{X}| \leq c) &= P(-c \leq \bar{X} \leq c) \\ &= P(\bar{X} \leq c) - P(\bar{X} \leq -c) \\ &= P(\bar{X} \leq c) - [1 - P(\bar{X} \leq c)] \\ &= 2 \cdot P(\bar{X} \leq c) - 1 = 2 \cdot \Phi\left(\frac{c-0}{\sqrt{V/16}}\right) - 1 \\ &= 2 \cdot \Phi(4c) - 1 = 0.5 \\ \Phi(4c) &= 0.75 \\ 4c &= \Phi^{-1}(0.75) \\ c &= 0.7734/4 \\ &= 0.19335 \end{aligned}$$

Find t_0 such that a) $P(T < t_0) = 0.9$ of a t_7 distribution

$$\begin{aligned} t_7 &= f(t) = \frac{\Gamma(7+1)/2}{\sqrt{7\pi} \Gamma(7/2)} \left(1 + \frac{t^2}{7}\right)^{-(7+1)/2} \\ &= \frac{\Gamma(4)}{\sqrt{7\pi} \Gamma(7/2)} \left(1 + \frac{t^2}{7}\right)^{-4} \end{aligned}$$

4. T follows a t_7 -distribution.

$$\begin{aligned} &= P(-t_0 \leq T \leq t_0) \\ &= P(T \leq t_0) - P(-t_0 \leq T) \\ &= P(T \leq t_0) - [1 - P(t_0 \leq T)] \\ &= 2P(T \leq t_0) - 1 = 0.9 \end{aligned}$$

$$P(T \leq t_0) = 0.95$$

$$T = \Phi^{-1}(0.95) = 1.895$$

5. If $X \sim F_{n,m}$, then $X^{-1} \sim F_{m,n}$.

$$F_{n,m} = W = \frac{U/m}{V/n} = X \Rightarrow X^{-1} = \frac{V/n}{U/m} = F_{m,n}$$

6. $T \sim t_n$, then $T^2 \sim F_{1,n}$; $T = tn = Z/\sqrt{V/n} \Rightarrow T^2 = Z^2/V/n = h Z^2/U = F_{1,n}$

7. Cauchy Distribution:

$$f(x) = \frac{1}{\pi} \left(\frac{1}{1+x^2} \right)$$

E-Distribution:

$$F(t) = \frac{\Gamma((n+1)/2)}{\sqrt{n\pi} \Gamma(n/2)} \left(1 + \frac{t^2}{n}\right)^{-(n+1)/2} \quad @df=1, f(t_1) = \frac{\Gamma(1)}{\sqrt{\pi} \Gamma(1/2)} \left(1 + t^2\right)^{-1}$$

$$= \frac{1}{\sqrt{\pi}} \left(\frac{1}{1+t^2} \right)$$

8. Exponential Random Variable:

$$f(x) = \lambda e^{-\lambda x}; \lambda = 1 \Rightarrow \frac{x}{y} = \left(\frac{1}{1}\right) e^{-x+y} = e^{y-x}$$

F-Distribution:

$$f(w) = \frac{\Gamma((m+n)/2)}{\Gamma(m/2) \Gamma(n/2)} \left(\frac{m}{n}\right)^{m/2} w^{(m+n)/2} \quad ; \quad \text{if } m, n = 1; F(w) = \frac{\Gamma(1)}{\Gamma(1/2) \Gamma(1/2)} \left(\frac{1}{1}\right) \left(1 + w\right)^{-1}$$

$$= 1 + \frac{w^2}{2} + \frac{w^3}{8} + \dots$$

$$= e^w = [e^{y-x}]$$

9. Find mean and variance of $S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$

$$\begin{aligned} S^2 &= \frac{1}{n} \sum_{i=1}^n \frac{1}{(n-1)} (X_i - \bar{X})^2 = \frac{1}{2} \left[\sum_{i=1}^n X_i \sum_{i=1}^n (X_i - \bar{X})^2 \right] = \\ &\quad P(a < S^2 / \sigma^2 < b) = P(S^2 / \sigma^2 < b) - P(S^2 / \sigma^2 < a) \end{aligned}$$

$$\begin{aligned} &\quad = \int_a^b f(v) dv = 1 = \frac{1}{2^{n/2} \Gamma(n/2)} \left[\Gamma(b+1) - \Gamma(a+1) \right] \\ &\quad = \frac{1}{2^{n/2} \Gamma(n/2)} (b-a) \Gamma(1) = 1 \Rightarrow (b-a) = 2^{n/2} \sqrt{\pi} \end{aligned}$$

10. Chi-Squared Distribution

$$f(v) = \frac{1}{2^{n/2} \Gamma(n/2)} v^{(n/2)-1} e^{-v/2}$$

10. $X_1, \dots, X_n \sim N(\mu_x, \sigma^2)$; $Y_1, \dots, Y_n \sim N(\mu_y, \sigma^2)$; Show how a F-distribution can find $P(S_x^2/S_y^2 \geq c)$

F Distribution:

$$f(w) = \frac{\Gamma[(m+n)/2]}{\Gamma(m/2)\Gamma(n/2)} \cdot \left(\frac{m}{n}\right)^{m/2} w^{(m+n)/2 - 1} \cdot \left(1 + \frac{m}{n}w\right)^{-(m+n)/2}; \int_{-c}^c f(w) dw = \int_{-c}^c \frac{S_x^2}{S_y^2} dx dy = 2 \int_0^c \int_0^c \frac{S_x^2}{S_y^2} dx dy$$

$$= 2 \cdot e^{\frac{(-2c^2 + 2\mu_x c + 2\mu_y c)/\sigma^2}{2(\mu_x^2/\sigma^2 + \mu_y^2/\sigma^2)}} = 1$$

$$+ \frac{(\mu_x^2/\sigma^2 + \mu_y^2/\sigma^2)^{-2}}{2\mu_x\mu_y} = 1$$

Chapter 7: Survey Sampling:

1. Sample: 1, 2, 2, 4, and 8;

$$E[X] = \bar{X} = \frac{1}{5} \sum_{i=1}^5 X_i = \frac{(1+2+2+4+8)}{5} = 17/5$$

$$E[X^2] = \frac{1}{5} \sum_{i=1}^5 X_i^2 = \frac{(1^2+2^2+2^2+4^2+8^2)}{5} = 89/5$$

$$\text{Var}(X) = \frac{89}{5} - \left(\frac{17}{5}\right)^2 = \frac{89 - (17)(17)}{5} = \frac{89 - 67.9}{5} = 4.2$$

Sampling Distribution

Sample size = 2

$$T = N\bar{X} = 2(17/5) = 1.7$$

$$1. E(T) = E(N\bar{X}) = 1.7$$

$$2. \text{Var}(T) = \frac{4.2}{5} \left(\frac{5-2}{5-1}\right) = \frac{12.6}{20} = \frac{1.26}{2} = 0.63$$

$$② n=2; \bar{X}=4, 8; T=N\bar{X}=N E(X)=1.7; \text{Var}(\bar{X})=0.63$$

③ a) A population mean [No] b) Population Size: [No] c) Sample Size [No]

d) The sample Mean [Yes] e) Variance of sample mean [No] f) The largest value of Data [Yes]

g) Population Variance [No] h) Estimated variance of sample mean [Yes]

④ Population I Population II Accuracy is better approximated by a large n -value.
 n_1, σ_1 $n_2=2n, \sigma_2=2\sigma$
 The law of large numbers states a sequence of independent values converge to $E(\bar{X}_n)$ as $n \rightarrow \infty$.

⑤ A random variable is defined as a variable which can take on only a finite number of values. The sample mean is a random variable because of the finite form.

$$⑥ N_1 = 100,000; N_2 = 10,000,000; n=25. \text{Var}(\bar{X}) = \frac{\sigma^2}{25} \left(\frac{100,000-25}{100,000-1} \right) = 0.04\sigma^2$$

$$\text{Yes, it is substantially easier to measure the smaller size because of finite solutions to sample mean.}$$

$$\text{Var}(\bar{X}) = \frac{\sigma^2}{25} \left(\frac{10^7-25}{10^7-1} \right) = 0.04\sigma^2$$

⑦ Standard Error: $\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}}$; $\text{Var}(\bar{X}) = \frac{\sigma^2}{n} \left(\frac{15}{100} \right) \Rightarrow \sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}} \frac{\sqrt{15}}{10} = 0.02; \frac{1}{\sqrt{n}} = \frac{0.2}{\sqrt{15}}; \frac{15}{0.14} = n = 375$

8. $n=100$; $p=1/5$ a) Find δ such that $P(|\hat{p} - p| \geq \delta) = 0.025$

sample proportion $\hat{p} = \sigma_{\hat{p}} = \sqrt{\frac{p(1-p)}{n}} = \sqrt{\frac{0.2(1-0.2)}{100}} = 0.057$ || $P\left(\frac{|\hat{p} - p|}{\sigma_{\hat{p}}} \geq \frac{\delta}{\sigma_{\hat{p}}}\right) = 0.025$
 standard error $P\left(\frac{|\hat{p} - p|}{\sigma_{\hat{p}}} \geq \frac{\delta}{\sigma_{\hat{p}}}\right) = 1 - 0.025$

b) $\hat{p}=0.25$; 95%:

$$p = \hat{p} \pm z(0.025) \sigma_{\hat{p}} = 0.25 \pm 1.96 \sqrt{\frac{0.25(1-0.25)}{100-1}}$$

$$= 0.25 \pm 0.0853$$

$$= (0.1647, 0.3353)$$

$$2P(z \leq \frac{\delta}{0.057}) - 1 = 0.975$$

$$P(z \leq \frac{\delta}{0.04}) = \frac{1.975}{2}$$

$$\Phi\left(\frac{\delta}{0.04}\right) = 0.9875$$

$$\frac{\delta}{0.04} = \phi^{-1}(0.9875)$$

$$\delta = 0.08964$$

Standard Error

$$\sigma_x \approx \frac{\sigma}{\sqrt{n}}$$

The original $p=0.2$ is within the range of

9. Proportion and of the true population.

$n=1,500$ voters, 55% planned to vote a particular proposition.

45% planned to vote against a proposition.

Margin of Victory [10%] Confidence Interval

10. False, $\bar{X} = 50\%$; $\bar{X} \pm z(0.025) \sigma_{\bar{X}} = 10\% \pm 1.96(2.66\%)$

as a population grows ($n \rightarrow \infty$), then a $= (4.90\%, 15.10\%)$

distinct mean(μ) and standard deviation(σ) become more distinct, and possibly less normal and more dichotomous.

11. $n=4$; X_1, X_2, X_3, X_4 a) $\binom{n}{k} = \binom{4}{2} = \frac{4!}{2!(4-2)!} = 6$ b) $\{X_1, X_2\}, \{X_2, X_3\}, \{X_3, X_4\}, \{X_1, X_4\}$

Mean Square error = variance + bias²; $E[X] = \frac{1}{6}$; $E[X^2] = \frac{1}{6}$; $\sigma = \sqrt{\frac{1}{6} - \frac{1}{6^2}} = \sqrt{\frac{5}{36}} = \frac{\sqrt{5}}{6}$

$\frac{1}{n} \sum (X_i - \mu)^2 = \sigma^2 + \beta^2$ // This case shows the sample mean is unbiased because

the choices are $\begin{array}{ccccccccc} & & & & & & & & \\ 1 & 2 & 3 & 4 & & & & & \\ \downarrow & \downarrow & \downarrow & \downarrow & & & & & \end{array}$ so $\frac{1}{n} \sum X_i = \frac{1+2+3+4}{4} = 3$

12. Random Sampling with replacement

$s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$ is the unbiased parameter of σ^2 . Variance of a Biased Sample

$$Vrr(\bar{X}) = \frac{1}{n} \sum_{i=1}^n \sum_{j \neq i} \text{Cov}(X_i, X_j) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) + \frac{1}{n^2} \sum_{i=1}^n \sum_{j \neq i} \text{Cor}(X_i, X_j) = \frac{\sigma^2}{n} - \frac{1}{n^2} n(n-1) \frac{\sigma^2}{N-1}$$

Expected Variance of a population

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n X_i^2 - \bar{X}^2; E(\hat{\sigma}^2) = \frac{1}{n} \sum_{i=1}^n E(X_i^2) - E(\bar{X}^2)$$

$$= \frac{\sigma^2}{n} \left[1 - \frac{(n-1)}{N-1} \right]$$

$$= \frac{1}{n} \sum \left[\text{Var}(X_i) + E(X)^2 \right] - \left[\text{Var}(\bar{X}) + E(\bar{X})^2 \right]$$

$$= \frac{\sigma^2}{n} \left[\frac{N-n}{N-1} \right]$$

$$= \frac{1}{n} \sum \left[\sigma^2 + \mu^2 \right] - \left[\frac{\sigma^2}{n} \left(1 - \frac{n-1}{N-1} \right) + \mu^2 \right]$$

$$= \frac{\sigma^2}{n} \sum \left[1 - \left(1 - \frac{n-1}{N-1} \right) \frac{1}{n} \right] = \frac{\sigma^2}{n} \left[1 - \frac{1}{n} + \frac{(n-1)}{n(N-1)} \right] = \frac{\sigma^2}{n} \left[\frac{n(N-1) - (N-1) + (n-1)}{n(N-1)} \right]$$

$$= \frac{\sigma^2}{n} \left[\frac{nN - N - N + 1 + n - 1}{n(N-1)} \right] = \boxed{\frac{\sigma^2}{n} \left[\frac{(n-1)N}{n(N-1)} \right]}$$

$$S_x^2 = \frac{\sigma^2}{n} \left(\frac{n}{n-1} \right) \left(\frac{N-n}{N-1} \right) + \left[\frac{\sigma^2}{n} \left(\frac{N-n}{N-1} \right) \right]^2 \left(\frac{1}{n} \right) \left(\frac{n-1}{n-1} \right) \left(\frac{N-1}{N-1} \right)$$

$$= \frac{\sigma^4}{n^2} \left(\frac{N-n}{N-1} \right)^2 \left(\frac{1}{n} \right) \left(\frac{N}{N-1} \right) \left(\frac{N-n}{N-1} \right) = \frac{\sigma^4}{n^3} \left(\frac{N-n}{N-1} \right) \left(\frac{1}{n-1} \right) \left(\frac{N-n}{N} \right) =$$

(12) $S^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2 ; E(S^2) = \frac{1}{n-1} E \left(\sum x_i^2 - n\bar{x}^2 \right) = \frac{1}{n-1} \left[\sum E(x^2) - E(\bar{x})^2 \right]$

$$= \frac{1}{n-1} \left[\sum [Var(X) + E(y_i)^2] - n[Var(Y) + E(Y)^2] \right]$$

$$= \frac{1}{n-1} [n\sigma^2 + n\bar{y}^2 - \sigma^2 - ny^2] = \frac{(n-1)}{(n-1)} \sigma^2 = \sigma^2$$

b) $E(S) = E \left(\sqrt{\frac{\sum (x-\bar{x})^2}{n-1}} \right) = \frac{1}{\sqrt{n-1}} E \left(\sqrt{\frac{\sum (x-\bar{x})^2}{n-1}} \sigma \right) = \frac{\sigma^2}{\sqrt{n-1}} E \left(\sqrt{\frac{\sum (x-\bar{x})^2}{\sigma^2}} \right) = \frac{\sigma^2}{\sqrt{n-1}} E(\sqrt{Y})$

$E(S) \neq \sigma$; It is not an unbiased estimate of σ

c) Show $\frac{s^2}{n}$ is an unbiased estimate of σ_x^2 :

$$E \left(\frac{s^2}{n} \right) = E \left(\frac{1}{n(n-1)} (\sum x_i^2 - n\bar{x}^2)^2 \right) = \frac{1}{n(n-1)} \sum E(x^2) - E(\bar{x})^2 =$$

$$= \frac{1}{n(n-1)} \left[\sum [Var(X_i) + E(y_i)^2] - n[Var(Y) + E(Y)^2] \right]$$

$$= \frac{1}{n(n-1)} [n\sigma^2 + n\bar{y}^2 - \sigma^2 - ny^2] = \frac{\sigma^2(n-1)}{n(n-1)}$$

$$E \left(\frac{s^2}{n} \right) = \frac{n^2 \sigma^2}{n}$$

$$\boxed{\sigma_x^2 = n^2 s^2}$$

These are ^{expected} estimators of the sample and population, separately.

Yes, $E \left(\frac{s^2}{n} \right)$ is an unbiased estimate.

$$\text{Being } \sigma_x^2 = \frac{\sigma^2}{n}; \sigma_x = \frac{\sigma}{\sqrt{n}}$$

c) $E \left(\frac{\hat{p}(1-\hat{p})}{(n-1)} \right) = \frac{1}{n-1} [E(\hat{p}) - E(\hat{p}^2)] = \frac{1}{n-1} [\hat{p} - [Var(\hat{p}) + E(\hat{p})^2]]$

$$= \frac{1}{n-1} \left[p - \left[\frac{p(1-p)}{n} + \hat{p}^2 \right] \right] = \frac{1}{n-1} \left[p(1-p) - \frac{p(1-p)}{n} \right] = \frac{n-1}{n-1} \frac{p(1-p)}{n}$$

Example A: 7.2:

Herkosen (1976); $N=393$; X_i = number of patients discharged from i^{th} hospital $\Rightarrow \sigma_p^2$

Suppose Total T is an estimate of size 50.

January 1968.

Denoting estimate T by the Central Limit theorem, to sketch the probability density of the error $T - T'$

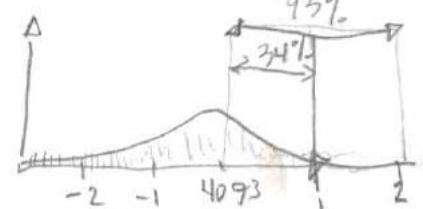
$$T = N\bar{X}, \sigma_T^2 = N^2 \sigma_x^2, S_T = N^2 S_x^2$$

$$\bar{X} = 314.6; \sigma_x^2 = \frac{\sigma^2}{n} = \frac{590^2}{393} = 996$$

$$S_x = 31.19$$

$$T = 50 \times 314.6; \sigma_T^2 = 221,500; S_T = 1647.954$$

$$= 4073$$



Huge Standard error with small total population

14. $p = 0.654$ Total Number (< 1000) discharges is from $n=25$. Apply central limit theorem to the distribution

$$n_{\text{Total}} = 393, \mu = 814.6, \sigma = 510$$

$$\sigma = \sqrt{\frac{0.654(1-0.654)}{25}} = 0.095$$

15. n = simple random sample. a) Sketch $P(|\bar{X} - \mu| > 200)$; $20 < n \leq 100$

b) For $n=20, 40$, and 80 . Find Δ such that $P(|\bar{X} - \mu| > \Delta) \approx 0.10$

$$n=20; P(|\bar{X} - \mu| > \Delta) \approx 0.1$$

$$P(\Delta < \bar{X} - \mu < \Delta) \approx 0.1$$

$$P(\bar{X} - \mu < \Delta) - [1 - P(\bar{X} - \mu < \Delta)] \approx 0.1$$

$$2 \left[1 - \Phi \left(\frac{\Delta}{\sigma / \sqrt{n} \sqrt{\frac{N-1}{N-n}}} \right) \right] \approx 0.1$$

$$\Phi \left(\frac{\Delta}{\sigma / \sqrt{n} \sqrt{\frac{N-1}{N-n}}} \right) \approx 0.95$$

$$\frac{\Delta}{\sigma / \sqrt{n} \sqrt{\frac{N-1}{N-n}}} = 1.65$$

$$\Delta = \frac{510}{\sqrt{20}} \cdot \sqrt{\frac{393-1}{393-20}} (1.65) = 222$$

$$\Delta_{0.5} = \frac{510}{\sqrt{20}} \sqrt{\frac{393-1}{393-20}} (0.68) = 91.9$$

$$n=40 \quad P(|\bar{X} - \mu| > \Delta) \approx 0.10 = 1 - P(|\bar{X} - \mu| < \Delta)$$

$$= 1 - P(-\Delta < |\bar{X} - \mu| < \Delta) = 1 - [\Phi(\bar{X} - \mu < \Delta) - \Phi(-\Delta < \bar{X} - \mu)] = 1 - [\Phi(\bar{X} - \mu < \Delta) - 1 + \Phi(-\Delta > \bar{X} - \mu)]$$

$$n=80 \quad \Delta_{0.1} = 122 \quad \Delta_{0.5} = 50$$

$$= 2 - [2\Phi(\bar{X} - \mu < \Delta)] = 2[1 - \Phi(\bar{X} - \mu < \Delta)] = 0.1 \therefore \Phi(\frac{\bar{X}-\mu}{\sigma_x} < \frac{\Delta}{\sigma_x}) = 0.95$$

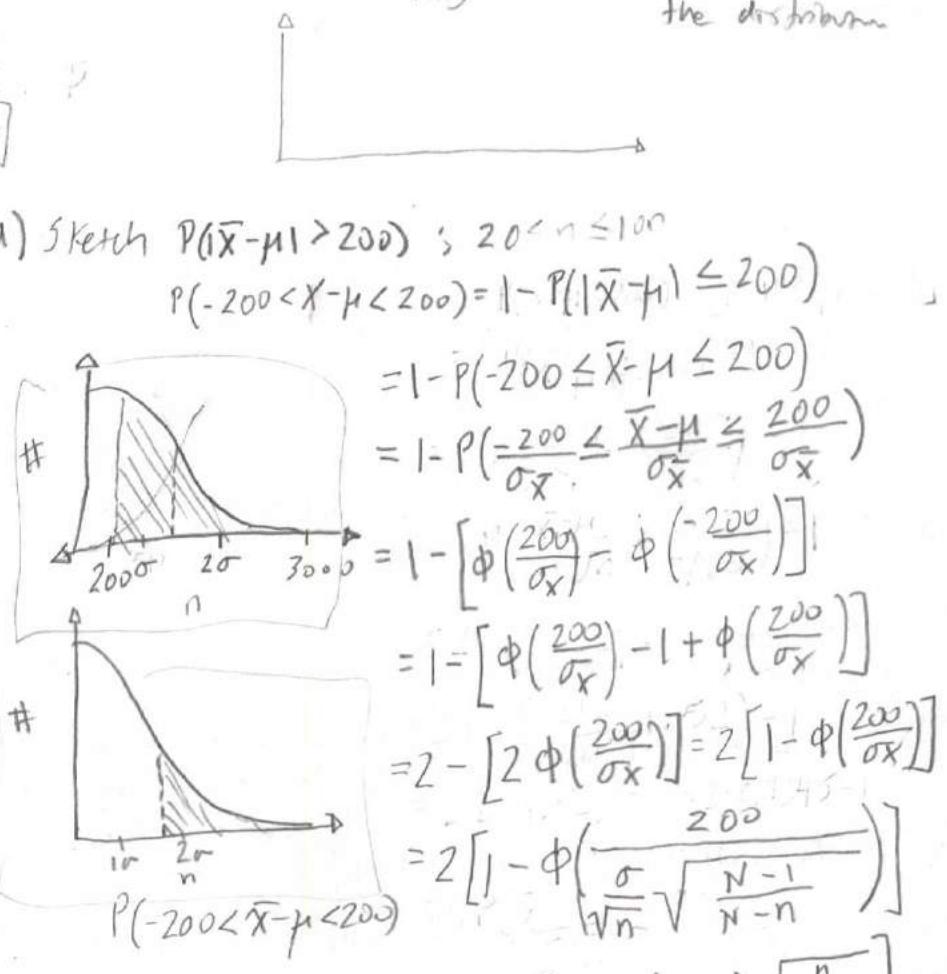
a) The mean is a random variable.

b) True, a 95% confidence interval contains the mean and has a total probability of 0.95

c) True, a 95% confidence interval contains 95% of the population

d) True, 95% of a 100 is 95.

17. A 90% confidence interval (l, u) for average number of children per household is $(\min=0.7, \max=2.1)$. Yes a confidence interval describes a random interval from a lower and upper bound that contains the mean.



$$\begin{aligned} P(-200 < \bar{X} - \mu < 200) &= 1 - P(|\bar{X} - \mu| \geq 200) \\ &= 1 - P(-200 \leq \bar{X} - \mu \leq 200) \\ &= 1 - P\left(\frac{-200}{\sigma_{\bar{X}}} \leq \frac{\bar{X} - \mu}{\sigma_{\bar{X}}} \leq \frac{200}{\sigma_{\bar{X}}}\right) \\ &= 1 - \left[\Phi\left(\frac{200}{\sigma_{\bar{X}}}\right) - \Phi\left(\frac{-200}{\sigma_{\bar{X}}}\right)\right] \\ &= 1 - \left[\Phi\left(\frac{200}{\sigma_{\bar{X}}}\right) - 1 + \Phi\left(\frac{200}{\sigma_{\bar{X}}}\right)\right] \\ &= 2 - \left[2\Phi\left(\frac{200}{\sigma_{\bar{X}}}\right)\right] = 2\left[1 - \Phi\left(\frac{200}{\sigma_{\bar{X}}}\right)\right] \\ &= 2\left[1 - \Phi\left(\frac{200}{\sigma / \sqrt{\frac{N-1}{N-n}}}\right)\right] \\ &= 2\left[1 - \Phi(6.71)\sqrt{\frac{n}{393-n}}\right] \\ @n=20: &= 2\left[1 - \Phi(6.71)\sqrt{\frac{20}{393-20}}\right] \\ &= 2[1 - \Phi(1.55)] = 0.12 \\ @n=100: &= 2[1 - \Phi(3.92)] = 0.002 \end{aligned}$$

$$\begin{aligned} \Delta_{0.1} &= \frac{510}{\sqrt{40}} \sqrt{\frac{393-1}{393-40}} (1.65) = 162 \\ \Delta_{0.5} &= \frac{510}{\sqrt{40}} \sqrt{\frac{393-1}{393-40}} (0.68) = 64.18 \end{aligned}$$

$$18. 90\% \text{ confidence Interval: } P(\text{Mean} | \text{Interval}) = \sum_{i=1}^n p_i^n = 90\% = 0.9$$

$$1 - P(\text{Mean} | \text{Interval}) = P(\text{Normal Interval}) \approx 1 - 0.91 = 0.09$$

19. One-sided Confidence Interval

k be chosen $(-\infty, \bar{x} + ks_x)$ that a 90% confidence interval for μ .

$$P(-\infty < \mu \leq \bar{x} + ks_x) = 90\%; P(\mu \leq \bar{x} + ks_x); 1.28 = \bar{x} + ks_x; k = \frac{1.28 - \bar{x}}{s_x}$$

$$P(\bar{x} - ks_x \leq \mu) = 0.15; \bar{x} - ks_x = 1.65; k = \frac{\bar{x} - 1.65}{s_x}$$

20. $N=8000$ condominium units; $n=100$ sample size; $\bar{x}=1.6$ motor vehicles; $s_x=0.8$

$$s_{\bar{x}} = \sqrt{\frac{s}{\sqrt{n}} \sqrt{1 - \frac{n}{N}}} = \frac{0.8}{\sqrt{10}} \sqrt{1 - \frac{100}{8000}} = 0.08; \text{ confidence interval } \bar{x} \pm z(0.025) s_{\bar{x}} = \bar{x} \pm 1.96 (0.08) = (1.44, 1.76)$$

Total Number of Motor Vehicles $T = 8000 \times 1.6 = 12,800; s_T = \sqrt{Ns_x} = 640 = (11544, 14056)$

12% respondents planned $\hat{p}=0.12$ with a proportion p .

$$\text{Standard Error: } s_{\hat{p}} = \sqrt{\frac{\hat{p}(1-\hat{p})}{n-1}} \sqrt{1 - \frac{100}{1200}} = 0.03$$

At 95% confidence interval suggests another sample size of 100 would contain a mean between 1.44 and 1.76.

$$\hat{p} \pm 1.96 s_{\hat{p}} = (0.06, 0.18)$$

$$T = N \hat{p} = 960; s_T = \sqrt{Ns_{\hat{p}}} = 240$$

$$T \pm 1.96 s_T; (490, 1480)$$

21. To halve the width of a 95% confidence interval

$$\frac{\bar{x}-\mu}{s_x} = \frac{\bar{x}-\mu}{\sigma/\sqrt{n}} = 95\%; \frac{\bar{x}-\mu}{\sigma/\sqrt{4}} = 95\%; \frac{\bar{x}-\mu}{\sigma/2} = 95\% / 2 = 47.5\%$$

$$22. \bar{x} \pm s_{\bar{x}} = \bar{x} \pm 1.96 s_{\bar{x}} \Rightarrow z(\bar{x}) = 1; z = 2(1 - 0.95) / 1.96 \Rightarrow \text{confidence interval: } 1 - \alpha = 0.682$$

$$23. a) \text{Show } s_x \text{ is largest when } p = \frac{1}{2}; \frac{d}{dp} s_x = \frac{d}{dp} \sqrt{\frac{\hat{p}(1-\hat{p})}{n-1}} \sqrt{1 - \frac{100}{8000}} = 0$$

$$b) s_{\hat{p}}^2 = \frac{\hat{p}(1-\hat{p})}{n-1} \left(1 - \frac{n}{N}\right) \quad \begin{array}{l} \text{"Unbiased Estimate} \\ \text{of Var}(\hat{p}) \end{array} \quad \frac{d}{dp} s_{\hat{p}}^2 = \frac{d}{dp} \left(\frac{\hat{p}(1-\hat{p})}{n-1} \right) \left(1 - \frac{1-2p}{\sqrt{\hat{p}(1-\hat{p})/(n-1)}} \right) = \frac{1}{2} (1-2p) = \frac{1}{2} - p \quad | p = 0.5$$

$$s_{\hat{p}}^2 = \frac{1}{2} \left(1 - \frac{1}{2}\right) \left(1 - \frac{1}{2}\right)$$

$$s_{\hat{p}} = \sqrt{\frac{1}{4} \left(\frac{N-n}{N(n-1)} \right)}; s_{\hat{p}} = \sqrt{\frac{1}{4} \left(\frac{N-n}{N(n-1)} \right)} = \frac{1}{2} \sqrt{\frac{N-n}{N(n-1)}}$$

$$c) \hat{p} \pm \sqrt{\frac{N-n}{N(n-1)}} \rightarrow \Phi(z) = \Phi(0.05)$$

$$P\left(\hat{p} - \sqrt{\frac{N-n}{N(n-1)}} < \frac{\bar{x}-\mu}{s_x} < \hat{p} + \sqrt{\frac{N-n}{N(n-1)}}\right) \rightarrow \Phi(z)$$

$$\lim_{n \rightarrow \infty} P\left(\hat{p} - \sqrt{\frac{N-n}{N(n-1)}} < \frac{\bar{x}-\mu}{s_x} < \hat{p} + \sqrt{\frac{N-n}{N(n-1)}}\right)$$

$$P(\hat{p} < 0 < \hat{p}) = \Phi(z) = 2P(0 < \hat{p}) - 1 = \Phi(z); z = 0.9995$$

24. Sample size = n ; Population size = N ; Estimate of $\mu = \bar{X}_c = \sum_{i=1}^n c_i X_i$

a) Find the condition $[c_i]$ such that the estimate is unbiased.

$$\bar{X} = E\left[\sum_{i=1}^n c_i X_i\right] = \sum_{i=1}^n c_i E(X_i) = \mu \sum_{i=1}^n c_i = \mu (1) \quad \boxed{\sum c_i = 1}$$

b) $Var(\bar{X}_c) = Var(\sum c_i X_i) = \sum c_i^2 Var(X_i) = \sum c_i^2 \sigma^2 = \sigma^2 \sum c_i^2$

Applying a Lagrangian Multiplier: $L(c_1, \dots, c_n, \lambda) = \sigma^2 \sum_{i=1}^n c_i^2 + \lambda (\sum c_i - 1)$

$$\frac{\partial L}{\partial c_i} = 0; \frac{\partial}{\partial c_i} \left[\sigma^2 \sum_{i=1}^n c_i^2 + \lambda (\sum c_i - 1) \right] = 0; \frac{\partial}{\partial c_i} \left[\sigma^2 \sum c_i^2 \right] + \frac{\partial}{\partial c_i} [\lambda (\sum c_i - 1)] = 0$$

$$\text{Therefore, } \sum c_i = \boxed{\sum \frac{-\lambda}{2\sigma^2}} = \frac{-n\lambda}{2\sigma^2} = 1 \quad \sigma^2 \frac{\partial}{\partial c_i} \left[\sum c_i^2 \right] + \lambda \frac{\partial}{\partial c_i} \sum c_i = 0$$

$$c_i = \frac{-1}{2\sigma^2} \left(\frac{-2\sigma^2}{n} \right) \quad \boxed{\lambda = -\frac{2\sigma^2}{n}} \quad \text{cov}(X_i, X_j) = -\sigma^2(N-1) \quad \boxed{2\sigma^2 c_i + \lambda = 0} \quad \boxed{2\sigma^2 c_i = -\lambda} \quad c_i = -\frac{\lambda}{2\sigma^2}$$

25. Lemma B $\boxed{1/n} = E(X_i X_j) - E(X_i) E(X_j)$

Section 7.3.2: $E(X_i X_j) = \sum_{k=1}^m \sum_{l=1}^m \zeta_k \zeta_l P(X_i = \zeta_k \text{ and } X_j = \zeta_l) = \sum_k \zeta_k P(X_i = \zeta_k) \prod_{l \neq k}^m P(X_j = \zeta_l | X_i)$
 where $P(X_j | X_i) = \begin{cases} n_i / (N-1) & k \neq i \\ (n_i - 1) / (N-1) & k = i \end{cases}$

$$\sum_k \zeta_k P(X_j | X_i) = \sum_{k \neq i} \zeta_k \frac{n_i}{N-1} + \zeta_i \frac{n_{N-1}}{N-1}$$

$$= \sum_{k=1}^m \zeta_k \frac{n_i}{N-1} - b_{ik} \frac{1}{N-1}$$

$$E(X_i X_j) = \sum_{k=1}^m b_{ik} \frac{n_k}{N} \left(\sum_l \zeta_l \frac{n_l}{N-1} - \frac{\zeta_k}{N-1} \right) = \frac{1}{N(N-1)} \left(\tau^2 - \sum_{k=1}^m \zeta_k^2 n_k \right)$$

$$= \frac{\tau^2}{N(N-1)} - \frac{1}{N(N-1)} \sum_{k=1}^m \zeta_k^2 n_k = \frac{N\mu^2}{N-1} - \frac{1}{N-1} (\mu^2 + \sigma^2)$$

$$= \mu^2 - \frac{\sigma^2}{N-1}$$

26. $V_i = 1$ if i^{th} population member $Cov(X_i X_j) = \mu^2 - \frac{\sigma^2}{N-1} - \mu^2 = \frac{-\sigma^2}{N-1}$ || $Cov(Y_i, Y_j) = E(Y_i Y_j) - E(Y_i) E(Y_j)$

$$= E(Y_i Y_j) - \sqrt{E(Y_i^2) - Var(Y_i)} \sqrt{E(Y_j^2) - Var(Y_j)}$$

$$= E(Y_i Y_j) - \sqrt{\mu^2 + \sigma^2} \sqrt{\mu^2 + \sigma^2}$$

a) Show $\bar{X} = \frac{1}{n} \sum_{i=1}^n V_i X_i$; $E(\bar{X}) = \frac{1}{n} \sum_{i=1}^n E(V_i X_i) = \frac{1}{n} \sum_{i=1}^n V_i E(X_i)$

b) $P(V_i = 1) = n/N$; $E(V_i) = \frac{1}{N} \sum_{i=1}^n V_i P(V_i = 1) = \frac{n}{N} (1) = \boxed{\frac{n}{N}}$

c) $Var(V_i) = E[V_i^2] - E[V_i]^2 = \frac{1}{N} \sum_{i=1}^n V_i^2 P(V_i = 1) - \left[\frac{n}{N} \sum_{i=1}^n V_i P(V_i = 1) \right]^2$

$$= \frac{n}{N} \frac{(n)^2}{(N)} = \boxed{\frac{n}{N} \left(1 - \frac{n}{N} \right)}$$

d) $E(V_i V_j) = \frac{1}{N^2} \sum_{i=1}^n \sum_{j=1}^n V_i V_j P(V_i, V_j) = \frac{n^2}{N^2}$

e) $Cov(V_i, V_j) = E(V_i V_j) - E(V_i) E(V_j) = \frac{n^2}{N^2} - \left(\frac{n}{N} \right) \left(\frac{n}{N} \right) = 0$

f) $Var(\bar{X}) = E(\bar{X}^2) - E(\bar{X})^2 = \frac{n^2}{N^2} - \frac{n}{N^2} = 0$

27. Population size (N) is unknown; $n \leq N$. Show will generate a simple random sample.

a) List $\{X_1, X_2, \dots, X_n, \dots, X_N\}$ b) For $k=1, 2, \dots$ i) $X_{(n+k)} = X_{n-1+k} + X_0 \Rightarrow X_{k+1} = X_1$
 $n = \{X_1, X_2, \dots, X_n\}$ $n < N$ ii) $\frac{n}{(n+k)} = \frac{X_1, X_2, \dots, X_n}{X_1, X_2, \dots, X_{n+k}}$

28. Randomized Response: Spin an Arrow - Draw ball from urn. $\underbrace{\text{choice A}}_{\text{Action}} \underbrace{\text{choice B}}_{\text{Result}} \left. \begin{array}{l} \text{Records Response} \\ \text{Interviewer} \end{array} \right\}$

$R = \text{Proportion Yes} ; p = P(\text{Response} | \text{Statement } \#1)$ "Randomized Device"

$r = P(\text{Yes})$ $q = \text{proportion of Characteristic A.} = P(\text{Statement } \#1)$

a) Show $r = (2p-1)q + (1-p)$; Hint: $P(\text{yes}) = P(\text{yes} | \text{Statement } \#1)P(\text{Statement } \#1) + P(\text{yes} | \text{Statement } \#2)P(\text{Statement } \#2)$

b) If r , what is q ?

$$q = \frac{r-1+p}{2p-1}$$

$$2pq - q + 1 - p = 1 - p(1-q) \\ 1 + pq - p = 2$$

c) $E(R) = r$ and propose Q for q . Show the expected estimator is unbiased.

$$E(R) = \sum_{i=1}^2 P(\text{yes} | \text{Statement } \#i)P(\text{Statement } \#i) = P(\text{yes} | \text{Statement } \#1)P(\text{Statement } \#1) + P(\text{yes} | \text{Statement } \#2)P(\text{Statement } \#2) = r$$

$$E(Q) = \frac{E[R - (1-p)]}{2p-1} = \frac{E(R) - (1-p)}{2p-1} = \frac{r - 1 + p}{2p-1} = q$$

d) Show $\text{Var}(R) = \frac{r(1-r)}{n} = E[R^2] - E[R]^2 = \frac{1}{(2p-1)^2} \text{Var}(R - (1-p)) = \frac{1}{(2p-1)^2} \frac{r(1-r)}{n} = \frac{r(1-r)}{n}$

$$e) \text{Var}(Q) = E[Q^2] - E[Q]^2 = \frac{1}{(2p-1)^2} \frac{r(1-r)}{n}$$

29. a. $P(\text{yes} | \text{Statement } \#3)$ $P(\text{Statement } \#2)$

$$b) E(Q) = \frac{E(R) - t(1-p)}{p} = q$$

$$c) \text{Var}(Q) = \frac{r(1-r)}{np^2} = \frac{[1p + t(1-p)][1 - qp + t(1-p)]}{np^2} = \frac{qp - q^2p^2 + qpt(1-p) + t(1-p) - qpt(1-p) + t^2(1-p)^2}{np^2}$$

30. Problem #28: $\text{Var}(Q) = \frac{r(1-r)}{(2p-1)^2 n}$

Problem #29: $\text{Var}(Q) = \frac{r(1-r)}{np^2}$

7. Poisson Distribution Likelihood Ratio: $\Lambda_0 = P(\lambda = \lambda_0 | H_0) / P(\lambda = \lambda_0 | H_1) = \left(\frac{\lambda_0}{\lambda_1}\right)^X e^{-(\lambda_0 - \lambda_1)}$

 $P(X) = \frac{\lambda^X}{X!} e^{-\lambda}$
 $\Lambda_{-n} = \left(\frac{\lambda_0}{\lambda_1}\right)^{\sum X_i - n} e^{n(\lambda_0 - \lambda_1)}; \ln \Lambda_{-n} = \sum X_i \ln \left(\frac{\lambda_0}{\lambda_1}\right) - n(\lambda_0 - \lambda_1)$
 $-2 \ln \Lambda = -2 \sum X_i \ln \left(\frac{\lambda_0}{\lambda_1}\right) - \phi = 2 \sum X_i \ln \left(\frac{\lambda_1}{\lambda_0}\right)$
 $-2 \ln \Lambda = -2 \sum X_i \ln \left(\frac{\lambda_0}{\lambda_1}\right) + \frac{1}{2} (X - \lambda_0)^2 \frac{1}{\lambda_0}$
 $-2 \ln \Lambda = 2 \underbrace{\sum (X - \lambda_0)}_{= 0} + \sum \frac{(X - \lambda_0)^2}{\lambda_0}$
 $-2 \ln \Lambda = \sum \frac{(X - \lambda_0)^2}{\lambda_0}$

Pearson's Chi-square statistic

$P\left(\frac{\sum (X - \lambda_0)^2 - \lambda_0}{\lambda_0 \sqrt{2} \cdot \nu} > Z(\alpha/2)\right) = \chi^2; \nu = \text{degrees of freedom}$

Taylor Series: $\ln(x) = \sum_{i=1}^n \frac{(x-x_0)^i}{i} x'(0) = (x-x_0) \ln(0) + \frac{1}{2}(x-x_0)^2 \frac{1}{x_0}$

8. $\lambda = \lambda_0$ $P\left(\frac{1}{\lambda_0 \sqrt{2} \cdot \nu} > Z(\alpha/2)\right) = \alpha$

Normal Z-table

Simple hypothesis

vs.

Composite hypothesis

9. Normal Distribution $\sigma^2 = 100$ $\mu_0 = 0.0$ $\Lambda = \frac{P(X|H_0)}{P(X|H_1)} = e^{-\sum (X-\mu_0)^2 + \sum (x-\mu_1)^2 / 2\sigma^2}$ "Measure of clustering"

 $P(X) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad \mu_1 = 1.5 \quad = e^{\frac{2n\bar{X}(\mu_0 - \mu_1) + n\mu_1^2 - n\mu_0^2}{2\sigma^2}}, \lambda > 1: \mu_0 - \mu_1 < 0; \bar{X} \ll 1$
 $\lambda \ll 1: \mu_0 - \mu_1 > 0; \bar{X} \gg 1$

$P(\bar{X} > X_0) = P\left(\frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} > \frac{X_0 - \mu_0}{\sigma/\sqrt{n}}\right); \frac{X_0 - \mu_0}{\sigma/\sqrt{n}} = Z(\alpha); X_0 = \frac{10}{\sqrt{n}} Z(0.1) = \frac{10 \cdot 1.28}{\sqrt{10}} = 2.56$ Unfavorable for H_0

$\alpha = 0.01; \Lambda = \frac{P(X|H_0)}{P(X|H_1)} = e^{-\frac{2n\bar{X}(\mu_0 - \mu_1) + n\mu_1^2 - n\mu_0^2}{2\sigma^2}}$

$Z = \frac{X_0 - \mu_1}{\sigma/\sqrt{n}} = \frac{2.56 - 1.5}{10/5} = 0.53; P(Z > 2.56) = 1 - \beta = 0.7019$

$\beta = 0.2981$

10. $P(\bar{X} > X_0) = P\left(\frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} > \frac{X_0 - \mu_0}{\sigma/\sqrt{n}}\right); \frac{X_0 - \mu_0}{\sigma/\sqrt{n}} = Z(\alpha); X_0 = \frac{10}{5} Z(0.01) = 2(0.5040) = 1.0080$

Suppose X_1, \dots, X_n

$f(x|\theta), T = \text{sufficient statistic}$

$Z = \frac{X_0 - \mu_1}{\sigma/\sqrt{n}} = \frac{1.0080 - 1.5}{10/5} = -0.21; P(Z > 1.23) = 1 - \beta = 0.8907$

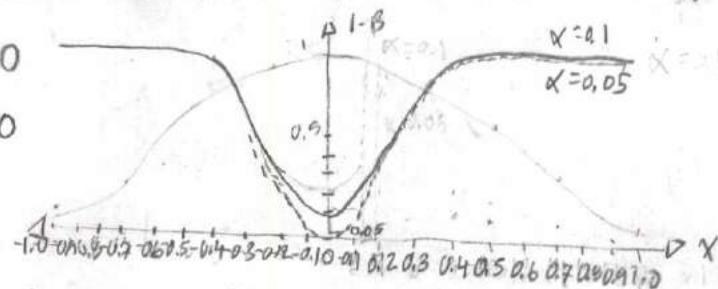
$\beta = 0.1093$

11. $n=25$ $\sigma^2 = 100$

Likelihood: $\Lambda = \frac{f(x|\theta_0)}{f(x|\theta_1)}$ The rejection region is determined from normalizing the threshold mean of the numerator $[f(x|\theta_0)]$, such that rejection value is greater than the significance level

Normal Distribution: $f(X|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2}$

$H_0: \mu = 0$
 $H_A: \mu \neq 0$



$\Lambda = \frac{(\theta\bar{X})^{-n} (\bar{X}\theta - 1)}{\theta^n [\bar{X} e^{-n\bar{X}\theta}]}$ (B. $\theta_0 = 1, n = 10, \alpha = 0.05$)

a) Show $\{\bar{X} \leq X_0\} \cup \{\bar{X} \geq X_1\} \equiv \{\bar{X} e^{-n\bar{X}\theta} \leq X_0^n\}$

b) The rejection region is chosen by a threshold value of c at a significance level.

c) The exponential distribution relates to the gamma through summation and $\theta = \frac{1}{\theta_0}$. d) Generating outputs from an exponential may be graphically similar to a gamma.

c) The exponential distribution relates to the gamma through summation and $\theta = \frac{1}{\theta_0}$.

Chapter 9: Goodness of Fit

1. $P(H|X) = 0.50$; $P(T|X) = 0.50$

a) $P(\text{reject } H_0) + P(\text{reject } H_1) =$
 $\binom{10}{0} 0.5^0 0.5^{10} + \binom{10}{1} 0.5^1 0.5^9 = 0.002$

b) Power of Test $[1-\beta] = \left(\frac{10}{0}\right)(0.1)^0 0.9^{10} + \left(\frac{10}{1}\right)(0.1)^1 0.9^9 = 0.3487$

2. a. X is uniform on $[0, 1]$

Simple Hypothesis: only null and alternative hypothesis.

Simple

Composite Hypothesis: when a probability distribution is not specified.

b. A die is unbiased

Composite

c. X follows a normal with mean 0 and var $\sigma^2 > 10$

Simple

Simple

3. $X \sim \text{bin}(100, p)$'s H_0 is rejected when: $p = 0.5$

H_0 is favored when: $p \neq 0.5$ for $|X - 50| > 10$

a) $K = P(|X - 50| > 10) = P\left(\frac{|X - 50|}{5} > 2\right) = 2P\left(\frac{|X - 50|}{5} < 2\right) \approx 2\Phi(-2)$

$= 2(1 - \Phi(2))$

$= 0.0456$

d. X follows a normal with mean $\mu = 0$

X	H_0	H_1
x_1	0.2	0.1
x_2	0.3	0.4
x_3	0.3	0.1
x_4	0.2	0.4

a) Likelihood Ratio:

	X_1	X_2	X_3	X_4
	2.0	0.75	3.0	0.5

λ	X_3	X_1	X_2	X_4
	3.0	2.0	0.75	0.5

b) $\lambda = 0.2$: 3 degrees of freedom

$$\lambda = \frac{P(x|H_0)}{P(x|H_1)} = \lambda; P(\lambda \leq \lambda_0 | H_0) = 0.2$$

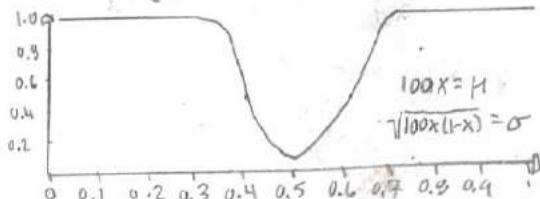
or

$$\lambda > \chi^2_{0.2} = 4.642$$

$$P(\lambda \leq \lambda_0 | H_0) = 0.5$$

$$\lambda > \chi^2_{0.5} = 2.366$$

[$1-\beta$]



[X]

λ corresponds to the decision rules for prior probabilities.

H_0 is accepted for $\lambda = 0.5$, but not $\lambda = 0.2$

5. a) False, the significance level of a statistical test is equal to the probability the likelihood is less than a threshold.
- b) False, the power $[1-\beta]$ is described by the null hypothesis rejection, while significance level is denoted as the threshold of rejection that the null hypothesis is true or $[1-\alpha]$.
- c) False, the probability the null hypothesis is falsely rejected is not rejected when it is false.
- d) False, the probability the null hypothesis is falsely rejected is less important than type I.
- e) False, a type I error occurs when the statistic crosses the significance level.
- f) False, a type II error tends to be less important than type II.
- g) False, the power of a test is determined by the alternative hypothesis.
- h) True, the likelihood is a random variable.

X	0	1	2	3	4	5	6	7	8	9	10
$P(x H_0)$	0.001	0.003	0.008	0.017	0.025	0.0246	0.0205	0.0172	0.0139	0.0098	0.0049
$P(x H_1)$	0.002	0.004	0.008	0.014	0.020	0.026	0.032	0.036	0.039	0.041	0.042
$P(x H_0) / P(x H_1)$	0.500	0.250	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$P(x H_1) / P(x H_0)$	1.4	0.84	0.50	0.30	0.19	0.11	0.07	0.04	0.02	0.01	

$P(x|H_0) = 0.5$

$P(x|H_1) = 0.7$

c) Significance Level of H_0 if $X \geq 8$

$$K = P(\text{Reject } H_0 | H_0) = P(X \geq 8 | H_0)$$

$$= 1 - P(X \leq 7 | 0.5) = 1 - \sum_{i=0}^7 (1-0.5)^{i+1} (0.5)^{8-i}$$

$$= 1 - \sum_{i=0}^7 0.5^i = 0.0078$$

d) The power of the test $[1-\beta] = P(\text{Reject } H_0 | H_1)$

$$= P(X \geq 8 | H_1) = 1 - P(X \leq 7 | 0.7) = 1 - \sum_{i=0}^7 (1-0.7)^{i+1} (0.7)^{8-i}$$

$$= 0.0002$$

$\frac{P(x|H_1)}{P(x|H_0)} < 1$: Favors H_0

$P(x|H_0)$

$P(x|H_1)$

$\frac{P(x|H_1)}{P(x|H_0)} > 1$: Favors H_1

b) If $P(H_0) / P(H_1) = 10$
then each of the outcomes favors
 H_0 .

$$68 \lambda = \text{mean} ; T = \sum_{i=1}^n X_i \quad a) P(X) = \prod_{i=1}^n \frac{\lambda^{x_i}}{x_i!} e^{-\lambda} = \frac{\lambda^{\sum X_i}}{\prod X_i!} e^{-n\lambda} ; \frac{P(X)}{P(Y)} = \frac{\lambda^{\sum X_i}}{\lambda^{\sum Y_i}} e^{-n\lambda} \frac{\prod y_i!}{\prod x_i!} e^{n\lambda} = \lambda^{\sum X_i - \sum Y_i} \frac{\prod y_i!}{\prod x_i!}$$

Poisson Distribution:

$$P(x) = \frac{\lambda^x}{x!} e^{-\lambda}$$

$$b) \frac{P(X_1)}{P(Y_1)} = \lambda^{\sum X_i - \sum Y_i} \frac{y_1}{x_1}, \quad X_1 = y_1 \text{, which is not independent.}$$

Independent if and only if $\sum X_i - \sum Y_i = 0$

$$\sum X_i = \sum Y_i = T$$

c) Theorem A : Section 9.9.1:

$$f(x_1, \dots, x_n | \theta) = g[T(x_1, \dots, x_n), \theta] h(x_1, \dots, x_n) ; \quad g[T(x_1, \dots, x_n), \theta] = \lambda = \lambda^{\sum X_i} ; \quad h(x_1, \dots, x_n) = \frac{e^{-\lambda}}{\prod X_i!}$$

Social
Physical
Mental
Provided

69. Geometric Distribution: Theorem A : Section 9.9.1 : $f(x_1, \dots, x_n | \theta) = g[T(x_1, \dots, x_n), \theta] h(x_1, \dots, x_n)$

$$P(X=k) = (1-p)^{k-1} p \quad P(X) = \prod_{i=1}^n (1-p)^{n(k_i-1)} p = (1-p)^{\sum k_i - n} p^n = (1-p)^{T-n} p^n$$

$$f(x_1, \dots, x_n | \theta) = (1-p)^{T-n} p^n ; \quad g[T(x_1, \dots, x_n), \theta] = (1-p)^{T-n} ; \quad h(x_1, \dots, x_n) = p^n$$

70. Factorization Theorem

$$f(x_1, \dots, x_n | \theta) = g[T(x_1, \dots, x_n), \theta] h(x_1, \dots, x_n) ; \quad \text{Exponential Distribution: } P(X) = \lambda e^{-\lambda X} ; \quad P(X) = \prod \lambda e^{-\lambda X_i}$$

$$71. F(X | \theta) = \frac{\theta}{(1+x)^{\theta+1}} ; \quad f(x_1, \dots, x_n | \theta) = \lambda e^{-\lambda \sum X_i} ; \quad g[T(x_1, \dots, x_n), \theta] = e^{-\lambda \sum X_i} = \lambda e^{-\lambda \sum X_i} ; \quad h(x_1, \dots, x_n) = \lambda$$

$$\frac{P(x | \theta)}{P(y | \theta)} = \frac{n\theta}{\prod (1+x)^{\theta+1}} \frac{\prod (1+y_i)^{\theta+1}}{n\theta} ; \quad \prod_{i=1}^n (1+x_i)^{\theta+1} = \prod (1+y_i)^{\theta+1} = T$$

$$72. \text{Gamma Distribution: } P(X) = \prod \frac{b^a}{\Gamma(a)} X_i^{a-1} e^{-bx_i} ; \quad \frac{P(X)}{P(Y)} = \frac{b^a}{\Gamma(a)} \prod X_i^{a-1} e^{-bx_i} \cdot \frac{\Gamma(a)}{b^n} \frac{1}{\prod y_i^{a-1} e^{-by_i}}$$

$$P(X) = \frac{b^a}{\Gamma(a)} X^{a-1} e^{-bx} ; \quad \prod X_i^{a-1} e^{-bx_i} = \prod y_i^{a-1} e^{-by_i}$$

$$73. \text{Rayleigh Density: } f(x | \theta) = \frac{x}{\theta^2} e^{-x^2/(2\theta^2)}$$

$$P(X | \theta) = \frac{\prod X_i}{\theta^2} e^{-\sum X_i^2/(2\theta^2)} ; \quad \frac{P(X | \theta)}{P(Y | \theta)} = \frac{\prod X_i}{\theta^2} e^{-\sum X_i^2/(2\theta^2) + \sum Y_i^2/(2\theta^2)}$$

$$\prod X_i e^{-\sum X_i^2/2\theta^2} = \prod X_i e^{-\sum Y_i^2/2\theta^2} ; \quad \text{sufficient statistic}$$

$$\prod X_i \text{ or } \sum X_i$$

74. Binomial Distribution:

$$P(k) = \sum_{i=1}^n \binom{n}{k} p^k (1-p)^{n-k}$$

$$P(k) = \exp \left[\log \sum \binom{n}{k} + \sum k \log p + (n-k) \log (1-p) \right]$$

$$\approx \exp \left[d(k) + \sum T_i(k) C_i(\theta) + S(k) \right]$$

$$P(r) = \exp \left[n \log \frac{b}{\Gamma(a)} + (a-1) \sum \log x - b \sum x \right]$$

$$\approx \exp \left[d(\theta) + \sum C_i(\theta) T_i(x) + S(x) \right]$$

Chapter 9.600

67. Negative Binomial Distribution

Frequency 1st Data Set:

$$P(X=r) = \binom{r-1}{r-1} p^r (1-p)^{r+r}$$

500 contiguous 20cm² quadrats

Poisson Distribution:

$$P(x) = \frac{\lambda^x}{x!} e^{-\lambda}$$

1 st Data Set: <i>Glaux maritima</i>			
Count	Frequency	Poisson	Negative Binomial
0	1	1.7	2
1	15	9.3	11
2	27	26.1	29
3	42	50.1	51
4	77	72.6	70
5	77	83.5	77
6	89	79.2	73
7	57	65	60
8	48	47	44
9	24	30	29
10	14	17	18
11	16	9	10
12	9	4	5
13	3	2	2
14	1	1	1
Total	500		

Mean 5.76
 S.D. 2.53
 λ 5.76
 r 50.29
 D. 0.1028

The negative binomial shows a goodness of fit with greater accuracy.

2nd Data Set: Potato Beetles

Count	Frequency	Poisson	Negative Binomial
0	10	2.0	1.5
1	264	9.5	254
2	304	22.6	57
3	260	35.7	52
4	294	42.3	44
5	219	40.1	36
6	183	31.6	29
7	150	21.4	23
8	104	12.6	17
9	90	6.7	13
10	60	3.2	10
11	46	1.4	7
12	29	0.5	5
13	36	0.2	4
14	19	0.1	3
15	12	0	2
16	11	0	2
17	6	0	1
18	10	0	0
19	2	0	0
20	4	0	0
21	1	0	0
22	3	0	0
23	4	0	0
24	1	0	0
25	1	0	0
26	0	0	0
27	0	0	0
28	1	0	0

Frequency 2nd Data Set:

48 rows wide and 96ft long

2304 sampling units of 2ft length

Method of Moments:

Negative Binomial:

$$Y = K - R$$

$$E[X] = \sum_{k=1}^{\infty} k \binom{k-1}{r-1} p^r (1-p)^{k-r} = \sum_{k=1}^{\infty} \binom{y+r-1}{r-1} K p^r (1-p)^{k-r}$$

$$E[Y] = \sum_{k=1}^{\infty} \binom{y+r-1}{y} y p^r (1-p)^{y-r} = \sum_{k=1}^{\infty} \frac{(y+r-1)!}{(y-1)! (r-1)!} p^r (1-p)^y$$

$$= \frac{r(1-p)}{p} \sum_{k=1}^{\infty} \frac{(y+r-1)!}{(y-1)! r!} p^{r+1} (1-p)^{y-1}$$

$$\text{Let } y-1 = Z; \quad y = Z + 1 \quad K =$$

$$y = 1; Z = 0$$

$$= \frac{r(1-p)}{p} \sum_{k=1}^{\infty} \frac{(Z+1+r-1)!}{Z! r!} p^{r+1} (1-p)^Z \quad \begin{array}{l} \text{Probability} \\ \text{Mass} \\ \text{Function} \end{array}$$

$$= \frac{r(1-p)}{p} \sum_{k=1}^{\infty} \binom{r+1+z-1}{z} p^{r+1} (1-p)^z = 1$$

$$[E[Y] = \frac{r(1-p)}{p}] ; [P = 1 - F[y]]$$

$$P = \frac{p}{(1-p)} E[Y]$$

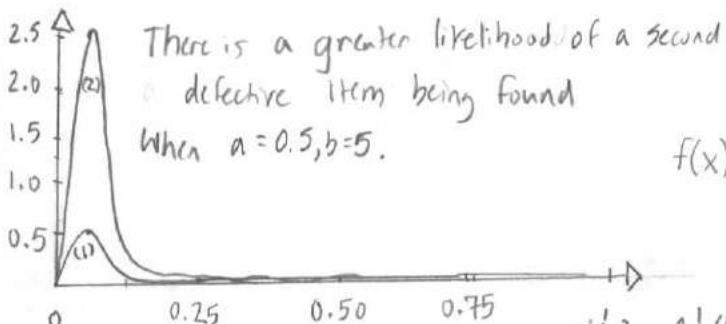
$$\text{Poisson: } E[X] = \int_0^\infty x \frac{x^x}{x!} e^{-\lambda} dx = e^{-\lambda} \int_0^\infty x \frac{x^x}{(x-1)!} dx; \quad x-1=t$$

$$= e^{-\lambda} \int_0^\infty t+1 \frac{t^t}{t!} dt = \lambda e^{-\lambda} \int_0^\infty \frac{t^t}{t!} dt = \lambda e^{-\lambda} e^\lambda = \lambda$$

The goodness of fit for the second data set did not accurately represent the data. χ^2 -values described by $\frac{(X-E)}{\sigma}$ were large. For both Poisson and Negative Binomial data.

63. $n=100$; $N=3$ defective items; Beta Distribution: $f(x) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1} (1-x)^{b-1}$ $E[x] = \frac{a}{a+b}$ $\text{Var}[x] = \frac{ab}{(a+b)^2(a+b+1)}$

1) $a=b=1$ 2) $a=0.5, b=5$



There is a greater likelihood of a second defective item being found when $a=0.5, b=5$.

$$f(x) = \sum_{k=1}^n \binom{n}{k} p^k (1-p)^{n-k}$$

$$\text{Posterior: } f(x|k, \beta) = \binom{n}{k} \frac{\Gamma(k+\beta)}{\Gamma(k)\Gamma(\beta)} x^{k+\beta-1} (1-x)^{(n-k)+\beta-1}$$

64. $X=0$ or 1 : 1) $a=b=1$ $f(x|a,b) = \binom{100}{1} \frac{\Gamma(1)}{\Gamma(1)\Gamma(1)} \int_0^1 x^{(4)} (1-x)^{99} dx$; $F(x|a,b) = \binom{99}{1} \frac{\Gamma(2)}{\Gamma(1)\Gamma(1)} \int_0^1 x^4 (1-x)^{98} dx$
 2) $a=0.5, b=5$ $f(x|a,b) = \binom{100}{1} \frac{\Gamma(1/2)}{\Gamma(1/2)\Gamma(5)} \int_0^1 x^{9/2} (1-x)^{103} dx$; $F(x|a,b) = \binom{99}{1} \frac{\Gamma(1/2)}{\Gamma(1/2)\Gamma(5)} \int_0^1 x^{7/2} (1-x)^{102} dx$

If I draw

65. $n=20$ $\mu=? \rightarrow \bar{x}=10$ $\sigma^2=1$ $f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ $\text{Normal Distribution: } \frac{-(x-\mu)^2}{2\sigma^2}$ $\text{Prior: } \mu=? \sigma^2=0.1$ $\text{Posterior: } \mu=15$

$$\begin{aligned} \text{Posterior} &= \text{Likelihood} \times \text{Prior} \\ &\propto e^{-\frac{\sum(x_i-\mu)^2}{2\sigma^2}} e^{-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}} \\ &\propto e^{-\frac{(\mu-\bar{x})^2}{2\sigma^2/n} - \frac{(\mu-\mu_0)^2}{2\sigma_0^2}} \\ &\propto e^{-\frac{\mu^2 + 2\mu\bar{x} + \bar{x}^2}{2\sigma^2/n} - \frac{\mu^2 + 2\mu_0\mu + \mu_0^2}{2\sigma_0^2}} \\ &\propto e^{-\frac{(\frac{1}{2\sigma^2/n} - \frac{1}{2\sigma_0^2})\mu^2 + 2(\frac{\mu_0}{\sigma_0^2} + \frac{\bar{x}}{\sigma^2/n})\mu - \bar{x}^2}{2\sigma^2/n} - \frac{\mu_0^2}{2\sigma_0^2}} \\ &\propto e^{-\frac{1}{2} \left(\frac{1}{\sigma^2/n} - \frac{1}{\sigma_0^2} \right) \mu^2 + \frac{2(\mu_0 + \bar{x})}{\sigma_0^2/n} \mu - \frac{\bar{x}^2}{2\sigma^2/n} - \frac{\mu_0^2}{2\sigma_0^2}} \\ &\propto e^{-\frac{1}{2} \frac{(\mu-\mu_n)^2}{\sigma_n^2}} \end{aligned}$$

#2 Draw

$$\begin{aligned} \text{Prior: } \mu &\sim N(\mu_0, \sigma_0^2) \propto \exp\left(-\frac{\sum(x_i-\mu)^2}{2\sigma_0^2}\right) \\ &= \exp\left(-\frac{(\bar{x}-\mu)^2}{2\sigma_0^2/n}\right) \end{aligned}$$

$$\begin{aligned} \sum(x_i-\mu)^2 &= \sum [x_i - \bar{x} - (\mu - \bar{x})]^2 = \sum (x_i - \bar{x})^2 + n(\mu - \bar{x})^2 \\ \text{Posterior: } P(x) &\propto \exp\left\{-\frac{\sum(x_i-\mu)^2}{2\sigma^2} - \frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right\} \\ &\propto \exp\left\{-\frac{(\mu-\bar{x})^2}{2\sigma^2/n} - \frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right\} \\ &\propto \exp\left\{-\frac{(\mu-\mu_n)^2}{2\sigma_n^2}\right\} \\ \mu_n &= \frac{\frac{1}{\sigma^2} \mu_0 + \frac{n}{\sigma^2} \bar{x}}{\frac{1}{\sigma^2} + \frac{n}{\sigma^2}} \\ \frac{1}{\sigma_n^2} &= \frac{1}{\sigma^2} + \frac{1}{\sigma^2/n} \end{aligned}$$

$$\frac{1}{\sigma_n^2} = \frac{1}{\sigma^2} + \frac{1}{\sigma^2/n} = \frac{1}{0.1^2} = \frac{1}{0.01} + \frac{1}{1/20}$$

$$\frac{1}{\sigma_n^2} = 100 + 20 = 120; \sigma_n = \sqrt{1/120}$$

$$\mu_n = \frac{\frac{1}{120} \cdot \mu_0 + \frac{20}{0.1^2} \cdot 10}{\frac{1}{120} + \frac{20}{0.1^2}} = 15 = \frac{120\mu_0 + 20000}{2120}; \mu_0 = \frac{15 \cdot 2120 - 20000}{120} = 99.33$$

66. θ is uniform $[0, 1]$.

$$P(X) = \frac{1}{b-a}$$

a) Posterior Density

b) Probability of a third shot

would be θ .

$$P(\text{Success}) = \theta$$

$$\boxed{P(X) = \frac{1}{b-a} \left(\frac{1}{b-a} \right) = \theta}$$

$$59. P(X|M) = 50\% ; P(X|F) = 50\% ; P(\alpha|M) = P(b|M) = \alpha ; P(\alpha|F) = P(b|F) = \alpha$$

$$a) P(MM) = P(I) \cdot P(I|M) + P(F) \cdot P(F|FF) = \frac{1}{2} \cdot \alpha + \frac{1}{4} (1-\alpha)$$

$$\text{WAP} = \frac{1}{2} \alpha + \frac{1}{4} - \frac{\alpha}{4} = \frac{1}{4} \alpha + \frac{1}{4} = \boxed{\frac{1+\alpha}{4}}$$

$$P(MF) = 1 - P(MM) - P(FF) = \boxed{\frac{(1-\alpha)+\alpha}{2}} = \boxed{\frac{1}{2}}$$

$$b) n_1 = MM; n_2 = FF; n_3 = MF$$

Maximum Likelihood Estimation: Multinomial

$$\ln P(X|M|F) = \ln n! - \ln \pi X_i + (n_1+n_2) \log(1+\alpha) + n_3 \log(1-\alpha)$$

$$\ln P(X|M|F) = \frac{n_1+n_2}{1+\alpha} - \frac{n_3}{1-\alpha} = 0 ; \alpha = \frac{n_1+n_2-n_3}{n_1+n_2+n_3}$$

$$\text{Variance of a Multinomial: } \text{Var}(\theta) = n \alpha (1-\alpha) = (n_1+n_2-n_3) \left(1 - \frac{n_1+n_2+n_3}{n_1+n_2+n_3}\right) = \frac{(n_1+n_2-n_3)(2n_3)}{n_1+n_2+n_3}$$

60. Exponential Distribution: a) Maximum Likelihood Estimate:

$$f(x|\tau) = \frac{1}{\tau} e^{-x/\tau}$$

$$\ln f(x|\tau) = -\ln \tau - \frac{x}{\tau} ; \frac{d \ln f(x|\tau)}{d \tau} = -\frac{1}{\tau} + \frac{x}{\tau^2} = 0 ; 1 = \frac{x}{\tau} ; \boxed{\tau = x}$$

$$b) \text{Sampling Distribution of the mle: } f(x|\hat{\tau}) = \frac{1}{\hat{\tau}^n} e^{-\frac{n}{\hat{\tau}}} = \frac{1}{x^n} e^{-\frac{1}{x}}$$

$$c) \text{Central Limit Theorem: } \lim_{n \rightarrow \infty} P\left(\frac{\bar{X}}{\sigma \sqrt{n}} \leq x\right) = \Phi(x) \quad d) \text{Bias: } E[\bar{X}] = \int_{-\infty}^{\infty} x e^{-x/\tau} dx = \frac{1}{\tau} \int_{0}^{\infty} x^{2-1} e^{-x/\tau} dx = \frac{1}{\tau} \int_{0}^{\infty} u^{2-1} e^{-u/\tau} du = \tau \Gamma(2)$$

$$\text{where } S = \sum_{i=1}^n X_i = \sum_{i=1}^n \frac{1}{e} ; \lim_{n \rightarrow \infty} P\left(\frac{\bar{X}}{\sigma \sqrt{n}} < \frac{1}{e}\right) = \Phi\left(\frac{1}{e}\right)$$

$$\hookrightarrow \text{Bias} = E[\bar{X}] - \tau = \tau \Gamma(2) - \tau = \boxed{0}$$

$$e) \text{Asymptotic Variance: } I(\theta) = -E\left[\frac{\partial^2}{\partial \tau^2} [\ln f(x|\tau)]\right] = -E\left[\frac{2}{\partial \tau} \left[\frac{-1}{\tau} + \frac{x}{\tau^2}\right]\right] = -E\left[\frac{2}{\tau^2} - \frac{2x}{\tau^3}\right] = \frac{2E[X]}{\tau^3} - \frac{1}{\tau^2} = \frac{2\tau}{\tau^3} - \frac{\tau}{\tau^2} = \frac{1}{\tau^2} ; \text{Var}(\bar{X}) = \frac{\tau^2}{n}$$

Method of Moments: $E[X] = \tau ; E[X^2] = 2\tau^2$; The method of moment estimate shows a similar

f) Confidence Interval for τ :

$$\hat{\tau} \pm 1.96 \sqrt{\text{Var}(\bar{X})} = \boxed{\hat{\tau} \pm \frac{1.96\tau}{\sqrt{n}}} \quad g) \text{The exact confidence interval for } \hat{\tau} \text{ would be } \boxed{\bar{X} \pm 1.96\tau}$$

61. $\lim_{n \rightarrow \infty} \frac{(n+1)}{(n+2)} = 1$; Laplace's rule of succession suggests the probability approaches 100% success.

62. Gamma Distribution: Exponential Distribution: Average time to serve = 5.1 minutes; $\lambda = 20/5.1 = 3.92 \frac{\text{customers}}{\text{min}}$

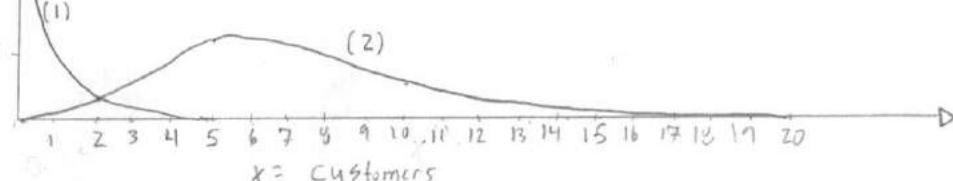
$$T(X) = \int_0^\infty b^a x^{a-1} e^{-bx} dx \quad F(x|\lambda) = \frac{1}{\lambda} e^{-x/\lambda} \quad \text{Unbiased estimate of variance:}$$

Conjugate prior Posterior

$$f(x|\lambda) \cdot T(X)$$

$$1) \bar{X}_{\text{Gm}} = 0.5 \quad \sigma_{\text{Gm}} = 1 \\ \alpha = 0.25 \quad b = 0.5$$

$$2) \bar{X}_{\text{Gm}} = 10 \quad \sigma_{\text{Gm}} = 20 \\ \alpha = 5 \quad b = 0.5$$



$$\text{Posterior Means: } \frac{X}{\text{Apost}} = bx + \frac{X}{\lambda \text{prior}}$$

$$\lambda_{\text{post}} = \frac{b}{b + \lambda_{\text{prior}}}$$

$$1) \lambda_{\text{post}} = 0.887$$

$$2) \lambda_{\text{post}} = 0.887$$

The posterior means represent exact average customers per minute, although with different priors, the cash waiting times for 1-2 or 4-8 customers in the restaurant are shifted.

Type	Count	Probab.ity
Starchy Green	1997	0.25(2+θ)
Starchy White	906	0.25(1-θ)
Sugary Green	904	0.25(1-θ)
Sugary White	32	0.25θ

b) 95% confidence Interval: Linkage Factors.

$$0.0357 \pm 1.61 \times 10^{-2}$$

c) Actual θ = $\frac{4}{3} \left(\frac{32}{333} \right) = 3.33 \times 10^{-2}$; SD = $\sqrt{np(1-p)} = \sqrt{32 \cdot 0.25(3.33 \times 10^{-2})} = 5.13 \times 10^{-3}$

56) $3.33 \times 10^{-2} \pm 1.01 \times 10^{-4}$

56. 1) $\bar{x} = n(2+θ)/4$ Bias:

$$\hat{\theta}_1 = \frac{4\bar{x}}{n} - 2$$

$$E[\hat{\theta}_1] = E\left[\frac{4\bar{x}}{n} - 2\right] = \frac{4}{n} E[\bar{x}] - 2 = \frac{4\bar{x}}{n} - 2$$

$$\bar{x} = n\theta_0/4$$

$$\hat{\theta}_2 = \frac{4\bar{x}}{n}$$

$$\text{Variance: } \text{Var}(\hat{\theta}_1) = \frac{1}{n} \sum (x_i - \bar{x})^2 - \frac{4\bar{x}}{n} + 2$$

$$\text{Var}(\hat{\theta}_2) = \frac{1}{n} \sum (x_i - \bar{x})^2 - \frac{4\bar{x}}{n} + 2$$

$$\text{Standard Error: } \sigma_{\hat{\theta}_1} = \sqrt{\frac{1}{n} \sum (x_i - \bar{x})^2 - \frac{4\bar{x}}{n} + 2} / \sqrt{n}$$

$$\sigma_{\hat{\theta}_2} = \sqrt{\frac{1}{n} \sum (x_i - \bar{x})^2 - \frac{4\bar{x}}{n} + 2} / \sqrt{n}$$

57. $(n-1)s^2 \sim \chi^2_{n-1}$ a) Which of the following is unbiased? $s^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$; $\hat{\sigma}^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$

$$\text{MSE} = \text{Var} + \text{Bias}^2 = \text{Var}(s^2) + \text{Var}(\bar{x}) + E[\bar{x}]^2$$

$$\text{Bias} = E[s^2] = E\left[\frac{n}{n-1} \hat{\sigma}^2\right] = \frac{n}{n-1} E[\hat{\sigma}^2] = \frac{n}{n-1} \hat{\sigma}^2 =$$

b) $\text{MSE}_{s^2} = \text{Var}(s^2) + \text{Bias}(s^2)^2 = \frac{2\sigma^4}{(n-1)} + 0 = \text{Var}$

b) $\text{MSE}_{\hat{\sigma}^2} = \text{Var}(\hat{\sigma}^2) + \text{Bias}(\hat{\sigma}^2)^2 = \text{Var}\left(\frac{n-1}{n}s^2\right) + [E(\hat{\sigma}^2) - \sigma^2]^2$

$$= \text{Var}\left(\frac{n-1}{n}s^2\right) + \frac{(n-1)}{n}\sigma^2 - \sigma^2 = \frac{\sigma^4}{n^2} \text{Var}\left(\frac{n-1}{n}s^2\right) - \frac{1}{n}\sigma^2 = \frac{(2n-1)\sigma^4}{n^2}$$

$$\text{Bias}_{\hat{\sigma}^2} = E[\hat{\sigma}^2] = E\left[\frac{(n-1)}{n} s^2\right] = \frac{(n-1)}{n} E[s^2] = \frac{n-1}{n} \sigma^2$$

c) $Y = p \sum (X_i \cdot \bar{X})^2; E[Y] = E[p(n-1)s^2] = p(n-1)\sigma^2$

$\text{Var}(Y) = V(p(n-1)s^2) = p^2(n-1)V(s^2) = 2p^2(n-1)\sigma^4; \text{MSE}[Y] = V[Y] + \text{Bias}^2(Y) = \sigma^4[2p^2(n-1) + (pn-p-1)^2]$

$$\text{MSE}[Y] = 2(n-1)\sigma^4(n+1) = 0$$

$$\text{MSE is minimized for } \frac{1}{n+1} \sum (X_i - \bar{X})^2$$

58. $P(AA) = (1-\theta)^2; P(Aa) = 2\theta(1-\theta); P(aa) = \theta^2$ a) Maximum Likelihood Estimate:

Haptoglobin Type		
Hp1-1	Hp1-2	Hp2-2
10	69	112

Total: 200

a)

$$P(\theta) = \frac{n!}{\prod X_i!} \prod x_i^{\theta_i}; \ln P(\theta) = \ln n! - \sum \ln x_i + \sum x_i \ln p(x_i)$$

$$\ln P(\theta) = \ln n! - \sum_{i=1}^3 \ln x_i + x_1 \ln(1-\theta)^2 + x_2 \ln(2\theta(1-\theta)) + x_3 \ln \theta^2$$

$$\ln P(\theta) = \frac{-2x_1}{(1-\theta)} + \frac{2x_2}{2\theta} + \frac{x_2}{1-\theta} + \frac{2x_3}{\theta} = \frac{(x_2+2x_3)}{\theta} - \frac{(x_2+2x_1)}{(1-\theta)} = 0$$

b) $\frac{\partial \ln P(\theta)}{\partial \theta} = (x_2+2x_3)(1-\theta) - (x_2+2x_1)\theta = (x_2+2x_1)\theta^2 + x_2+2x_3 = \frac{x_2+2x_3}{x_2+2x_1+x_2+2x_3} = \frac{x_2+2x_3}{2x_1+2x_3+2x_2} = \frac{+68+2(112)}{2(10)+2(112)+2(69)} = 0.769$

Asymptotic Variance:

$$I(\theta) = -E\left[\frac{\partial^2}{\partial \theta^2} [\ln n! - \sum \ln x_i + x_1 \ln(1-\theta)^2 + x_2 \ln(2\theta(1-\theta)) + x_3 \ln \theta^2]\right]$$

$$= -E\left[\frac{2}{\partial \theta} \left[\frac{-2x_1}{(1-\theta)} + \frac{2x_2}{2\theta} - \frac{x_2}{1-\theta} + \frac{2x_3}{\theta} \right]\right] = -E\left[\frac{-2x_1}{(1-\theta)^2} - \frac{x_2}{\theta^2} - \frac{2x_3}{(1-\theta)^2}\right] = \frac{2n(1-\theta)^2}{(1-\theta)^2} - \frac{n2\theta(1-\theta)}{\theta^2} - \frac{2n2\theta(1-\theta)}{(1-\theta)^2} - \frac{2\cdot n2\theta(1-\theta)}{\theta^2}$$

$$= 2(1-\theta) - 2n\theta - 2n = -2n + 2$$

$$\frac{2}{\theta(1-\theta)}$$

$$\text{Var}(\hat{\theta}) = \frac{1}{n I(\theta)} = \frac{\theta(1-\theta)}{2n^2} = \frac{1}{2} \cdot 2.23 \times 10^{-6}$$

$$0.769 \pm 3.85 \times 10^{-3}$$

$$0.748 \pm 3.94 \times 10^{-3}$$

$$\text{mle : } \text{SD} = 1.43 \times 10^{-3}$$

50. Rayleigh Distribution a) Method of Moments Estimate: $x^2 = u; dx = \frac{1}{2}u^{-1/2}du$

$$f(x|\theta) = \frac{x}{\theta^2} e^{-x^2/2\theta^2}$$

$$E[X] = \int_0^\infty \frac{x^2}{\theta^2} e^{-x^2/2\theta^2} dx = \frac{1}{\theta^2} \int_0^\infty u e^{-u/2\theta^2} \frac{du}{2\sqrt{u}} = \frac{1}{2\theta^2} \int_0^\infty u^{1/2} e^{-u/2\theta^2} du = \frac{1}{2\theta^2} \int_0^\infty u^{3/2} e^{-u/2\theta^2} du$$

b) Maximum Likelihood Estimate:

$$\frac{d\sum \ln f(x|\theta)}{d\theta} = \frac{-2n}{\theta} + \frac{\sum x_i^2}{\theta^3} = 0$$

$$-2n + \frac{\sum x_i^2}{\theta^2} = 0; \frac{\sum x_i^2}{2n} = \theta^2; \hat{\theta} = \sqrt{\frac{1}{2n} \sum x_i^2}$$

$\Delta = +2 \frac{E[x^2]}{\theta^3}; \text{Var}(\hat{\theta}) \approx \frac{1}{n I(\theta)} = \frac{\hat{\theta}^3}{2E[x^2]} = \frac{\hat{\theta}}{4}$

c) Asymptotic Variance of Maximum Likelihood:

$$I(\theta) = -E\left[\frac{\partial^2}{\partial \theta^2} \ln f(x|\theta)\right] = -E\left[\frac{\partial}{\partial \theta}\left[-2n + \frac{\sum x_i^2}{\theta^2}\right]\right]$$

51. Double Exponential Distribution

$$f(x|\theta) = \frac{1}{2}e^{-|x-\theta|}; -\infty < x < \infty; n=2m+1$$

52. $f(x|\theta) = (\theta+1)x^\theta; 0 \leq x \leq 1$ a) Method of Moments Estimate:

$$E[X] = \int_0^1 (\theta+1)x^{\theta+1} dx = \frac{(\theta+1)}{(\theta+2)} x^{\theta+2} \Big|_0^1 = \frac{(\theta+1)}{(\theta+2)}; \theta(E[X]-1) = 1 - 2E[X]$$

b) Maximum Likelihood Estimate:

$$\frac{d\sum \ln f(x|\theta)}{d\theta} = \frac{1}{\theta+1} + \sum \ln x_i = 0; \hat{\theta} = \frac{1 - \sum \ln x_i}{\sum \ln x_i}$$

c) Asymptotic Variance of MLE:

$$I(\theta) = -E\left[\frac{\partial^2}{\partial \theta^2} \ln f(x|\theta)\right] = -E\left[\frac{\partial}{\partial \theta}\left[\frac{1}{\theta+1} + \ln x_i\right]\right] = \frac{1}{(\theta+1)^2}; \text{Var}(\hat{\theta}) = \frac{1}{n I(\theta)} = \frac{(1+\hat{\theta})^2}{n} = \frac{\left(1 + \frac{1 - \sum \ln x_i}{\sum \ln x_i}\right)^2}{n}$$

d) Sufficient Statistic: X^θ

53. X_1, \dots, X_n uniform on $[0, \theta]$ a) Find the Method of moments estimate of θ , mean, and variance.

Uniform Distribution:

$$P(X) = \frac{1}{b-a} [a, b]$$

$$= \frac{1}{\theta-0} [0, \theta]$$

b) Maximum Likelihood Estimate: $\frac{d\sum \ln p(x)}{d\theta} = \frac{1}{\theta} = 0; \hat{\theta} = \Theta_{\max}$

c) $F(X_n|\theta) = n \frac{X_n^{n-1}}{\theta^{n-1}}; E[X] = \int_0^\theta \frac{nx^n}{\theta^n} dx = \frac{n}{\theta^n} \int_0^\theta x^n dx = \frac{n}{(n+1)\theta^n}$

$$E[X^2] = \int_0^\theta \frac{n}{\theta} x^{n+1} dx = \frac{n\theta^{n+2}}{n+2}; \text{Var}(X) = \frac{n\theta^2 - n^2\theta^2}{n+2(n+1)^2} = \frac{n\theta^2}{(n+1)^2(n+2)}$$

d) Bias of Maximum Likelihood Estimate:

$$\text{Bias} = E[X - \hat{\theta}] = B\left[\frac{n}{n+1} - 1\right] = \frac{1-\theta}{n+1}$$

Bias of Method of Moments:

$$\text{Bias} = E[X - \hat{\theta}] = \Theta_{\max} - \hat{\theta}$$

54. $n=15; \bar{x}=10; s^2=25$
90% confidence Interval

$$P\left(-\frac{x-\mu}{\sigma_x} < Z(0.95) = 0.90\right)$$

$$P(0.05 < \frac{x-\mu}{\sigma_x} < 0.95) = 0.90$$

$$P(\mu \pm 1.65 \sigma_x < X_{14, 0.95}) = 0.90$$

$$P(10 \pm 2.13) < \sigma_x^2 < 57$$

$P\left(\chi_{n-1}^2 < \frac{n\hat{\sigma}^2}{\sigma_x^2} < \chi_{n-1}^2(0.95)\right) = 0.90$ d) $\hat{\theta} = ?$

$$P\left(\frac{n\hat{\sigma}^2}{\sigma_x^2} < \sigma_x^2 < \frac{n\hat{\sigma}^2}{\chi_{14, 0.95}^2}\right) = 0.90$$

$E[\hat{\theta}] = E[\max(X_i)] = \frac{n\theta}{(n+1)}$

$\hat{\theta} = \frac{n+1}{n} \max X_i$

47. Pareto Distribution:

$$f(x|x_0, \theta) = \theta x_0^\theta x^{-\theta-1}, x \geq x_0, \theta > 1$$

b) Maximum Likelihood Estimate:

$$\ln f(x|x_0, \theta) = \ln \theta + \theta \ln x_0 - (\theta+1) \ln x$$

$$\sum \ln f(x|x_0, \theta) = n \ln \theta + n \theta \ln x_0 - (\theta+1) \sum \ln x_i$$

$$\frac{d \sum \ln f(x|x_0, \theta)}{d \theta} = \frac{n}{\theta} + n \ln x_0 - \sum \ln x_i = 0$$

$$\hat{\theta} = \frac{n}{\sum \ln x_i - n \ln x_0}$$

a) Method of Moments Estimate for θ :

$$E[X] = \int_{x_0}^{\infty} x \theta x_0^\theta x^{-\theta-1} dx = \frac{\theta x_0^\theta x^{-\theta+1}}{-\theta+1} \Big|_{x_0}^{\infty} = \left(\frac{\theta}{1-\theta}\right) x_0^\theta x_0^{-\theta+1} = \left(\frac{\theta}{1-\theta}\right) x_0$$

$$E[X^2] = \int_{x_0}^{\infty} x^2 \theta x_0^\theta x^{-\theta-1} dx = \frac{\theta x_0^\theta x^{-\theta+2}}{-\theta+2} \Big|_{x_0}^{\infty} = \left(\frac{\theta}{1-\theta}\right) x_0^\theta x_0^{-\theta+2} = \left(\frac{\theta}{1-\theta}\right) x_0^2$$

$$\text{Var}[X] = \left(\frac{\theta}{1-\theta}\right) x_0^2 - \left(\frac{\theta}{1-\theta}\right)^2 x_0^2 = \left(\frac{\theta - \theta^2}{(1-\theta)^2}\right) x_0^2 = \frac{(1-2\theta)\theta}{(1-\theta)^2} x_0^2$$

$$\hat{\theta} = \frac{E[X]}{(x_0 + E[X])}$$

$$c) \text{Asymptotic Variance: } I(\theta) = -E\left[\frac{\partial^2}{\partial \theta^2} \ln f(x|x_0, \theta)\right] = -E\left[\frac{\partial}{\partial \theta}\left(\frac{n}{\theta} + n \ln x_0 - \sum \ln x_i\right)\right] = \frac{n}{\theta^2}$$

$$\text{Var}(\hat{\theta}) \approx \frac{1}{n I(\theta)} = \frac{\hat{\theta}^2}{n^2 (\sum \ln x_i - n \ln x_0)^2}$$

d) Sufficient Statistic $[X \geq X_0 \text{ and } \theta \geq 2.]$

48. Observation: $p_0 = P(X=0) = c \Rightarrow$ Method of Propagation Error: (Expansion of $F(x)$ about the mean)

Poisson Distribution: Note: $Y \sim \text{Bin}(n, p_0)$

$$P(X) = \frac{x^x}{x!} e^{-\lambda} \quad \hat{\lambda} = -\log(Y/n); p_0 = e^{-\lambda} = \frac{Y}{n}; E[Y] = np_0$$

$$\text{Approximate Expression of Variance: } \hat{\sigma}_p^2 = \sum_{i=1}^n \left| \frac{dF}{dx} \right|_{x_i}^2 \sigma_0^2 = \sum_i \frac{1}{y^2} \lambda = \frac{\lambda}{y^2}$$

$$\text{Bias: } \sum \frac{\partial F}{\partial x_i} E[X_i] - \lambda = \left[-\frac{n\lambda}{y} - \lambda \right];$$

$$\text{Maximum Likelihood Estimate: } \frac{d \sum \ln p(x)}{d \lambda} = \frac{\sum x_i - n}{\lambda} = 0; \quad \hat{\lambda}_{\text{MLE}} = \frac{\sum x_i}{n} = \bar{X}$$

$$\text{Variance Maximum likelihood Estimate: } \text{Var}(\hat{\lambda}_{\text{MLE}}) = \frac{\lambda}{n} \quad \text{Efficiency: } \frac{\text{Var}(\hat{\lambda}_{\text{MLE}})}{\text{Var}(\hat{\lambda}_{\text{MAP}})} = \frac{\frac{\lambda}{n}}{\frac{n\lambda}{y^2}} = \frac{1}{n} \frac{y^2}{\lambda}$$

49. Muon Decay Binomial Distribution

$$a) f(x|\alpha) = \frac{1+\alpha x}{2} \quad p(k) = \binom{n}{k} p^k (1-p)^{n-k}$$

$$\begin{aligned} -1 \leq x \leq 1 \\ \int_0^n f(x|\alpha) dx = \int_0^1 \frac{1+\alpha x}{2} dx \\ -1 \leq \alpha \leq 1 \\ = \left[\frac{1}{2} + \frac{\alpha}{4} \right] = \frac{2+\alpha}{4} = p \end{aligned}$$

$$E[X] = \mu = \frac{\alpha}{2}$$

Method of Moments:

$$\text{Binomial}(n, p) = \text{Bin}(n, \frac{2+\alpha}{4})$$

$$E[\hat{p}] = E\left[\frac{\bar{x}}{n}\right] = \frac{2+\alpha}{4} = p; \quad \text{Var}(4p-2) = 4^2 \text{Var}(p) = 16p(1-p)$$

$$\text{Var}(4\frac{\bar{x}}{n}-2) = \frac{4^2}{n^2} \text{Var}(p) = \frac{16}{n^2} p(1-p)$$

b) Binomial Variance: $\text{Var}[k] = np(1-p)$; Muon Decay Variance

K	Var Bin	Var Bin	Var Mome
0	0	3.99	$3.99/n^2$
0.1	0.53	3.96	$3.96/n^2$
0.2	0.55	3.91	$3.91/n^2$
0.3	0.58	3.84	$3.84/n^2$
0.4	0.60	3.75	$3.75/n^2$
0.5	0.63	3.64	$3.64/n^2$
0.6	0.65	3.51	$3.51/n^2$
0.7	0.68	3.51	$3.51/n^2$
0.8	0.70	3.36	$3.36/n^2$
0.9	0.73	3.19	$3.19/n^2$

Maximum Likelihood Estimate

$$\frac{d \sum \ln p(x)}{dp} = \frac{\sum x}{p} - \frac{n - \sum x}{1-p} = 0$$

$$(1-p) \sum x = (n - \sum x) p$$

$$\sum x - p \sum x = np - p \sum x$$

$$\begin{aligned} \text{Var}(4p-2) \\ = 16p(1-p) \end{aligned}$$

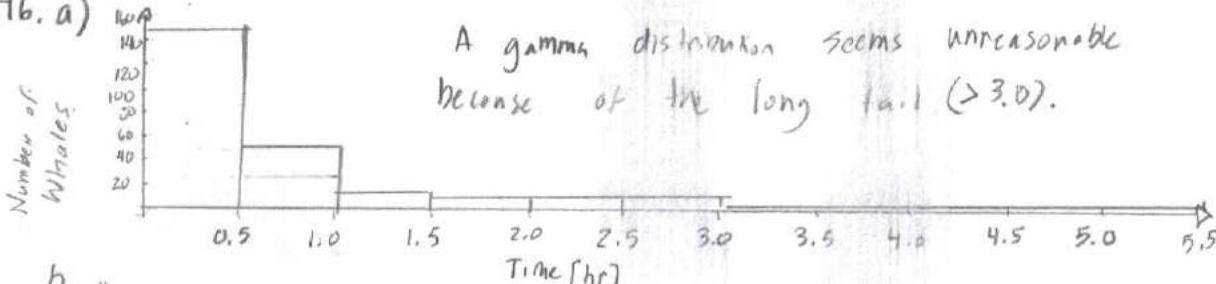
Method of Moments (WNR)

more efficient than

Binomial Bootstrap or

Maximum Likelihood.

46. a)



b. Method of Moments

$$E[X] = \int_0^\infty x \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-x\beta} dx = \frac{\beta^\alpha}{\Gamma(\alpha)} \int_0^\infty x^\alpha e^{-x\beta} dx = \frac{\beta^\alpha}{\Gamma(\alpha)} \frac{\Gamma(\alpha+1)}{\beta^{\alpha+1}} = \frac{\alpha}{\beta}; \quad \alpha = \beta - 1$$

$$E[X^2] = \int_0^\infty x^2 \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-x\beta} dx = \frac{\beta^\alpha}{\Gamma(\alpha)} \int_0^\infty x^{\alpha+1} e^{-x\beta} dx = \frac{\beta^\alpha (\alpha+1) \alpha \Gamma(\alpha)}{\Gamma(\alpha) \beta^{\alpha+2}} = \frac{(\alpha+1)\alpha}{\beta^2}; \quad \text{Var}[X] = E[X^2] - E[X]^2$$

$$\frac{(\alpha+1)\alpha}{\beta^2} - \frac{\alpha^2}{\beta^2} = \frac{\alpha}{\beta^2}$$

From data:	$\text{Mean} = 0.6060$	$\text{Variance} = 0.4595$
	$\text{Shape}(\alpha) = 0.7991$	$\text{Rate} = 1.3198$

c. Maximum Likelihood Estimate:

$$\ln f(x|a, b) = \alpha \ln \beta - \ln \Gamma(\alpha) + (\alpha-1) \ln x - \beta x$$

$$\sum \ln f(x|a, b) = n \alpha \ln \beta - n \ln \Gamma(\alpha) + (\alpha-1) \sum \ln x_i - \beta \sum x_i$$

$$\frac{\sum \ln f(x|a, b)}{d\alpha} = n \ln \beta - n \frac{\Gamma'(\alpha)}{\Gamma(\alpha)} + \sum \ln x_i = 0$$

$$\frac{\sum \ln f(x|a, b)}{d\beta} = n \alpha - \sum x_i = 0, \quad \frac{\alpha}{E[x]} = \beta$$

Solve with roots

$$n = 210 \\ E[X] = 0.6066$$

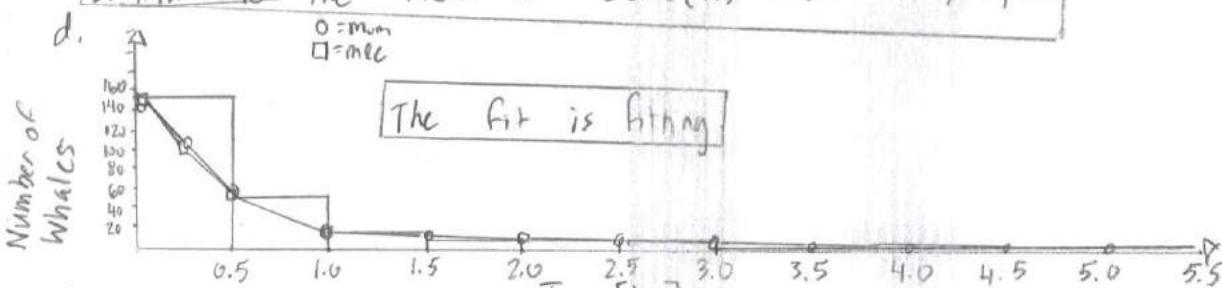
$$n \ln \alpha - n \ln E[x] - n \frac{\Gamma'(\alpha)}{\Gamma(\alpha)} + \sum \ln x_i = 0$$

The values from M.O.M. in part b) are

$$\alpha = 0.7569; \beta = 1.2491$$

Similar to the MLE of $\text{shape}(\alpha)$ and $\text{shape}(\beta)$.

d.



e. Method of Moments:

$$\text{Variance} = 0.4595; \text{Standard Deviation} = 0.6779; n = 210; \text{Standard Error} = \sigma_x = \frac{\sigma}{\sqrt{n}} = 4.60 \times 10^{-2}$$

$$\text{Sampling Distribution: } P\left(\frac{X - \mu}{\sigma_x} < Z_{upper}\right) = 0.95; Z_{upper} = 1.556$$

f. Maximum Likelihood/Mom:

$$\text{Variance} = \frac{E[X]^2}{\alpha} = \frac{0.6060^2}{0.7569} = 0.4852; \text{Standard Deviation} = 0.6966; \text{Standard Error} = \sigma_x = \frac{\sigma}{\sqrt{n}} = 4.81 \times 10^{-2}$$

$$\text{Sampling Distribution: } P\left(\frac{X - \mu}{\sigma_x} < Z_{upper}\right) = 0.95; Z_{upper} = 1.66$$

Similar result to part c

g. Confidence Interval: 95%; $0 < \bar{x} < 0.700$

45. a. Maximum Likelihood Estimate: Rayleigh Distribution: $f(r|\theta) = \frac{r}{\theta^2} \exp\left(-\frac{r^2}{2\theta^2}\right)$

Log Rayleigh Distribution: $\ln f(r|\theta) = \ln r - 2n \ln \theta - \frac{\sum r^2}{2\theta^2}$

b. Method of Moments Estimate:

$$\text{MLE Estimate: } \frac{\partial \ln f(r|\theta)}{\partial \theta} = -\frac{2n}{\theta} + \frac{\sum r_i^2}{\theta^3}; \hat{\theta} = \left(\frac{1}{2n} \sum r_i^2\right)^{1/2}$$

$$E[r] = \int_0^\infty \frac{r^3}{\theta^2} \exp\left(-\frac{r^2}{2\theta^2}\right) dr = \frac{1}{\theta^2} \int_0^\infty r^2 \exp\left(-\frac{r^2}{2\theta^2}\right) dr = \frac{1}{\theta^2} \int_0^\infty u \exp\left(-\frac{u}{2\theta^2}\right) \frac{du}{2\sqrt{u}} = \frac{1}{2\theta^2} \int_0^{\frac{u}{2\theta^2}} u^{\frac{3}{2}} \exp\left(-\frac{u}{2\theta^2}\right) du$$

$$M(r) = \frac{\Gamma(3/2)}{2\theta^2} (2\theta)^{3/2} = \sqrt{2}\theta \Gamma(\frac{3}{2}) = \sqrt{2}\theta \times (\frac{1}{2})\Gamma(\frac{1}{2}) = \theta \left(\frac{\sqrt{\pi}}{\sqrt{2}}\right)$$

c. Approximate Variance of MLE:

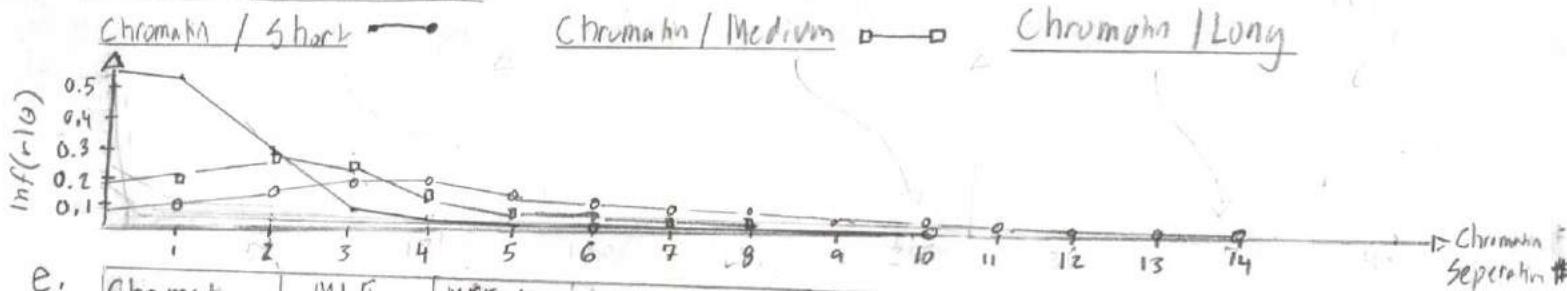
$$I(\theta) = -E\left[\frac{\partial^2}{\partial \theta^2} \ln f(r|\theta)\right] = -E\left[\frac{2}{\theta^2} - \frac{3r^2}{\theta^4}\right] = \frac{3E[r^2]}{\theta^4} - \frac{2}{\theta^2} = \frac{6\theta^2}{\theta^4} - \frac{2}{\theta^2} = \frac{4}{\theta^2}$$

$$\text{Var}(\hat{\theta}) \approx \frac{1}{n I(\theta)} = \frac{1}{4n} \hat{\theta}^2$$

Approximate Variance of Method of Moments:

$$I(\theta) = \frac{4}{\theta^2}; \text{Var}(\hat{\theta}) = \frac{1}{n I(\theta)} = \frac{\hat{\theta}^2}{4n} = \frac{\sum r_i^2}{2n^2\pi}$$

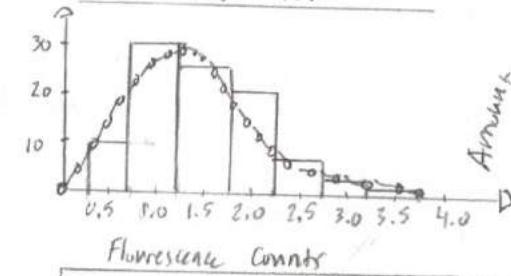
d. Plot of Likelihood Function



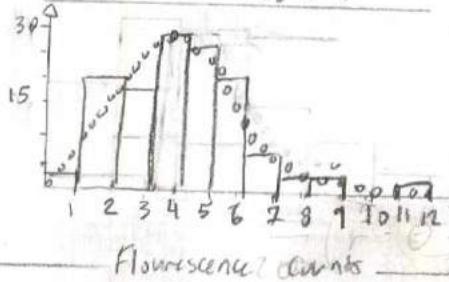
e.

Chromatin	MLE	MLE Asymptotic Variance	MOM	MOM Asymptotic Variance
Short	1.12	3.27×10^{-3}	1.17	3.04×10^{-3}
Medium	3.36	2.08×10^{-2}	3.39	2.18×10^{-2}
Long	2.08	4.34×10^{-3}	2.07	4.30×10^{-3}

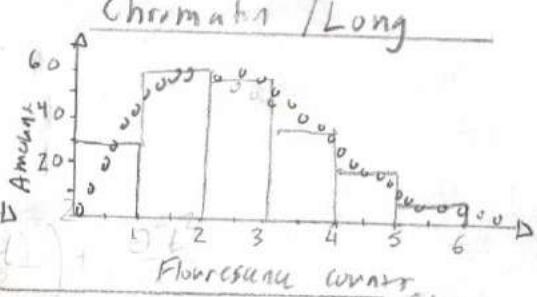
f. Chromatin / Short



Chromatin / Medium



Chromatin / Long



The distributions for the domain [0, 12] fit similarly to datasets.

g. Both short and long strands of DNA show fluorescence signals with a mle of ~1.12, and medium strands ~3.04.

Gender	Mean Temperature ($^{\circ}\text{F}$)	Standard Deviation ($^{\circ}\text{F}$)	Mean Rate (beats/min)	Standard Deviation (beats/min)
Male	98.1	0.69	73.37	5.83
Female	98.39	0.74	74.15	9.04
95% - Confidence Interval	Male: $98.1^{\circ}\text{F} \pm 0.18$ Female: $98.39^{\circ}\text{F} \pm 0.18$		Male: $73.37 \text{ beats/min} \pm 1.4$ Female: $74.15 \text{ beats/min} \pm 1.97$	

Folklore of 98.6°F does not fit inside the confidence interval for male or female.

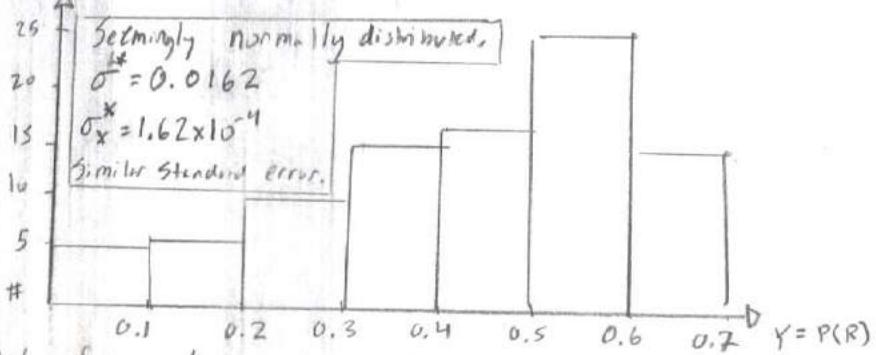
45. began on other side:

h. Proposition D: Section 2.3 e. If the domain $[0, 1]$ for $X = F^{-1}(U)$, then the cdf of X is F .

Pseudorandom variables were generated on the domain $[0, 1]$ with $\Delta r = 0.1$

r	G=1, P(r)	CDF
0.0	0	0
0.1	0.17	0.17
0.2	0.34	0.56
0.3	0.46	1.02
0.4	0.29	1.31
0.5	0.60	1.91
0.6	0.12	2.03
0.7	0.55	2.58
0.8	0.56	3.14
0.9	0.24	3.38
1.0	0.60	3.99

$$B=100, \Delta r=0.01, \Theta^*=0.32$$



i. $B=1000, \Theta^*=0.43$. A value generated from large sample theory.

42. Poisson Distribution

$$P(k) = \frac{\lambda^k}{k!} e^{-\lambda}$$

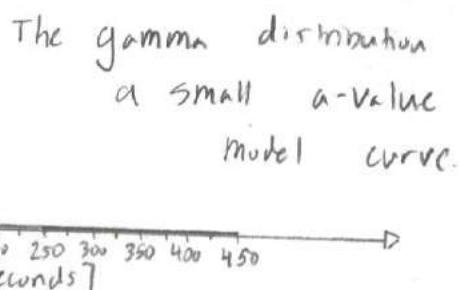
$$\lambda = 6,004207 \text{ counts/sec}$$

$$\sigma_x = \sqrt{\frac{\lambda}{n}} = 0.00004207 \text{ count/sec}$$

An informal determination that emission rate is constant would be sampling the dataset for similar values.

43.

a) Histogram of Interarrival Times:



The gamma distribution would fit if a small a -value represented model curve.

b) Method of Moments

$$\text{Gamma Distribution: } P(x|a,b) = \frac{b^a}{T(a)} x^{a-1} e^{-bx}$$

$$M(t) = \int_0^\infty e^{-tx} \frac{b^a}{T(a)} x^{a-1} e^{-bx} dx = \frac{b^a}{T(a)} \left(\frac{T(a)}{(b-t)^a} \right) = \left(\frac{b}{b-t} \right)^a$$

$$M'(0) = E[X] = \frac{a}{b}$$

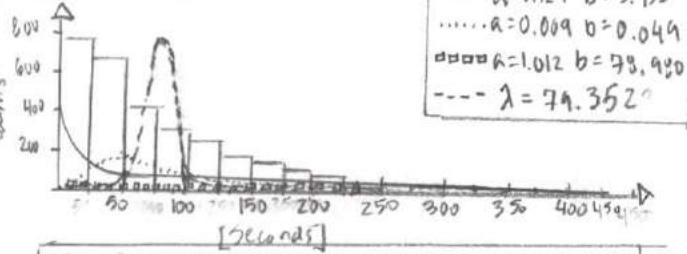
$$M''(0) = E[X^2] = \frac{a(a+1)}{b^2}$$

$$\text{Var}(x) = \frac{a(a+1)}{b^2} - \frac{a^2}{b^2} = a/b^2$$

$$\begin{aligned} b &= \frac{E[X]}{\text{Var}(x)} = 1.012 \\ a &= \frac{E[X]^2}{\text{Var}(x)} = 78.980 \end{aligned}$$

The method of moments does not fit, and decays to zero by sight.

c) Plot of the fittings:



The fits are of wrong scale, but $a=0.729, b=3.935$ models at half-height.

e) Confidence Interval of Method of Moments

$$P(c_1 \leq \frac{n\bar{x}}{a} \leq c_2) = 0.95$$

$$P(\frac{1}{c_1} \leq \frac{a}{n\bar{x}} \leq \frac{1}{c_2}) = 0.95$$

$$P(\frac{n\bar{x}}{c_1} \leq a \leq \frac{n\bar{x}}{c_2}) = 0.95$$

$$\min \left[\int_{c_1}^{\frac{n\bar{x}}{c_2}} \text{Gam}(x|a,b) dx = 0.95 \right] \text{ for } c_1 \text{ & } c_2$$

$$\begin{aligned} &= \prod_{k=0}^n \frac{\lambda^k}{k!} e^{-\lambda} \cdot \frac{b^a}{T(a)} \lambda^{a-1} e^{-b\lambda} \\ &= \frac{\lambda^{\sum k}}{\prod k!} e^{-\lambda} \cdot \frac{b^a}{T(a)} \lambda^{a-1} e^{-b\lambda} \\ &= \frac{\lambda^{(a-1)+\sum k} b^a}{\prod k! T(a)} e^{-(b+\lambda)\lambda} \end{aligned}$$

Maximum Likelihood

$$\ln P(x|a,b) = \ln b^a - \ln T(a) + (a-1) \ln x - bx$$

$$\prod \ln P(x|a,b) = n \ln b^a - n \ln T(a) + (a-1) \sum \ln x - b \sum x$$

$$\frac{d(\prod \ln P(x|a,b))}{da} = \frac{n}{b} - \sum x = 0 ; b = \frac{\sum x}{n}$$

$$\frac{d(\prod \ln P(x|a,b))}{db} = n \ln a - \ln \bar{x} - n \frac{T'(a)}{T(a)} + \sum \ln x = 0$$

"Solving for roots"

$$a = 0.72898, 3.93466$$

$$b = 0.00912, 0.049223$$

The MLE shows two solutions because of two roots, when graphically evaluating shape(a). A fit is of the wrong scale.

d) Bootstrap Estimate of S.E.

Method of Moments S.E.

$$\text{Shape}(a) = \bar{x}^2 / \text{Var}(x)$$

$$\text{Scale}(b) = \bar{x} / \text{Shape}(a)$$

The variance does not change for parameters.

$$\text{so } S.E. = \sqrt{\frac{\text{Var}(x)}{n}} = 1.27$$

Maximum Likelihood S.E.

$$\text{Shape}(a) = \text{Solved Numerically}$$

$$\text{Scale}(b) = \text{Solved via bootstrap.}$$

The variance of parameters depends on precision of mean and standard deviation. S.E. = 1.27

Confidence Interval of Maximum Likelihood Estimate:

$$a = 0.72898, b = 3.93466$$

$$\min \left[\int_{c_1}^{\frac{n\bar{x}}{c_2}} \text{Gam}(x|a,b) dx = 0.95 \right]$$

$$a = 3.93466, b = 0.049223$$

$$\min \left[\int_{\frac{n\bar{x}}{c_1}}^{\frac{n\bar{x}}{c_2}} \text{Gam}(x|a,b) dx = 0.95 \right]$$

F. See part
or (part C)

35. $U_1, U_2, \dots, U_{1029}$. $X_1 = U_1 < 0.331$; $X_2 = 0.331 < U_2 < 0.489$; $X_3 = 0.489 < U_3 < 0.820$; Why X_1, X_2 and X_3 multinomial with probabilities 0.331, 0.489, and 0.180 and $n=1029$? Multinomial Distribution:

The example of section 8.5.1 described gene frequencies modeled with Hardy-Weinberg Equations: $p(n_i, n_r) = \binom{n}{n_1, \dots, n_r} p_1^{n_1} p_2^{n_2} \dots p_r^{n_r}$

frequency modeled with Hardy-Weinberg Equations: $I = [\theta + (1-\theta)]^2 = \theta^2 + 2\theta(1-\theta) + (1-\theta)^2$.

If the maximum likelihood estimate is $\hat{\theta} = 0.4247$, then each probability of M, MN , and N representing $\theta, 2\theta(1-\theta)$, and $(1-\theta)^2$, respectively, show probabilities of existence 0.331, 0.489, and 0.180.

36. The 90% confidence intervals of Example E: section 8.5.3 were determined to be $(\hat{\theta} - \bar{\theta}, \hat{\theta} + \bar{\theta}) = (0.404, 0.523)$, along with $\lambda_0 = (1.462, 2.321)$; however, a normal approximation generated $S\hat{\theta} = (0.407, 0.443)$ and $S\lambda = \left(\frac{\sqrt{(n-1)s}}{X_{0.05, df}^2}, \frac{-\sqrt{(n-1)s^2}}{X_{0.95, df}^2} \right) = (?, ?)$.

37. Lower Bound $\underline{\theta}$ } Quantiles of Distribution θ^* . Prove the bootstrap confidence interval
Upper Bound $\bar{\theta}$ is $(2\hat{\theta} - \bar{\theta}, 2\hat{\theta} + \bar{\theta})$.

$$(\hat{\theta} - \underline{\theta}, \hat{\theta} - \bar{\theta}) = (\hat{\theta} - \underline{\theta}^* + \hat{\theta}, \hat{\theta} - \bar{\theta}^* + \hat{\theta}) = (2\hat{\theta} - \underline{\theta}^*, 2\hat{\theta} + \bar{\theta}^*)$$

38. $P(\underline{\theta} \leq \theta^* \leq \bar{\theta}) = P(\underline{\theta}, \bar{\theta})$ 39. If the distribution were considered $\hat{\theta}/\theta$, then the argument would proceed with the a bootstrap interval of $\left(\frac{\hat{\theta} - \underline{\theta}}{\theta}, \frac{\hat{\theta} - \bar{\theta}}{\theta} \right)$.

40. a) $P(|\hat{\theta} - \theta_0| > 0.01) = P(-0.01 < \hat{\theta} - \theta_0 < 0.01) = 0.5080$
Sample the probability distribution 1000 times and determine if 50.80% of the values are found inside the interval -0.01 to 0.01.

b). $E(|\hat{\theta} - \theta_0|) = \frac{1}{n} \sum_i^N (|\hat{\theta}_i - \theta_0|) P(|\hat{\theta}_i - \theta_0|) = \frac{1}{n} \sum_i^N (|\hat{\theta}_i - \theta_0|)(\hat{\theta}_i - \theta_0 - (1 - |\hat{\theta}_i - \theta_0|))^2$ if sampled 1000 times

would generate a substitute expectation for the mle estimate.

c) $P(|\hat{\theta} - \theta_0| > \Delta) = 0.5$ would be determined by sampling 1000 times and checking if

the point fit between 0.25 and 0.75.

41. Efficiency: Given two estimates, $\hat{\theta}$ and $\tilde{\theta}$, the ratio of variances $\text{var}(\hat{\theta})/\text{var}(\tilde{\theta})$.

9.4 Example C: Gamma Distribution:

$$\mu_1 = \frac{x}{\lambda} ; \mu_2 = \frac{x(x+1)}{\lambda^2} = \mu_1^2 + \frac{\mu_1}{\lambda}$$

$$\lambda = \frac{\mu_1}{\mu_2 - \mu_1^2} ; \alpha = \lambda \mu_1 = \frac{\mu_1^2}{\mu_2 - \mu_1^2}$$

$$\hat{\lambda} = \frac{\bar{X}}{\frac{\bar{X}^2}{\sigma^2}} ; \hat{\lambda} = \frac{\bar{X}^2}{\sigma^2}$$

Method of Moments

9.5: Example C: Gamma Distribution

$$f(x|x, \lambda) = \frac{1}{\Gamma(x)} \lambda^x x^{x-1} e^{-\lambda x}$$

$$I(x|\lambda) = \sum_{i=1}^n [\alpha \log \lambda + (x-i) \log \lambda_i - \lambda x_i - \log \Gamma(x)] \quad \text{Eff}(\hat{\lambda}) = 0.95$$

$$\frac{\partial L}{\partial \lambda} = n \log \lambda + \sum \log \lambda_i - n \frac{\Gamma'(x)}{\Gamma(x)}$$

$$\frac{\partial L}{\partial \lambda} = \frac{n x}{\lambda} - \sum x_i$$

$$\hat{\lambda} = \frac{\bar{X}}{\bar{X}} ; \hat{\lambda} = \bar{X} \bar{\lambda}$$

Efficiency

$$\text{Eff}(\hat{\lambda}) = 0.44$$

Maximum Likelihood Estimate

28. The intervals on the left panel represent 20-trials of a sample size of $n=11$, each with a unique μ and confidence interval.

29. Yes, variance estimates of 20 trials are represented in Figure 8.8b from a sample sizes of $n=11$. The intervals are short and long because of individual trials, which each have their own confidence interval. Variance with smallest span is trial #4, and largest trial #10.

30. $f(x; \lambda) = \lambda e^{-\lambda x}$ and $E(X) = \lambda^{-1}$; $F(x) = P(X \leq x) = 1 - e^{-\lambda x}$; $x_1 = 5, x_2 = 3, x_3 > 10$.

a) The likelihood function is: $\ln f(x; \lambda) = \ln \lambda - \lambda x$ b) The mle is $\frac{d \ln f(x; \lambda)}{d \lambda} = \frac{1}{\lambda} - x \Rightarrow \lambda = \frac{1}{x}$

Trial	#1	#2	#3	Trial	#1	#2	#3	#4
Side	T	T	T	Side	T	T	T	H

Hilary

George

b) The mle of $\hat{\theta}$ is $\frac{d \ln p(x, y | \theta)}{d \theta} = \frac{-6}{(1-\theta)} + \frac{1}{\theta} = 0$

$$\theta = \frac{1}{7}$$

$$(1-\theta) = 6$$

32.

a. mean $[\mu] = \frac{\sum x_i}{n} = \frac{57.77}{16} = 3.61$; variance $[\sigma^2] = E[X^2] - E[X]^2 = \frac{260}{16} - 3.61^2 = 3.21$

b) 90%: $3.61 \pm 1.65 \sigma_x = 3.61 \pm 0.74$

95%: $3.61 \pm 1.96 \sigma_x = 3.61 \pm 0.88$

99%: $3.61 \pm 2.58 \sigma_x = 3.61 \pm 1.26$

1.6631 2.645 $\mu = 3.6$

c) 90%: $\sigma \pm 1.34$

95%: $\sigma \pm 2.12$

99%: $\sigma \pm 2.69$

d) $\frac{1}{2}0.74 = 1.65 \sigma_x$

$$= 1.65 \sqrt{\frac{\sigma^2}{n}}$$

$$0.74 = 1.65 \sigma_x \cdot \sqrt{\frac{2}{16}}$$

$$n = 205.$$

a) $p(x | \theta) = \binom{n}{x} \theta^x (1-\theta)^{n-x}$

$$p(0 | \theta) = \binom{3}{0} \theta^0 (1-\theta)^3 = (1-\theta)^3$$

$$p(4 | \theta) = (1-\theta)^{4-1} \cdot \theta^3 = 4 \cdot (1-\theta)^3 \cdot \theta$$

$$p(x, y | \theta) = p(x=0 | \theta) \cap p(y=4 | \theta) = (1-\theta)^3 (1-\theta)^3 \theta = (1-\theta)^6 \theta$$

$$\frac{(n-1)\sigma^2}{X_{1,12, df}} < \sigma^2 < \frac{(n+1)\sigma^2}{X_{1,12, df}}$$

$$\frac{(16-1)\sigma^2}{X_{2,16-1}} = \frac{15 \times 3.21}{7.26} = 6.63 < \sigma^2 < \frac{(16+1)\sigma^2}{X_{2,16-1}} = \frac{15 \times 3.21}{2.5} = 1.92$$

$$\frac{(16-1)\sigma^2}{X_{2,16-1}} = 6.63 < \sigma^2 < \frac{(16+1)\sigma^2}{X_{2,16-1}}$$

$$P = 0.10 \quad \sigma^2 \pm 1.29$$

$$\frac{(16-1)\sigma^2}{X_{2,16-1}} = \frac{15 \times 3.21}{27.49} = 1.79 < \sigma^2 < \frac{(16+1)\sigma^2}{X_{2,16-1}} = \frac{15 \times 3.21}{6.26} = 7.69$$

$$\frac{(16-1)\sigma^2}{X_{2,16-1}} = 1.79 < \sigma^2 < \frac{(16+1)\sigma^2}{X_{2,16-1}}$$

$$P = 0.05 \quad \sigma^2 \pm 4.48$$

$$\frac{(16-1)\sigma^2}{X_{2,16-1}} = \frac{15 \times 3.21}{32.90} = 1.47 < \sigma^2 < \frac{(16+1)\sigma^2}{X_{2,16-1}} = \frac{15 \times 3.21}{4.60} = 10.47$$

$$P = 0.01 \quad \sigma^2 \pm 7.25$$

33. X_1, X_2, \dots, X_n i.i.d. $N(\mu, \sigma^2)$. How should c be chosen for $(-\infty, \bar{X} + c)$ to be 95%

confidence interval for μ ; so that $P(-\infty < \mu \leq \bar{X} + c) = 0.95$;

c) The bootstrap estimate would be $N(\hat{\mu}_2, \frac{\hat{\sigma}^2}{m})$, because

this method's distribution is representative of the sampling distribution

34. X_1, X_2, \dots, X_n i.i.d. $N(\mu, \sigma^2)$ b) The bootstrap estimate of $\hat{\mu} - \mu_0$ is $N(0, \hat{\sigma}^2/m)$, due to the

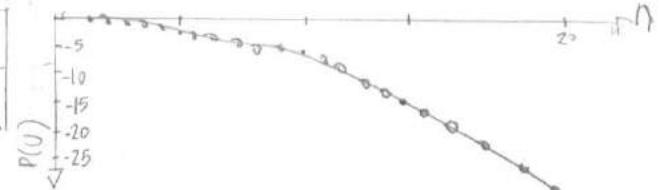
c) $\hat{\mu} \pm z(1-\alpha/2) \hat{\sigma} = \pm z(1-\alpha/2) \hat{\sigma}$ fact $\hat{\mu} = \bar{X}$ and $\mu_0 = \bar{X}$, therefore $\hat{\mu} - \mu_0 = 0$.

$$\hat{\mu} \pm z(1-\alpha/2) \hat{\sigma}$$

n=20

Trial	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Side	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	U

$$P(U) = \frac{1}{20}, P(D) = \frac{19}{20}, \pi = 0.05$$



n=5

Trials	1	2	3	4	5
Side	D	D	D	D	U

Posterior Distribution of a Binomial:

Posterior \propto Likelihood \times Prior where Prior

$$p(\theta) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1} (1-\theta)^{b-1}$$

likelihood

$$\propto \binom{n}{k} \theta^k (1-\theta)^{n-k} \theta^{a-1} (1-\theta)^{b-1}$$

$$p(k|\theta) = \binom{n}{k} \theta^k (1-\theta)^{n-k}$$

$$\text{Posterior Mean: } E[\theta|k] = \int_0^1 \theta p(k|\theta) d\theta = \int_0^1 \theta \binom{n}{k} \theta^k (1-\theta)^{n-k} d\theta = \int_0^1 \text{Beta}(k+1, n+1-k) \theta^k (1-\theta)^{n-k} d\theta$$

$$= \frac{k+1}{n+2}; \quad k=1, E[\theta|k] = \frac{2}{7}, k=2, E[\theta|k] = \frac{3}{7}, k=3, E[\theta|k] = \frac{4}{7}, k=4, E[\theta|k] = \frac{5}{7}$$

$$k=5, E[\theta|k] = \frac{6}{7}$$

26.

n=100

$$n_2=50, p(\text{tagged}) = \frac{20}{50}$$

$$p(\text{tagged}) = \frac{\binom{n_1}{t} \binom{n-n_1}{n_2-t}}{\binom{n}{n_2}}$$

$$= \binom{100}{20} \binom{n-100}{30}$$

$$f(t|\tau) = \frac{e^{-t/\tau}}{\tau}; t \geq 0$$

$$\text{Var}[\theta|k] = \frac{(1+k)(n+1-k)}{(n+2)^2(n+3)}, \quad k=5, n=20, \text{Var}[\theta|k] = 0.0081$$

Maximum Likelihood

$$\frac{L_n}{L_{n-1}} = \frac{\binom{n_1}{t} \binom{n-n_1}{n_2-t}}{\binom{n_1}{t-1} \binom{n-n_1-1}{n_2-t}} = \frac{(n-n_1)(n-n_2)}{n(n-n_1-n_2+t)}; \quad \frac{n_2 \cdot n_1}{n_2-t} = \frac{5000}{30} = 166$$

27.

The assumptions about the capture and recapture process include dependent data sets, and no bias to solution

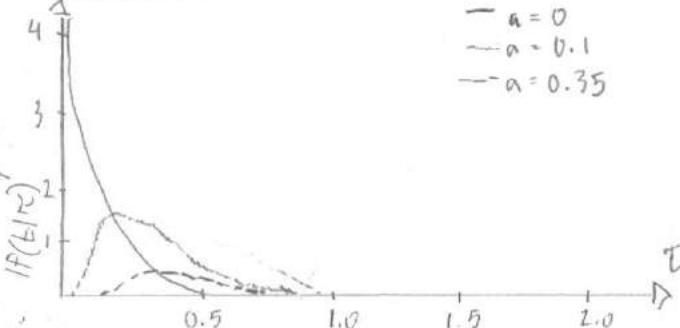
Five components are tested, the first fails in 100 days.

a) The maximum likelihood function of τ is

$$l(f(t|\tau)) = \ln \frac{e^{-t/\tau}}{\tau} = -\frac{t}{\tau} - \ln \tau$$

c) The sampling distribution of the maximum likelihood estimate:

$$\begin{aligned} \alpha &= 0 \\ \alpha &= 0.1 \\ \alpha &= 0.35 \end{aligned}$$



d) Standard Error of Maximum Likelihood Estimate:

$$\sigma_\tau = \sqrt{\frac{\sigma^2}{n}} = \sqrt{\frac{E[\tau^2] - E[\tau]^2}{n}}, \text{ seemingly impossible}$$

Asymptotic Variance: $\text{Var}(\tau) \approx \frac{1}{n I(\tau)} = \frac{1}{n E\left[\frac{\partial^2 l(t|\tau)}{\partial t^2}\right]}$

$$I(\tau) = -E\left[-\frac{3t}{\tau^3} - \frac{1}{\tau}\right] = 3\tau^2 - \frac{1}{\tau}$$

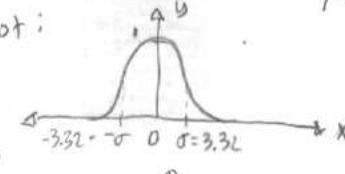
$$\sigma_\tau = \sqrt{\frac{1}{n} \left(3\tau^2 - \frac{1}{\tau} \right)}$$

$$b. I(\mu, \sigma^2) = \prod_{i=1}^n \log \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i-\mu)^2}{2\sigma^2}\right); \text{ From part a)} \quad \hat{\sigma}^2 = \sqrt{\frac{1}{n} \sum (x_i - \mu)^2}$$

c. An unbiased estimate of μ would be $\hat{\mu} = \frac{\sum x_i}{n} = \bar{x}$ $n\hat{\sigma}^2 = \sum (x_i - \mu)^2 = \sum x_i^2 - \sum \mu^2$

20. $X_1, X_2, \dots, X_{25} \sim N(\mu, \sigma^2)$, $\mu = 0$, $\sigma = 10$. Plot:

$$\hat{\mu} = \frac{\sum x_i - n\hat{\sigma}^2}{n} = \bar{x} - \sigma^2$$



a) Method of Moments Estimate of θ .

$$\mu_1 = E(X) = \int_0^\infty x e^{-(x-\theta)} dx = \int_0^\infty x^{2-1} e^{-(x-\theta)} dx = e^\theta \int_0^\infty x^{2-1} e^{-x} dx = e^\theta (\theta+1) e^{-\theta} = \theta + 1; \hat{\theta} = \mu_1 - 1$$

$$\mu_2 = E(X^2) = \int_0^\infty x^2 e^{-(x-\theta)} dx = e^\theta \int_0^\infty x^2 e^{-x} dx = (\theta^2 + 2\theta + 2)$$

272

b) Maximum Likelihood Estimate: $f(x|\theta) = e^{-(x-\theta)}$; $\frac{d \ln(f(x|\theta))}{d\theta} = 1$; Undefined solution

c) The sufficient statistic for the function $\frac{f(x|\theta)}{f(\theta)}$ in Analytically search for $\min(X_i)$

$f(x|\theta)$ is the minimal value of $\frac{f(x|\theta)}{f(\theta)}$

22. Weibull Distribution

Cumulative: $F(x) = 1 - e^{-(x/\alpha)^\beta}$, $x \geq 0$, $\alpha > 0$, $\beta > 0$

Weibull Distribution: $F(x) = \frac{\beta}{\alpha} e^{-(x/\alpha)^\beta}$ || The Weibull distribution would fit a lifetime by approximating the decay of a process, where α is the decay constant and β is the scaling factor.

To find the standard error of the Weibull fitting, one must solve the second-moment (or variance), and compare observed to predicted model.

23. 1...N, where N = # objects manufactured. A random object is selected with serial number 889.

3:36
3:44
3:445

$$\mu_1 = \sum_{k=1}^n k P(N) = \sum_{k=1}^n k \frac{1}{N} = \frac{1}{N} \frac{N(N+1)}{2} = \frac{N+1}{2}$$

$$\hat{N} = 2\mu_1 - 1 = 17.75$$

$$\text{MLE} = \frac{1}{N} \left[\frac{1}{889} \right]$$

Trial	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Face	T	T	T	H	T	H	T	H	T	H	H	H	H	T	T	H	T	H	T	

$$n\text{-heads} = 9, n\text{-tails} = 11, \pi = \frac{9}{20}$$

25.

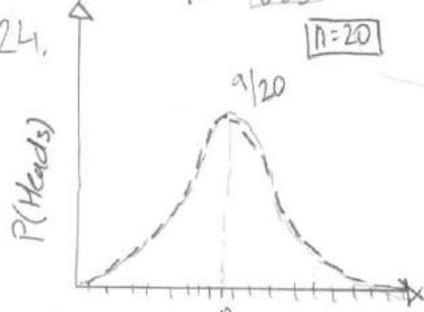
Trial	1	2	3	4	5	6	7	8	9	10
Face	H	H	H	T	H	T	T	H	T	H

$$n\text{-heads} = 6, n\text{-tails} = 4, \pi = \frac{3}{5}$$

$$P(k) = \binom{n}{k} p^k (1-p)^{n-k}$$

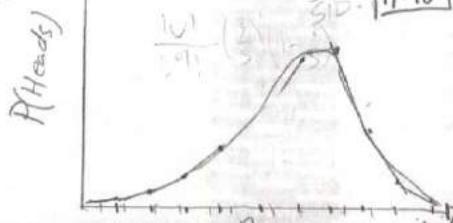
Log likelihood of a thumbtack

$$\log(P(k)) = \log(\binom{n}{k}) + n \log p + (n-k) \log(1-p)$$



Predicted max at $\pi = 1/20$, where $p = 1/20$

$$P(n) = \binom{n}{k} p^k (1-p)^{n-k}$$



a. Find the sufficient statistic. Sufficient statistic $[T]$ is the limit of knowledge for x_1, \dots, x_n

Possibly when the variance of $\text{Var}(\theta) = \frac{\sigma^2}{n}$ is set to 1 (e.g. $n = \sigma^2$).

$$17. f(x|\alpha) = \frac{T(2\alpha)}{T(\alpha)^2} [x(1-x)]^{\alpha-1}, \text{ where } x > 0. E(X) = \frac{1}{2} \Rightarrow \text{Var}(X) = \frac{1}{4(2\alpha+1)}$$

- a. The shape of the density depends on the α -variable through adjustment of the continuity.
- b. The method of moments will aid in the estimation of α through the variance of the second-moment.
- c. Maximum Likelihood estimates denote the equation $\log f'(x|\alpha) = \frac{(x-1)(2\alpha-1)}{x(x-1)} + 2\alpha^{(0)}(2\alpha)$

$$d. \text{The asymptotic variance } I(\theta) = -E\left[\frac{\partial^2}{\partial \theta^2} \log f(x|\theta)\right] = -E\left[\frac{\partial}{\partial \alpha}\left[\frac{(x-1)(2\alpha-1)}{x(x-1)} + 2\alpha^{(0)}(2\alpha)\right]\right]$$

e). The sufficient statistic is:

$$\frac{f(x, \alpha)}{f(x)} = \frac{T(2\alpha)/T(\alpha)^2 [x(1-x)]^{\alpha-1}}{T(2\alpha)/T(\alpha)^2 \binom{n}{2} [x(1-x)]^{\alpha-1}}$$

$$\begin{aligned} &= -E\left[44^{(0)}(2\alpha) - \frac{(x-1)(2\alpha^2 - 2\alpha + 1)}{(x^2)(x-1)^2}\right] \\ &= -2 \left[\int_0^1 44^{(0)}(2\alpha) \frac{T'(2\alpha)}{T(\alpha)^2} x(x-1)^{\alpha-1} dx - \int_0^1 \frac{(x-1)(2\alpha^2 - 2\alpha + 1)}{x^2(x-1)^2} \frac{T'(2\alpha)}{T(\alpha)^2} x(x-1)^{\alpha-1} dx \right] \end{aligned}$$

18. Suppose $\hat{\theta} = 1/\binom{n}{2}$

$$f(x|\alpha) = \frac{T(3\alpha)}{T(\alpha)T(2\alpha)} x^{\alpha-1} (1-x)^{2\alpha-1}; x > 0$$

$$E(X) = \frac{1}{3}; \text{Var}(X) = \frac{2}{9(3\alpha+1)}$$

a) Method of Moment Estimate for α .

$$\mu_1 = \frac{1}{3} \Rightarrow \mu_2 = \sigma^2 + \mu_1^2 = \frac{2}{9(3\alpha+1)} + \left[\frac{1}{3}\right]^2$$

b) What is the maximum log likelihood?

$$\mu_2 - \frac{1}{9} = \frac{2}{9(3\alpha+1)}; 9(3\alpha+1) = \frac{2 \cdot 9}{9\mu_2 - 1}$$

$$\begin{aligned} l(\alpha) &= \log \prod f(x|\alpha) = \sum \log f(x|\alpha) = \sum \log \frac{T(3\alpha)}{T(\alpha)T(2\alpha)} x^{\alpha-1} (1-x)^{2\alpha-1} \\ &= n \log \frac{T(3\alpha)}{T(\alpha)T(2\alpha)} + (\alpha-1) \sum \log x_i + (2\alpha-1) \sum \log (1-x_i) \end{aligned}$$

$$\alpha = \frac{2}{3} \left(\frac{1}{9\mu_2 - 1} \right) - \frac{1}{3}$$

$$\frac{\partial l(\alpha)}{\partial \alpha} = \left[\frac{n T(3\alpha)}{T(3\alpha)} \binom{3}{2} - \frac{n T(\alpha)}{T(\alpha)} \binom{1}{1} - \frac{n T(2\alpha)}{T(2\alpha)} \binom{2}{2} \right] + \sum \log x_i + 2 \sum \log (1-x_i) = 0$$

$$\hat{\alpha} = \frac{2}{3} \left[\frac{1}{9(\hat{\mu}_2 + \bar{x}^2) - 1} \right] - \frac{1}{3}$$

c) Solve for alpha.

Compute the asymptotic variance. $I(\alpha) = -E\left[\frac{\partial^2}{\partial \alpha^2} l(\alpha)\right] = \mu_0^2; \frac{1}{n I(\alpha)} = \frac{1}{n \mu_0^2} = \frac{1}{\hat{\alpha}^2}$

d) Find the sufficient statistic for α . $L = \prod f(x|\alpha) = \left[\frac{T(3\alpha)}{T(\alpha)T(2\alpha)} \right] \left[\prod x_i \right] \left[\prod (1-x_i) \right]^{2\alpha-1}$

19. The sufficient statistics are

$$F(x|\alpha) = \left[\sum \log x_i + \sum \log (1-x_i) \right]$$

a) Suppose $N(\mu, \sigma^2)$. If μ is unknown, what

is the mle of σ^2 ?

$$l(\mu, \sigma) = \frac{1}{2\sigma^2} \log \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma^2}\right) = -\frac{n}{2} \log 2\pi\sigma^2 - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2$$

$$\frac{\partial l(\mu, \sigma)}{\partial \sigma^2} = \frac{n}{2} \frac{4\pi\sigma^2}{(2\pi\sigma^2)^2} + \sum_{i=1}^n (x_i - \mu)^2 / \sigma^2 - n + \sum_{i=1}^n (x_i - \mu)^2 / \sigma^2 = 0; \hat{\sigma}^2 = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2}$$

b) Approximate 95% confidence Interval: Likelihood Function: $p(1-p)^{X_i-1}$

$$\text{Log likelihood} \log L(p) = \sum_{i=1}^n \log p + (X_i-1) \log (1-p) = n \log p - n \log (1-p) + \log (1-p) \sum X_i$$

$$\begin{array}{l} \text{Maximum Log Likelihood} \\ \log L(p)' = \frac{n}{p} + \frac{n}{1-p} - \frac{\sum X_i}{(1-p)} ; \bar{p} = \frac{1}{\sum X_i} \end{array} \quad \boxed{\text{Mean}}$$

$$\log L(p)'' = \frac{-n}{p^2} + \frac{n}{(1-p)^2} - \frac{\sum X_i}{(1-p)^2} @ \bar{p} = \frac{1}{\sum X_i}$$

$$= \frac{n}{p^2(1-p)^2} [-(1-p)^2 + p^2 - \bar{X}p^2] = \frac{-n}{p^2(1-p)} \quad \text{Variance } V = \frac{1}{\log L(p)''} @ \bar{p}$$

$$= \frac{\bar{p}^2(1-\bar{p})}{n}$$

$$95\%- \text{Confidence Interval}, 95\% CI = \bar{p} \pm 1.96 \sigma = 0.36 \pm 0.5$$

c) Goodness of Fit (Comparison.)

# Hops	Frequency	Fit	$P(X) = n \bar{p}(1-\bar{p})^{k-1}$	$(O-E)/\sqrt{E}$	$(O-E)^2/E$
1	43	47.		0.15	0.21
2	31	30		-0.10	0.33
3	20	19		0.23	0.53
4	9	12		-0.06	0.75
5	6	8		+0.71	+0.25
6	5	5		0.0	0
7	4	3		0.57	0.33
8	2	2		0.0	0
9	1	1	$\bar{p} = \frac{1}{8} = 0.394$	0.0	0
10	1	1		0.9	0
11	2	7		0.0	1
12	1	0		Undefined	Undefined

$$\chi^2 \text{ cdf: } 1.71$$

Degree Freedom: 5

$P \sim 0.8$

d) Posterior Distribution, Posterior Mean, and Standard Deviation.

$$\text{Prior: Beta}(1,1) = \frac{T(a+b)}{T(a)T(b)} x^{a-1} (1-x)^{b-1} = X(1-X)$$

$$\text{Likelihood: } p(x|\theta) = (1-\theta)^{x-1} \theta$$

$$\text{Posterior: } \Pi(\theta|x, a, b) = \frac{(1-\theta)^{x-1} \theta^{a-1}}{T(a)T(b)} (1-x)^{b-1}$$

$$\text{Posterior Mean: } \frac{a}{a+b} \quad \text{Posterior S.D.: } \sqrt{\frac{ab}{(a+b)^2(a+b+1)}} \quad = (1-0.394)^{x-1} (0.394) \frac{T(a+b)}{T(a)T(b)} x^{a-1} (1-x)^{b-1}$$

$\lambda = E(X)$; $\hat{\lambda}_i = \hat{X} = \frac{1}{n} \sum_{i=1}^n X_i$; $\hat{\lambda} = \bar{X}$... The mean of a probability distribution is considered a random variable while the standard deviation is not.

10. Normal Approximation of a Poisson Distribution. $P(\hat{\lambda} = v) = \frac{(n \lambda_0)^v e^{-n \lambda_0}}{(n v)!}$

What is $P(|\lambda_0 - \hat{\lambda}| > \delta)$ for $\delta = 0.5, 1, 1.5, 2$, and 2.5 .

$$P(|\lambda_0 - \hat{\lambda}| > \delta) = P(|\lambda_0 - \bar{X}| > \delta) = P\left(\frac{|\lambda_0 - \bar{X}|}{\sqrt{\lambda_0}} > \sqrt{n} \frac{\delta}{\sqrt{\lambda_0}}\right)$$

$$\approx P(|N(0,1)| > \sqrt{n} \frac{\delta}{\sqrt{\lambda}})$$

$$\cong P(|N(0,1)| > \frac{\sqrt{23}}{\sqrt{24.9}} \delta)$$

$$\text{Standard Error: } \delta_X = \sqrt{\frac{\lambda_0}{n}} = \sqrt{\frac{\lambda}{n}} = 1.04$$

$$= 2(1 - \Phi(-\sqrt{23}/\sqrt{24.9} \times \delta))$$

$$\delta = 0.5: 63\% ; \delta = 1: 33\% ; \delta = 1.5: 24\% ; \delta = 2: 10\% ; \delta = 2.5: 0.4\%$$

11. $s_{\hat{\lambda}} = \sqrt{\frac{\lambda}{n}}$; Poisson Distribution: $n=23, \lambda=24.9$

The bootstrap method of sampling a large population, then averaging the estimator will approach $s_{\hat{\lambda}}$ because $\lim_{B \rightarrow \infty} \frac{1}{B} \sum_{i=1}^B \left[\sum_{j=1}^B X_{ij} / n \right] = \frac{\sum X_{ij}}{N} = \bar{X}$

12. The method of moments is best when n is small, but approaches Maximum likelihood estimates as $n \rightarrow \infty$. The answer of choice depends on n -amount.

13. Example D: $\theta, 4$: $f(x|\lambda) = \frac{1+\lambda x}{2}, -1 \leq x \leq 1, -1 \leq \lambda \leq 1$; $x = \cos \theta$ if $|x| \leq \frac{1}{3}$

a) $\mu = \int_{-1}^1 \frac{1+\lambda x}{2} dx = \frac{\lambda}{3}$; Thus, $\hat{\lambda} = 3\bar{x}$ $E[X^2] = \int_{-1}^1 x^2 \frac{1+\lambda x}{2} dx$

Show $E(\hat{\lambda}) = \lambda$; $E(\hat{\lambda}) = E(3\bar{x}) = 3E(\bar{x}) = 3 \cdot \frac{\lambda}{3} = \lambda$ || $= \int_{-1}^1 x^2 + \frac{\lambda x^3}{2} dx = \frac{x^3}{6} \Big|_{-1}^1 + \frac{\lambda x^4}{8} \Big|_{-1}^1$

b) Show $\text{Var}(\hat{\lambda}) = (3-\lambda^2)/n$; $\text{Var}(\hat{\lambda}) = \text{Var}(3\bar{x}) = 9\text{Var}(\bar{x}) = 9 \cdot \frac{1}{n} [E[X^2] - E[X]^2] = 9 \left[\frac{1}{3} - \lambda^2 \right]$ $= \frac{1}{6} + \frac{1}{6} + \frac{\lambda}{9} - \frac{\lambda}{9} = \frac{1}{3}$

c) $n=25, \lambda=0$. $P\left(\frac{|X-\bar{X}|}{\sigma_X} > 0.5\right) = P\left(\frac{|X-\bar{X}|}{(3-\lambda^2)/n^{1/2}} > 0.5\right) = P\left(\frac{|X-\bar{X}|}{3/25^{1/2}} > 0.5\right) = P(|X-\bar{X}| > 0.012) = 0.5040$

14. Example C: Section 8.5:

a) $P(|\hat{\lambda} - \lambda_0| > 0.05) = 0.5660$

Through comparing the probability to a normal distribution. By comparing the expectation, variance, and standard error.

c) $P(|\hat{\lambda} - \lambda_0| > \Delta) = 0.5$

By comparing the probability of the norm to Δ .

15. $F(q_{0.25}) = 0.75$. Gamma Distribution: $g(t) = \frac{\lambda^\alpha}{T(\alpha)} t^{\alpha-1} e^{-\lambda t}$: Upper quantile is dependent on $q(\alpha, \lambda)$.

Example C of Section 8.5:

To estimate the standard error of $q(\lambda, \alpha)$ with the bootstrap method, then $q(\hat{\lambda} - \lambda_0, \hat{\alpha} - \alpha_0)$ should be evaluated.

16. $f(x|\sigma) = \frac{1}{2\sigma} \exp\left(-\frac{|x|}{\sigma}\right)$ a) Find the method of moments of σ
 $\mu_2 = E[X|\sigma] = \int_{-\infty}^{\infty} \frac{|x|^2}{2\sigma} \exp\left(-\frac{|x|}{\sigma}\right) dx = \int_0^{\infty} \frac{|x|^2}{\sigma} \exp\left(-\frac{|x|}{\sigma}\right) dx = \frac{1}{\sigma} \int_0^{\infty} u^2 e^{-u} du$

b) Find the maximum likelihood estimate $\hat{\sigma}$

$$\log \prod f(x|\sigma) = \log \prod \frac{1}{2\sigma} \exp\left(-\frac{|x|}{\sigma}\right) = \sum \log \frac{1}{2\sigma} \sum \exp\left(-\frac{|x|}{\sigma}\right)$$

$$= n \log\left(\frac{1}{2\sigma}\right) + \sum \frac{|x_i|}{\sigma} = -n \log 2\sigma - \sum \frac{|x_i|}{\sigma}$$

$$\frac{\partial \log L(\sigma|x)}{\partial \sigma} = \frac{-n}{2\sigma} + \sum \frac{|x_i|}{\sigma^2} = 0; \hat{\sigma} = \sqrt{\frac{\sum |x_i|}{n}}$$

"Asymptotic Unbiased"

c) Find the asymptotic variance of mle.

$$I(\theta) = E\left[\frac{\partial^2}{\partial \theta^2} \log F(X|\theta)\right] = -E\left[\frac{2}{\theta^2} \left[\frac{n}{\theta} + \sum \frac{|x_i|}{\theta^2}\right]\right] = -E\left[\frac{n}{\theta^2} - \frac{2 \sum |x_i|}{\theta^3}\right] = -2 \int_0^{\infty} \frac{n}{\theta^2} \left(\frac{1}{2\theta} \exp\left(-\frac{|x|}{\theta}\right) - \frac{2}{\theta^3} \sum |x| \exp\left(-\frac{|x|}{\theta}\right)\right) dx$$

$$= \frac{n}{\theta^2} \int_0^{\infty} 2 \sum |x| \frac{1}{2\theta} \exp\left(-\frac{|x|}{\theta}\right) dx = \frac{n}{\theta^2} I(\theta_0)$$

b. Maximum likelihood of p : $P(X=k) = p(1-p)^{k-1}$; $\frac{dp(X=k)}{dp} = (1-p)^{k-1} + (k-1)p(1-p)^{k-2} = 0$

c. Asymptotic Variance of mle:

$$I(\theta) = E\left[\frac{\partial}{\partial \theta} \log F(X|\theta)\right]^2; I(\theta) = E\left[\frac{\partial}{\partial p} \log p + (X-1) \log(p-1)\right]$$

$$= E\left[\frac{1}{p} - \frac{X-1}{(1-p)}\right]^2 = E\left[\frac{1}{p^2} - \frac{2(X-1)}{p(1-p)} + \frac{(X-1)^2}{(1-p)^2}\right] = \frac{1}{p^2}(1-p)$$

$$I(\theta) = E\left[\frac{\partial^2}{\partial \theta^2} \log F(X|\theta)\right]; I(\theta) = -E\left[\frac{\partial^2}{\partial p^2} \log p(1-p)^{k-1}\right] = -E\left[\frac{2}{p^2} - \frac{X-1}{(1-p)^2}\right]$$

$$\boxed{I(\theta) = \frac{2}{p^2}(1-p)}$$

$$(1-p)^{k-1} = (k-1)p(1-p)^{k-2}$$

$$(1-p) = (k-1)p; 1-p(1-(k-1)) = 0$$

$$1-p = 0$$

$$k-1-1 = \frac{1}{p}$$

d) Let p be uniform from $[0, 1]$. What is the posterior distribution? What is the posterior mean?

Posterior Distribution: $f_{\theta|X}(\theta|X) = \frac{f_{X|\theta}(x|\theta) f(\theta)}{P_X(x)} = \frac{f_{X|\theta}(x|\theta) f(\theta)}{\int f_{X|\theta}(x|\theta) f_\theta(\theta) d\theta}$; Posterior \propto Likelihood \times prior.

Posterior Mean: Most probable value of the posterior mode [Requires calculation]

Prior of a Geometric Function $[f(\theta)]$: Beta($1, 1$) = $\frac{1}{B(1,1)} p^{1-1} (1-p)^{1-1} = 1$

Likelihood of a Geometric Function $[f_{X|\theta}(x|\theta)]$: $p(x|\theta) = (1-\theta)^{x-1} \theta$

Posterior Distribution $[f_{\theta|X}(\theta|X)]$: $X=1, f_{\theta|X}(\theta|X) \propto \theta(1-\theta)^{x-1}$

$X=2$, Prior: Beta($2, 1$) = $\theta^2 (1-\theta)^{x-1}$
Likelihood: $p(x|\theta) = \prod \theta(1-\theta)^{x-1} = \theta^2 (1-\theta)^{x-1}$

Posterior: $\theta(1-\theta)^2 \theta(1-\theta)^{x-1} = \theta^3 (1-\theta)^x = \boxed{\text{Beta}(a+2, b+2)}$

Posterior Mean: Expectation of a Beta Distribution - $E(X) = \frac{a}{a+b}$

B. Number of Hops | Frequency | ~~$P(X=k)$~~ | ~~$P(X=k)$~~ | ~~θ~~ | ~~θ_X~~ | ~~$P(X=k) = p(1-p)$~~

Number of Hops	Frequency	$P(X=k)$	$P(X=k)$	θ	θ_X	$P(X=k) = p(1-p)$
1	48	0.39	0.37	0.62	0.18	$P(X=1) = 0.18$
2	31	0.24	0.18	1.05	0.303	$P(X=2) = 0.303$
3	20	0.15	0.11	1.77	0.51	$P(X=3) = 0.51$
4	9	0.07	0.06	3.97	1.15	$P(X=4) = 1.15$
5	6	0.05	0.04	5.62	1.62	$P(X=5) = 1.62$
6	5	0.04	0.03	7.07	2.04	$P(X=6) = 2.04$
7	4	0.03	0.02	9.47	2.73	$P(X=7) = 2.73$
8	2	0.02	0.02	14.29	4.13	$P(X=8) = 4.13$
9	1	0.01	0.01	28.72	9.28	$P(X=9) = 9.28$
10	1	0.01	0.01	57.44	9.28	$P(X=10) = 9.28$
11	2	0.01	0.02	14.29	4.13	$P(X=11) = 4.13$
12	1	0.01	0.01	28.72	9.28	$P(X=12) = 9.28$
Total:	130					

- a) Fit a geometric distribution to the data
 b) Find a 95% confidence interval

$$E(X) = \frac{1}{B(2,1)} [1.48 + 2.31 + 3.20 + 4.9 + 5.6 + 6.5 + 7.4 + 8.2 + 9 + 10 + 11.2 + 12] = 7.41$$

$$\bar{p} = \frac{1}{X} = 0.36$$

5. $P(X=1) = \theta; P(X=2) = 1-\theta \quad | \quad X_1=1, X_2=2, X_3=2$ || a) Find the method of moment estimator.

a) $E[X] = \sum_{i=1}^2 i \cdot P(X=i) = 1\theta + 2(1-\theta) = 2 \quad ; \quad E[X^2] = \frac{1}{3} \sum_i X_i^2 = \left(\frac{1}{3}\right) + \left(\frac{2}{3}\right)^2 = \frac{5}{3}$

$E[X^2] = \sum_{i=1}^2 X_i^2 \cdot P(X=i) = 1^2 \theta + 2^2 (1-\theta) = \theta + 4 - 4\theta = 4 - 3\theta; E[X^2] = \frac{1}{n} \sum_i X_i^2 = \frac{1}{3}(1) + \left(\frac{2}{3}\right)^2 = \frac{19}{3}; 4 - 3\theta = \frac{19}{3} \Rightarrow \theta = \frac{1}{3}$

b) $\ell(X_1, X_2 | p_1, p_2) = \frac{n!}{\prod_{i=1}^2 X_i!} \prod_{i=1}^2 p_i^{X_i} = \frac{2!}{2!} (\theta)(1-\theta)^2 = \theta(1-\theta)^2$

c) $\frac{d\ell(X_1, X_2 | p_1, p_2)}{d\theta} = (1-\theta)^2 - 2\theta(1-\theta) = (1-\theta)(1-\theta-2\theta) = (1-\theta)(1-3\theta) = 0 \Rightarrow \hat{\theta} = 1 \text{ or } 1/3$

d) $a=2, b=3, f(x) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1} (1-x)^{b-1}; f(x) = \frac{\Gamma(5)}{\Gamma(2)\Gamma(3)} \cdot x^1 (1-x)^2 = \frac{12}{2} x (1-x)^2 = 6x(1-x)^2$

6. Suppose $X \sim \text{bin}(n, p)$ a) Show mle of p is $\hat{p} = X/n$

a) $p(x) = \binom{n}{x} \prod_{i=1}^n p_i^{X_i} \log p(x) = \log n! - \sum_{i=1}^n \log X_i + \sum_{i=1}^n X_i \log p_i; I = \sum_{i=1}^n p_i$; Lagrange on

b) Cramér-Rao Lower Bound:

Measure of concentration: $\frac{d \log p(x)}{d p} = \sum_{i=1}^n \frac{X_i}{p_i} + \lambda = 0; \lambda = -\sum_{i=1}^n \frac{X_i}{p_i}; \sum_{i=1}^n p_i = \frac{-\sum_{i=1}^n X_i}{\lambda}; I = -\frac{n}{\lambda}$

MSE($\hat{\theta}$) = $E(\hat{\theta} - \theta)^2$

$= \text{var}(\hat{\theta}) + (E(\hat{\theta}) - \theta)^2$

Efficiency: $\text{eff}(\hat{\theta}, \tilde{\theta}) = \frac{\text{Var}(\hat{\theta})}{\text{Var}(\tilde{\theta})}$

Moment estimate is similar to mle when n tends to 1.

Cramer-Rao Lower Bound for $X \sim \text{bin}(n, p)$: $\text{var}(\tau) \geq \frac{1}{n I(\theta)}$ where $I(\theta) = E\left[\frac{\partial}{\partial \theta} \log \text{bin}(n, p)\right]^2$

C. $n=10, X=5$ plot $\log \text{lik}(x_1, \dots, x_n | p_1, \dots, p_n)$

$p(x) = \frac{10!}{5!(5)!} p^5 (1-p)^5$

$\log p(x) = \log \frac{10 \cdot 9 \cdot 8 \cdot 7 \cdot 6}{5 \cdot 4 \cdot 3 \cdot 2 \cdot 1} + 5 \log(p - p^2)$

Graph of $\log p(x)$ vs x :

$I(\theta) = E\left[\frac{\partial}{\partial p} \log \left[\frac{n!}{\prod_{i=1}^n p_i} \prod_{i=1}^n X_i\right]\right]^2$

$= E\left[\frac{x}{p} + \frac{(n-x)}{1-p}\right]^2 = E\left[\frac{x(1-p) - p(n-x)}{p(1-p)}\right]^2 = E\left[\frac{(x-pn)^2}{p(1-p)}\right]$

$= \frac{\text{var}(X)}{p^2(1-p)^2} = \frac{\text{var}(X)}{p^2(1-p)^2} = \frac{m}{p^2(1-p)}$

$\text{var}(\tau) \geq \frac{1}{n I(\theta)}$

7a. Geometric Distribution $p(X=k) = p(1-p)^{k-1}$

Methods of Moments:

$\mu_1 = \frac{1}{n} \sum_{k=1}^{\infty} k p(1-p)^{k-1} = \frac{p}{n} \sum_{k=1}^{\infty} k(1-p)^{k-1} = \frac{p}{n} \frac{d}{dp} \sum_{k=0}^{\infty} (1-p)^k = \frac{p}{n} \frac{d}{dp} \left(\frac{1-p}{1-(1-p)} \right) = \frac{p}{n} \frac{1}{(1-p)^2} = \frac{p}{n(1-p)^2}$

4. Suppose X is a discrete Random Variable : $P(X=0) = \frac{2}{3}\theta$ where $0 \leq \theta \leq 1$

a) Find the method of moment estimates of θ

$$\mu_1 = E(X) ; \hat{\mu}_1 = E(\bar{X}) = \frac{1}{10} [3+0+2+1+3+2+1+0+2+1] = \frac{3}{2}$$

$$P(X=1) = \frac{1}{3}\theta \quad n=10 \text{ observation}$$

$$P(X=2) = \frac{2}{3}(1-\theta) \quad (3, 0, 2, 1, 3, 2, 1, 0, 2, 1)$$

$$P(X=3) = \frac{1}{3}(1-\theta)$$

① Parameter Estimate

$$\hat{\mu}_2 = E(X^2) = \frac{1}{10} [3^2 + 0^2 + 2^2 + 1^2 + 3^2 + 2^2 + 1^2 + 0^2 + 2^2 + 1^2] = 3.3$$

② Moment Estimates

$$E(X) = \sum_{i=0}^3 i P(x) = 0\left(\frac{2}{3}\theta\right) + 1\left(\frac{1}{3}\theta\right) + 2\left(\frac{2}{3}(1-\theta)\right) + 3\left(\frac{1}{3}(1-\theta)\right) = \frac{1}{3}\theta + \frac{4}{3}(1-\theta) = -2\theta + \frac{7}{3}$$

$$E(X^2) = \sum_{i=0}^3 i^2 P(x) = 0^2\left(\frac{2}{3}\theta\right) + 1^2\left(\frac{1}{3}\theta\right) + 2^2\left(\frac{2}{3}(1-\theta)\right) + 3^2\left(\frac{1}{3}(1-\theta)\right) = \frac{1}{3}\theta + \frac{9}{3}(1-\theta) + 3(1-\theta) = \frac{-16\theta}{3} + \frac{17}{3}$$

③ Estimates in terms
of Moments

$$\text{If } \frac{3}{2} = -2\theta + \frac{7}{3} ; \theta = \frac{5}{12} ; \text{ then } \hat{\theta}_1 = \frac{7}{6} - \frac{\hat{\mu}_1}{2}$$

$$\text{If } \frac{33}{10} = -\frac{16\theta}{3} + \frac{17}{3} ; \theta = \frac{71}{240} ; \text{ then } \hat{\theta}_2 = \frac{17}{16} - \frac{3}{16}\hat{\mu}_2$$

$$\begin{aligned} \text{Var}(\hat{\theta}) &= \text{Var}\left(\frac{7}{6} - \frac{1}{2}\hat{\mu}_1\right) = \left(-\frac{1}{2}\right)^2 \text{Var}(\hat{\mu}_1) = \frac{1}{4} \text{Var}(X) = \frac{1}{4} \frac{1}{10} \left[\frac{-16\theta}{3} + \frac{7}{3} - (-2\theta + \frac{7}{3})^2 \right] \\ &= \frac{1}{40} \left[\frac{-16\theta}{3} + \frac{17}{3} - 4\theta^2 + \frac{28}{3}\theta - 4\frac{49}{9} \right] = \frac{1}{40} \left[-4\theta^2 + 4\theta + \frac{49}{9} \right] \end{aligned}$$

b) Standard Error
of Estimates

$$\sigma_x = \sqrt{\frac{\sigma^2}{n}} = \sqrt{\frac{E[X^2] - E[X]^2}{n}} = \sqrt{\frac{1}{40} \left[\frac{-16\theta}{3} + \frac{17}{3} - 4\theta^2 + \frac{49}{9} \right]} = \sqrt{\frac{43}{1440}} = 0.173$$

c) Maximum Likelihood of Estimate

Multinomial because multiple X and $p(x)$.

$$\log[f(x_1 \dots x_n | p_1 \dots p_m)] = \log n! - \sum_{i=1}^m \log x_i + \sum_{i=1}^m x_i p_i$$

$$f(x_0, x_1, \dots, x_n | p_0(\theta), \dots, p_3(\theta)) = \prod_{i=0}^3 p(x=i) = \left(\frac{2}{3}\theta\right)^2 \left(\frac{1}{3}\theta\right)^3 \left(\frac{2}{3}(1-\theta)\right)^3 \left(\frac{1}{3}(1-\theta)\right)^2 \frac{n!}{3!}$$

$$\log f(x_0, x_1, \dots, x_n | p_0(\theta), \dots, p_3(\theta)) = 2\log\left(\frac{2}{3}\theta\right) + 3\log\left(\frac{1}{3}\theta\right) + 2\log\left(\frac{2}{3}(1-\theta)\right) + 2\log\left(\frac{1}{3}(1-\theta)\right) + \log\left(\frac{n!}{3!}\right)$$

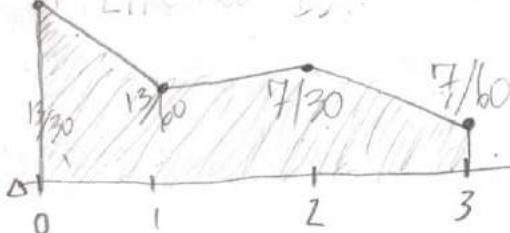
$$\frac{d \log f(x_0, x_1, \dots, x_n | p_0(\theta), \dots, p_3(\theta))}{d\theta} = 2\left(\frac{3}{2}\right)\left(\frac{2}{3}\right) + 3\left(\frac{3}{1}\right)\left(\frac{1}{3}\right) + 2\left(\frac{3}{2}\right)\left(\frac{2}{3}\right) + \frac{\frac{2}{3}\left(\frac{n!}{3!}\right)\left(\frac{1}{3}\right)}{(1-\theta)} = 0 ; \frac{5}{\theta} - \frac{8}{3} \frac{1}{1-\theta} = 0$$

$$\theta = 5(1-\theta) = \frac{8}{3}(1-\theta) \quad 15(1-\theta) = 80 \quad 15 - 15\theta = 80 \quad 15 = 23\theta$$

$$\hat{\sigma}_x(\hat{\theta}) = \sqrt{\frac{1}{40} \left[-4\left(\frac{15}{23}\right)^2 + 4\left(\frac{15}{23}\right) + \frac{2}{9} \right]} = 0.168$$

e) Plot of Likelihood Function

The mode of the posterior density to be at $x=1$



$$\frac{15}{23} = \theta$$

$$= 0.65$$

iv) Average Family income. With a sample size of 500 could be represented as a propositional distribution by region. $\bar{X} = \frac{1}{n} \sum X_i$, $\text{Var}(\bar{X}_{sp}) = \frac{1}{n} \left[\text{We} \left(1 - \frac{n-1}{N-1} \right) \sigma^2 \right]$

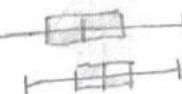
b) i) 100 samples of $n=400$; Average Family income: $\bar{H} = \frac{1}{N} \sum_{n=1}^N \sum_{k=1}^{N_k} x_{ik}$

$$\text{ii) } 50[\sigma] \cdot \sqrt{\frac{\sum(x_i - \bar{x})^2}{n}}$$

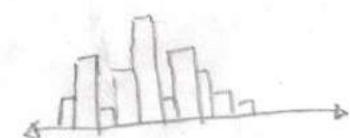
$$\text{iv) } CDF = \int f(x) dx = n \sum F(x)^2 - (\sum F(x))^2$$

iii) Not applicable

vi) $\bar{x} \pm 1.96 s_r$... vii) ... c) Boxplot:



Histogram



d);) see c) ii) iii) see c) e) f). - see c)

Chapter 8: Estimation of Parameters and Fitting of Probability Distribution

<u>n</u>	<u>Observed</u>	Poisson $[F(\lambda) = \frac{\lambda^k}{k!} e^{-\lambda}]$; $\lambda = \frac{\text{Counts}}{\text{total}} = \frac{10,220}{12,169} = 0.8393$	Expected
0	5267	5254	24
1	4436	4413	46
2	1800	1853	60
3	534	519	59
4	111	109	46
5+	21	957 COUNTS.	30
	12,169		16.5
			8.05
			3.5
			1.36

3. a) Estimate λ for each data set.

3. a) Estimate λ for each dataset.

Total 1:	Total 2:	Total 3:	Total 4:
400	400	400	400

$$\lambda_1 = 0.6825 \quad \lambda_2 = 1.3225 \quad \lambda_3 = 1.80 \quad \lambda_4 = 4.65$$

N	Frequency	Expected: $\lambda =$
0	14	24
1	30	46
2	36	60
3	68	59
4	43	46
5	43	30
6	30	16.5
7	14	80.5
8	10	3.5
9	6	1.36
10	4	0
11	1	
12	0	
13+		

$$\lambda_1 = 0.6825 \quad \lambda_2 = 1.3225 \quad \lambda_3 = 1.50 \quad \lambda_4 = 1.65$$

$$b) \text{ Mean } \bar{x} = 1.28, \text{ Std Dev } S_x = 0.46, \text{ SE} = \sqrt{\frac{\sigma^2}{n}} = 0.045$$

$$95\% \text{ confidence Interval: } P\left(\frac{|X-\bar{X}|}{\sigma_x} \leq Z(0.95)\right) = 0.95; \quad \bar{X} \pm 1.96 \sigma_x$$

Concentration #2: $E_2(X) = \lambda_2$; $Var_2(X) = E[X^2] - E[X]^2 = 3.03 - 1.3225 = 1.71$; $SE = \sqrt{\frac{\sigma^2}{n}} = 0.064$

$$95\% \text{ Confidence Interval: } P\left(\frac{|X-\bar{X}|}{\sigma_x} \leq Z(0.95)\right) = 0.95; \quad \bar{X} \pm 1.96\sigma_x$$

$$\text{Concentration #3: } E_3(x) = \lambda_3; \text{Var}_3(x) = E_3[X^2] - E[X]^2 = 5.20 \quad SE = \sqrt{\frac{\sigma^2}{n}} = 0.114$$

$$95\% \text{ Confidence Interval: } P\left(\frac{|X-\bar{X}|}{\sigma_x} \leq Z(0.95)\right) = 0.95; \quad \bar{X} \pm 1.96 \sigma_x$$

Concentration #4: $E_4(X) = \lambda_4$; $\text{Var}_4(X) = E_4[X^2] - E_4[X]^2 = 34.5 - 4.65^2$ 1.80 ± 0.223

95% Confidence Interval: $\bar{x} \pm t_{\alpha/2} \cdot SE = 12.86 \pm 1.96 \cdot 0.179$

P($\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}}$ $\leq z(K/2)$) = 0.95										$\therefore \bar{X} \pm 1.96\sigma_{\bar{X}}$	
n	Observed		Expected		Observed		Expected		Observed		Exp.
0	2	3	2	4	103	106	75	66	0	4	
1	1	8	1	4	143	141	103	119	2	13	
2	37	42	9	9	93	93	121	109	43	41	
3	13	9	42	41	54	54	64	53	65		
4	3	36	8	14	30	29	36	36	75		
5	1	0	4	4	13	10	10	9	69		
6	0	0	2	1	2	3	24	54			
7	0	0	0	0	1	1	37	36			
8	0	0	0	0	0	0	13	21			
9	0	0	0	0	1	0	0	11			
10	0	0	0	0	0	0	0	5			
11	0	0	0	0	0	0	0	2			
12	0	0	0	0	0	0	0	1			

The expected and observed counts are fitting.

54a) $C = C_0 + C_1 n$; L strata; Find a function which minimizes the variance.

Start-up Cost per Observation $\xrightarrow{\text{Cost}}$ Lagrangian Multiplier: $L(n_1, \dots, n_L, \lambda) = \sum_{e=1}^L \frac{W_e \sigma_e^2}{n_e} + \lambda \left(\sum_{e=1}^L n_e - n \right)$

$$L(n_1, \dots, n_L, \lambda) = \sum_{e=1}^L \frac{W_e \sigma_e^2}{n_e} + \lambda \left(\sum_e C_e n_e - C_1 n \right) \quad \left| \begin{array}{l} \frac{\partial L}{\partial n_e} = -\frac{W_e \sigma_e^2}{n_e^2} + \lambda = 0 \\ n_e = \frac{W_e \sigma_e}{\sqrt{\lambda}} \end{array} \right.$$

$$\frac{\partial L}{\partial n_e} = -\frac{W_e \sigma_e^2}{n_e^2} + \lambda C_e = 0 \quad ; \quad n_e = \frac{W_e \sigma_e}{\sqrt{\lambda C_e}} ; \quad n = \frac{1}{\sqrt{\lambda}} \sum_{e=1}^L \frac{W_e \sigma_e}{\sqrt{C_e}}$$

$$\text{Var}(X_{\bar{s}_0}) = \sum_{e=1}^L W_e^2 \left(\frac{1}{n_e} \right) \left(1 - \frac{n_e - 1}{n_e} \right) \sigma_e^2$$

Neglecting infinite population correction:

$$= \sum_{e=1}^L \frac{W_e^2 \sigma_e^2}{n_e} = \frac{\sum_e W_e^2 \sigma_e^2}{n} \sum_e \frac{W_e \sigma_e}{\sqrt{C_e}}$$

$$= \frac{\sum_{e=1}^L (W_e \sigma_e)^2}{n} / \sqrt{C_e}$$

$$c) \quad (n_e = n W_e \sigma_e \sum_{e=1}^L \frac{\sqrt{C_e}}{W_e \sigma_e})$$

b) $\boxed{\text{Var}(X_{\bar{s}_0}) = \frac{\sum (W_e \sigma_e)^2 / \sqrt{C_e}}{n}}$

$$\begin{aligned} n &= \frac{1}{\sqrt{\lambda}} \sum_{e=1}^L W_e \sigma_e \\ \frac{1}{\sqrt{\lambda}} &= \frac{n}{\sum_{e=1}^L W_e \sigma_e} \\ n_e &= n \frac{W_e \sigma_e}{\sum_{e=1}^L W_e \sigma_e} \end{aligned}$$

55. a) Proportional Allocation of a population mean $\bar{X}_{sp} = \sum_{e=1}^L W_e \bar{X}_e = \sum_e W_e \left(\frac{1}{n_e} \sum_i X_{ie} \right)$
is utilized when W_L is large representation.

$$= \frac{1}{n} \sum_{e=1}^L \sum_{i=1}^{n_e} X_{ie}$$

Optimal Allocation of a population mean $\bar{X}_{\bar{s}_0} = \sum_{e=1}^L W_e \bar{X}_e$

is utilized when a sample of each stratum is taken.

Being that $(H_s = 100, H_T = 100,000)$ and $(L_s = 200, L_T = 500,000)$ then optimal allocation of a population seems best fit model $\frac{1}{6} \bar{X}_H + \frac{5}{6} \bar{X}_L = \bar{X}_T$

b) $\sigma_H = 20, \sigma_L = 10$; Standard Error: $S_{\bar{X}_H} = \sqrt{\frac{20^2}{100} \left(1 - \frac{100}{100,000} \right)} = 2.00$ $s_f = 0.6775$

$$S_{\bar{X}_L} = \sqrt{\frac{10^2}{200} \left(1 - \frac{200}{500,000} \right)} = 0.71$$

c) A 95% confidence interval would be best to determine allocation error. The current allocation $(H_s = 100, L_s = 200)$ provides an interval of $(\pm 3.92, \pm 1.39)$ by increasing the allocation to $(H_s = 200, L_s = 100)$ would shift the interval to $(\pm 2.77, \pm 1.96)$. Also, the standard error of the population would shift from 0.6775 to 0.866 and be of greater error.

d) Proportional Allocation provides a standard error of:

$$\cdot 10_s = \bar{X}_s \cdot 0.925, \text{ which is worse.}$$

53. a. $n=100$ Sample size Methods or Allocation: Sample size ($n_e = n \frac{W_L \sigma_e^2}{\sum_{k=1}^L W_k \sigma_k^2}$)

$$\sum_{k=1}^L W_k \sigma_k^2 = \frac{394}{2010} \cdot 3 + \frac{461}{2010} \cdot 13.3 + \frac{391}{2010} \cdot 15.1 + \frac{334}{2010} \cdot 14.3 + \frac{169}{2010} \cdot 24.5 + \frac{113}{2010} \cdot 26 + \frac{102}{2010} \cdot 38.2$$

$$= 1.63 + 3.05 + 2.94 + 3.29 + 2.06 + 1.46 + 2.59$$

$$= 17.7$$

$$\text{Var}(X_S) = \text{Var}(Y_{kp}) / \text{Var}(Y_{kR})$$

b. Farm Size $\text{Var}(X) = \frac{1}{n_e} \left(1 - \frac{n_e - 1}{N_e - 1}\right) \sigma_e^2$ "a scaled variance"

Farm Size	$W_L \sigma_L$	$\text{Var}(X)$
0-40	7.01	
41-80	9.51	
81-120	12.62	
121-160	19.09	
161-200	43.23	
201-240	73.27	
241+	73.64	

c. Farm Size: $E(\bar{X}_S) = \sum_i W_i E(\bar{X}_i)$

Farm Size	n_e
0-40	9.61
41-80	17.9
81-120	17.3
121-160	19.4
161-200	12.71 + 33.4 + 16.1 + 13.4
201-240	8.6
241+	15.2

"A scaled sample size to the true value."

$$\text{Var}(\bar{X}_S) = \sum_{i=1}^L W_i^2 \left(\frac{1}{n_e}\right) \left(1 - \frac{n_e - 1}{N_e - 1}\right) \sigma_e^2$$

0-40	1.93×10^{-2}
41-80	7.30×10^{-2}
81-120	6.44×10^{-2}
121-160	7.61×10^{-2}
161-200	1.74×10^{-2}
201-240	2.48×10^{-2}
241+	2.19×10^{-2}

"Population Variance"

Proportional Allocation

d. $n=10$ farms "Population Expectation"

Farm Size	$\text{Var}(\bar{X}_S)$
0-40	2.59×10^{-1}
41-80	9.12×10^{-1}
81-120	0.42×10^{-1}
121-160	1.05
161-200	4.02×10^{-1}
201-240	1.96×10^{-1}
241+	6.30×10^{-1}

e) $n=70$ samples

Farm Size
0-40
41-80
81-120
121-160
161-200
201-240
241+

$\text{Var}(\bar{X}_S)$
2.69×10^{-1}
5.00×10^{-1}
4.78×10^{-1}
5.27×10^{-1}
3.06×10^{-1}
2.32×10^{-1}
3.99×10^{-1}

"Smaller sample size variance"

b) $\text{Var}(\bar{X}_{S0}) = \frac{\left(\sum_{i=1}^L W_i \sigma_i^2\right)^2}{n}$ "Optimal Allocation" to stratified population

$$\text{Var}(\bar{X}_{Sp}) = \sum_{i=1}^L W_i^2 \text{Var}(\bar{X}_i) = \sum_{i=1}^L W_i^2 \frac{\sigma_i^2}{n_e}$$

Stratified
"Proportional Allocation" to total stratified population

$$\begin{aligned} \text{Var}(\bar{X}_{SRS}) &= \sum_{i=1}^L W_i^2 \frac{\sigma_i^2}{n_e} + \sum_{i=1}^L W_i^2 \left(\frac{n_e - 1}{N_e - 1}\right)^2 \\ &= \sum_{i=1}^L W_i^2 \left(\frac{\sigma_i^2}{n_e} + \left(\mu_i - \bar{\mu}\right)^2\right) \end{aligned}$$

Stratified Random Sampling increases precision
for diverse values of population.

$$\text{Var}(\bar{X}_{S0}) =$$

$$d) T_R = \frac{\bar{Y}}{X} T_X = R T_X \\ = \frac{150}{3000} 1000 \cdot \left(\frac{3000}{50} \right) = 3000$$

$$S_{TR} = \sqrt{\frac{N^2}{n} \left(1 - \frac{n-1}{N-1} \right) (R^2 S_x^2 + S_y^2 - 2RS_{xy})} = N S_{Tr} \\ = \sqrt{\frac{1000^2}{50^2} \left(1 - \frac{50-1}{1000-1} \right) \left(\left(\frac{1}{20}\right)^2 30^2 + 2^2 - 2\left(\frac{1}{20}\right) 40 \cdot 8 \right)} \\ = 20.7 \text{ the standard error is much worse}$$

50. Standard Error of a Ratio Estimate:

$$\frac{|E(R) - r|}{\sigma_R} \leq \frac{\sigma_{\bar{X}}}{\mu_X} = \frac{\sigma_X}{\mu_X} \sqrt{\frac{1}{n} \left(1 - \frac{n-1}{N-1} \right)}$$

$$b) \frac{\text{Var}(\bar{Y}_R)}{\text{Var}(\bar{Y})} = 1 + \frac{c_x}{c_y} \left(\frac{c_x}{c_y} - 2p \right)$$

$$\left| \frac{E(R) - \bar{Y}_R}{\sigma_{\bar{X}} / \mu_X} \right| = 1 + \frac{c_x}{c_y} \left(\frac{c_x}{c_y} - 2p \right)$$

51. $E(\hat{\theta}) = \hat{\theta} + \frac{b_1}{n} + \frac{b_2}{n^2} + \dots$; $\hat{\theta}$ = estimate of θ

$\frac{1}{n}$	\dots	$\frac{1}{n}$
m	\dots	n
p	\dots	$n=mp$

For ($j=1 \dots p$)

Estimate $\hat{\theta}_j$ from $M(p-1)$

$$E(\hat{\theta}) = \hat{\theta} + \frac{b_1}{m(p-1)} + \frac{b_2}{[m(p-1)]^2} + \dots$$

P-pseudo values: $V_j = p\hat{\theta} - (p-1)\hat{\theta}_j$

$$\hat{\theta}_j = \frac{1}{p} \sum_{j=1}^p V_j$$

$$E(\hat{\theta}_j) = \hat{\theta} + \frac{b_1}{m(p-1)} + \frac{b_2}{[m(p-1)]^2} + \dots = \frac{1}{p} \sum_{j=1}^p V_j + \frac{b_1}{m(p-1)} + \frac{b_2}{[m(p-1)]^2} + \dots = p\hat{\theta} - (p-1)\hat{\theta}_j + \frac{b_1}{m(p-1)} + \frac{b_2}{[m(p-1)]^2} + \dots$$

$$\frac{dE(\hat{\theta}_j)}{dp} = \hat{\theta} - \hat{\theta}_j + \frac{b_1}{m(p-1)^2} - \frac{2b_2}{[m(p-1)]^3} + \dots$$

$$\frac{d^2 E(\hat{\theta}_j)}{dp^2} = \frac{+2b_1}{m(p-1)^2} + \frac{6b_2}{m(p-1)^4} + \dots = 0$$

$$\frac{b_1}{m(p-1)^2} + \frac{3b_2}{m(p-1)^4} + \dots = 0$$

$$b_1 = \frac{-3b_2}{m(p-1)^4}$$

52. $N_1 = N_L = 1000$

$N_3 = 500$

10 observations

Stratum #1: 94 99 106 106 101 102 122 104 97 97

Stratum #2: 183 183 179 211 178 179 192 192 201 177

Stratum #3: 343 302 296 317 289 284 357 288 314 296

$$\bar{x}_1 = 103 \quad \sigma_1 = 7.4$$

$$\bar{x}_2 = 188 \quad \sigma_2 = 11$$

$$\bar{x}_3 = 278 \quad \sigma_3 = 38$$

$$T_1 = N \cdot X_1 = 103,000; T_2 = N \cdot X_2 = 188,000; T_3 = N \cdot X_3 = 139,000$$

$$103 \pm 12 \quad 188 \pm 18 \quad 278 \pm 63$$

47. $n=64$: Corollary B of Section 7.4 : Approximate Bins of the ratio estimate of μ_y

$$E(\bar{Y}_R) - \mu_y \approx \frac{1}{64} \left(1 - \frac{64-1}{395-1} \right) \frac{1}{274.8} (2.96 \cdot 213.2^2 - 0.91 \cdot 213.2 \cdot 539.7)$$

$$n=128 = 0.96$$

$$\approx \frac{1}{128} \left(1 - \frac{64-1}{395-1} \right) \frac{1}{274.8} (2.96 \cdot 213.2^2 - 0.91 \cdot 213.2 \cdot 539.7)$$

$$E(\bar{Y}_R) - \mu_y \approx \frac{1}{n} \left(1 - \frac{n-1}{N-1} \right) \frac{1}{\mu_x} (r \sigma_x^2 - r \rho \sigma_x \sigma_y)$$

48. $n=100$ Households ; # people in Household $[X]$; Weekly Expenditure for Food $[Y]$

$$\text{Total Number of Households} = 100,000$$

$$\begin{aligned} \text{a) Estimate the ratio } r &= \frac{\mu_y}{\mu_x} \\ &= \frac{(\sum X_i)/N}{(\sum Y_i)/N} \end{aligned}$$

$$\sum X_i = 320 : \text{Total sum # people in Household}$$

$$\sum Y_i = 10,000 : \text{Total Weekly Expenditure for Food}$$

$$\begin{aligned} \sum X_i^2 = 1250 &\quad \text{b) Confidence Interval (95%)}: r \pm 1.96 \sigma_r \\ &125 \pm 1.96 \cdot \left(\frac{1}{n} \left[1 - \frac{n-1}{N-1} \right] \frac{1}{\mu_x^2} (r^2 \sigma_x^2 + \sigma_y^2 - 2r \rho \sigma_x \sigma_y) \right) \end{aligned}$$

$$\sum Y_i^2 = 1,100,000$$

$$\frac{125}{4} \pm 1.96 \left(\frac{1}{100} \left[1 - \frac{10^2-1}{100^2-1} \right] \frac{1}{320^2} \left(\frac{125}{4} \left[\frac{125}{100} - \frac{(320)^2}{100} \right] + \left(\frac{1,100,000}{100} - \left(\frac{10,000}{100} \right)^2 \right) - 2 \left(\frac{125}{4} \right) \left(\frac{320}{100} - \frac{10,000}{100} \right) \right) \right)$$

$$\sum X_i Y_i = 36,000$$

$$\boxed{\frac{125}{4} \pm 1.34}$$

$$\text{C. } T = N \bar{Y} = 100,000 \cdot \frac{10,000}{100} = 10^7, \quad \left(1 - \frac{1}{10^5} \right) S^2 = \left(\frac{1}{99999} \right) \frac{1}{100-1} \left(\frac{1,100,000}{100} - \left(\frac{10,000}{100} \right)^2 \right) = 1.68 \times 10^{-4}$$

49. $N=1000$ squares

$n=50$ sampled

$Y = \# \text{ of birds}$

$X = \text{Area covered by vegetation}$

$$\text{a) } r = \frac{\sum Y_i / n}{\sum X_i / n} = \frac{150}{3000} = \frac{1}{20}$$

$$P\left(\left|\frac{Y-\bar{Y}}{\sigma_Y}\right| < z\left(1 - \frac{\alpha}{2}\right)\right) = 0.90 \quad \boxed{100 \pm 1.65 \cdot 1.66 \times 10^{-4}}$$

$$\boxed{100 \pm 0.00027}$$

$$\sum X_i = 3,000 \quad \text{b) Standard Error:}$$

$$\sum Y_i = 150$$

$$S_R = \sqrt{\text{Var}(R)} = \sqrt{\frac{1}{n} \left(1 - \frac{n-1}{N-1} \right) \frac{1}{\mu_x^2} (r^2 \sigma_x^2 + \sigma_y^2 - 2r \rho \sigma_x \sigma_y)}$$

$$\sum X_i^2 = 225,000$$

$$\sigma_X = \sqrt{\frac{1}{50-1} [225,000 - 50 \cdot 30^2]} = 30, \quad \sigma_{XY} = \sqrt{\frac{1}{50-1} [11,000 - 50 \cdot 30 \cdot 3]} = 40.8$$

$$\sum Y_i^2 = 650$$

$$\sigma_Y = \sqrt{\frac{1}{50-1} [650 - 50 \cdot 3^2]} = 21, \quad \rho = 0.68$$

$$\sum X_i Y_i = 11,000$$

$$\begin{aligned} S_R &= \sqrt{\frac{1}{50} \left(1 - \frac{50-1}{1000-1} \right) \left(\frac{1}{3000^2} \right) \left(\left(\frac{1}{20} \right)^2 \cdot 30^2 + 21^2 - 2 \left(\frac{1}{20} \right) \cdot 30 \cdot 21 \cdot 0.68 \right)} \\ &= 7.34 \times 10^{-4} \end{aligned}$$

95% Confidence Interval:

$$95\% \text{ Confidence Interval: } \frac{1}{20} \pm 1.96 S_R = \frac{1}{20} \pm 1.65 \cdot 7.34 \times 10^{-4} = 0.05 \pm 0.0001$$

c) Total Number of Birds:

95% Confidence Interval

$$T = N \cdot \bar{Y} = 1000 \cdot \frac{150}{50} = 3,000$$

Standard Error:

$$T \pm 1.96 \cdot \sqrt{3000} = 3000 \pm 1.96 \cdot 275 = 3000 \pm 540$$

$$= 3,000$$

$$S_T = S_T \sqrt{\frac{N(N-n)}{n}}$$

$$= \sqrt{N} S_X = \sqrt{1000} \sqrt{\frac{S_R^2}{n} \left(1 - \frac{50}{1000} \right)} = \sqrt{1000} \sqrt{\frac{4}{50} \left(1 - \frac{50}{1000} \right)} = 2.75$$

b.) Variance of Estimator: $\text{Var}(N\bar{D}) = E[N\bar{D}^2] - E[N\bar{D}]^2 = N^2 E[\bar{D}^2] - N^2 E[\bar{D}]^2 = N^2 [E[\bar{D}^2] - E[\bar{D}]^2]$

c.) Population Parameter $[T]$: Estimate $T = N\bar{X}$; Variance of Estimator $\sigma_T^2 = N^2 \sigma_x^2 = N^2 [E[X^2] - E[X]^2]$
 The proposed method would be as accurate.

$$= N^2 \sigma_0^2 + N^2 [E[D^2] - E[D]^2]$$

d.) Estimation of Ratio: $r = \frac{\sum y_i}{\sum x_i} = \frac{\mu_2}{\mu_1}$

A ratio estimate would provide advantages to a differently sized pool of populations. In the listed case of part a, b, or c, then there would be no difference.

42. Population Correlation Coefficient: $r = \frac{\sigma_{xy}}{\sigma_x \cdot \sigma_y} = \frac{\frac{1}{N} \sum (x_i - \mu_x)(y_i - \mu_y)}{\sqrt{\frac{1}{N} \sum (x_i - \mu_x)^2} \sqrt{\frac{1}{N} \sum (y_i - \mu_y)^2}}$

43. Example D: Section 7.3.3,

44. $\bar{X} = 2.2$, $\sigma = 0.7$, $p(\# \text{occupants} | \# \text{motor vehicles}) = 0.85$

$$= \frac{1}{N} \left(\frac{1}{\sum (x_i - \mu_x) \sum (y_i - \mu_y)} \right)$$

Estimate population ratio of # Motor Vehicles per Occupant + S.E.

Population Ratio: $\frac{\mu_2}{\mu_1} = \frac{\bar{X}_2}{\bar{X}_1} = \frac{1.8 \text{ motor vehicle per car}}{2.2 \text{ motor vehicle per car}} = 0.818$

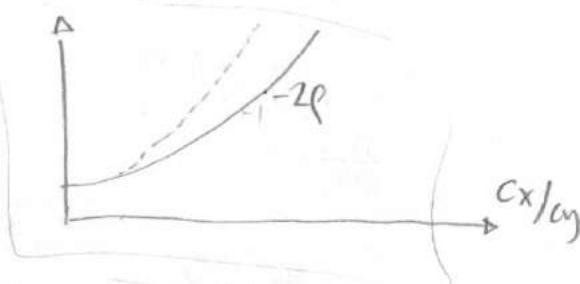
Standard Error: $\text{Var}(r) = \frac{1}{n} \left(1 - \frac{n-1}{N-1} \right) \frac{1}{\mu_1^2} (r^2 \sigma_x^2 + \sigma_2^2 - 2r \sigma_x \sigma_2)$
 $= \frac{1}{n} \left(1 - \frac{n-1}{N-1} \right) \frac{1}{\mu_1^2} (r^2 \sigma_x^2 + \sigma_2^2 - 2r \rho \sigma_x \sigma_y)$
 $= \frac{1}{100} \left(1 - \frac{100-1}{9000-1} \right) \frac{1}{2.2^2} (0.818^2 \cdot 0.7^2 + 0.3^2 - 2(0.818)(0.35)(0.7))$
 $= 4.285 \times 10^{-4} ; SE = 2.05 \times 10^{-2}$

Confidence Interval (95%): $0.95 = P\left(\frac{X - \bar{X}}{\sigma_x} < Z(1 - \alpha/2)\right) ; 2.05727 \pm 1.96(0.05)$

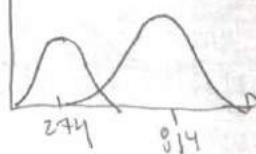
44. $\frac{\text{Var}(\bar{Y}_R)}{\text{Var}(\bar{Y})} \approx 1 + \frac{c_x}{c_y} \left(\frac{c_x}{c_y} - 2\rho \right) = 1 + x^2 + x$

$$2.05727 \pm 1.96(2.05 \times 10^{-2})$$

$$2.05727 \pm 0.04$$



46. $\sigma_{\bar{Y}_R} \approx 30.0$ or 32.76
 $\sigma_{\bar{Y}} = 66.3$



45. $\rho = 0.91$ $\text{Var}(\bar{Y}_R) ; \text{Plot } \text{Var}(\bar{Y}_R) \text{ for } n=64$

$$\text{Var}(\bar{Y}_R) = \frac{1}{n} \left(1 - \frac{n-1}{N-1} \right) \frac{1}{\mu_1^2} (r^2 \sigma_x^2 + \sigma_2^2 - 2r \rho \sigma_x \sigma_2)$$

$$\text{Var}(\bar{Y}_R) = \frac{68617.4}{n}$$



36. Simple Random Sampling: \bar{X}^2 is unbiased estimate of μ^2 . Simple random sampling is an unbiased estimator of μ^2 . When there is true random sampling, for example, each value has equal probability. Otherwise, the \bar{X}^2 is not random, and biased.

37. Population Mean = μ : Survey #1 + Survey #2

$$\bar{X}_1 = \text{Mean} \quad \bar{X}_2 = \text{Mean} \quad \left\{ \begin{array}{l} \text{Unbiased} \\ \text{ } \end{array} \right. \quad X = \alpha \bar{X}_1 + \beta \bar{X}_2$$

$$\sigma_{\bar{X}_1} = \text{Standard Error}$$

$$\sigma_{\bar{X}_2} = \text{Standard Error}$$

a) Find conditions for α and β which are an unbiased combination.

$$\begin{aligned} \text{Var}(\mu) &= E[\mu^2] - E[\mu]^2 = \frac{(\alpha \bar{X}_1 + \beta \bar{X}_2)^2}{n} - \left[\frac{(\alpha \bar{X}_1 + \beta \bar{X}_2)}{n} \right]^2 = \frac{(\alpha \bar{X}_1)^2 n + 2(\alpha \bar{X}_1 \bar{X}_2) n + (\beta \bar{X}_2)^2 n}{n^2} - \frac{(\alpha \bar{X}_1)^2 + 2(\alpha \beta \bar{X}_1 \bar{X}_2) + (\beta \bar{X}_2)^2}{n^2} \\ &= \frac{(\alpha \bar{X}_1)^2 (n-1) + 2(\alpha \beta \bar{X}_1 \bar{X}_2)(n-1) + (\beta \bar{X}_2)^2 (n-1)}{n^2} = \frac{n-1}{n^2} [\alpha^2 \bar{X}_1^2 + \beta^2 \bar{X}_2^2] \end{aligned}$$

$$\text{Var}(\mu) = \text{Var}(\alpha \bar{X}_1 + \beta \bar{X}_2) = \alpha^2 \text{Var}(\bar{X}_1) + \beta^2 \text{Var}(\bar{X}_2) + \frac{(n-1)}{n^2} [\alpha^2 \bar{X}_1^2 + \beta^2 \bar{X}_2^2]$$

$$\begin{aligned} E(X) &= \alpha E(\bar{X}_1) + \beta E(\bar{X}_2) \\ &= \frac{\alpha}{n} \sum_{i=1}^n x_i + \frac{\beta}{n} \sum_{i=1}^n x_i = \frac{n-1}{n^2} [\alpha \bar{X}_1^2 + 2 \alpha \beta \bar{X}_1 \bar{X}_2 + \beta \bar{X}_2^2] \\ &= (\alpha + \beta) \mu \end{aligned}$$

$$(\alpha + \beta) = 1$$

$$\alpha^2 \text{Var}(\bar{X}_1) + \beta^2 \text{Var}(\bar{X}_2) = \alpha^2 [\sigma_{\bar{X}_1}^2] + (1-\alpha)^2 [\sigma_{\bar{X}_2}^2] (\beta \bar{X}_2)^2$$

$$\begin{aligned} b) \frac{d}{d\alpha} [\alpha^2 [\sigma_{\bar{X}_1}^2] + \sigma_{\bar{X}_2}^2 + \alpha [\sigma_{\bar{X}_2}^2] - 2 \alpha [\sigma_{\bar{X}_2}^2]] &= \alpha^2 [\sigma_{\bar{X}_1}^2] + \sigma_{\bar{X}_2}^2 + \alpha^2 [\sigma_{\bar{X}_2}^2] - 2 \alpha [\sigma_{\bar{X}_2}^2] \\ &\stackrel{\text{"Unbiased"}}{=} \alpha^2 \frac{\sigma_{\bar{X}_1}^2}{\sigma_{\bar{X}_1}^2 + \sigma_{\bar{X}_2}^2} + \beta^2 \frac{\sigma_{\bar{X}_2}^2}{\sigma_{\bar{X}_1}^2 + \sigma_{\bar{X}_2}^2} \end{aligned}$$

38. X_1, \dots, X_n be random sample. Show $\frac{1}{n} \sum_{i=1}^n X_i^3$ is an unbiased estimator of $\frac{1}{N} \sum_{i=1}^N X_i^3$.

$$E[X^3] = \frac{1}{N} \sum_{i=1}^N X_i^3 \leftarrow \text{No } \beta \text{ to incorporate, no bias and no shift.}$$

39. N = population of items. How large should a sample be to find a defective item?

Assuming $p=0.95$; n = sample size; $R=1$; $P(1 \leq \frac{X-M}{\sigma_x} < k) = 0.95$

$$1 - \frac{N-k}{N} \times \frac{N-k-1}{N-1} \times \dots \times \frac{N-n+1}{N-n+1} > 0.95 \quad \text{if } k=1.95$$

$$1 - \frac{N-1}{N} \times \frac{N-1-1}{N-1} \times \dots \times \frac{N-n}{N-n+1} > 0.95; \quad \text{40. } i^{\text{th}} \text{ member has } P(i) = \frac{N-n}{N-i+1}$$

$$= \frac{(N-n)n!}{N!} = \frac{N-n}{N-(i-1)} = \frac{1}{(N-i+1)}$$

$$1 - \frac{N-n}{N} > 0.95$$

$$\left(\frac{N-n}{N} \right)^n < 0.05$$

$$\log(N-n) - \log(N) \approx \log(0.05)$$

$$n \approx N - e^{\frac{\log(0.05)}{R} + \log(N)}$$

$$\approx 501$$

41. $D = \text{Audited Value} - \text{Book Value}$
 \bar{D} , where $N = \text{population size}$.

Inventory value.

a) Prove unbiased estimate

$$E[N(\bar{D})] = \frac{N}{n} \sum_{i=1}^n i D = N E[D]$$

Q. 99% confidence Interval: $\hat{d} - Z\left(\frac{1-0.01}{2}\right) \cdot \hat{s}_d < \hat{d} < \hat{d} + Z\left(\frac{1-0.01}{2}\right) \cdot \hat{s}_d$

$$\hat{d} - 2.57 \left(\sqrt{\frac{0.12(1-\alpha/2)}{100} + 0.18(1-\alpha/2)} \right) \quad \left[1 - \frac{4000}{100^4} \frac{(100-1)}{(4000-1)} \right]$$

$$-0.06 - 2.57(5.03 \times 10^{-2}) < d < \frac{3}{50} + 2.57(5.03 \times 10^{-2})$$

$$-\frac{3}{25} < d < 6.927 \times 10^{-2}$$

95% confidence Interval: $-0.06 - 1.96(5.03 \times 10^{-2}) < d < 0.06 + 1.96(5.03 \times 10^{-2})$
 $-0.159 < d < \frac{3}{25}$
 $-0.143 < d < 0.029$

No, there is little difference for a 99% confidence interval ranging from $(-\frac{3}{25}, \frac{6.927}{100})$.

33. n = simple random samples, two proportions, \hat{p}_1 and $\hat{p}_2 \approx 0.5$. What should the sample size be for $\hat{p}_1 - \hat{p}_2 < 0.02$?

Standard error of proportions: $s_{\hat{p}_1, \hat{p}_2} = \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}} < 0.02$

34. P(Problem #1) = 3% population

P(Problem #2) = 40% population

a) $s_{\hat{p}_1, \hat{p}_2} = \sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}$

Sample population size

$$s_{\hat{p}_1, \hat{p}_2} = 0.01 > \sqrt{\frac{0.03(0.97) + 0.4(0.6)}{n}}$$

2 $n > \frac{2.691 \times 10^{-1}}{1 \times 10^{-4}}$

$\boxed{n > 2691}$

a) Calculate unbiased estimate of population mean.

b) $n > 2.691 \times 10^{-1}$

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n X_i = \frac{1}{25} [104 + \dots + 97] = \boxed{98}$$

c) Calculate unbiased estimate of population variance

$$\begin{aligned} \hat{\sigma}_{\bar{x}}^2 &= \left(1 - \frac{1}{n}\right) s^2 = \left(1 - \frac{1}{200}\right) \cdot \frac{1}{25} [E[X^2] - E[\bar{x}]^2] \\ &= \frac{1999}{200} \cdot \frac{1}{25} \left[\sum_{i=1}^{25} x_i^2 + \left(\frac{1}{n} \sum_i (X_i) \right)^2 \right] = \frac{1999}{200} \cdot \frac{243505}{25} - \left(\frac{2450}{25} \right)^2 \end{aligned}$$

c) Approximate a 95% confidence interval.

$$P\left(\left|\frac{X - \bar{X}}{\sigma_{\bar{x}}}\right| < Z\left(\frac{1-\alpha}{2}\right)\right) = 0.95 ; \quad \sigma_{\bar{x}} = \sigma_x \sqrt{1 - \frac{1}{n}}$$

$$2P\left(\frac{X - \bar{X}}{\sigma_{\bar{x}}} < Z\left(\frac{1-\alpha}{2}\right)\right) = 1.95 ; \quad \sigma_{\bar{x}} = \sigma_x / \sqrt{n}$$

$$\begin{aligned} &\left(98 + 1.96 \sqrt{5.37} \times \sqrt{1 - \frac{1}{200}} \right) \cdot \bar{X} = 196,000 \\ &98 \pm 4.54, \quad 196,000 \pm 23,323 \end{aligned}$$

31. $N = 3000$ condominium units; $n = 100$ sample size; $\bar{X} = 1.6$ motor vehicles
 $s_{\bar{X}} = \frac{s}{\sqrt{n}} \sqrt{1 - \frac{n}{N}} = \frac{0.8}{\sqrt{100}} \sqrt{1 - \frac{100}{3000}} = 0.08$ } $\sigma = 0.8$ motor vehicles
 standard error

$$\left. \begin{array}{l} \text{confidence interval} \\ \text{interval} \end{array} \right\} \bar{X} \pm 1.96 s_{\bar{X}} = (1.44, 1.76); T = 3000 \times 1.6 = 12,000 \} \text{Total}$$

$$s_T = N s_{\bar{X}} = 640; T \pm 1.96 s_T (11546, 14054) \} \text{Interval of Total}$$

Total standard error

$$12\% \text{ planned to sell their condo } [\hat{p} = 0.12]; s_{\hat{p}} = \sqrt{\frac{\hat{p}(1-\hat{p})}{n-1}} \sqrt{1 - \frac{100}{3000}} = 0.03$$

$$\hat{p} \pm 1.96 s_{\hat{p}} (0.06, 0.18); T = N \hat{p} = 960; s_T = N s_{\hat{p}} = 240; T \pm 1.96 s_T (480, 1440)$$

What is the sample size for 95% confidence interval to have 500 width (AT) of 500?

$$\bar{X} + 1.96 s_T - \bar{X} - 1.96 s_T = 2 \cdot 1.96 s_T = 500; s_T = 500 / 2 \cdot 1.96 = 127.55$$

$$= N s_{\hat{p}} = 8000 s_{\hat{p}}; s_{\hat{p}} = \frac{127.55}{8000} = 1.59 \times 10^{-4} = \sqrt{\frac{0.12(1-0.12)}{n-1}} \sqrt{1 - \frac{n}{8000}}$$

$$2.53 \times 10^{-4} = \frac{0.12(0.98)}{n-1} \left(\frac{8000-n}{8000} \right) \Rightarrow 2.53 \times 10^{-4} n - 2.53 \times 10^{-4} = \frac{0.06}{625} \left(\frac{8000-n}{8000} \right)$$

$$2.53 \times 10^{-4} n - 2.53 \times 10^{-4} = \frac{66}{625} - \frac{33}{250000} n; 2.66 \times 10^{-4} n = 0.1058; n = 397.9$$

32. $N = 12,000$ units; $n = 200$ sample size; $\hat{p} = 0.18$

a) What is $s_{\hat{p}}$? $s_{\hat{p}} = \sqrt{\frac{\hat{p}(1-\hat{p})}{n-1}} \sqrt{1 - \frac{n}{N}} = \sqrt{\frac{0.18(1-0.18)}{200-1}} \sqrt{1 - \frac{200}{12000}} = 0.027$

$$P\left(\frac{|\hat{p} - p|}{s_{\hat{p}}} < z(\alpha/2)\right) = 1 - \alpha = 0.90; \alpha = 0.05; z(0.1/2) = z(0.05) = z(1-0.05) = z(0.95)$$

$$P(|\hat{p} - p| \leq s_{\hat{p}} \cdot 1.96) = 0.95; P(-1.96 s_{\hat{p}} \leq p - \hat{p} \leq 1.96 s_{\hat{p}}) = P(\hat{p} - 1.96 s_{\hat{p}} \leq p \leq \hat{p} + 1.96 s_{\hat{p}})$$

$$= P(p \leq \hat{p} + 1.96 s_{\hat{p}}) - P(\hat{p} - 1.96 s_{\hat{p}} \leq p) = P(p \leq \hat{p} + 1.96 s_{\hat{p}}) - (1 - P(p \leq \hat{p} + 1.96 s_{\hat{p}}))$$

$$= 2P(p \leq \hat{p} + 1.96 s_{\hat{p}}) - 1 = 0.95; P(p \leq \hat{p} + 1.96 s_{\hat{p}}) = \frac{1.95}{2} = 0.975 \rightarrow \text{solve}$$

$$\dots \text{or.} \dots (\hat{p} - 1.65 s_{\hat{p}}, \hat{p} + 1.65 s_{\hat{p}}) = (0.13 - 1.65 \cdot 0.027, 0.18 + 1.65 \cdot 0.027)$$

b) $\hat{p}_1 = 0.12, \hat{p}_2 = 0.13; \hat{d} = \hat{p}_1 - \hat{p}_2$ $= (0.135, 0.225)$

$$\text{Var}(\hat{d}) = s_{\hat{d}}^2 = E[\hat{d}^2] - E[\hat{d}]^2 = 1$$

$$= E[(\hat{p}_1 - \hat{p}_2)^2] - E[\hat{p}_1 - \hat{p}_2]^2$$

$$= E[\hat{p}_1^2] - 2E[\hat{p}_1 \hat{p}_2] + E[\hat{p}_2^2] - E[\hat{p}_1 - \hat{p}_2]^2$$

$$= \hat{p}_1 - 2\hat{p}_1 \hat{p}_2 + \hat{p}_2 - (\hat{p}_1 - \hat{p}_2)^2$$

$$= \hat{p}_1 - 2\hat{p}_1 \hat{p}_2 + \hat{p}_2 - \hat{p}_1^2 + 2\hat{p}_1 \hat{p}_2 - \hat{p}_2^2$$

$$= \hat{p}_1 (1 - \hat{p}_1) + \hat{p}_2 (1 - \hat{p}_2)$$

Standard Error (unbiased):

$$s_{\bar{X}}^2 = \frac{1}{n} \sum_i^n [E(X_i^2) - E(\bar{X})^2] = \frac{1}{n} \sum_i^n [Var(X_i) + E(X_i)^2] - [Var(\bar{X}) + E(\bar{X})^2]$$

$$= \frac{1}{n} \left[p_1 (1-p_1) + p_2 (1-p_2) + E(\hat{d})^2 \right] - \left[\frac{1}{n^2} \sum_i^n Var(X_i) + \frac{1}{n^2} \sum_i^n Cov(X_i, X_j) \right] + E(\bar{X})^2$$

$$= \frac{p_1 (1-p_1) + p_2 (1-p_2)}{n} \left[1 - \frac{1}{n^2} \sum_i^n \frac{N}{n^2} \frac{(n-1)}{(N-1)} \right]$$

$$= \frac{p_1 (1-p_1) + p_2 (1-p_2)}{n} \left[1 - \frac{N(n-1)}{n^4 (N-1)} \right]$$

14. $P(X|H_0) = N(0, \sigma^2)$ $\frac{P(H_0|X)}{P(H_1|X)} = \frac{P(H_0)}{P(H_1)} \frac{P(X|H_0)}{P(X|H_1)} = 2e^{\frac{(x-1)^2 - x^2}{2\sigma^2}} = 2e^{\frac{-2x+1}{2\sigma^2}}$; $\ln(\frac{1}{2}) = \frac{-2x+1}{2\sigma^2} \Rightarrow x = \frac{2\sigma^2 \ln(\frac{1}{2}) - 1}{-2}$

$P(X|H_1) = N(1, \sigma^2)$

$P(H_0) = 2 \times P(H_1)$

σ^{-2}	0.1	0.5	1.0	5.0
$X: H_0 \geq 1$	0.57	0.95	1.19	3.96

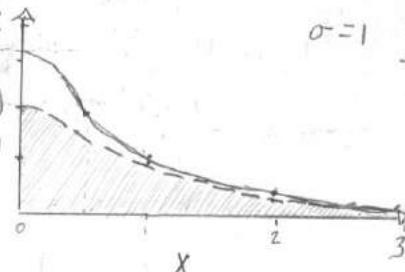
b) $\frac{2}{3}$

15.

$P(X|H_0) = N(0, \sigma^2)$

$P(X|H_1) = N(1, \sigma^2)$

$P(H_0) = P(H_1)$



$\sigma = 1 \quad \frac{P(H_0|X)}{P(H_1|X)} = \frac{P(H_0)}{P(H_1)} \cdot \frac{P(X|H_0)}{P(X|H_1)} = e^{\frac{-2x+1}{2\sigma^2}}$

The P-value of $P(H_0|X)/P(H_1|X)$ and $P(H_0)$ show similarly symmetric graphs, so their P-values are similarly symmetric. Another, or will show equivalent results because are scaled proportions.

16. $\alpha = 0.05$

$\frac{P(H_0|X)}{P(H_1|X)} = e^{\frac{-2x+1}{2\sigma^2}} > 1; |x > \frac{1}{2}|; \frac{P(H_0|X)}{P(H_1|X)} = e^{\frac{-2x+1}{2\sigma^2}} < 1; |x < \frac{1}{2}|$

17. $P(X|H_0) = N(0, \sigma_0^2)$
 $P(X|H_1) = N(0, \sigma_1^2)$

$\sigma_1 > \sigma_0$

a) $\Lambda = \frac{P(X|H_0)}{P(X|H_1)} = \frac{N(0, \sigma_0^2)}{N(0, \sigma_1^2)} = e^{\frac{-x^2/\sigma_0^2 + x^2/\sigma_1^2}{2}} = e^{\frac{-(\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2})x^2}{2}}$

The rejection region of a level α test: $\ln \Lambda = -\frac{(\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2})x^2}{2} + \ln \sigma_1/\sigma_0 < -2\ln \alpha$

$P((\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2})\sum X_i^2 - 2\ln \sigma_1/\sigma_0) > \chi^2(\alpha)$

Assuming largest term is $\frac{1}{\sigma_0^2} \sum X_i^2$ because $\sigma_1 \gg \sigma_0$.

b. X_1, X_2, \dots, X_n

$P(\frac{1}{\sigma_0^2} \sum X_i^2 > \chi^2(\alpha)) = \alpha; |\frac{\sigma_0^2}{\sigma_1^2} X^2 < \chi^2|$

$P((\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2})\sum X_i^2 - 2\ln \sigma_1/\sigma_0) > \chi^2(\alpha); |\frac{\sigma_0^2}{\sigma_1^2} X_n(\chi) < \sum X_i^2|$

c. Yes, because the rejection level is a simple hypothesis.

18. X_1, X_2, \dots, X_n i.i.d.

Double Exponential Distribution

$f(x) = \frac{1}{2} \lambda \exp(-\lambda|x|)$

Maximum Likelihood:

$d \ln f(x) = \frac{n}{\lambda} - \sum |x_i|$

$\hat{\lambda} = \frac{1}{\bar{x}}$

Likelihood Ratio Test: $\Lambda = \frac{f(x|\lambda_0)}{f(x|\lambda_1)} = \left(\frac{\lambda_0}{\lambda_1}\right)^{\frac{1}{\lambda}(\bar{x} - \bar{x}_1)}$

$-\ln \Lambda = \sum \ln \left(\frac{\lambda_0}{\lambda_1}\right) + \sum \frac{(\bar{x} - x_i)^2}{\bar{x}_1 \bar{x}} = 0$

$\ln \Lambda = \sum \ln \left(\frac{\lambda_0}{\lambda_1}\right) = \sum (x_i - \bar{x}) + \frac{1}{2} \sum (x_i - \bar{x})^2 / \bar{x}$

$2 \ln \Lambda = 2 \sum (x_i - \bar{x})^2 / \bar{x} = 2 \bar{X}^2$

The test is uniformly most powerful because of the squared terms.

$\lambda > \lambda_0$ vs $\lambda_1 > \lambda_0$ are equivalent outcomes.

19. $H_0: F_0(x) = x^2$

$0 \leq x \leq 1$

$H_1: F_1(x) = x^3$

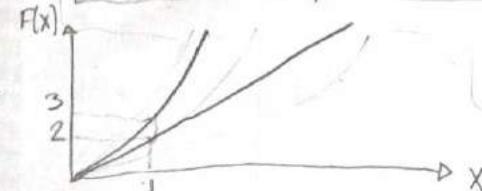
$0 \leq x \leq 1$

c) $P(X: \frac{2}{3} > Z(\chi/2)) = 1 - \alpha$

d) $P(X: \frac{2}{3} > Z(\chi/2)) = 1 - \beta$

$X = \sqrt{1 - \alpha}$

$\beta = 1 - \frac{(1 - \alpha)^3}{2}$



20. $[0, 1]$: $f_0(x) = 1$, $f_1(x) = 2x$; $\alpha = 0.10$; $P\left(\frac{f_0(x)}{f_1(x)} \leq c\right) = P\left(\frac{1}{2x} \leq c\right) = P\left(X \geq \frac{1}{2c}\right)$

H_0 H_1

Null Hypothesis $= \int_{1/2c}^1 f_0(x) dx = \int_{1/2c}^1 1 dx = 1 - \frac{1}{2c} = 0.1 \Rightarrow c = 5/9$

21. $[0, \theta]$; $H_0: \theta = 1$ vs $H_1: \theta = 2$ Uniform

a. $\alpha = 0$. What is the power? $F(\theta) = \frac{1}{\theta}$

$P\left(\frac{f_0(\theta|H_0)}{f_1(\theta|H_1)} < c\right) = P(2 < c) = \int_c^\theta d\theta = \theta - c = 0$

$P\left(\frac{f_0(\theta|H_0)}{f_1(\theta|H_1)} < c\right) = P(2 < c) = P(Z > c) = P(2 > 1) = \int_1^\theta \frac{1}{2} d\theta = \frac{1}{2}(\theta - 1) = \frac{1}{2}$

b. $0 < \kappa < 1$; $X \in [0, \kappa]$; $P(b < X < a) = P(X < a) - P(X < b) = \int_b^a d\theta = a - b = \kappa$

$P(1 < X < 1-\kappa) = P(X < 1-\kappa) - P(X < 1) = \int_{1-\kappa}^1 \frac{1}{2} d\theta = \frac{1}{2}(1-\kappa - 1) = \frac{1-\kappa}{2}$

c. $X \in [1-\kappa, 1]$; $P(1-\kappa < X < 1) = P(X < 1) - P(X < 1-\kappa)$

$P(X \in [(1-\kappa)/2, (1+\kappa)/2]) = \int_{1-\kappa}^{1+\kappa} d\theta = x - 1 - x + 1 + \kappa = \kappa$

$P(\kappa < X < 1) = P(X > 1) - P(X < \kappa) = \int_{\kappa}^1 \frac{1}{2} d\theta - \int_x^{\kappa} \frac{1}{2} d\theta = \frac{1}{2}(1-\kappa - x) - \frac{1}{2}(x - 1) = \frac{1-\kappa}{2}$

e. The likelihood ratio test determines unique rejection for $\kappa > 0$.

f. $H_0: \theta = 2$; $H_1: \theta = 1$; $P\left(\frac{f_0(\theta|H_0)}{f_1(\theta|H_1)} < c\right) = P\left(\frac{1}{2} < c\right) = \int_c^\theta \frac{1}{2} d\theta = \frac{\theta - c}{2} = 0 \Rightarrow c = \theta$

$P\left(\frac{f_0(\theta|H_0)}{f_1(\theta|H_1)} < c\right) = P\left(\frac{1}{2} < c\right) = P\left(\frac{1}{2} < 1\right) = \int_1^\theta d\theta = \theta - 1 = 0$

22. Example A: Section 8.5.3

The rejection region is not capable of being determined.

$(\hat{\mu}_0^2, \hat{\sigma}_0^2)$ $P(X|H_0) = P(X|\hat{\sigma}_0^2)$ $A(\hat{\sigma}_0^2) = \{X | \hat{\sigma}_0^2 EC(X)\}$

Theorem B: Section 9.3

Significance level: κ

$P[\theta_0 \in C(X)|\theta = \theta_0] = 1 - \kappa$

X_1, X_2, \dots, X_n

$A(\theta_0) = \{X | \theta_0 \in C(X)\}$ $\sigma_0 = 1, n = 15, \kappa = 0.05$

$P(\hat{\sigma}_0^2 EC(X)|\hat{\sigma}_0^2 = \hat{\sigma}_0^2) = 1 - \kappa$

$P\left(\frac{19}{100} \sum_{i=1}^{15} (X_i - \bar{X})^2 > 1 > \frac{4}{100} \sum_{i=1}^{15} (X_i - \bar{X})^2\right) = 0.95$

$A(\hat{\sigma}_0^2) = \left\{X \mid \frac{19}{100} \sum_{i=1}^{15} (X_i - \bar{X})^2 > \hat{\sigma}_0^2 > \frac{4}{100} \sum_{i=1}^{15} (X_i - \bar{X})^2\right\}$

23. 99% Confidence Interval: \hat{H}

Normal Distribution: $P(-Z(\kappa/2) < H < Z(\kappa/2)) = 1 - \kappa = 0.99$

$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$; $P(-2, 0, 3, 0) = P(\sigma^2 Z(\kappa/2) < H < \sigma^2 z(\kappa/2))$

$\kappa = 0.01$; $Z(0.005) = 2.57$ $\sigma^2 = 0.195$;

$\lambda = e^{-\frac{2\mu_1 x + \mu_1^2 - 6x + 9}{2(0.195)}} = e^{-\frac{-2\mu_1 x + \mu_1^2 + 2\mu_0 x + \mu_0^2}{2(0.195)}} = e^{-\frac{(2\mu_1 + 6)x + \mu_1^2 + \mu_0^2}{0.39}}$

$P((2\mu_1 + 6)x + \mu_1^2 + 9 > 0) = P(x > \frac{\mu_1^2 + 9}{2\mu_1 + 6})$; Yes, the rejection region demonstrates
 $H_A: H_A \neq -3$ does not suffice.

24. n = trials, p = prob success

Binomial Random Variable

a) $H_0: p = 0.5$ $H_A: p \neq 0.5$

$P(1) = p$

$P(0) = 1 - p$

$P(X) = 0; X \neq 0, X \neq 1$

$\lambda = \frac{P(X|H_0)}{P(X|H_A)} = \frac{P(1|H_0)}{P(0|H_A)} = \frac{p(1-p)^{n-1}}{P(0|H_A) \cdot P(1|H_A)^{n-1}} = \frac{p(1-p)^{n-1}}{\left(\frac{n}{n+1}\right) \left(\frac{n-1}{n}\right)^{n-1}}$

b. Rejection Region: $\lambda = \frac{(\lambda/2)^n}{\left(\frac{n}{n+1}\right)^{n+1/2} \left(1 - \frac{n-1}{n}\right)^{n-1/2}}$

$= \frac{(\lambda/2)^n}{\left(\frac{1}{2} + \frac{1}{n}\right)^{n+1/2} \left(\frac{1}{2} - \frac{1}{n}\right)^{n-1/2}}$

$\lambda > 4Xp; 0.1 < X < 0$ \rightarrow

25. Example B: Section 9.5

	Number per Square	0	1	2	3	4	5	6	7	8	9	10	19
Frequency	56	104	80	62	42	27	9	9	5	3	2	1	

Likelihood Ratio
for a Poisson

$$\Lambda = \frac{\prod \hat{\lambda}^{x_i} e^{-\bar{x}} / x_i!}{\prod \hat{\lambda}^{x_i} e^{-\bar{x}_i} / x_i!} = \prod_{i=1}^n \left(\frac{\bar{x}}{x_i} \right) e^{x_i - \bar{x}} ; \bar{x} = \frac{0 \times 56 + 1 \times 104 + 2 \times 80 + \dots + 19 \times 1}{400} = 2.44$$

	Number Per Square	0	1	2	3	4	5	6	7	8	9	10	19
log likelihood	266.21	20.19	14.92	12.01	10.27	7.72	5.26	3.00	1.83	1.00	0.54	0.27	-2.44

$$-2 \log \Lambda = -2 \sum x_i \log \left(\frac{\bar{x}}{x_i} \right) + (x_i - \bar{x}) = -2 \sum x_i \log \left(\frac{x_i}{\bar{x}} \right) \approx -2 \sum (x_i - \bar{x}) - \frac{(x_i - \bar{x})^2}{2 \bar{x}} + \dots$$

$$\approx \sum_{i=1}^n \frac{(x_i - \bar{x})^2}{\bar{x}} = 5.8$$

$$-1/\Lambda = 2.54 \times 10^{-13}$$

26. a) False, the generalized likelihood ratio statistic favors or rejects at a boundary of less than or greater than 1

b) True, the corresponding test would reject at $\alpha = 0.02$

c) False, the p-value is 0.06 and not less than.

d) False, p-value is the smallest value at which the test would be rejected.

e) False, p-value is a threshold for rejection and simple hypotheses depend on a single value.

f) False, the p-value would be greater than 0.05.

27. $df = 7$

$\chi^2_{0.95} = 12.02$	$\chi^2_{0.9} = 14.07$	$\chi^2_{0.975} = 16.01$
$\chi^2_{0.99} = 18.48$	$\chi^2_{0.995} = 20.28$	

28a) $P(T > t_0 | H_0) = \alpha$; $P(1.5 > t_0 | H_0) \Rightarrow 1.5 = Z(\alpha)$

b) $Z(\alpha) > 0.9901$ $0.9332 = \alpha$

29. Yes, the monotone increasing function $S > g(t_0)$ is a test.

30a) Show $V = 1 - F(T)$; $F(t) = \int_{-\infty}^t f(t) dt = P(T > X_0 | H_0) = 1 - V = 1 - \alpha$

b) $P(V \leq z) = P(T \leq F^{-1}(z)) = F(F^{-1}(z)) = z$

c) $P(V < \alpha) = P(F(T) < \alpha) = P(T < F^{-1}(\alpha)) = P(F^{-1}(1-\alpha) < T)$

31) $\chi^2_{0.1} = 0.0158$ $= F(F^{-1}(\alpha)) = z = \alpha$

$$-2 \log \Lambda = \frac{n}{\sigma^2} (X - \mu)^2 \geq \chi^2_{0.1} = 0.0158$$

χ^2_p	$\chi^2_{0.1}$	$\chi^2_{0.05}$	$\chi^2_{0.01}$	$\chi^2_{0.001}$
2.6×10^{-1}	9.9×10^{-3}	3.4×10^{-4}	6.8×10^{-7}	

The similarities of likelihood [Λ] and chi-square [χ^2] are within 23% of each other indicating error of measurement from maximum likelihood estimate applied to observed vs expected values.

24. continued..

c) $n = 100, k = 2$

$$P(X-5 > 2) = P(X=0, 1, 2, 8, 9, 10) = \frac{7}{64} = 0.1094$$

d) $n = 100, k = 2$

$$P(X-50 > 10) = P(X-50 \geq 11)$$

$$E(X) = 100 \times 0.5 = 50$$

$$V(X) = 100 \times 0.5 \times 0.5 = 25$$

32. Object A: $\mu_A = 100$; $\sigma_A = 25$; Object B: $\mu_B = 125$; $\sigma_B = 25$

$$X = 120 \quad a) \lambda = \frac{e^{-\frac{(X-\mu_A)^2}{2\sigma^2}}}{e^{-\frac{(X-\mu_B)^2}{2\sigma^2}}} = e^{\frac{-(120-100)^2 + (120-125)^2}{2 \cdot 25^2}} = 0.74$$

b) $P(A) = P(B) = \frac{1}{2}$; $\frac{P(H_A|X)}{P(H_B|X)} = \frac{P(H_A)}{P(H_B)} \frac{P(X|H_A)}{P(X|H_B)} = 0.74$

c) $P(X > 125 | H_0) = P(X > 125) = \lambda$; $120 = z(\lambda/2)\sigma$; $z(\lambda) = 0$; $X = 0.519$

d) Power of Test: $B = \int_{125}^{\infty} e^{-\frac{(x-\mu_B)^2}{2\sigma^2}} \frac{1}{\sqrt{2\pi\sigma^2}} dx = 0.5$

e) $X = 120$; $\frac{|X-125|}{\sigma} = z(\lambda)$; $\frac{-5}{25} = z(\lambda)$; $\frac{-1}{5} = z(\alpha)$; $\frac{1}{5} = 1 - z(\alpha)$; $Z(\lambda) = 0.8$; $\lambda = 0.7931$

33.

	Jewish	Chinese & Japanese
Deaths Before Holiday	922	418
Deaths After Holiday	997	434
Pearson's χ^2	2.93	3.00
Likelihood Λ	2.93	3.004
p-value (df=1)	0.05 - 0.10	0.05 - 0.10

No evidence for capability of postponing death.

35.

Haptoglobin Type		
Hp1-1	Hp1-2	Hp2-2
10	68	112
$(1-\theta)^2$	$2\theta(1-\theta)$	θ^2

$\lambda = 0$; $\chi^2 = 0$
 $df = 2$; p-value < 0.01
 $\chi^2 = 7.39$

Cannot reject null hypothesis.

36.

Month	# Suicides	Days/Month	Probability
Jan	1867	31	0.085
Feb	1789	28	0.077
Mar	1944	31	0.085
Apr.	2094	30	0.082
May	2097	31	0.085
June	1931	30	0.092
July	1837	31	0.085
Aug	2024	31	0.085
Sep	1928	30	0.082
Oct	2032	31	0.085
Nov	1978	30	0.082
Dec	1859	31	0.085

$\chi^2 = (1867-1957)^2 + \dots + (1859-1957)^2$; $P(\theta|H_0) = \frac{1}{12}$; $P(\theta|H_1) = \sum p(\theta_i) = 1$

$n = 23480$; $E = np = 1957$

$= 51.79$

$\chi^2_{0.005} = 26.76$; p-value < 0.005

Since $\chi^2 > \chi^2_{0.9995}$ a rejection

of the null hypothesis occurs

and suicide is not constant at p-value = 0.005.

34. Problem #55: Chapter 8

0.035

Type	O	E	Likelihood Λ	Chi-squared χ^2
Starchy Green	1999	1953		
Starchy White	906	925	5.98	1.97
Sugary Green	904	925		
Sugary White	32	34		

p-value ~ 0.1 p-value ~ 0.9

$$\chi^2_{0.9} = 6.23 \quad \chi^2_{0.1} = 0.584$$

There is consideration to reject null hypothesis.

Multinomial: $f(\theta) = \frac{n!}{x_1! \cdots x_m!} p_1(\theta)^{x_1} \cdots p_m(\theta)^{x_m}$

$$mle = \bar{x} = np \quad p_i = \frac{x_i}{n}$$

Likelihood Ratio:

$$\Lambda = \frac{\frac{n!}{x_1! \cdots x_m!} p_1(\theta)^{x_1} \cdots p_m(\theta)^{x_m}}{\frac{n!}{x_1'! \cdots x_m'!} \frac{x_1}{p_1} \cdots \frac{x_m}{p_m}} = \prod_{i=1}^n \left(\frac{p_i(\theta)}{p_i} \right)^{x_i}$$

$$-2 \log \Lambda = -2 \sum x_i \left(\frac{p_i(\theta)}{p_i} \right)$$

$$= -2n \sum p_i \left(\frac{p_i(\theta)}{p_i} \right)$$

$$= 2n \sum p_i \left(\frac{p_i}{p_i(\theta)} \right)$$

37.

Month	# of Deaths
Jan	1668
Feb	1407
Mar	1370
Apr	1309
May	1341
June	1338
July	1406
Aug	1446
Sep.	1332
Oct	1363
Nov	1410
Dec	1526

$$P(H_0) = \text{Same "rate" of deaths} = \frac{1}{12}$$

$$P(H_1) = \text{Different "rate" of Deaths} = \sum P(X_i) = 1$$

$$\chi^2 = (1668 - 1410)^2 + \dots + (1526 - 1410)^2 / 1410$$

$$= 79$$

$$\chi^2 = 26.76 \quad ||_{0.995}$$

$\chi^2 > \chi^2_{0.995}$ which is

a rejection of null

hypothesis at p-value ≈ 0.005 .

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Male	3755	3251	3777	3706	3717	3660	3661	3626	3481	3590	3605	3392
Female	1362	1244	1496	1452	1448	1376	1370	1301	1337	1351	1416	1226

Male

Female

38.

Month	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
Male	3755	3251	3777	3706	3717	3660	3661	3626	3481	3590	3605	3392
Female	1362	1244	1496	1452	1448	1376	1370	1301	1337	1351	1416	1226

$$n=43229; E[X] = \bar{x} = 3602; \chi^2 = 74.6; \chi^2_{0.995} = 26.76; \text{Reject } H_0$$

$$n=16379; E[X] = \bar{x} = 1364.9; \chi^2 = 20.4; \chi^2_{0.995} = 21.92; \text{Accept } H_0$$

at p-value of 0.025.

$$P(H_0) = \text{Same "rate" of sickness} = 1/12$$

$$P(H_1) = \text{Different "rate" of sickness} = \sum P(X_i) = 1$$

Lunar Day	16,17,18	19,20,21	22,23,24	25,26,27	28,29,30	1,2,3	4,5,6,7	8,9,10	11,12,13	14,15
# of Bites	137	150	163	201	269	155	142	146	143	110

$$E[X] = \bar{x} = 162.1; \chi^2 = 107; \chi^2_{0.995} = 23.59; \text{Reject } H_0$$

$$P(H_0) = \text{Same "rate" of bites} = 1/10$$

No temporal trends

$$P(H_1) = \text{Different "rate" of bites} = \sum P(X_i) = 1 \quad n=280$$

40. Multinomial Distribution!

$$f(\theta) = \frac{n!}{x_1! x_2! \dots x_n!} p_1^{x_1} p_2^{x_2} \dots p_n^{x_n}$$

Observation
x_1
x_2

Pearson Chi-Squared:

$$\sum_{i=1}^2 \frac{(x_i - np_i)^2}{np_i} = \frac{(x_1 - np_1)^2}{np_1} + \frac{(x_2 - np_2)^2}{np_2}$$

$$= \frac{(x_1 - np_1)^2}{np_1} + \frac{(x_2 - n(1-p_1))^2}{n(1-p_1)}$$

$$= \frac{(x_1 - np_1)^2}{np_1(1-p_1)} + \frac{(x_2 - n(1-p_1))^2}{np_1(1-p_1)}$$

$$= X_1^2 - 2np_1 + n^2 p_1^2 - X_1^2 + 2np_1^2 - np_1^3 + X_2^2 p_1 - 2n(1-p_1)p_1 + n^2(1-p_1)p_1$$

$$n p_1 (1-p_1)$$

$$= \frac{(X_1^2 - np_1)^2}{np_1(1-p_1)}$$

$$\text{Relationships: } p_1 X_1 = X_1 X_2, np_1 = X_1 + X_2 = np_1^2 + np_1(1-p_1) = np_1^2 + np_1 - np_1^2 = np_1 - np_1^2$$

$$p_2 X_2 = X_2 X_1^2 + 4np_1^2$$

Breaks	Frequency
0	157
1	69
2	35
3,4,5	19

$$\chi^2 = (0-0.71)^2 + (1-0.71)^2 + (2-0.71)^2 + (3-0.71)^2$$

$$= 1.06; \chi^2_{0.95} = 1.250; \text{Reject above p-value 0.15.}$$

$$p_i = \frac{x_i}{n}$$

$$= 0.71$$

$$c) L = \frac{\prod_{i=1}^n p_i^{n_i p_i} (1-p_i)^{n_i(1-p_i)}}{\prod_{i=1}^n \hat{p}_i^{n_i \hat{p}_i} (1-\hat{p}_i)^{n_i(1-\hat{p}_i)}}$$

$$-2 \log L = \sum \frac{(x_i - n_i \hat{p}_i)^2}{n_i \hat{p}_i (1-\hat{p}_i)} = 2.701$$

$$L \approx 0$$

$$41. X_i = \text{bin}(n_i, p_i); i=1 \dots m$$

$$H_0: p_1 = p_2 = \dots = p_m$$

$$H_1: p_1 \neq p_2 \neq \dots \neq p_m; \sum p_i = 1$$

$$\Lambda = \frac{P(X|H_0)}{P(X|H_1)} = \frac{P(X|H_0)}{(1-P(X|H_0))} = \frac{\prod_{i=1}^m \binom{n_i}{x_i} p_i^{x_i} (1-p_i)^{n_i-x_i}}{1 - \prod_{i=1}^m \binom{n_i}{x_i} p_i^{x_i} (1-p_i)^{n_i-x_i}}$$

43. a) 9207 heads; 8743 tails in 17,950 coin tosses. $\hat{p} = \frac{x}{n} = 0.975$; $X^2 = \frac{(9207-8975)^2 + (8743-8975)^2}{8975} = 11.99$

# Heads	Freq.
0	100
1	524
2	1080
3	1126
4	655
5	105

$$P(X) = \binom{n}{x} p^x (1-p)^{n-x} = \binom{5}{x} (0.5)^x (0.5)^{5-x}; x=0,1,2,3,4,5$$

$$\chi^2 = 21.6$$

$$\chi^2 = 5.893; \text{ Reject } H_0 \text{ above } p\text{-value} = 0.001$$

$$C) P(x|H_0) = P(\text{coin } \#1|H_0) = P(\text{coin } \#2|H_0) = \dots = P(\text{coin } \#5|H_0) = \frac{1}{2}$$

$$\chi^2 = \sum \frac{[X_i - np(\theta)]^2}{np_i(\theta)} = 8.75; \chi^2_{0.9995} = 6.87 \quad \text{Reject } P(x|H_0) \text{ above } p\text{-value} = 0.0005$$

44.

Haplotypes Type		
H01-1	H01-2	H02-2
0:	10	68
E:	12	72

$$-2 \ln \Lambda \approx 0.91$$

$$\hat{\theta} = 0.748$$

Multinomial Distribution:

$$f(\theta) = \frac{n!}{x_1 \cdots x_m} p_1(x_1) \cdots p_m(x_m)$$

$$\text{Likelihood Ratio: } \Lambda = \prod_{i=1}^m \left(\frac{p_i(\theta)}{\hat{p}_i} \right)^{x_i}; -2 \ln \Lambda = 2 \sum O_i \ln \left(\frac{O_i}{E_i} \right)$$

$$P(\theta = Y_2, H_0); P(\theta \neq Y_2, H_1); \chi^2_{0.95} = 2.92; \text{ Accept } P(\theta = Y_2, H_0) \text{ at } p\text{-value of 0.05}$$

45. n = 6115 families

#	Frequency	Expected Freq.
0	7	4
1	45	39
2	181	180
3	478	511
4	929	980
5	1112	1336
6	1343	1327
7	1033	969
8	670	516
9	286	195
10	104	50
11	24	9
12	3	1

Binomial Random Variable

$$P(N) = P$$

$$P(D) = 1-P$$

$$P(X) = 0$$

$$P(X) = \binom{n}{k} p^k (1-p)^{n-k}$$

$$\bar{X} = 5.5 \quad P(X|H_0) = \text{Binomial}$$

$$P(\bar{X}) = 0.46 \quad P(X|H_1) \neq \text{Binomial}$$

$$\chi^2 = 5.51 \quad \boxed{\text{Reject } P(X|H_0) \text{ at } p\text{-value} = 0.0005}$$

$$47. \lambda = \text{mean}; Y = \sqrt{\lambda}; Y' = \frac{1}{2\sqrt{\lambda}}$$

Poisson Distribution

$$P(X) = \frac{\lambda^X e^{-\lambda}}{X!};$$

$$\lim_{n \rightarrow \infty} \sqrt{n}(P(X) - \theta) \rightarrow N(0, \theta)$$

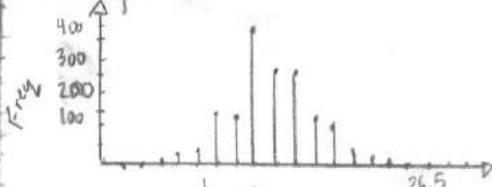
$$(2\sqrt{P(X)} - \frac{S}{Z\sqrt{n}}, 2\sqrt{P(X)} + \frac{S}{Z\sqrt{n}})$$

$$((\sqrt{P(X)} - \frac{S}{Z\sqrt{n}})^2, (\sqrt{P(X)} + \frac{S}{Z\sqrt{n}})^2)$$

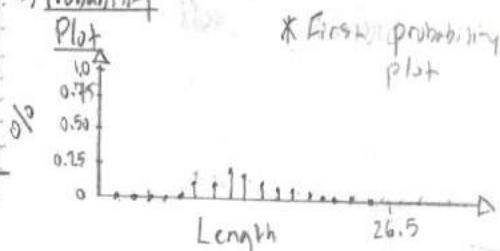
49.

Len	Freq.
13.5	0
14.0	1
14.5	3
20.0	33
20.5	39
21.0	156
21.5	152
22.0	342
22.5	238
23.0	296
23.5	100
24.0	86
24.5	21
25.0	12
25.5	2
26.0	0
26.5	1

a) Histogram:



b) Probability Plot:

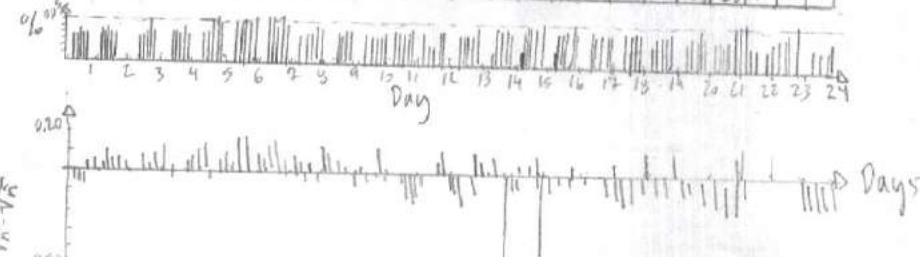
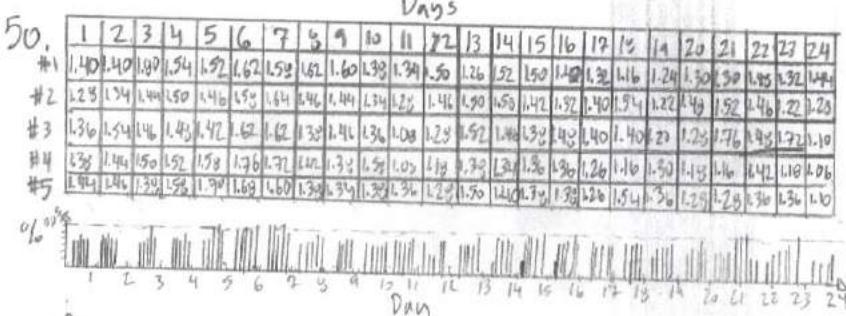
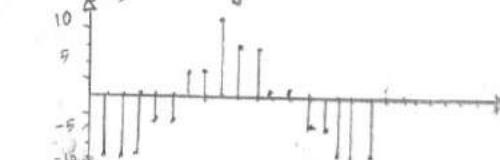


$$n = 1572$$

$$E[X] = 22.3$$

$$\hat{n} = 87$$

c) Hanging Rootogram



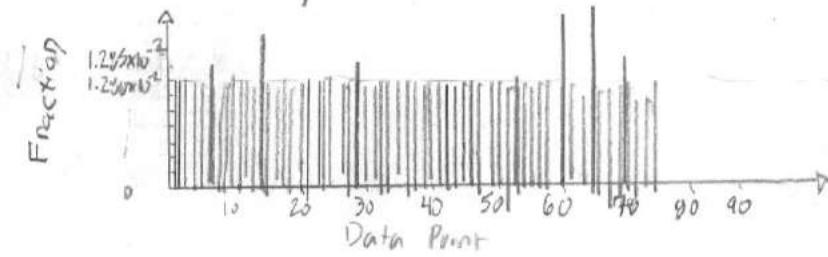
Note: Probability plots were correctly modelled by Problem #64

51. The horizontal bands of Figure 9.6 represent groupings of data with similar observations.

52. See chapter 9: problem 52.

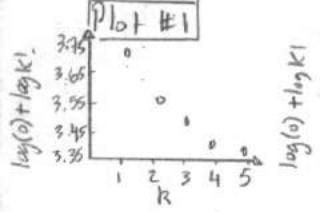


Probability Plot.

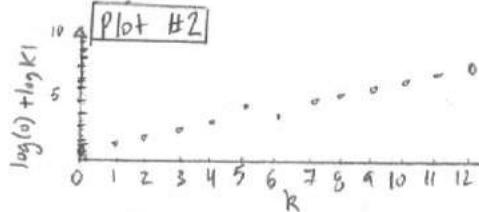


$$53. E_K = n P(X=k) = n e^{-\lambda} \frac{\lambda^k}{k!}; \log E_K = \log n - \lambda + k \log \lambda - \log k!$$

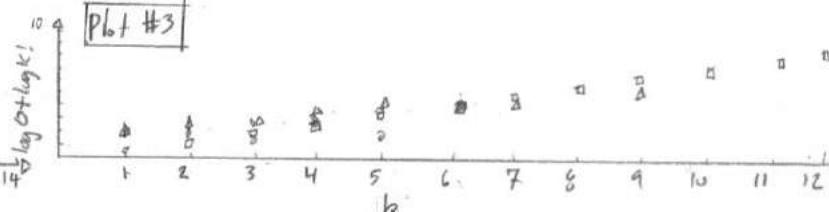
Plot #1



Plot #2



Plot #3



The plots contain regions of linearity.

54. $y = \log(x)$ a) Log Normal Distribution

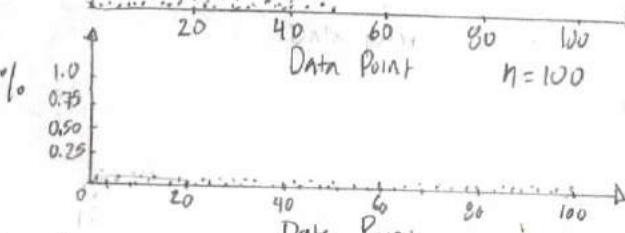
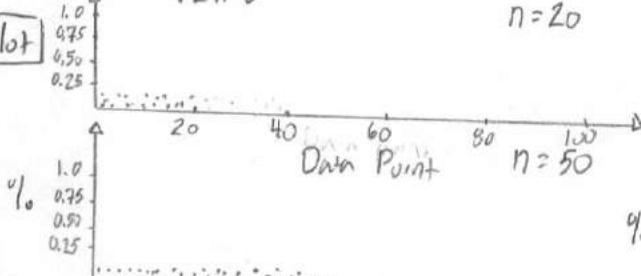
$$f(x|\mu, \sigma^2) = \ln p(x|\mu, \sigma^2) = \frac{-(x-\mu)^2}{2\sigma^2} - \ln \sqrt{2\pi\sigma^2}$$

b) a) Normal Distribution:

$$f(x|\mu, \sigma^2) = \frac{-\ln(x-\mu)^2/2\sigma^2}{\sqrt{2\pi\sigma^2}}$$

Plot

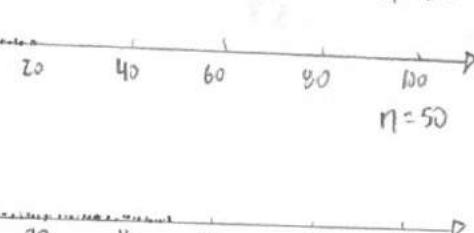
$n=20$



The data fits lognormal until length 115mm which is above a p-value of 0.05.

$$C) Y = Z/V; Z \sim N(0,1); V \sim U[0,1]$$

$n=20$.

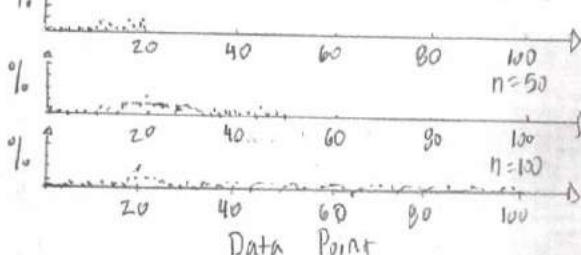


Note: Probability plots were correctly modelled by problem #64.

b) Chi-square Distribution

$$P(X|n) = \frac{1}{Z^{n/2} T(n/2)} X^{n/2-1} e^{-X/2}$$

$n=20$



$n=100$

$n=50$

$n=100$

$n=50$

$n=100$

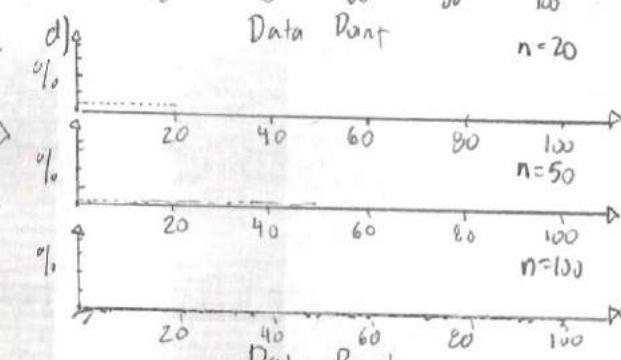
$n=50$

$n=100$

$n=50$

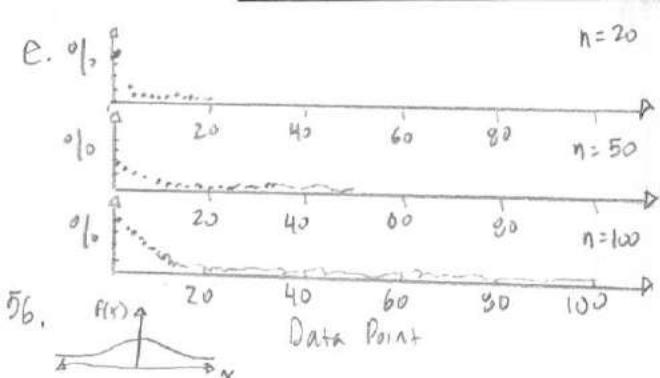
$n=100$

Degrees of Freedom = 10.



Uniform Distribution

$$f(x) = \frac{1}{b-a}$$



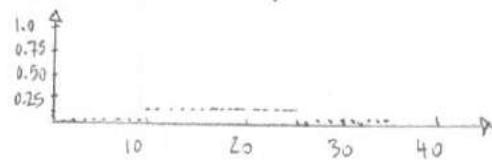
57. Cauchy Distribution $f(x) = \frac{1}{\pi(1+x^2)}$



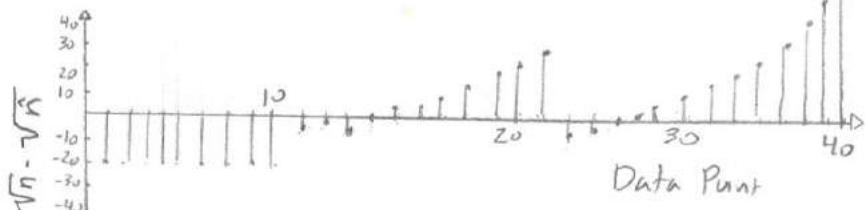
58. $F(x) = 1 - e^{-\lambda x}$; $\lambda = \frac{1}{x}$

F. The distributions plotted are separable from each other, and a normal distribution

$$F(x) = 1 - e^{-\lambda x}; \lambda = \frac{1}{x}$$

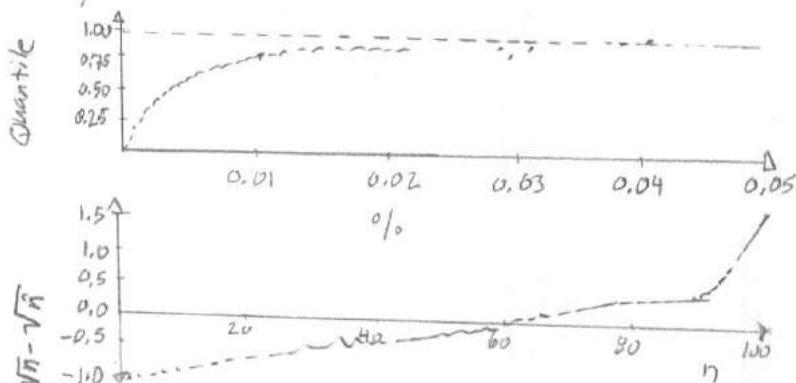


Data Point



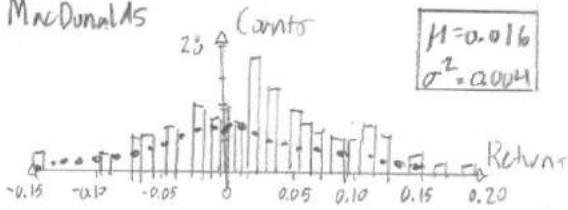
Data Point

59. $n=76$ a)

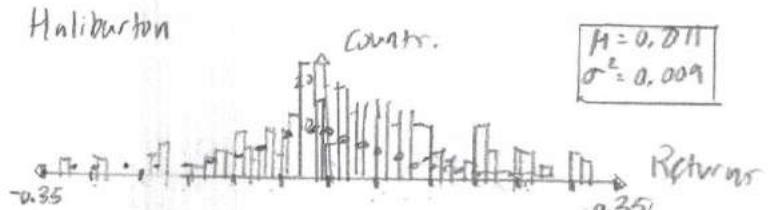


The appearance of the plot represents a convergence of % Stress Failure for Kevlar 49/epoxy against quantile grouping of an exponential distribution.

61. a) MacDonalts



Haliburton



b) [The more volatile stock company is Haliburton]

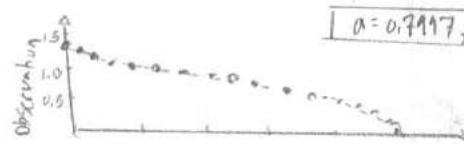
62. Poisson Dispersion Test: 63.

$$\Lambda = \prod (x_i) e^{x_i - \bar{x}}$$

$$-2 \log \Lambda = 2 \sum x_i \log \left(\frac{x_i}{\bar{x}} \right) \approx \frac{1}{\bar{x}} \sum_{i=1}^n (x_i - \bar{x})^2$$

$$= 3476.5.$$

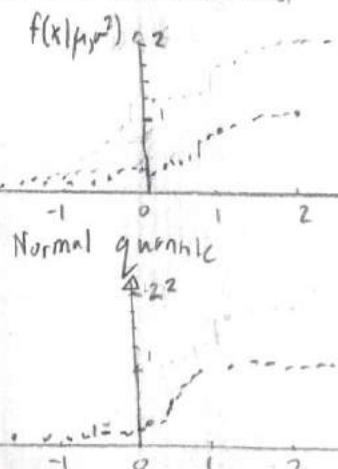
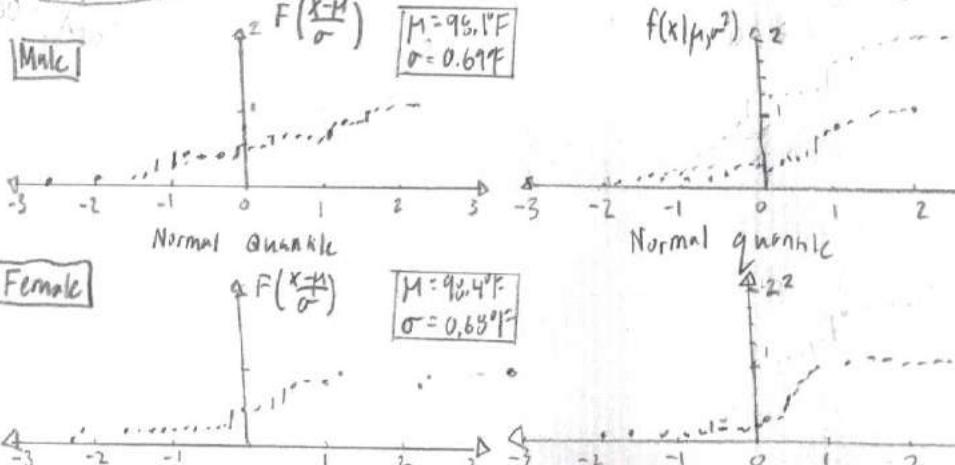
$$a = 0.7117, b = 1.3188$$



Ordered Quantiles of a Gamma Distribution

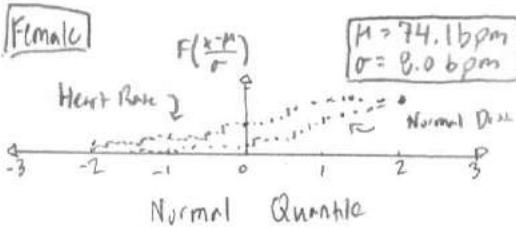
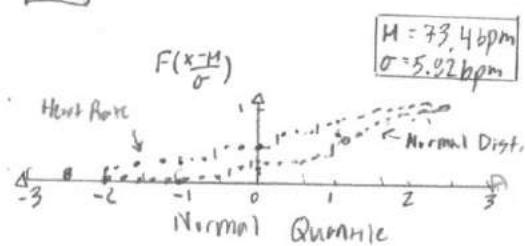
Note: Probability plots were correctly modelled by problem #64

64. a) Male



The assessment of body temperatures for both male and female demonstrate a higher proportion near the mean than normally distributed.

b) Male

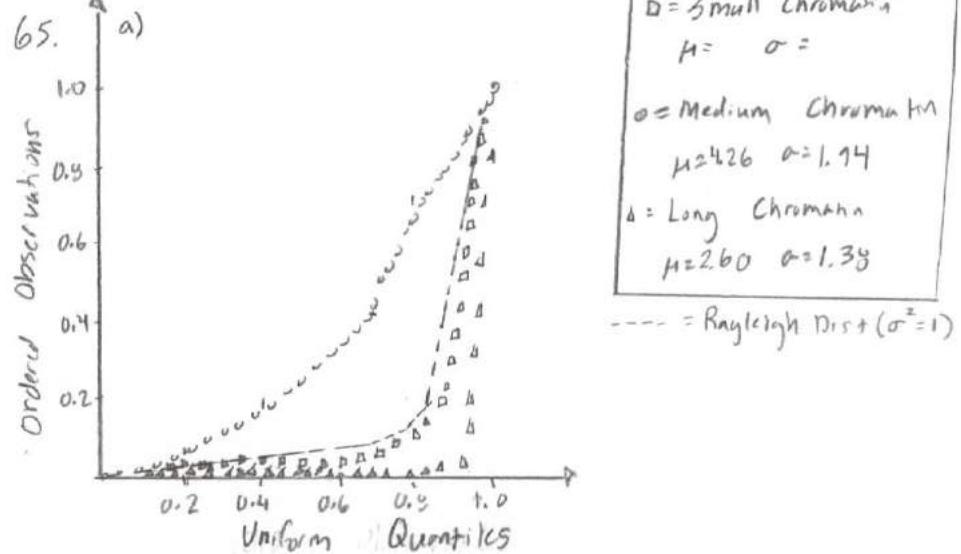


Male and Female heart rate both contain a larger proportion of reading near the mean than a normal distribution.

c. $P(x = 93.6^\circ F | H_0)$ vs $P(x \neq 93.6^\circ F | H_1)$ Male

 $\bar{X}^2 = 0.3185 ; \chi^2_{65, 0.005} = 39.39$; Accept $P(x | H_0)$ at p-values > 0.995

$P(x = 93.6^\circ F | H_0)$ vs $P(x \neq 93.6^\circ F | H_1)$

 $\bar{X}^2 = 0.3956 ; \chi^2_{65, 0.005} = 39.39$; Accept $P(x | H_0)$ at p-values > 0.995
 

b) $\bar{X}_{\text{short}}^2 = 24.43$ $\bar{X}_{\text{med}}^2 = 117.4$ $\bar{X}_{\text{long}}^2 = 192.0$

$df = 9.5$ $df = 131$ $df = 248$

$\chi^2_{95, 0.995} = 63.25$ $\chi^2_{131, 0.75} = 119.750$ $\chi^2_{243, 0.995} = 194.391$

Accept at
p-value > 0.005

Reject at
p-value > 0.25

Accept at
p-value > 0.005

$$28. n=3 \Rightarrow P(X_{(1)} < n < X_{(2)}) = 1 - P(n < X_{(1)} \text{ or } n > X_{(2)}) = 1 - P(n < X_{(1)}) - P(n > X_{(2)})$$

$$= 1 - \frac{1}{2^3} \sum_{j=0}^1 \binom{4}{j} = 1 - \frac{1}{8} (1+4) = 37.50\%$$

$$P(X_{(1)} < n < X_{(3)}) = 1 - P(n < X_{(1)} \text{ or } n > X_{(3)}) = 1 - P(n < X_{(1)}) - P(n > X_{(3)}) = 1 - \frac{1}{2^{n-1}} \sum_{j=0}^1 \binom{5}{j} = 62.50\%$$

29. a) The distribution is binomial because probability for success and failure exist when considering a outlier distribution.

b) $P(N \geq 10) = Bi(n=10, p=\frac{5}{26}) = 0.013$

c) The probability of 1000 bootstrap sampler would be $1000 \cdot Bi(n \geq 10, p=5/26)$

d) The probability that every sample is an outlier would be $(\frac{5}{26})^{1000} = 1.80$

30. By sampling 1000 times without replacement the bootstrap standard deviation was 0.64 vs. the actual standard deviation of 0.97. $= 2.42 \times 10^{-10}$

31. a) $n = \text{Number of samples}; p = \text{probability}; \boxed{n^p}$

b) $n=3, X_1=1, X_2=3, X_3=4;$

$$X \in \{(1,1,1), (1,1,3), (1,1,4), (1,3,1), (1,4,1), (3,1,1), (4,1,1), (1,3,4), (14,1,3), (3,3,3), (3,1,3), (3,4,3), (1,3,3), (4,3,3), (3,3,1), (3,3,4), (3,1,4), (3,4,1), (4,4,4), (4,4,1), (4,4,3), (4,1,4), (4,3,4), (14,4), (3,4,4), (4,1,3), (4,3,1)\}$$

c)

Sample	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
Mean	1.00	1.67	2.00	1.67	2.00	1.67	2.00	2.67	2.67	3	2.33	2.00	2.33	2.00	2.33	2.33	2.67	2.67	4.00	5.00	3.67	3.00	3.67	3.00	3.67	2.67	

\bar{X}_i	1.00	1.67	2.00	2.33	2.67	3.00	3.33	3.67	4.00
$P(\bar{X})$	1/27	3/67	3/67	3/67	6/27	3/27	3/27	1/27	1/27

d) $S_E = \sqrt{\frac{1}{n-1} (\bar{X}_i - \bar{X})^2} = 0.5366 \text{ vs } 0.5469$

32. The Median Absolute Deviation from the median (MAD) as defined by the median of $|X_i - \bar{X}|$ is

approximated by a bootstrap through sampling the ~~the~~ set produced by the definition.

33. The mean and standard deviation.

34. $f(x) = |x|$; $f'(x) = 0 @ x=0$; Median of $f(x)=|x|$ is 0.

35. The proportion of points marked by an asterisk would be 15% of sample because of the inner quartile range (IQR).

36. The IQR is divided by 1.35 because for a double sided distribution each tail is subdivided by 0.675 or which each represent Q_1 and Q_3 of the sample.

Median Absolute Deviation from the median (MAD) contains 0.675 because of the quartile range being 0.675 or.

37. a) Mean = 14.98, Median = 14.57, Mean (10%) = 14.59, Mean (20%) = 14.59

b) $14.58 \pm 1.27\% \text{ WAX}$

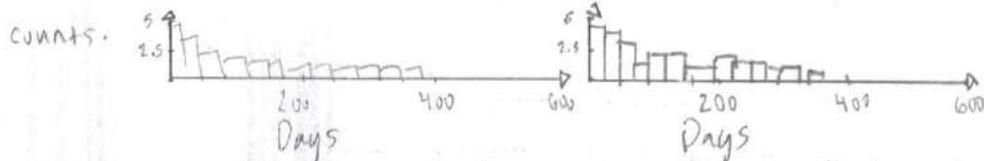
d) $S.E. = \frac{\sigma}{\sqrt{n}} \sqrt{1 - \left(\frac{1-1}{n-1}\right)} = 0.05\%$

c) $C.I. = (13.31, 15.85)$

$S.E. = 0.03\%$

22. Survival Function: $S(t) = 1 - F(t)$; $S_n(t) = 1 - \hat{F}(t)$

23. $X_{(n)} \& Y_{(n)} = \frac{k}{n+1}$;



Linear Interpolation Function:

$$y = y_0 \left(\frac{x_1 - x}{x_1 - x_0} \right) + y_1 \left(\frac{x - x_0}{x_1 - x_0} \right); \frac{k}{n+1} \leq p \leq \frac{(k+1)}{n+1} \therefore \frac{-k}{n+1} \geq -p \geq \frac{-(k+1)}{n+1} \therefore 1 - \frac{k}{n+1} \geq 1 - p \geq 1 - \frac{(k+1)}{n+1}$$

$$f(x) = X_{(k)} \left(\frac{k+1}{n+1} - p \right) + X_{(k+1)} \left(p - \frac{k}{n+1} \right); 1, 2, 3, 4, 5, 6, \dots$$

24. Empirical Distribution: $F_n = y$ -axis

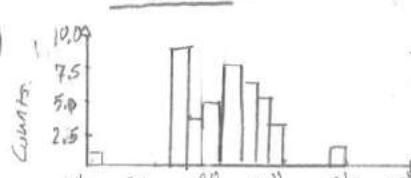
Theoretical Distribution: $F = x$ -axis

$$\begin{aligned} L.Q. &= \frac{(n+1)}{4} = 2 \\ \text{Median} &= 3.5 \\ U.Q. &= \frac{3(n+1)}{4} = 5 \end{aligned}$$

$$25. Y_p = G(X_p); F(x) = p; X = F^{-1}(p) = \frac{Y_p}{c}; F\left(\frac{Y_p}{c}\right) = p = G\left(\frac{Y_p}{c}\right)$$

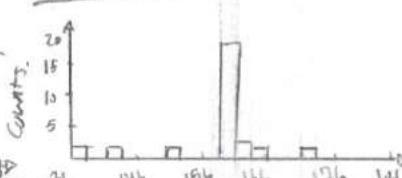
26.

Rhodium:



Temp (°C)

Iridium:



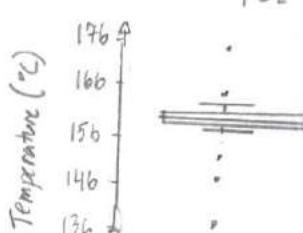
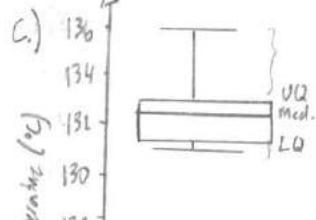
Temp (°C)

b.)

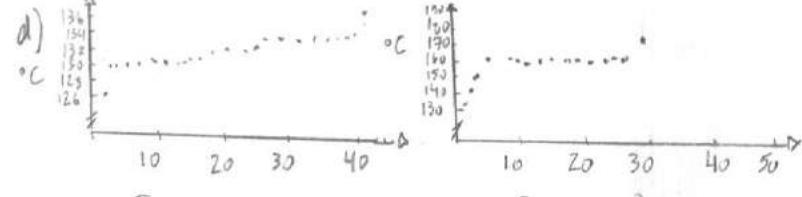
Stem Leaf

1	1	126	: 4
13	12	131	: 1234569
25	12	132	: 123456789
37	12	133	: 03450
39	2	134	: 12
40	1	135	: 7

c.)



d.)



Data point

Data Point

e.) Yes, independent and identically distributed
from the experimental measurement, in addition
to Plots of data.

f. Rhodium

$$\begin{aligned} \mu &= 132.42^\circ\text{C} \\ \mu_{90\%} &= 132.46^\circ\text{C} \\ \mu_{95\%} &= 132.47^\circ\text{C} \end{aligned}$$

$$\begin{aligned} SE &= 0.24^\circ\text{C} \\ 132.42 &\pm 0.40^\circ\text{C} \end{aligned}$$

$$CI = (132.02^\circ\text{C}, 132.82^\circ\text{C})$$

$$\begin{aligned} 10\% \text{ trim} & \\ SE &= 0.25^\circ\text{C} \end{aligned}$$

$$\begin{aligned} 20\% \text{ trim} & \\ SE &= 0.23^\circ\text{C} \end{aligned}$$

$$\text{Median} = 132.65^\circ\text{C}$$

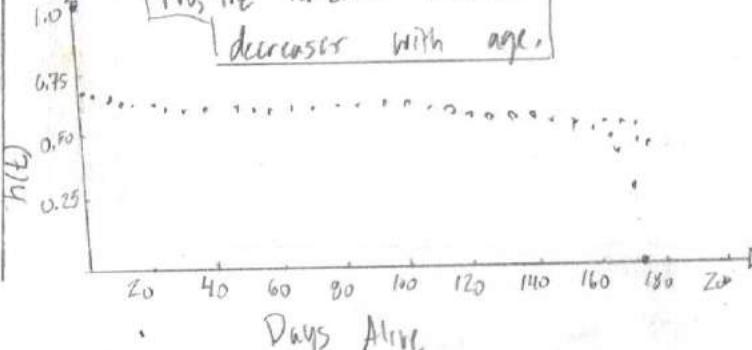
$$10\% \text{ trim} \quad CI = (132.05^\circ\text{C}, 132.87^\circ\text{C})$$

$$20\% \text{ trim} \quad CI = (132.00^\circ\text{C}, 132.95^\circ\text{C})$$

$$10\% \text{ trim} \quad CI = (157.67^\circ\text{C}, 162.05^\circ\text{C})$$

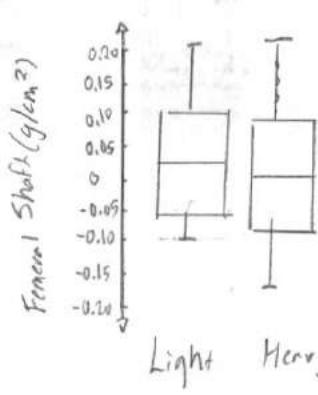
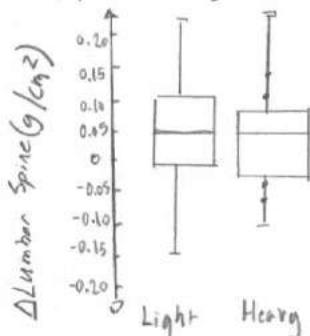
$$20\% \text{ trim} \quad CI = (157.23^\circ\text{C}, 162.45^\circ\text{C})$$

$$27. \quad \text{No, the hazard function decreases with age.}$$



43. When evaluating Kevlar [70%, 80%, 90%], the data's mean, median, and standard deviation demonstrate increasing skew for increasing stress levels.

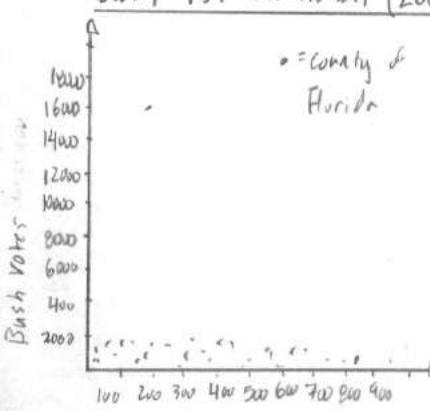
44. Light Smoking (≤ 7 cigarettes/day); Heavy Smoking (> 7 cigarettes/day)



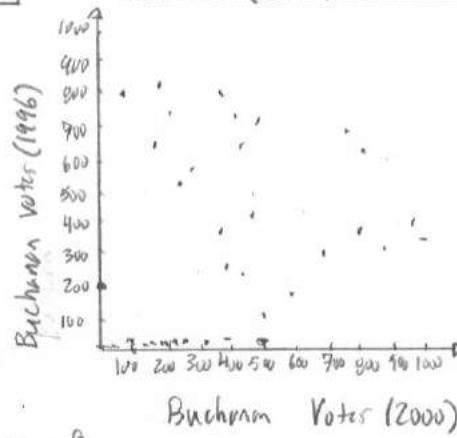
The bone density of light vs heavy smoking twins led to different conclusions. Although both light and heavy smoking twins had larger change to bone mass than the nonsmoking group.

Data not shown.

45. Bush vs. Buchanan (2000)

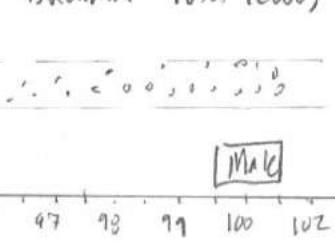
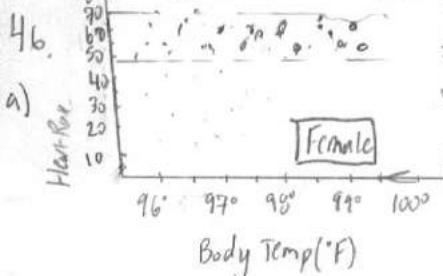


Buchanan (1996) vs Buchanan (2000)



The Buchanan (1996) vs.

Buchanan (2000) shows similar amount of popular voters, while Bush's entry into presidency was led with 2x amount of voters, and in Monroe County 16,000+ voters.



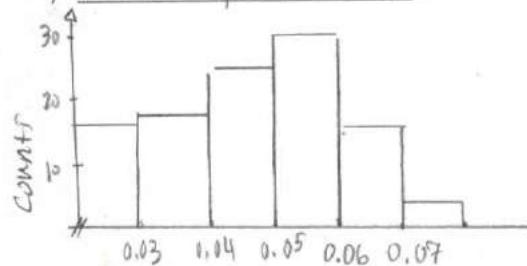
Heart rate for males and females remained within the same range, but male temperature did contain maximum upwards of 100°F.

b) $r_{\text{Male}} = 1.72 ; r_{\text{Female}} = 2.61 ; p_{\text{Male}} = 0.034 ; p_{\text{Female}} = 0.077$

Heart rate and body temperature show positive correlation.

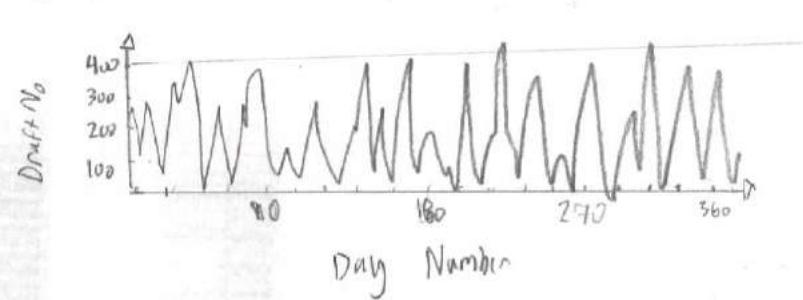
c) The female body temperature shows greater linear correlation than males.

47. a) Duration per Interval (min/interval)



b) Duration per Interval (min/interval)

Old Faithful when measured tends to erupt for 3.6 seconds per "gush".



No trend

f. $SD = 0.761\%$ wax; $IQR = 1.09\%$ wax; $MAD = 0.58\%$ wax	$15.13, 15.15, 15.18, 15.21, 15.22, 15.31, 15.38, 15.4, 15.47$
g. $SE = 0.17\%$ wax; Sampling Distribution	$15.47, 15.49, 15.56, 15.63, 15.91, 17.09.$

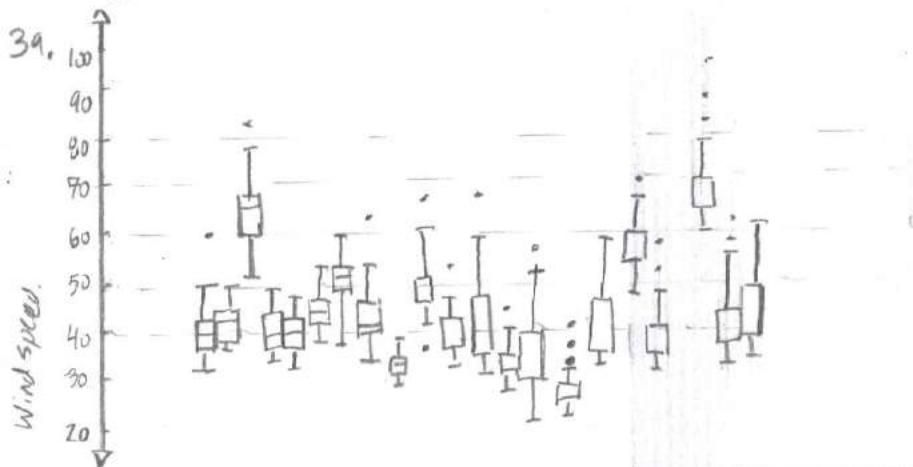
38. Cauchy Distribution:

$$f(x) = \frac{1}{\pi} \left(\frac{1}{1+x^2} \right); -\infty < x < \infty$$

$$\mu = 0.009813 \text{ b } SD = 0.039019.$$

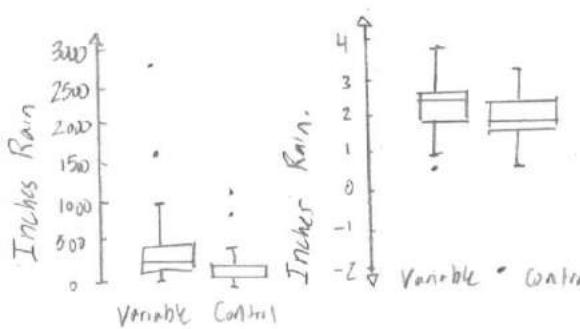
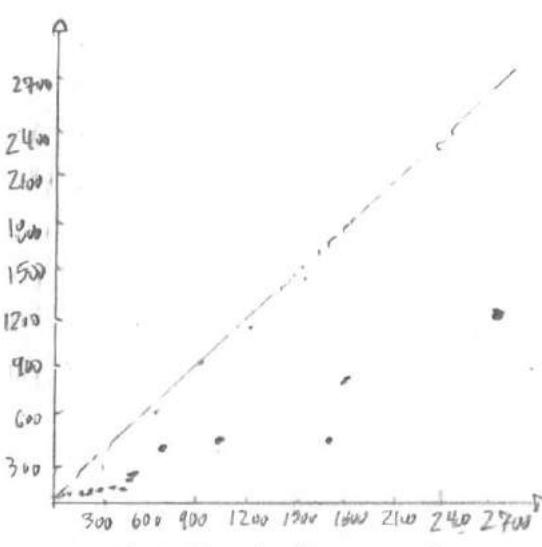
Median = 0

Distribution



Sample.

40.



The variable of "seeded" clouds produced more inches of rain than the control group of clouds.

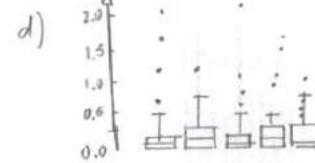
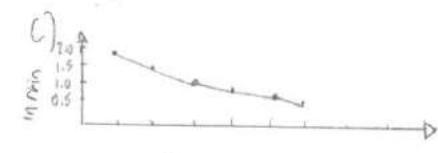
$$41. P(X > X_p) = 1-p; P(X < X_p) = p;$$

$$= 1 - P(X < p) = 1 - \sum_{i=0}^n \binom{n}{i} p^i (1-p)^{n-i}$$

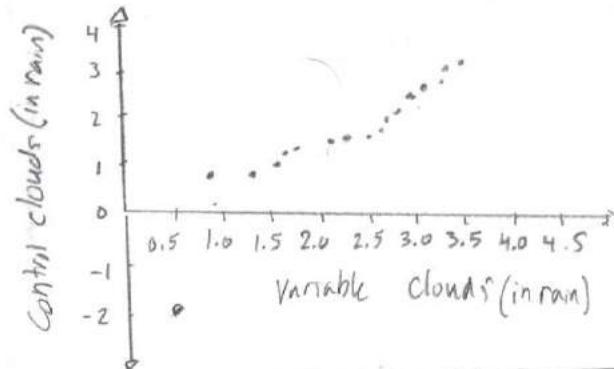
42. a) Skewed b)

Year	'60	'61	'62	'63	'64
Average	0.72	0.27	0.19	0.26	0.19
Median	0.015	0.075	0.02	0.11	0.055

The median is different from average because of the large skew of the datasets.

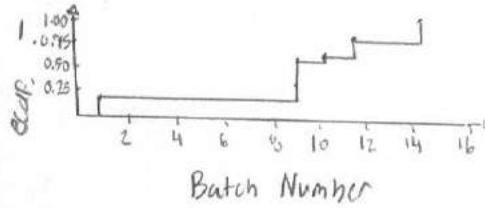


e) The wet years were '61 and '63, while dry years were '62 and '64. The reason for wet years was because of storms not daily rain fall.

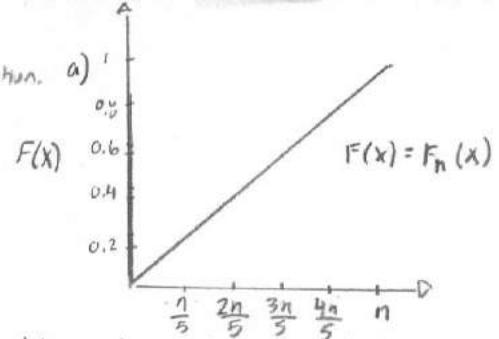


The above plots show the variable clouds produce more inches of rain than the control group of clouds. Seeded clouds produced more rain exponentially vs control set. The box plots of each graph would be much different because of mean and standard deviation differences.

Chapter 10:



2. X_1, X_2, \dots, X_n with Uniform Distribution.
 a) $F_{n,k}(x)$ is a monotonically increasing function, while $F_n(x) - F_{n,k}(x)$ is a decreasing function.

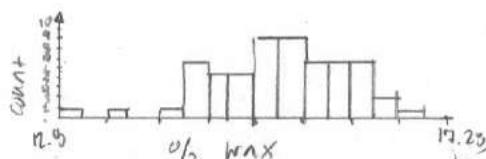
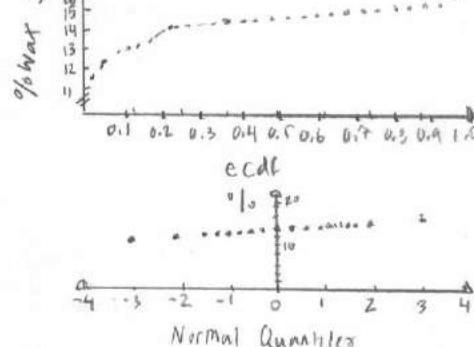


3. Lower quantile ($T < 63.9^{\circ}\text{F}$)
 Upper quantile ($T > 63.8^{\circ}\text{F}$)

4. $I_{(-\infty, x]}(X_i)$ are independent random variables because the data are independent.

$$5. \text{Cov}[F_n(u), F_n(v)] = \frac{1}{n} [F(m) - F(u)F(v)] : m = \min(u, v) \therefore \text{Cov}(F_n(u), F_n(v)) = E(F_n(u)F_n(v)) - E(F_n(u))E(F_n(v))$$

6. a)



$$q_{0.90} = 16.6\% \quad q_{0.50} = 14.7\% \quad q_{0.10} = 12.8\% \\ q_{0.75} = 15.9\% \quad q_{0.25} = 13.5\%$$

b) Average (%) Wax = 85% ; A dilution of 1%, 3%, and 5% microcrystalline wax are measurable quantities with a standardized average (%) wax.

7. The 10% weakest guinea pigs die within 200 days, and the 10% strongest survive until 400 days. While the median population live until 350 days.

$$8. n=100 \text{ s } \lambda=1 \text{ a) } S(t) = P(T > t) = 1 - F(t) ; S_n(t) = 1 - F_n(t) = 1 - e^{-t} ; \text{Var}[\log(1 - F_n(t))] = \frac{1}{n} \left(\frac{F(t)}{1 - F(t)} \right)$$

b) Survival plots show exponentially growing standard deviation for the survival function.

9. Method of Propagation Error: $Y = g(X) \approx g(\mu_X) + (X - \mu_X)g'(\mu_X)$
 $E[Y] \approx g(\mu_X) + \frac{1}{2} \sigma_X^2 g''(\mu_X)$

$$g(\mu_X) = \log S_n(\mu_X) \\ = \log(1 - F(\mu_X))$$

$$g'(\mu_X) = \frac{-F'(\mu_X)}{1 - F(\mu_X)} = \frac{1}{n} \left(\frac{-F(X)}{1 - F(X)} \right)$$

$$E[Y] \approx \log(1 - F(\mu_X)) - \frac{1}{2n} \frac{F(X)}{1 - F(X)} \\ | (-), \text{Error} |$$

$$10. X_1, \dots, X_n = X_{(1)} \dots X_{(n)} \quad f_R(x) = n \binom{n-1}{R-1} [F(x)]^{R-1} [1 - F(x)]^{n-R} f(x)$$

a) Uniform Distribution

$$f_R(x) = \frac{1}{b-a}, [a=0, b=1] \quad E(X_R) = \int_0^1 x f_R(x) dx = n \binom{n-1}{R-1} \int_0^1 x \left[\int_0^x f(x) dx \right]^{R-1} [1 - \int_0^x f(x) dx]^{n-R} dx \\ = n \binom{n-1}{R-1} \int_0^1 x (1-x)^{n-R} dx = n \binom{n-1}{R-1} \cdot \text{Beta}(R+1, n-R+1) \\ = n \frac{(n-1)!}{(R-1)!(n-R)!} \cdot \frac{\Gamma(R+1)\Gamma(n-R+1)}{\Gamma(n+2)} = n \frac{(n-1)!}{(R-1)!(n-R)!} \\ = \frac{(R-1)!(n-R)!}{(n+1)!} \frac{1}{\binom{n}{R}}$$

$$\Gamma(p) = (p-1)\Gamma(p-1) = (p-1)!$$

$$E[X_R^2] = \int_0^1 x^2 f_R(x) dx = n \binom{n-1}{R-1} \int_0^1 x^{R+1} (1-x)^{n-R} dx = n \binom{n-1}{R-1} \times \text{Beta}(R+2, n-R+1) ; \text{Var}(X) = \frac{k(R+1)}{(n+1)(n+2)} - \frac{k^2}{(n+1)^2} \\ = n \frac{(n-1)!}{(R-1)!(n-R)!} \times \frac{\Gamma(R+2)\Gamma(n-R+1)}{\Gamma(n+3)} = n \frac{(n-1)!}{(R-1)!(n-R)!} \cdot \frac{(R+1)(n-R)!}{(n+2)!} = \frac{k(R+1)}{(n+1)(n+2)}$$

$$= \frac{1}{(n+2)} \left(\frac{k}{n+1} \right) \left(1 - \frac{k}{n+1} \right)$$

b. $X_i = F(Y_i)$; $Y_i = F^{-1}(X_i)$; $F(Y_i) = \int f(y) dy = y$; $X_i = Y_i$; $Y_{(k)} = F^{-1}(X_{(k)}) \approx F^{-1}\left(\frac{k}{n+1}\right) + \left(X_{(k)} - \frac{k}{n+1}\right) \frac{d}{dx} F'(x)\Big|_{k/n+1}$

c. If $p = \frac{k}{n+1}$; $\text{Var}(Y_k) = p(1-p) \cdot \frac{1}{f(x)^2} \cdot \frac{1}{n+2} \approx \frac{p(1-p)}{n F(x)^2}$

d. $N(\mu, \sigma^2)$; Median = $x = Y_2$

$$\text{Var}\left(\frac{1}{2}\right) = \frac{1}{n} \frac{p(1-p)}{f(Y_2)^2}$$

$$\frac{1}{n} - \frac{*}{n+2}$$

$$= E[Y_k] + \frac{1}{2} \sigma_{Y_k}^2 f''(Y_k)$$

$$E[Y_k] = F^{-1}\left(\frac{k}{n+1}\right)$$

$$\text{Var}(Y_k) = \frac{k}{n+1} \left(1 - \frac{k}{n+1}\right) \frac{1}{F'(F^{-1}[k/(n+1)])^2} \left(\frac{1}{n+2}\right)$$

11. $F(t) = 1 - e^{-\kappa t^p}$; Hazard Function: $P(t \leq T \leq t+\delta | T \geq t) = \frac{P(t \leq T \leq t+\delta)}{P(T \geq t)}$

$$= \frac{F(t+\delta) - F(t)}{1 - F(t)} = \frac{-e^{-\kappa(t+\delta)^p} + e^{-\kappa t^p}}{1 - e^{-\kappa t^p}}$$

$$- \int_0^t \frac{F(s)}{1-F(s)} ds = - \int_0^t \frac{1-u}{u} du = - \int_0^t \frac{u+1}{u} du = - \int_0^t 1 + \frac{1}{u} du$$

$$= F(s) - 1 \Big|_0^t - \ln(|F(s) - 1|) \Big|_0^t = F(t) - F(0) - \ln(|F(t) - 1|) + \ln(|F(0) - 1|)$$

$$= F(t) - \ln(F(t) - 1); f(t) = \frac{F(t)}{1-F(t)} e^{-F(t)} - \ln(F(t)-1) \Big|_{-F(t)} = -F(t) e^{-F(t)}$$

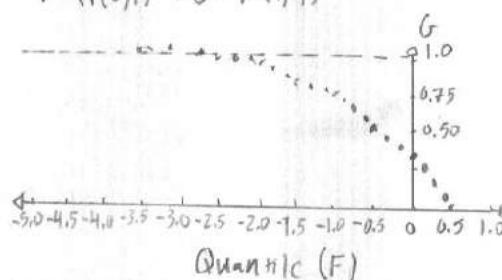
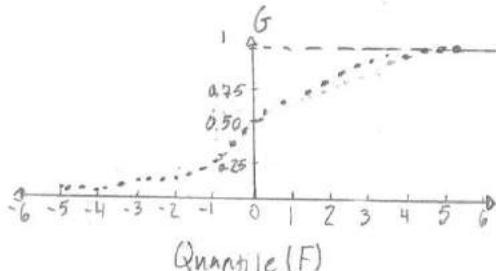
13. A probability distribution with increasing failure rate would be a Pareto distribution because $h(t)$ is positive. The uniform distribution has form $e^{-t/L}$ too.

14. A probability distribution with decreasing failure rate would be the exponential distribution with the form $-F(t)e^{-F(t)}$.

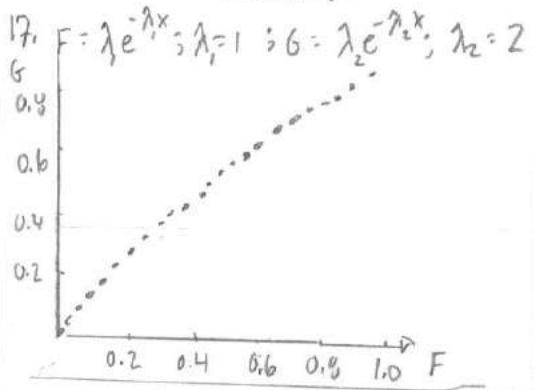
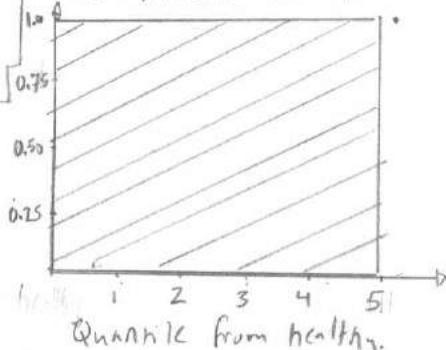
15. $T = \text{Time of release}$. $h(t) = \frac{f(t)}{1-F(t)} = \frac{\frac{1}{24}}{1-\frac{t}{24}} = \frac{1}{24-t}$; The smallest of t is 0 hours while largest 24 hours.

$$h(5) = \frac{1}{19} \text{ vs } h(1) = \frac{1}{24} \text{; The prisoner has greater likelihood.}$$

$$F = N(0, 1); G = N(1, 4)$$



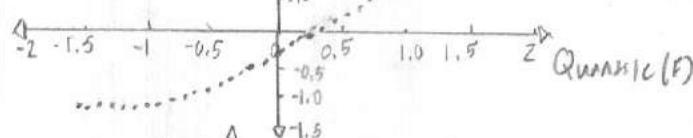
16. III & longer lifetime
Healthy & shorter lifetime
 $P(\text{healthy}_j | \text{PInecho}) = P(\text{healthy})$
 $P(\text{III} | \text{PInecho}) = P(\text{III})$



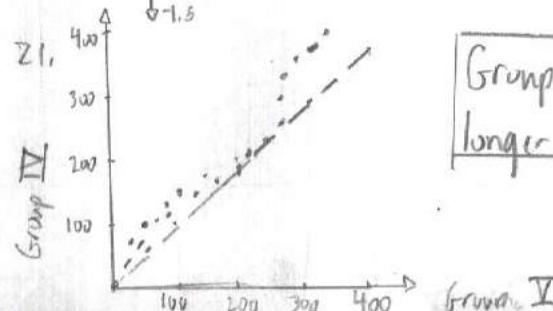
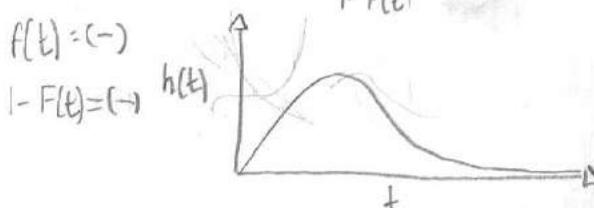
$$18. F(x) = x; 0 \leq x \leq 1$$

$$G(x) = x^2; 0 \leq x \leq 1$$

$$\text{Quantile}(G)$$



19. Hazard Function: $h(t) = \frac{f(t)}{1-F(t)}$



b) Pearson Rank Correlation Coefficient (r) = -2.0×10^{-5}

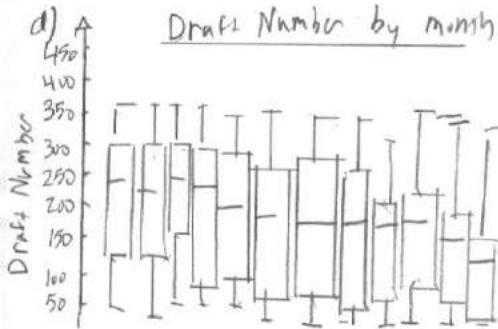
No linear correlation or trend!

Spearman Rank Correlation Coefficient (ρ) = -0.23.

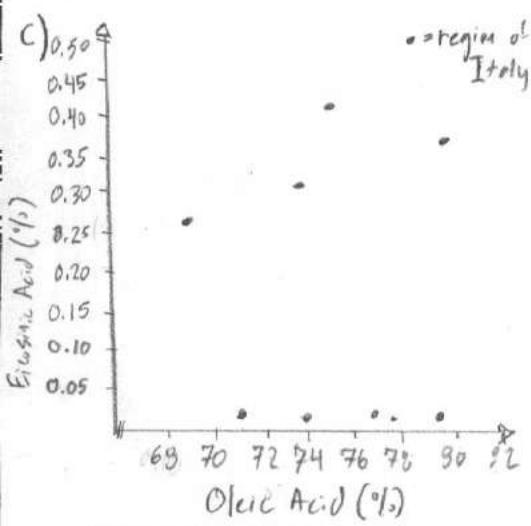
Little negative correlation to justify

c) Statistical Significance via method listed in the book justified no correlation

d) Draft Number by month 49. a.



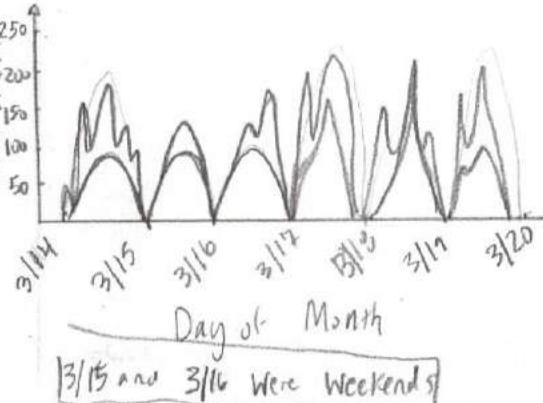
No pattern for 1970 lottery
because max/min were
equivalent and mean within
50 drafts.



d) 2% separation as a principle analysis

The regions are distinguishable
with simple tools and scale.

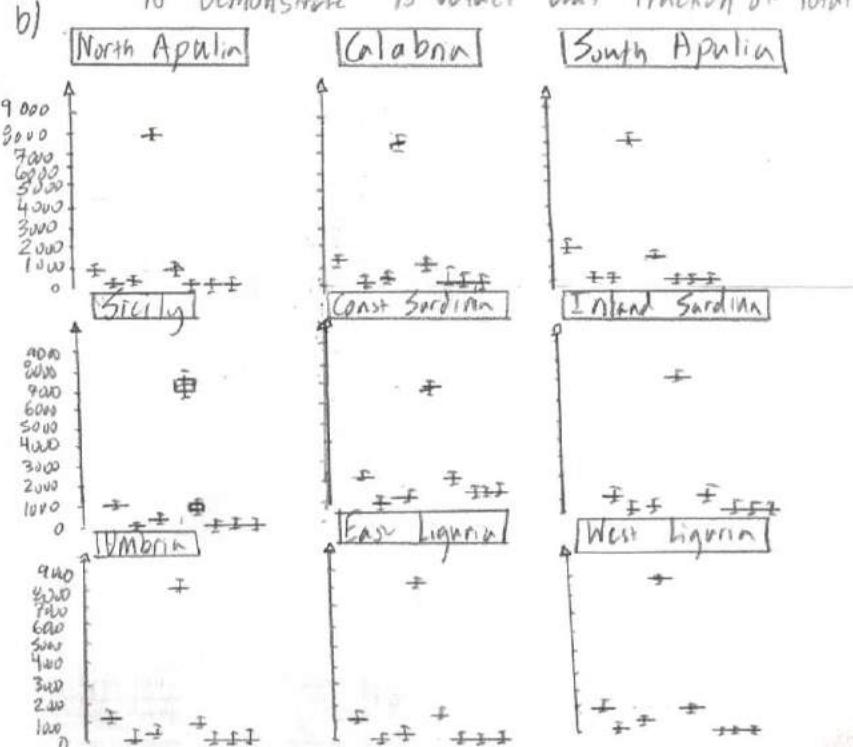
e) Completed.



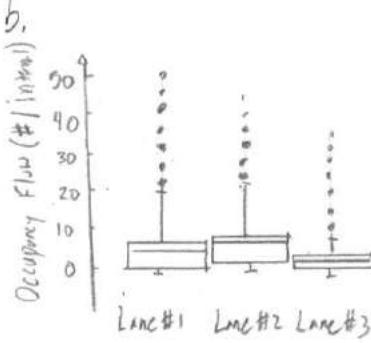
3/15 and 3/16 Were Weekends

Oil Type	Palmitic	Palmitoleic	Stearic	Oleic	Linoleic	Linolenic	Arachidonic	Eicosanoic	
North Apulia	Mean	10.3%	0.6%	2.3%	70.2%	7.1%	0.4%	0.7%	0.3%
	Median	10.5%	0.6%	2.4%	70.2%	7.0%	0.5%	0.8%	0.3%
Calabria	Mean	13.0%	1.2%	2.6%	73.1%	8.2%	0.5%	0.6%	0.2%
	Median	13.0%	1.2%	2.6%	73.0%	8.3%	0.5%	0.7%	0.3%
South Apulia	Mean	14.0%	1.8%	2.1%	69.1%	11.7%	0.3%	0.6%	0.2%
	Median	13.7%	1.8%	2.1%	69.1%	11.7%	0.3%	0.6%	0.2%
Sicily	Mean	12.3%	1.0%	2.7%	73.6%	0.3%	0.4%	0.6%	0.3%
	Median	12.2%	1.0%	2.7%	73.6%	0.3%	0.4%	0.8%	0.4%
Coast Sardinia	Mean	11.4%	1.0%	2.4%	70.9%	13.4%	0.2%	0.7%	0.0%
	Median	11.4%	1.0%	2.4%	70.9%	13.4%	0.2%	0.7%	0.0%
Inland Sardinia	Mean	11.0%	0.9%	2.2%	73.6%	11.3%	0.3%	0.7%	0.0%
	Median	11.0%	1.0%	2.2%	73.7%	11.2%	0.3%	0.7%	0.0%
Umbria	Mean	10.9%	0.6%	1.9%	79.6%	6.0%	0.3%	0.4%	0.0%
	Median	10.9%	0.6%	1.9%	79.6%	6.0%	0.4%	0.4%	0.0%
East Ligurian	Mean	11.5%	0.8%	2.4%	77.5%	6.1%	0.3%	0.6%	0.0%
	Median	11.6%	0.8%	2.4%	77.4%	6.8%	0.3%	0.7%	0.0%
West Ligurian	Mean	10.5%	1.1%	2.6%	76.8%	9.0%	0.0%	0.0%	0.0%
	Median	10.4%	1.0%	2.5%	77.0%	9.1%	0.0%	0.0%	0.0%

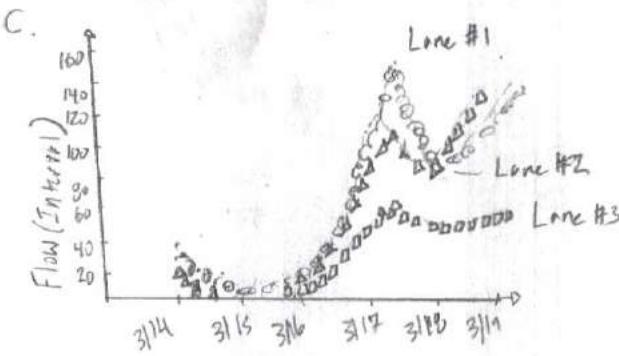
Note: Dataset inconsistent with % values. A modification to demonstrate % values was fraction of total.



Oleic and eicosanoic fatty acids demonstrate a paired measurement of Italy's regions with a composite of ±2% differences.



Lane #2 is busiest



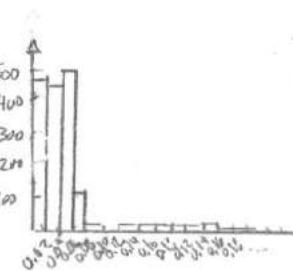
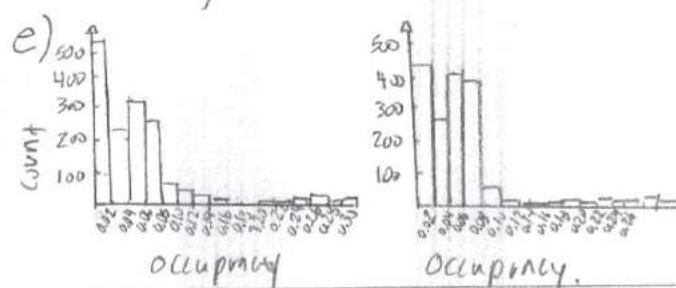
In terms of solely flow and not occupancy, Lane #1 is the busiest lane.

The flow of Lane #2 is twice that of Lane #3.

d)

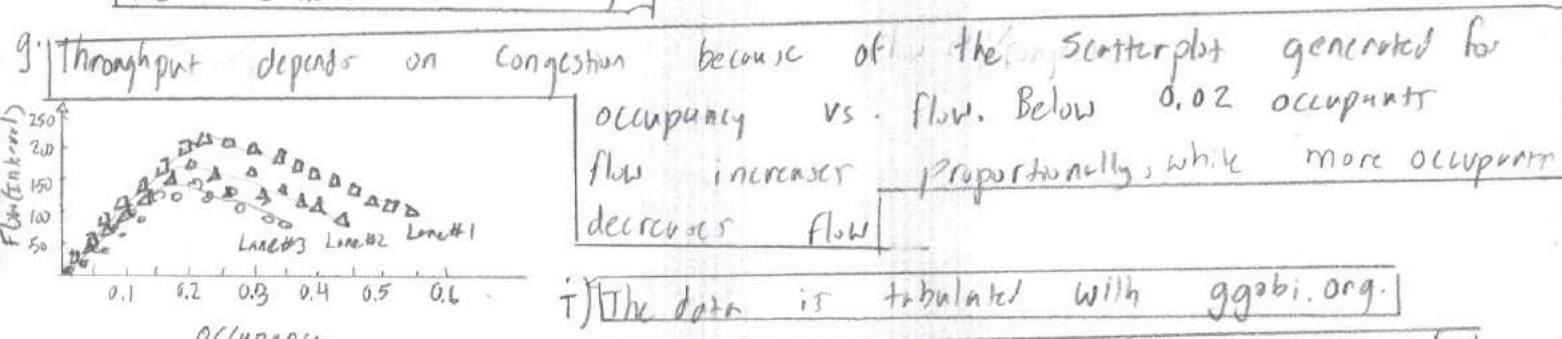
	Mean	Median
Lane #1	0.061	0.048
Lane #2	0.061	0.055
Lane #3	0.051	0.041

The distributions within each lane contribute to higher average because of the proportion of higher occupancy days.



The bins from 0-0.16 occupancy seem to be good representation of the weekly activity. Although, a smaller distribution exists from 0.16-0.22 occupants.

f.) The scatter plot of part c is evidence to argue "when one lane is busy the others are busy."



i.) The data is tabulated with ggobi.org.

j.) March 14th aided with finding the maximum of part g's plot of occupancy vs. flow.

k.) In the higher dimensional scatterplots, the points generate a surface.

- i.) the points are scattered over three dimensions because occupancy vs flow vs day of the week is 3-dimensional.
- ii.) Again, 3-dimensions because of triplet per datapoint.
- iii.) The differences begin to occur near 3/17.

l.) The right lane has lowest mean occupancy, so the taxi driver must merge right.

Chapter 11: Comparing Two Samples:

1. $X \in \{1.1650, 0.6268, 0.0751, 0.3516\}$; $Y \in \{0.3035, 2.6961, 1.0591, 2.7971, 1.2641\}$
- a) $\mu_x = 0.55$; $\mu_y = 1.62$; $\mu_x - \mu_y = -1.07$ b) Pooled Sample Variance: $s_p^2 = \frac{(n-1)s_x^2 + (m-1)s_y^2}{m+n-2}$; $s_x^2 = \frac{1}{n-1} \sum_{i=1}^{n-1} (X_i - \bar{X})^2$
- c) Pooled Standard Error: $s_{\bar{x}-\bar{y}} = s_p \sqrt{\frac{1}{n} + \frac{1}{m}} = 2.30$ $= 11.71$ $| = 1.95 |$
- d) Pooled Confidence Interval: $(\bar{X} - \bar{Y}) \pm t_{m+n-2}(X/2) s_{\bar{x}-\bar{y}}$
 $1.07 \pm t_7(0.05) \cdot 2.30 = 1.07 \pm 3.25$ $= 19.03$

- e) A two-sided test seems appropriate because of the statement "normal dist."
- f) The p-value of a two-sided test of a null hypothesis represents the probability an alternative hypothesis is accepted.
- g) Yes because the model for a 90% confidence interval is $90\% = 100\%(1-\alpha)$ when $\alpha = 0.1$.
- h) The argument may change by refining the confidence interval to an $\alpha < 0.1$.

2. The standard error of the mean $s_{\bar{x}-\bar{y}} = s_p \sqrt{\frac{1}{n} + \frac{1}{m}}$ will halve by doubling the sample size and reduce difference of mean error of Sampling.

3. $\text{Var}(\bar{X} - \bar{Y})$; $s_p^2 \left(\frac{1}{n} + \frac{1}{m} \right)$; $\frac{s_x^2}{n} + \frac{s_y^2}{m} = \frac{(n-1) \sum (X_i - \bar{X})^2}{n} + \frac{(m-1) \sum (Y_i - \bar{Y})^2}{m} = s_x^2 \left[\frac{1}{n} + \frac{1}{m} \right] = s_p^2 \left[\frac{1}{n} + \frac{1}{m} \right]$

4. The t-distribution is valid when sample sizes are small and standard deviation is not known, or both.

5. The expected measurement of any two methods can equal each other. By testing $\mu_x = \mu_y$, a comparison of method accuracy occurs and is beneficial to scientists.

6. A test certifies foundational reasoning with others and when alone.

7. 1) X_1, X_2, \dots, X_n are independent random variables. \rightarrow When the normal distribution is drawn.
- 2) Y_1, Y_2, \dots, Y_n are independent random variables \rightarrow When the samples are drawn from a normal.
- 3) X 's and Y 's are independent \rightarrow When analyzing and making inferences about the data.

8. a) Yes, because the sample size is < 30 total.

b) Yes, because the sample size is < 30 for each group.

9.

Concentration	$\bar{X} - \bar{Y}$	s_p	$s_{\bar{x}-\bar{y}}$	df	t	t_{m+n-2}
10.2 mM	2.23	41.64	13.84	17	0.1612	-1.69
0.3 mM	0.89	11.72	37.24	17	0.0229	-1.69

 Accept till significance level of $\alpha = 0.05$ for a one-sided distribution.
- Accept till significance level of $\alpha = 0.05$ for a one-sided distribution.

10. $t = \frac{\mu_x - \mu_y}{s_{\bar{x}-\bar{y}}} = 0 < -t_{m+n-2}$ rejects and $0 > t_{m+n-2}$ rejects

$$12. P(X_{(n)} \leq \eta_0 = n \leq X_{(n-k+1)}) = 100\%(1-\alpha)$$

$$\text{if } \eta_0 = 0; P(\eta_0 = 0 < k-1) = \frac{1}{2^n} \sum_{j=0}^{k-1} \binom{n}{j} = Y_2$$

From section 11.3.3.

$$S = \sum D_i = 14 = \text{Bin}(n=24, p=0.5) = P(S \leq 14) = 0.8463$$

$$P(S \geq 14) = 1 - P(S \leq 13) = 1 - \text{Bin}(n=24, p=0.5) = 0.2706$$

$$\text{P-value} = \min(0.2706, 0.8463)$$

11. $H_0: \mu_x = \mu_y + \Delta$ vs $H_A: \mu_x \neq \mu_y + \Delta$

$$t = \frac{\bar{X} - \bar{Y}}{s_{\bar{x}-\bar{y}}} = \frac{\Delta}{s_{\bar{x}-\bar{y}}} : \text{Reject}$$

$$H_0 \left\{ \begin{array}{l} |t| > t_{m+n-2}(X/2) \\ t > t_{m+n-2}(\alpha) \\ t < -t_{m+n-2}(\alpha) \end{array} \right.$$

13. X_1, \dots, X_{25} i.i.d. $N(0.3, 1)$ $P(\mu = 0 | H_0)$ vs $P(\mu > 0 | H_A)$ at $\alpha = 0.05$

$H_1: \mu_x - \mu_y = -\Delta = -0.3 = \Delta$; $\frac{|(\bar{X}-0)-\mu_x|}{\sigma/\sqrt{n}} > Z(0.025) ; \frac{\mu_x}{\sqrt{25}} > 1.96 ; \mu_x > 0.392$; $1-\beta = P(\bar{T} \geq k) = 1 - \Phi\left(\frac{0.392 - 0.3}{1/\sqrt{5}}\right) = 1 - \Phi(0.37)$

$\sum Y_i \sim \text{Bin}(25, 0.25) \sim N\left(\frac{25}{2}, \frac{25}{4}\right); 0.05 = P(T \geq k-1) \approx 1 - \Phi\left(\frac{k-0.5-12.5}{4}\right) = 1 - \Phi(-1.3) = 0.34$

14. X_1, \dots, X_n are i.i.d. $N(\mu, \sigma^2)$; $H_0: \mu = \mu_0$, the test is often $t = \frac{\bar{X} - \mu_0}{S_x}; df = n-1$. $\Lambda = \prod N(\mu, \sigma^2) \prod N(\mu_0, \sigma^2)$

$$= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(1/2)(X_i - \mu_0)^2/\sigma^2} \prod_{i=1}^m \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(1/2)(Y_i - \mu_0)^2/\sigma^2}$$
 $I(\mu, \mu_0, \sigma^2) = -\frac{(m+n)}{2} \log 2\pi - \frac{(m+n)}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \left[\sum (X_i - \mu_0)^2 + \sum (Y_i - \mu_0)^2 \right]$
 $\frac{dI(\mu, \mu_0, \sigma^2)}{d\mu_0} = \frac{1}{(m+n)} \left(\sum X_i + \sum Y_i \right) + \frac{dI(\mu, \mu_0, \sigma^2)}{d\sigma^2} = \frac{1}{(m+n)} \left[\sum (X - \mu_0) + \sum (Y - \mu_0) \right] - \sum \sigma_0^2$
 $\hat{\mu}_0 = \frac{1}{(m+n)} \left(\sum X_i + \sum Y_i \right); \hat{\sigma}_0^2 = \frac{1}{(m+n)} \left[\sum (X - \hat{\mu}_0)^2 + \sum (Y - \hat{\mu}_0)^2 \right]$
 $I(\hat{\mu}_0, \hat{\sigma}_0^2) = -\frac{(m+n)}{2} \log 2\pi - \frac{(m+n)}{2} \log \hat{\sigma}_0^2 - \frac{(m+n)}{2}; I(\mu_x, \mu_y, \sigma^2) = -\frac{(m+n)}{2} \log 2\pi - \frac{(m+n)}{2} \log \hat{\sigma}_1^2 - \frac{(m+n)}{2}$
 $\Lambda = \frac{I(\mu_x, \mu_y, \sigma^2)}{I(\hat{\mu}_0, \hat{\sigma}_0^2)} = \frac{m+n}{2} \log \left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_0^2} \right); \frac{\hat{\sigma}_0^2}{\hat{\sigma}_1^2} = \frac{\sum (\bar{X} - \mu_0)^2 + \sum (\bar{Y} - \mu_0)^2}{\sum (X_i - \bar{X})^2 + \sum (Y_j - \bar{Y})^2} = \frac{\sum (\bar{X} - \mu_0)^2}{\sum (X_i - \bar{X})^2}; \text{ if } Y = X \quad \bar{X} = \bar{Y}$

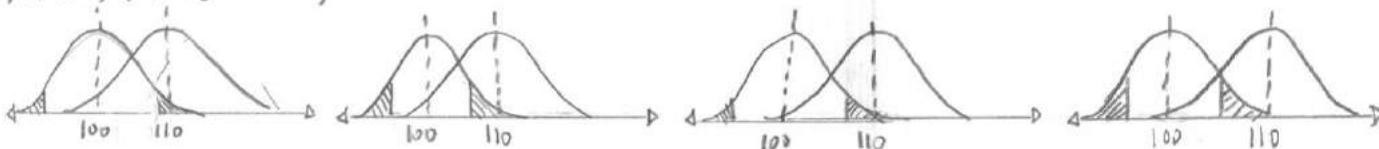
15. $n = m = \text{treatment} = \text{control}$
 $\sigma_b = \sigma_c = 10; n? 95\% \text{ confidence Interval for } \mu_x - \mu_y = 2$

 $P\left(\left|\frac{\bar{X} - \bar{Y}}{\sigma/\sqrt{n}}\right| > Z(0.025)\right) = P\left(\bar{X} - \bar{Y} > Z(0.025)\sqrt{\frac{2}{n}\sigma^2}\right) - P\left(\bar{X} - \bar{Y} < -Z(0.025)\sqrt{\frac{2}{n}\sigma^2}\right) = 2 \cdot 1.96 \cdot \sqrt{\frac{2}{n}} \cdot 10 = 2; \boxed{n = 768}$

$$\boxed{t = \Lambda = \frac{\bar{\sigma}_0}{\sigma_0} = \frac{\bar{X} - \mu_0}{S_x}}$$

16. $H_0: \mu_x = \mu_y; H_A: \mu_x > \mu_y; \Delta = 0.5 \text{ if } \mu_x - \mu_y = 2; K = 10. 2 \cdot 1.64 \cdot \sqrt{\frac{2}{n}} \cdot 10 = 2; \boxed{n = 538}$

17. a) $n = 20, K = 0.05$ b) $n = 20, K = 0.10$ c) $n = 40, K = 0.05$ d) $n = 40, K = 0.10$



18. $H_0: \mu_x = \mu_y$

18. m = subjects
 a) $|\mu_x - \mu_y| \pm z(\alpha/2) \sigma \sqrt{\frac{2}{m}}$; The total subject allocation is independent of confidence interval and can be allocated in random proportions.
 b) $H_0: \mu_x = \mu_y$; $\Delta = \mu_x - \mu_y$ is already as powerful as possible being $H_A: \Delta = \mu_x - \mu_y = 0$. The sample proportions are independent of the argument.

19. n = 25; m = 25; Normal Distribution

$$f(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}; \sigma = 5,$$

a) Pooled Standard Error: $s_{\bar{x}-\bar{y}} = s_p \sqrt{\frac{1}{n} + \frac{1}{m}}$; where $s_p = \sqrt{\frac{(n-1)s_x^2 + (m-1)s_y^2}{m+n-2}} = \sqrt{\frac{2 \cdot 24 \cdot 10^2}{48}} = 10$

b) $\alpha = 0.05$; $H_0: \mu_x = \mu_y$ vs $H_A: \mu_y > \mu_x$; $\mu_y = \mu_x + 1$; $t = \frac{\bar{X} - \bar{Y}}{s_p \sqrt{\frac{1}{n} + \frac{1}{m}}} = \frac{1}{10\sqrt{\frac{2}{25}}} = \frac{1}{2\sqrt{2}} = 0.35$ $s_{\bar{x}-\bar{y}} = 2\sqrt{2}$

$t_{0.975, 24} = 2.064$ is the rejection region.

c) Power of Test if $\mu_y = \mu_x + 1$

$$1 - \beta = t/2 = 0.17$$

d) p-value is 0.07; Would H_0 reject if $\alpha = 0.10$? The test would reject because for a two-sided normal distribution $\alpha/2 = 0.05$ and the test arrived to a p-value greater than $\alpha/2$.

20. Example A: 11.3.1 Bayes = $P(X|A) = \frac{P(X|B) \cdot P(B)}{P(A)}$

$$f(x|\mu, \sigma^2) = f(x|\theta, \xi) \cdot f(\theta) F(\xi) = \underbrace{\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\theta)^2}{2\sigma^2}\right)}_{\text{Likelihood}} \cdot \underbrace{\exp\left(-\frac{5\theta}{2} - (\theta - \theta_0)^2\right)}_{\text{Prior}} \cdot \underbrace{5^{x-1} \exp(-\lambda \xi)}_{\text{Gamma prior}}$$

= 99.99% positive

21. a) $t = \frac{\bar{X} - \bar{Y}}{s_{\bar{x}-\bar{y}}} = \frac{10.693 - 6.75}{1.80} = 4.88$

$\alpha = 0.05$ 133

If p-value = 0.05, $\alpha = 0.05$, for a one-sided distribution.

$df = 9$; $t_{0.95} = 1.933$. The null hypothesis of $H_0: \mu_x = \mu_y$

is rejected.

b) Mann-Whitney Test [Nonparametric]

Type I	Rank	Type II	Rank
3.03	1	3.19	2
5.53	3	4.26	3
5.60	9	4.47	4
9.30	11	4.53	5
9.92	13	4.67	6
12.51	14	4.69	7
12.95	17	12.78	16
15.21	18	6.79	10
16.04	19	9.37	12
16.84	20	12.75	15
R	130	R	90
R'	80	R'	130
R*(0.05)	78	R*(0.05)	78

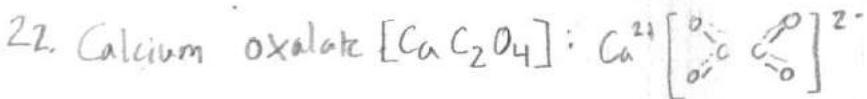
The null hypothesis (H_0) is rejected at a significance level of $\alpha = 0.05$, because $R' > R^*$.

c) Either the t-test or Mann-Whitney Test is applicable to determining the null hypothesis point of rejection. The key qualifiers for each test are $(m, n) < 30$, and are chosen by the case of extreme outliers which are not representative of this data set.

d) π is the probability that a component of one type will last longer than the components of another type (effect), or the probability that an observation from one distribution is smaller than the independent observation from another distribution.

$$\pi = \frac{1}{mn} \sum_{i=1}^{10} \sum_{j=1}^{10} Z_{ij}; \text{ where } Z_{ij} = \begin{cases} 1 & \text{if } X_i < Y_j \\ 0 & \text{otherwise} \end{cases}$$

$$= \frac{1}{100} \cdot 25 = \boxed{\frac{1}{4}} \quad \text{e) } \hat{\pi} = \frac{1}{mn} \sum_{i=1}^{10} \sum_{j=1}^{10} Z_{ij} = \boxed{\frac{1}{4}} \quad \text{f. CI} = \left\{ \frac{9}{40}, \frac{5}{15} \right\}$$



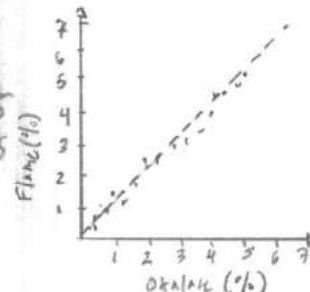
Parametric Test:

$$\begin{array}{ll} \text{oxalate} & \text{flame} \\ \mu = 2.39 & \mu = 2.35 \\ \sigma = 1.45 & \sigma = 1.42 \\ & S_{x-y} = 0.19 \\ & Z = 0.43 \\ & t = 3.38 \\ & \text{p-value} = 0.0995 \end{array}$$

Nonparametric Test:

$$\begin{array}{ll} \text{oxalate:} & \text{flame:} \\ R = 14146.5 & R = 13819.5 \\ R' = 6798.5 & R' = 7125.5 \\ Z-\text{statistic} = 0.31 & \\ p\text{-value} = 0.62 & \end{array}$$

Graphical:



The parametric test + t-statistic advised to accept the null hypothesis. Nonparametric adviser to not reject the null hypothesis and the graphs do look similar.

23. X_1, \dots, X_n i.i.d. with cdf F ; Y_1, \dots, Y_m i.i.d. with cdf G . $H_0: F = G$ vs $H_A: F \neq G$. $(m+n)/2 = 0$

a) Hypergeometric Distribution

$$P(X=R) = \frac{\binom{r}{k} \binom{n-r}{n-k}}{\binom{n}{m}}$$

$$P(T=t) = \frac{\binom{(m+n)/2}{t} \binom{(m+n)/2}{n-t}}{\binom{m+n}{n}} ; \begin{array}{l} r = (m+n)/2 \text{ or total} \\ \text{of values below median} \\ n-r = (m+n)/2 \text{ or total of values greater} \\ \text{than median.} \end{array}$$

$$\begin{array}{l} (m+n)/2 \leq n \\ (m+n)/2 > n \end{array}$$

k = amount total without replacement.

r = Total of type

$n-r$ = Total of second type

m = total chosen

R = amount of X 's chosen without replacement below the median.

n = total X 's chosen.

A rejection region would be discovered by $P(T \leq t) = 1 - K$.

b. CI for $G = P(X_{(j)} < n < X_{(i)})$ where n = median

The hypergeometric distribution is approximated by a binomial distribution.

$$P(T=t) = \frac{\binom{(m+n)/2}{t} \binom{(m+n)/2}{n-t}}{\binom{m+n}{n}} = \binom{n}{t} \prod_{k=1}^t \frac{\binom{m+n}{2} - k + k}{\binom{m+n - k}{2}} \cdot \prod_{j=t+1}^{n-t} \frac{\binom{m+n - t - (j-k)}{2}}{\binom{m+j}{2}}$$

$$\lim_{N \rightarrow \infty} P(T=t) = \binom{n}{t} p(1-p) ; \lim_{N \rightarrow \infty} P(X_{(j)} < n < X_{(i)}) = \sum_{k=i}^j \binom{n}{k} p^k (1-p)^{n-k} = \text{Bin}(j-i, n, p) - \text{Bin}(i-1, n, p)$$

With $E(x) = F(x - \Delta)$, then $\text{Bin}(j-i-\Delta, n, p) - \text{Bin}(i-1-\Delta, n, p)$

25. a) If 79.14 is arbitrarily small, say 0.001, then the new mean is 69.985 and standard deviation 26.455.

The pooled variance became 9.755, with a standard error of 1.405.

The final t-statistic was evaluated to 7.16.

All $t_{14}(0.005) = 2.861 < 7.16$ and would reject with a significance of $\alpha = 0.001$.

24. Mann-Whitney Statistic

$$R' = n(m+n+1) - R$$

$$E(V) = \frac{mn}{2}$$

$$\text{Var}(V) = \frac{mn(m+n+1)}{12}$$

$$m=3, n=2$$

$$\frac{U - E(V_y)}{\sqrt{\text{Var}(V_y)}} = N(0, 1) ; U = N(0, 1) \sqrt{\text{Var}(V_y)} + E(V_y) = \frac{x^2/2}{\sqrt{2\pi}} + 1/3$$

5. If method B (80.03 J) became 10,000 J, $\mu = 1319.95$, $\sigma = 3280.74$, $S_p^2 = 1208.69$, $S_{x-y} = 15.62$

C.

Method A	Method B
74.85(7.5)	80.03(15)
80.04(19)	79.94(17)
80.02(11)	79.98(9.5)
80.04(16)	79.97(4.5)
80.03(15)	79.97(4.5)
80.03(15)	80.03(15)
80.04(16)	79.95(2)
79.97(4.5)	79.97(4.5)
80.05(21)	
80.03(15)	
80.04(11)	
80.01(1)	
80.02(11)	

Modifying 79.94 to an arbitrary low value had no effect on the data because 79.94 is the lowest rank. While raising 80.03 to a larger value of 10,000 changed the Z-statistic to 12.64 with a null hypothesis also rejecting.

Z-statistic = -79.37

The null hypothesis would reject

R 177 54

R' 232

Z-statistic: 13.04

t₂₀(0.005) = 2.85

Null hypothesis would reject.

26. X_1, \dots, X_n be from $N(0, 1)$: Y_i be from $"(1, 1)"$:

a) $T_x = V_x + \frac{n(n+1)}{2}$; $V_x = \sum \sum Z_{ij}$; $Z_{ij} = \begin{cases} 1 & X_i < Y_j \\ 0 & \text{otherwise} \end{cases}$

$$\begin{aligned} E[T_x] &= E[V_x] + E\left[\frac{n(n+1)}{2}\right] = E\left[\sum \sum Z_{ij}\right] + \frac{n(n+1)}{2} = \sum \sum E[Z_{ij}] + \frac{n(n+1)}{2} \\ &= \sum \sum P(X_i < Y_j) + \frac{n(n+1)}{2} = n^2 P(X_i - Y_j > 0) + \frac{n(n+1)}{2} \\ &= n^2 p\left(\frac{X_1 - X_2 - E(X_1 - X_2)}{\sqrt{\sigma_{X_1}^2 + \sigma_{X_2}^2}} > \frac{0 - E(X_1 - X_2)}{\sqrt{\sigma_{X_1}^2 + \sigma_{X_2}^2}}\right) + \frac{n(n+1)}{2} \\ &= n^2 p\left(Z > \frac{1}{\sqrt{2}}\right) + \frac{n(n+1)}{2} = n^2 \left[1 - \Phi\left(\frac{1}{\sqrt{2}}\right)\right] + \frac{n(n+1)}{2} = n^2 (1 - 0.761) + \frac{n(n+1)}{2} \end{aligned}$$

b. $\text{Var}(T_x) = \text{Var}\left(V_x + \frac{n(n+1)}{2}\right) = \text{Var}(V_x) = \sum \sum \text{Var}(Z_{ij}) + \sum \text{Cov}(Z_{ij}, Z_{kl})$ $= 0.2354n^2 + \frac{n(n+1)}{2}$

$$= n^2 p(1-p) + \sum \left(E(Z_{ij} Z_{kl}) - E[Z_{ij}] E[Z_{kl}] \right) = n^2 p(1-p) + \sum \left[E(Z_{ij} Z_{kl}) - p^2 \right] = n^2 p(1-p)$$

27. Exact Null Distribution $E[\alpha] = W_f$ where $n=4$

$W_f = \sum_{k=1}^n k I_k$ where $I_k = \begin{cases} 1 & \text{if the } k^{\text{th}} \text{ largest } |D_i| \text{ has } D_i > 0 \\ 0 & \text{otherwise} \end{cases}$

$W_f = \sum_{k=1}^4 k I_k$; Total values: $\frac{n(n+1)}{2} = 10$; "Above Diagonal"

Uncorrelated

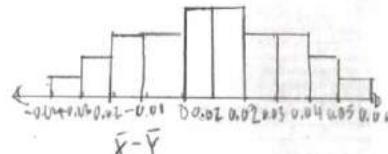
W	0	1	2	3	4	5	6	7	8	9	10
P(W)	1/16	1/16	1/16	1/16	1/16	1/16	1/16	1/16	1/16	1/16	1/16

1	-1	1	1	-1	-1	-1	1	1	-1	-1	-1
2	2	-2	2	2	-2	2	2	-2	-2	2	-2
3	3	3	-3	3	3	-3	3	-3	3	-3	-3
4	4	4	4	-4	4	4	-4	4	-4	4	-4
Total (W_f)	10	9	8	7	6	7	6	5	5	4	3

28. $n=10, 20, 30$ find $\alpha=0.05$ and 0.01 for a two sided rank test

n	10	20	30
0.05	8	52	137
0.01	3	37	109
$E(W_f)$	27.5	105	233
$\text{Var}(W_f)$	9.25	11.5	25.64
$Z(0.05)$	-1.98	-1.17	-1.17
$Z(0.01)$	-2.49	-2.54	-2.55

29. a)



b) The process of randomizing two samples, then comparing the difference is similar to the Mann-Whitney test, but more commonly the Wilcoxon Signed Rank test. Each of these methods compares to a randomized distribution.

30. $X_A - X_B$; Standard Error: $\sigma_y = \sqrt{\text{Var}(Y_0)} / \sqrt{n} = \sqrt{\frac{(m+n+1)}{12}}$

31. Section 11.2.3: A Nonparametric Method: The Mann-Whitney Test; $F = G$; $E(\hat{\pi}) = E\left[\frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n Z_{ij}\right]$

32. $X \sim N(\mu_X, \sigma_X^2)$; $Y \sim N(\mu_Y, \sigma_Y^2)$; $\pi = P(X < Y)$

$$\pi = P(X - Y) = \text{Sign}((N(X_i | \mu_X, \sigma_X^2) - N(Y_i | \mu_Y, \sigma_Y^2))) = n(n+1) \\ = \text{Sign}\left(\frac{1}{2\pi\sigma_X\sigma_Y} e^{-(x_i - \mu_X)^2/2\sigma_X^2 - (y_i - \mu_Y)^2/2\sigma_Y^2}\right)$$

33. $N(\mu_X, \sigma_X^2) \sim N(\mu_Y, \sigma_Y^2)$; $H_0: \sigma_X = \sigma_Y \Rightarrow \frac{s_x^2}{s_y^2} \sim F_{n-1, m-1}$

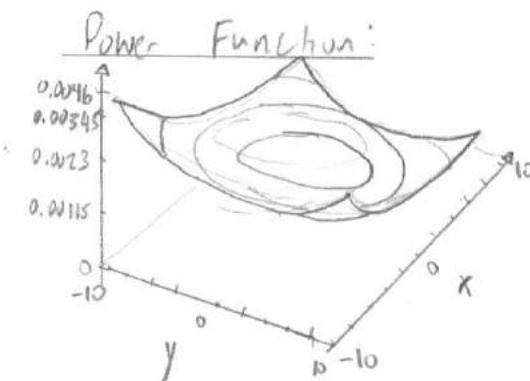
$$F_{n-1, m-1} = \frac{s_x^2}{s_y^2} = \frac{N(\mu_X, \sigma_X^2)}{N(\mu_Y, \sigma_Y^2)} = \frac{\sigma_X}{\sigma_Y} \quad \text{a) } H_0: \sigma_X = \sigma_Y \quad \text{one-sided:} \\ H_1: \sigma_X \neq \sigma_Y \quad \boxed{\frac{\sigma_X^2}{\sigma_Y^2} > F_{n-1, m-1}(\kappa)}$$

b) CI: $(\frac{s_x^2}{s_y^2} F_{n-1, m-1}(\alpha/2) < \sigma_X^2/\sigma_Y^2 < \frac{s_x^2}{s_y^2} F_{n-1, m-1}(1 - \alpha/2))$

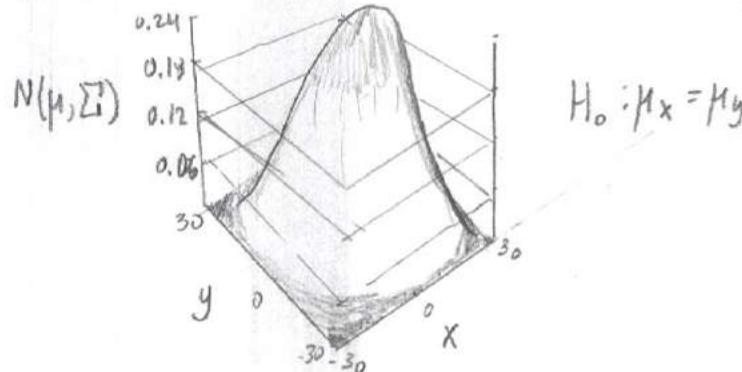
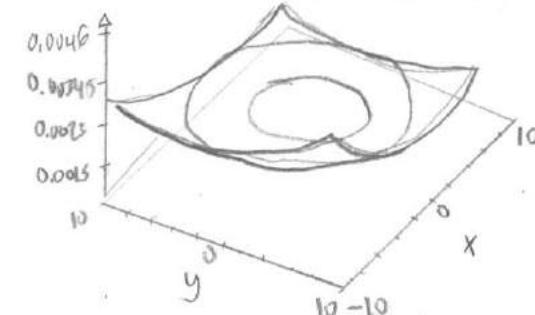
c) One-sided Two-sided: $\boxed{0.29 < 0.59 < 2.17}$

34. $H_0: \mu_X = \mu_Y$ a) Paired: $\text{Cov}(X_i, Y_i) = 50$, $\sigma_X = \sigma_Y = 10$, $i = 1 \dots 25$ if $H_1: \mu_X \neq \mu_Y$; $p = \frac{\text{cov}(XY)}{\sqrt{\sigma_X^2 \sigma_Y^2}} \cdot \frac{1}{2}$

$$\Sigma = \begin{bmatrix} \sigma_X^2 & \text{cov}_{XY} \\ \text{cov}_{XY} & \sigma_Y^2 \end{bmatrix} = \begin{bmatrix} 10^2 & 50 \\ 50 & 10^2 \end{bmatrix}; \mu = \begin{pmatrix} \mu_X \\ \mu_Y \end{pmatrix} \sim N(\mu, \Sigma)$$



b) Power Function



$H_0: \mu_X = \mu_Y$

$$N(\mu_X, \mu_Y, \frac{\sigma_X^2}{n^2}, \frac{\sigma_Y^2}{n^2}) = N(\mu_X - \mu_Y, \sigma)$$

Power function is the only requirement.

35. $n=22$; $t=70$ days, exposure time = 7 days to ozone
 $n=23$; $t=70$ days, exposure time = 0 days to ozone.

$H_0: \mu_{\text{control}} = \mu_{\text{ozone}}$

$H_1: \mu_{\text{control}} \neq \mu_{\text{ozone}}$

Nonparametric

$$R(\text{control}) = 661; R(\text{ozone}) = 374$$

$$R'(\text{ozone}) = 638$$

$$Z\text{-statistic} = 0.74$$

$$Z(0.05) = 1.96$$

Parametric

$$S_p = 225.43g$$

$$S_{x-y} = 67.22g$$

$$t\text{-statistic} = 2.55$$

$$t_{43}(0.05) = 1.68$$

	Mean	Median	SD
Control(22)	22.43g	22.7g	10.54g
Ozone(22)	11.01g	11.1g	18.60g

36.

For both parametric and nonparametric analysis, the null hypothesis (H_0) is rejected. The parametric pooled study shows a t-statistic greater than a significance of $\alpha=0.05$. While the nonparametric test, Mann-Whitney demonstrates a Z-statistic above the rejection level of 1.96, purporting a rejection of the null hypothesis.

	$E[\bar{x}]$	$SD[\bar{x}]$	$\bar{x}-\bar{y}$	S_p	S_{x-y}
Microbiological Method	85.26%	20.48%	0.44%	20.65%	7.54%
Hydroxylamine Method	84.82%	20.82%			

$$H_0: \bar{x} = \bar{y}; H_1: \bar{x} \neq \bar{y}$$

Outcomes would be similar by randomizing the sample sets.

$$t\text{-statistic} = 0.06; t_{30}(0.05) = 2.04.$$

The null hypothesis is not rejected.

37 a)

Ward A		Ward B	
$\Delta Dose$	$\Delta Placebo$	$\Delta Dose$	$\Delta Placebo$
0.8	-0.4	-0.45	0.01
0.1	0.4	0.15	0.44
0.55	-0.1	-0.19	-0.55
0.6	-0.9	0.12	-0.05
0.34	0.2	0.03	0.04
1.42	0.78	-0.15	-1.16
1.74	0.3	0.43	-0.16
-0.29	0.64		
0.53	0.42		
$E[\bar{x}]$	0.64	0.15	
$SD[\bar{x}]$	0.59	0.51	
S_p	0.55	0.36	
S_{x-y}	0.26	0.19	
Z	1.92	1.28	

b) Pooled Variance of $\Delta Dose$ of Ward A and Ward B:

$$S_{pd}^2 = \frac{(10-1)0.59^2 + (7-1)0.28^2}{(10+7-2)} = 0.24$$

Pooled variance of $\Delta Placebo$ of Ward A and Ward B:

$$S_{pp}^2 = \frac{(10-1)0.51^2 + (7-1)0.43^2}{(10+7-2)} = 0.23$$

Standard Error of $\Delta Dose$ of Ward A and Ward B

$$S_{A-B} = S_p \sqrt{\left(\frac{1}{10} + \frac{1}{7}\right)} = 0.24$$

Standard Error of $\Delta Placebo$ of Ward A and Ward B.

$$S_{A-B} = S_p \sqrt{\left(\frac{1}{10} + \frac{1}{7}\right)} = 0.24$$

Z-Statistic of $\Delta Dose$ of Ward A and Ward B.

$$= \frac{0.64 + 0.01}{0.24} = 2.67$$

Z-Statistic of $\Delta Placebo$ of Ward A and Ward B.

$$H_0: \overline{\Delta Placebo(A)} = \overline{\Delta Placebo(B)} = \frac{0.15 + 0.25}{0.24} = 1.67$$

$$H_1: \overline{\Delta Placebo(A)} \neq \overline{\Delta Placebo(B)}$$

$$[H_0 \text{ rejected}: Z(0.05) < Z = 1.67]$$

Part B:

$$H_0: \overline{\Delta Dose}(\text{Ward A}) = \overline{\Delta Dose}(\text{Ward B}) \text{ Rejected}$$

$$H_1: \overline{\Delta Dose}(\text{Ward A}) \neq \overline{\Delta Dose}(\text{Ward B}) \text{ Accepted}$$

$$[Z(0.05) < Z = 2.67]$$

$$[H_0 \text{ rejected}: Z(0.05) < Z = 1.67]$$

$$38. \Delta = \text{Added}(\%) - \text{Found}(\%)$$

	$E[X]$	$SD[X]$	$S_{\bar{x}-\bar{y}}$	t
Δ Sulfonic Acid	0.007	0.015	0.014	-0.006
Δ Pyrazolone-T	0.006	0.013		0.19

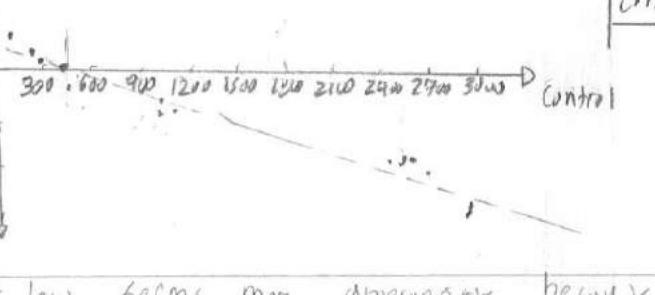
$$\left. \begin{array}{l} H_0: \Delta \text{Sulfonic Acid} = \Delta \text{Pyrazolone-T} \\ H_1: \Delta \text{Sulfonic Acid} \neq \Delta \text{Pyrazolone-T} \end{array} \right\} \text{Measurements at HPLC}$$

The null hypothesis (H_0) is not rejected because the t -statistic = 0.19 is below $t(0.005) = 2.845$.

Bailey, Cox, and Springer's HPLC measurements were consistent for two sets of data.

39.

40. Difference Fault Rate

- g) 
- b/c) A t-test seems more appropriate because of the sample size, but skew of the control demonstrates for one of the datasets suggests examination with a ranked test.

b/c)

	$E[X]$	$SD[X]$	Median	$S_{\bar{x}-\bar{y}}$	$S_{\bar{x}-\bar{y}}$
Tcst	434.21	161.27	442.50	550.60	208.106
Control	395.50	761.73	616.00		

$$\bar{x} - \bar{y} = 523.3$$

$$CI = \{115, 931\}$$

$$CI = \{nq - z(0.05)\sqrt{nq(1-q)}\}$$

$$nq + z(0.05)\sqrt{nq(1-q)}\}$$

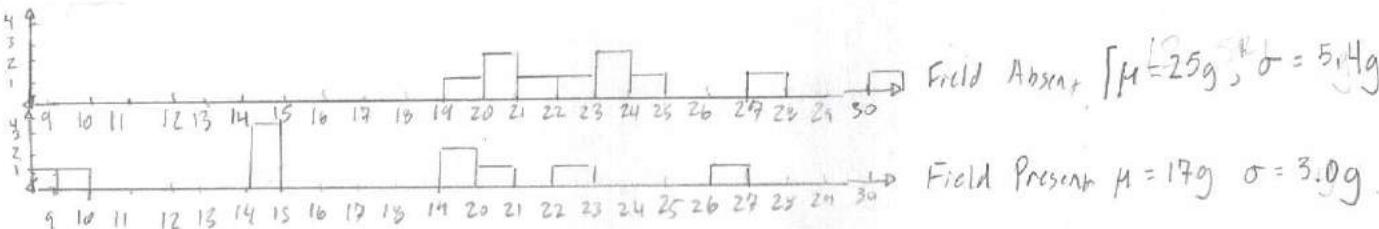
$$= \{R(4.46), R(12.54)\}$$

$$= \{-587, -163\}$$

41. n=10 cages, t = 30-day old mice Treated: 3 T = 12 days 80 Oe/cm.

longe = 3 rats. Control: 30 mice.

a)



b)

Weight Gain (g)

	$E[X]$	$SD[X]$	$S_{\bar{x}-\bar{y}}$	Lower CI	Upper CI
Field Absent	25g	5.4g	4.4g	1.9g	4.3g
Field Present	17g	3.0g			11.7g

d)

	R	R'	U
Field Absent	143		
Field Present	67	153	6.09

e)

	Median	Mean
Field Absent	25g	5g
Field Present	17g	5g

f) SE of Mean = 1.9g: Bootstrap. $\bar{\sigma}_{\text{Median}} = 1.253 \sigma_x = 2.4g$

$$g) CI = \{R(1.9), R(8.1)\} = \{5, 11.83\}$$

$$t_{18} = 3.93$$

$$H_0: \text{Mean Field Absent} = \text{Mean Field Present}$$

$$p\text{-value} = 8 \times 10^{-5}$$

The null hypothesis is rejected at a significance of $\alpha = 0.05$ and alternative hypothesis accepted.

41. a) $E(\hat{\Delta}) = E(\text{median}(X_i - Y_j)) = \mu_x - \mu_y$ b) $\hat{\Delta}$ is robust to outliers because the method is rank-based.

$$c) \sigma_{\text{Median}}^2 < \hat{\Delta}^2 = 4g^2 < \Delta_{\text{Median}}$$

$$d) \hat{\Delta} = 1.253 \sigma_x; \sigma_x = 3.19g. f(x|\mu, \frac{1}{8f(\mu)^2 \cdot 10})$$

$$e) CI = \{-2.3g, 10.3g\}$$

42. a) $\pi = \frac{1}{mn} \sum \sum Z_{ij}$; when $Z_{ij} = \begin{cases} 1 & X_i > Y_j \\ 0 & \text{otherwise} \end{cases}; \pi = \frac{229}{26 \cdot 9} = 0.3388$

- b) $SE = 0$ because matrix was generated with exact values. Alternative methods include generating a sampling distribution for
- c) The confidence interval = {0.3388}, but with a sampling distribution $CI = \{\pi - 1.96s_x, \pi + 1.96s_x\}$

$$s_x = \sqrt{\frac{1}{B} \sum (\bar{\pi}_i - \pi)^2}$$

43. $X_1 \dots X_n, Y_1 \dots Y_m, \mu_{20\%}$; A bootstrap could be used to estimate the standard error of a 20% trimmed mean vs. 0% trimmed mean by producing a sampling distribution $\bar{x} \sim f(\bar{x} | \bar{Y} - \bar{Y}, s_p^2)$, and then fit with those parameters.

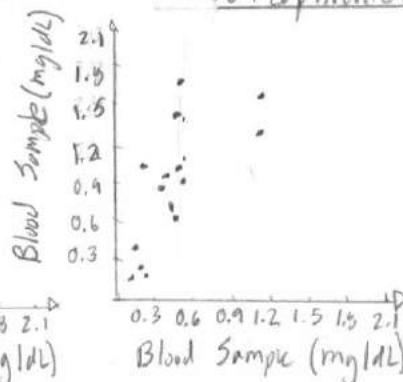
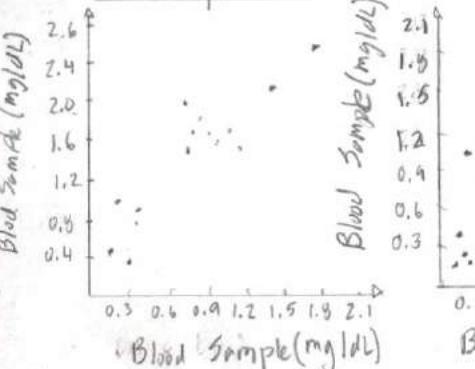
44. $n=20, m=15$ at 2 months. Volume = 2 mL of blood at breakfast and urination.

a)

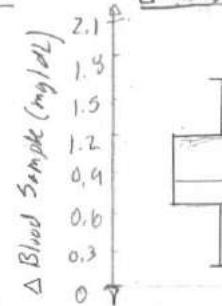
Post-treatment: Ig ascorbic acid.

$t_1 = 6$ hours urine collection; $t_2 = 2$ hours after dose of Vitamin C.

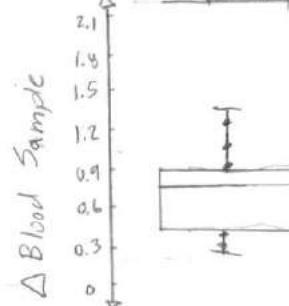
Non Schizophrenics:



Non Schizophrenic



Schizophrenic



b)

	$E[X]$	$SD[X]$	s_p	$s_{\bar{x}-\bar{y}}$	t	df	t
Nonschizo (0hr)	0.62	0.42	0.34	0.12	2.45	15	1.69
Schizo (0hr)	0.33	0.26				20	
Nonschizo (2hr)	1.45	0.59	0.50	0.17	2.92	15	
Schizo (2hr)	0.95	0.42				20	1.69
Δ Nonschizophrenic	0.61	0.33	0.33	0.11	1.69	15	1.69
Δ Schizophrenic	0.83	0.34				20	

$H_0: \text{Nonschizophrenic (0hr)} = \text{Schizophrenic (0hr)}$	Reject at $\alpha = 0.05$
$H_1: \text{Nonschizophrenic (0hr)} \neq \text{Schizophrenic (0hr)}$	Accept at $\alpha = 0.05$
$H_0: \text{Nonschizophrenic (2hr)} = \text{Schizophrenic (2hr)}$	Reject at $\alpha = 0.05$
$H_1: \text{Nonschizophrenic (2hr)} \neq \text{Schizophrenic (2hr)}$	Accept at $\alpha = 0.05$
$H_0: \Delta \text{Nonschizophrenic (2hr)} = \Delta \text{Schizophrenic (2hr)}$	Reject at $\alpha = 0.05$
$H_1: \Delta \text{Nonschizophrenic (2hr)} \neq \Delta \text{Schizophrenic (2hr)}$	Accept at $\alpha = 0.05$

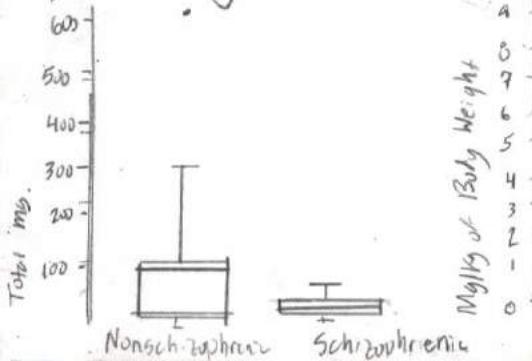
c)

	R	R'	U
Nonschizo (0hr)	324		
Schizo (0hr)	306	234	2.8
Nonschizo (2hr)	345		
Schizo (0hr)	285	255	3.15
Δ Nonschizophrenic	319		
Δ Schizophrenic	311	229	2.61

$H_0: \text{Nonschizophrenic (0hr)} = \text{Schizophrenic (0hr)}$	Reject at $\alpha = 0.05$
$H_1: \text{Nonschizophrenic (0hr)} \neq \text{Schizophrenic (0hr)}$	Accept at $\alpha = 0.05$
$H_0: \text{Nonschizophrenic (2hr)} = \text{Schizophrenic (2hr)}$	Reject at $\alpha = 0.05$
$H_1: \text{Nonschizophrenic (2hr)} \neq \text{Schizophrenic (2hr)}$	Accept at $\alpha = 0.05$
$H_0: \Delta \text{Nonschizophrenic} = \Delta \text{Schizophrenic}$	Accept at $\alpha = 0.05$
$H_1: \Delta \text{Nonschizophrenic} \neq \Delta \text{Schizophrenic}$	Reject at $\alpha = 0.05$

d) Total mg Vitamin C

Mg/Kg of Body Weight



	$E[X]$	$SD[X]$	s_p	$s_{\bar{x}-\bar{y}}$	df	t
Nonschizophrenic (Total mg)	122.7	153.7			116.9	39.9
Schizophrenic (Total mg)	85.8	79.6			33	-2.2
Nonschizophrenic (mg/kg)	1.78	2.0			1.6	0.5
Schizophrenic (mg/kg)	0.53	1.3			33	-1.2

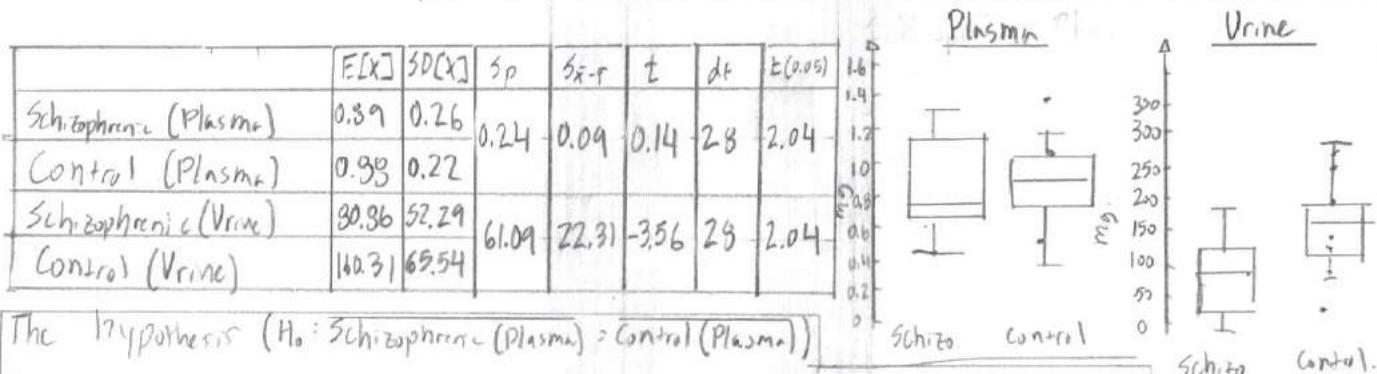
The data shows a hypothesis of mean weights are not equivalent.

e) Assuming Normality is standard for Z-statistics, but the mean and median show normal distribution may not best fit the data.

	R	R'	V
Nonschizophrenic (Total)	344		
Schizophrenic (Total)	286	254	3.47
Nonschizophrenic (mg/Kg)	312		
Schizophrenic (mg/Kg)	233	207	2.34

If a hypothesis ($H_0: \text{Nonschizophrenic (Total mg)} = \text{Schizophrenic (Total mg)}$) or ($H_{OB}: \text{Nonschizophrenic (mg/Kg)} = \text{Schizophrenic (mg/Kg)}$) were proposed, then they would be rejected at $\alpha=0.05$.

g)



The hypothesis ($H_0: \text{Schizophrenic (Plasma)} = \text{Control (Plasma)}$) is accepted with the alternative ($H_1: \text{Schizophrenic (Plasma)} \neq \text{Control (Plasma)}$) because the t-statistic for 28 degrees of freedom is less than a standard curve at the significance level. While the urine samples show an argument or rejection of hypothesis ($H_0: \text{Schizophrenic (Urine)} = \text{Control (Urine)}$).

h) The normality is reasonable because the mean is within 10% off the median for each set of data.

	R	R'	V
Schizo (Plasma)	161.5	3035	7.92
Control (Plasma)	233.2		
Schizo (Urine)	96.0	369	10.63
Control (Urine)	365.1		

Unlike part (g), the Mann-Whitney shows reason to reject the hypothesis that the means are equivalent, which is argued against by the table of part g: Urine samples tested with Mann-Whitney list a similar outcome to part g.

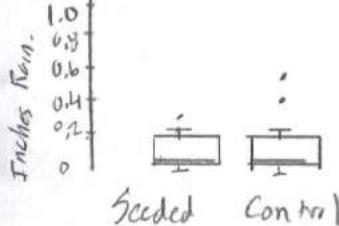
Year	Experiment	E[X]	SD[X]	Sp	S _{x-p}	t	df	t(0.05)
1957	Seeded	0.07	0.07	0.08	0.03	-0.31	30	2.04
	Unseeded	0.06	0.05					
1958	Seeded	0.06	0.08	0.09	0.03	0.55	30	2.04
	Unseeded	0.04	0.11					
1959	Seeded	0.02	0.04	0.16	0.06	-1.20	38	2.02
	Unseeded	0.09	0.22					
1960	Seeded	0.02	0.04	0.05	0.02	-1.13	30	2.04
	Unseeded	0.03	0.05					

Tabulated data of each experiment individually demonstrate seeding did not influence the rhinocill mid-day ($H_0: \mu_x = \mu_y$). The pooled years or seeding was tested to $t < t(0.05)$ and lead to outcome of accepting the null hypothesis.

Years	Experiment	E[X]	SD[X]	Sp	S _{x-p}	t	df	t(0.05)
57-60	Seeded	0.04	0.06	0.11	0.02	-0.95	134	1.93
	Unseeded	0.06	0.14					

Pooled Years of Cloud Seeding Experiment:

b) The day on which seeding should be chosen at random because daily parameter cycle throughout the month. Days are paired in the experiment because of similar conditions.



46.

Type	Experiment	$E[x]$	$SD[x]$	S_p	S_{x-y}	t	df	$t(0.05)$
I	Seeded	0.14	0.08	0.01	-0.03	-0.38	33	2.03
I	Control	0.12	0.10					
II	Seeded	0.13	0.10	0.01	-0.03	-0.96	33	2.03
II	Control	0.10	0.10					

Hypotheses:

- $H_0, \text{Type I} : \text{Seeded Mean (Type I)} = \text{Control Mean (Type I)}$
- $H_1, \text{Type I} : \text{Seeded Mean (Type I)} \neq \text{Control Mean (Type I)}$
- $H_0, \text{Type II} : \text{Seeded Mean (Type II)} = \text{Control Mean (Type II)}$
- $H_1, \text{Type II} : \text{Seeded Mean (Type II)} \neq \text{Control Mean (Type II)}$

The analysis accepts the null hypothesis for each type (I/II) at a significance level of $\alpha=0.05$. ACN-cloud seeding project had no effect on outcomes of rain, and including analysis of cloud formations rather than years.

47. a)

Experiment	Variable	$E[X]$	$SD[X]$	S_p	S_{x-y}	t	df	$t(0.05)$
Seeded	Target	11.72	12.11	11.24	3.06	0.48	50	2.01
	Control	10.24	10.29					
Unseeded	Target	13.46	17.12	14.18	3.72	0.96	54	2.00
	Control	9.89	10.41					

$t < t(0.05)$ for each Experiment suggesting the null hypothesis cannot be rejected with the supplied information.

b) The square root transformation should play no effect on the data set or analysis because of the 1:1 relationship of input to output.

c) A control area provides a control variable to test against. Comparing seeded to unseeded limits experimental variability and requires a control variable to reference.

48.

Parametric

Experiment	R	R'	V
Before	165		
After	106	134	3.58

$V > Z\text{-statistic}(0.05, \text{Two-tailed})$

$3.58 > 1.96$: Reject $H_0: \mu_x = \mu_y$

Nonparametric

Experiment	Mean	S. d.	S_p	S_{x-y}	t	df	b
Before	9.27	4.14	4.26	1.74	2.69	22	2.07
After	4.58	2.64					

$t > t_{22}(0.05)$: Reject $H_0: \mu_x = \mu_y$

$2.69 > 2.07$

Chapter 12: Analysis of Variance

1.

$$\frac{s_p^2 = \frac{(n-1)s_x^2 + (m-1)s_y^2}{m+n-2}}{2(J-1)} = \frac{\sum_{i=1}^J (J-1) s_i^2}{2(J-1)} = \frac{(J-1)s_1^2 + (J-1)s_2^2}{2J-2}$$

3, $I=2$ treatment groups ; F-statistic

$$F = \frac{SS_B / (I-1)}{SS_W / [I(J-1)]} ; \text{ where } SS_B = J \sum_{i=1}^I X_i^2 + (I-1)\sigma^2; SS_W = \sum_{i=1}^I (J-1) s_i^2$$

t-statistic:

$$t = \frac{(\bar{X}-\bar{Y}) - (\mu_X - \mu_Y)}{s_p \sqrt{\frac{1}{n} + \frac{1}{m}}} ; \quad = \frac{J \sum_{i=1}^I X_i^2 + (I-1)\sigma^2}{(2-1)} \frac{Z(J-1)}{\sum_{i=1}^I (J-1) s_i^2} = \frac{[J(\alpha_1^2 + \alpha_2^2) + \sigma^2] Z(J-1)}{(J-1) s_1^2 + (J-1) s_2^2} = \frac{J(\alpha_1^2 + \alpha_2^2) + \sigma^2}{s_p^2} \\ t^2 = \frac{(\bar{X}-\bar{Y})^2 - 2(\bar{X}-\bar{Y})(\mu_X-\mu_Y) + (\mu_X+\mu_Y)^2}{s_p^2 \left(\frac{1}{n} + \frac{1}{m} \right)} = \frac{\sigma^2}{s_p^2} = \frac{\sigma^2}{s_p^2}$$

$$t^2 = F @ I=2$$

4. Theorem A:

$$E(SS_W) = \sum_{i=1}^I \sum_{j=1}^J E(Y_{ij} - \bar{Y}_{i..})^2 = \sum_{i=1}^I \sum_{j=1}^J (\mu_i - \bar{\mu})^2 + \frac{J-1}{J} \sigma^2$$

From section 12.2.1: $Y_{ij} = \mu + \kappa_i + \epsilon_{ij}$ $\Rightarrow E(SS_W) = \sum_{i=1}^I \sum_{j=1}^J (\mu_i - \bar{\mu})^2 + I(J-1)\sigma^2$

$$E(SS_B) = J \sum_{i=1}^I E(\bar{Y}_i - \bar{Y}_{..})^2 = J \sum_{i=1}^I (\mu_i - \bar{\mu})^2 + \frac{(I-1)}{IJ} \sigma^2 = J \sum_{i=1}^I \kappa_i^2 + \frac{(I-1)\sigma^2}{IJ}$$

Theorem B: $\mu=0; \sigma^2; SS_W/\sigma^2 = \chi^2_{I(J-1)}$

$$\frac{SS_W}{\sigma^2} = \frac{\sum_{i=1}^I (J-1) s_i^2}{\sigma^2} = (J-1) \sum_{i=1}^I \left(\frac{X_i - \bar{X}}{\sigma} \right)^2 = \chi^2_{I(J-1)}$$

$$\frac{SS_B/\sigma^2}{\sigma^2} = \frac{\sum_{i=1}^I \kappa_i^2 + (I-1)\sigma^2}{\sigma^2} = \frac{\sum \kappa_i^2}{\text{Var}(\bar{Y}_i)} + (I-1) \left(\frac{\bar{X} - \mu}{\sigma} \right)^2 = \chi^2_{I-1}$$

5. F-statistic

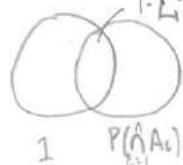
Null hypothesis:

$$F = \frac{SS_B / (I-1)}{SS_W / [I(J-1)]} \quad H_0: \kappa_1 = \kappa_2 = \dots = \kappa_I = 0 \text{ means } F_i \approx 1, \text{ while } H_1: \kappa_1 \neq \kappa_2 \neq \dots \neq \kappa_I \neq 0 \text{ variation of groups and within groups exist.}$$

Assuming normal distribution, likelihood (L) = $\frac{V/m}{V/n} \frac{e^{-\frac{1}{2}\sum V_i/m}}{\prod V_i/n} = \frac{N(X|\mu, \sigma^2)/m}{\sum N(X_i|\mu, \sigma^2)/n}$

if $m = I(J-1), n = (I-1)$; $\frac{\chi^2_{I(J-1)}}{I(J-1)} / \frac{\chi^2_{I-1}}{(I-1)}$

6. Bonferroni Inequality: $P(\bigcap_{i=1}^I A_i) \geq 1 - \sum P(A_i^c)$; A_i is the input to the probability space.
 A_i^c is the complement input to the probability space.



7. Show Theorem B of Section 12.2.1: $SS_B/\sigma^2 \sim \chi_{I-1}^2$

$$\begin{aligned} SS_B/\sigma^2 &= \frac{\sum_{i=1}^I k_i \bar{x}_i^2 + (I-1)\sigma^2}{\sigma^2} = \frac{\sum k_i \bar{x}_i^2}{\text{Var}(P_i)} + (I-1) = \frac{\sum k_i \bar{x}_i^2}{\text{Var}(\bar{Y}_i)} + (I-1) \\ &= (I-1) \sum_{i=1}^I \left(\frac{\bar{x}_i - \bar{Y}_i}{\sigma} \right)^2 \stackrel{D}{=} \chi_{I-1}^2 \end{aligned}$$

8. Total

9. The columns of a t-Distribution relate to Studentized ranges because of similar derivation Tukey's method on the probability of random variable led from a max of mean differences per pooled standard deviation per degrees of freedom for a normal distribution to $\frac{s_p}{\sqrt{J}}$; nevertheless, t-distribution was closely derived from mean differences, but per standard deviation per degrees freedom of two normal distributions. Thus t-distribution columns have a $\sqrt{2}$ for two distributions.

10. $I=7, J=10$. Tukey's Method: $(\bar{Y}_{i_1} - \bar{Y}_{i_2}) \pm q_{7,63}(\alpha) \frac{s_p}{\sqrt{J}} = 1 \pm \frac{q_{7,63}(\alpha)}{t_{63}(\alpha/n)} \sqrt{\frac{5}{J}} = 1 \pm \frac{4.31}{3.16} \sqrt{\frac{5}{10}} = 1 \pm 0.96$
 Bonferroni Method: $(\bar{Y}_{i_1} - \bar{Y}_{i_2}) \pm s_p \frac{t_{63}(\alpha/n)}{\sqrt{5}}$
 Regular t-statistic: $(\bar{Y}_{i_1} - \bar{Y}_{i_2}) \pm t_{63}(0.025) s_p \sqrt{\frac{2}{J}} = 1 \pm 0.053$

11. Factors

I	A	B	C	D
II	A	B	C	D
III	A	B	C	D

12. Factors

Diagonal	\bar{X}_1	\bar{X}_2	\bar{X}_3	\bar{X}_4
Level 1	\bar{X}_2	\bar{X}_3	\bar{X}_4	\bar{X}_5
Level 2	\bar{X}_3	\bar{X}_4	\bar{X}_5	\bar{X}_6

Mean Space:

$$\bar{X}_1, \bar{X}_2, \bar{X}_3, \bar{X}_4, \bar{X}_5$$

49. $n=126$ police officers; $\bar{X} = \text{Blood concentration of Lead } (\mu\text{g/dL}) = 29.2 \mu\text{g/dL}$

$$S_{\bar{X}} = 7.5 \mu\text{g/dL}$$

$$H_0: \bar{X} = \bar{y} \quad H_1: \bar{X} \neq \bar{y}$$

$$S_p = 7.1 \mu\text{g/dL}; S_{\bar{x}-\bar{y}} = 1.2 \mu\text{g/dL}$$

$$df = 174; t = 9.3 > t_{0.05}(1.05)$$

$n=50$ police officers; $\bar{y} = 18.2 \mu\text{g/dL}$; $S_y = 5.9 \mu\text{g/dL}$

50. a. $CI_{\text{Male-Female Temp}} = \{-0.53^\circ F, -0.04^\circ F\}$

The use of normal approximation is reasonable because the mean \approx median, and indicates low skew.

b. $CI_{\text{Male-Female Heart rate}} = \{-2.7 \text{ bpm}, 1.2 \text{ bpm}\}$

Application of a normal approximation better fits the male heart rate because of little skew, but the females mean heart rate (74 bpm) is low to the median (76 bpm) and may indicate the need for a parametric test.

c. Parametric:

Experiment	R	R'	U
Temperature (Males)	98.2	4733	122
Temperature (Females)	97.3		
Heart Rate (Males)	76.9	4442	10.3
Heart Rate (Females)	74.7		

Nonparametric:

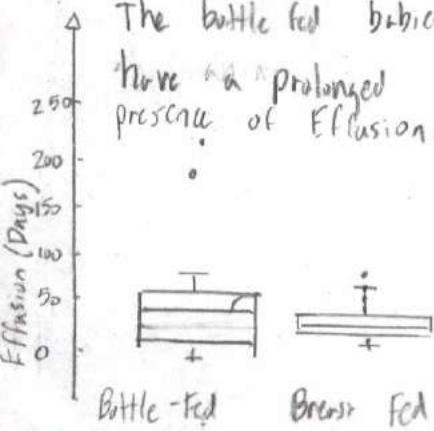
Experiment	ECx	SD(x)	S _p	B _{x-y}	df	t
Temperature (Males)	98.1	0.69	0.71	0.13	125	-2.30
Temperature (Females)	98.4	0.77				
Heart Rate (Males)	73	6.49	7.12	1.23	128	-0.63
Heart Rate (Females)	74	3.10				

The nonparametric test is showing rejection of the null hypothesis for male and female mean temperatures while acceptance of the alternative hypothesis for heart rate means.

Although, since the sample size is large (>30), the parametric test should be established as the leading indicator, and demonstrates corresponding p-values greater than a significance of $\alpha = 0.05$.

51. a.

The bottle fed babies have a prolonged presence of effusion.



b) A parametric test seems applicable because of the large skew between means and median values.

$$H_0: \text{Bottle Fed (days)} = \text{Breast Fed (days)}$$

The model suggests rejection of the null hypothesis in favor of the alternative.

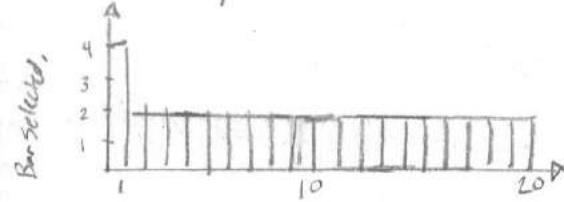
Experiment	R	R'	U
Bottle Fed	515	660	7.69
Breast Fed	660		

that the Breast Fed babies do not have prolonged effusion.

- 52.
- "Run fast" does not indicate which disease.
 - Insufficient evidence to conclude the wife does or does not smoke.
 - How does breakfast relate to industrial accidents?
 - Did the student scores compare to the majority or minority school?
 - Would a questionnaire better be prepared if other days were tested?
 - A comparator would help determine if beer or alcohol should be reported.
 - Did the 15-year study have a controlled variable?
 - What about the other 35% of married couples?
 - Were the elderly of the same age group?

53. Both lettuce leaves and unlit cigarettes represent placbos to the experimental design. Lettuce leaves contain no amount of nicotine, while unlit cigarettes do, but are not inhaled and solely behaviorally considered.

54. The length of bar was not randomized, and yet the error would be detectable if not randomized over time because of selection bias being time independent.



$$\begin{array}{ccc} A & B & C \\ \hline I & \bar{x}_1, \bar{x}_2, \bar{x}_3 & \text{Sample Space} \\ II & \bar{x}_2, \bar{x}_3, \bar{x}_4 & \end{array}$$

13. Kruskal-Wallis Test:

Mann-Whitney:
Average Rank $\bar{R} = \frac{(N+1)}{2}$

$$\text{Variance} = \frac{12}{N(N+1)} = K$$

$$14. \text{ Friedman's Test: } SS_A = J \sum_{i=1}^I (\bar{R}_i - \bar{R}_{..})^2$$

$$Q = \frac{12J}{I(I+1)} \sum_i (\bar{R}_i - \bar{R}_{..})^2$$

Sign Test: $P = P(X > Y)$; $H_0: p = 0.50$

m pairs: $\{x_1, y_1\}, \dots, \{x_n, y_n\}$

$$15. W = \# \text{ pairs } y_i - x_i > 0 \sim \text{bin}(m, p)$$

$$K = \frac{12}{N(N+1)} \sum_{i=1}^I J_i (\bar{R}_i - \bar{R}_{..})^2$$

$$= \frac{12}{N(N+1)} \sum_{i=1}^I J_i (\bar{R}_i^2 - 2\bar{R}_i \bar{R}_{..} + \bar{R}_{..}^2)$$

$$= \frac{12}{N(N+1)} \sum_{i=1}^I J_i \bar{R}_i^2 - 2 \sum_{i=1}^I J_i \left(\frac{N+1}{2} \right) \frac{1}{J_i} \sum_{j=1}^J R_{ij} + \sum_{i=1}^I J_i \left(\frac{N+1}{2} \right)^2$$

$$= \frac{12}{N(N+1)} \sum_{i=1}^I J_i \bar{R}_i^2 - \frac{12 \cdot I}{N(N+1)} \cdot \frac{N(N+1)}{2} \cdot \frac{N(N+1)}{2} + \frac{12}{N(N+1)} \frac{(N+1)^2}{4} = \frac{12}{N(N+1)} \sum_{i=1}^I J_i \bar{R}_i^2 - 3(N+1)$$

R_{ij} = the rank of y_{ij} in the combined sample

$$\bar{R}_i = \frac{1}{J_i} \sum_{j=1}^{J_i} R_{ij} = \text{Average rank in } i^{\text{th}} \text{ group}$$

$$\bar{R}_{..} = \frac{1}{N} \sum_{i=1}^I \sum_{j=1}^{J_i} R_{ij} = \frac{N+1}{2} = \text{Average total rank}$$

$$SS_B = \sum_{i=1}^I J_i (\bar{R}_i - \bar{R}_{..})^2 = \text{Variance between ranks}$$

$K = \frac{12}{N(N+1)} SS_B = \text{Chi-squared Distribution with } (I-1) \text{ degrees of freedom.}$

$$= \frac{12}{N(N+1)} \left(\sum_{i=1}^I J_i \bar{R}_i^2 \right) - 3(N+1)$$

The tested probability of a-Signed rank test ($p = P(X > Y)$) is K in to Friedmans probability ($P(X_{k-1}^2 \geq Q)$)

When two categories are presented ($k=2$)

$$16. \text{ Prove } SS_{\text{Tot}} = SS_A + SS_B + SS_{AB} + SSE = JK \sum_{i=1}^I (\bar{Y}_{i..} - \bar{Y}_{...})^2 + IK \sum_{j=1}^J (\bar{Y}_{.j} - \bar{Y}_{...})^2 + K \sum_{i=1}^I \sum_{j=1}^J (\bar{Y}_{ij} - \bar{Y}_{i..} - \bar{Y}_{.j} + \bar{Y}_{...})^2$$

17. Find mle's of $\kappa_i, \beta_j, \delta_{ij}$, and μ .

$$l = -\frac{IJK}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (Y_{ijk} - \mu - \kappa_i - \beta_j - \delta_{ij})^2$$

$$\frac{dl}{d\kappa_i} = \frac{\kappa_i}{\sigma^2} \sum_{j=1}^J \sum_{k=1}^K (Y_{ijk} - \mu - \kappa_i - \beta_j - \delta_{ij}) = 0$$

$$\hat{\kappa}_i = \bar{Y}_{i..} - \bar{Y}_{...}$$

$$\frac{dl}{d\beta_j} = \frac{\beta_j}{\sigma^2} \sum_{i=1}^I \sum_{k=1}^K (Y_{ijk} - \mu - \kappa_i - \beta_j - \delta_{ij}) = 0$$

$$\hat{\beta}_j = \bar{Y}_{.j} - \bar{Y}_{...}$$

$$\frac{dl}{d\delta_{ij}} = \frac{\delta_{ij}}{\sigma^2} \sum_{k=1}^K (Y_{ijk} - \mu - \kappa_i - \beta_j - \delta_{ij}) = 0$$

$$\hat{\delta}_{ij} = \bar{Y}_{ij} - \bar{Y}_{i..} - \bar{Y}_{.j} + \bar{Y}_{...}$$

$$\frac{dl}{d\mu} = \frac{\mu}{2\sigma^2} \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (Y_{ijk} - \mu - \kappa_i - \beta_j - \delta_{ij}) = 0$$

$$\hat{\mu} = \bar{Y}_{...}$$

$$\begin{aligned} &= \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (\bar{Y}_{i..} - \bar{Y}_{...})^2 + \sum_{i=1}^I \sum_{j=1}^J (\bar{Y}_{.j} - \bar{Y}_{...})^2 + \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (\bar{Y}_{ij} - \bar{Y}_{i..} - \bar{Y}_{.j} + \bar{Y}_{...})^2 \\ &= \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K [(\bar{Y}_{i..} - \bar{Y}_{...})^2 + (\bar{Y}_{.j} - \bar{Y}_{...})^2 + (\bar{Y}_{ij} - \bar{Y}_{i..} - \bar{Y}_{.j} + \bar{Y}_{...})^2 + (\bar{Y}_{ijk} - \bar{Y}_{ij})^2] \\ &= \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K [(Y_{ijk} - \bar{Y}_{ij})^2] \end{aligned}$$

18.

19. One-Way Layout

$Y_{ij} = j^{\text{th}}$ observation of i^{th} treatment

$$= \mu + K_i + E_{ij} \quad \begin{matrix} \text{overall mean} \\ \text{Differential effect of } i^{\text{th}} \text{ treatment} \end{matrix}$$

$\sum_i K_i = 0$: Normalized

$$\sum_i \sum_j (Y_{ij} - \bar{Y}_{..})^2 = \sum_i \sum_j (Y_{ij} - \bar{Y}_i)^2 + J \sum_i (\bar{Y}_i - \bar{Y}_{..})^2$$

Where $\bar{Y}_i = \frac{1}{J} \sum_j Y_{ij}$: Average observation of i^{th} treatment

$$\bar{Y}_{..} = \frac{1}{IJ} \sum_i \sum_j Y_{ij} : \text{Overall Average}$$

$$SS_{\text{TOT}} = SS_A + SS_B = \sum_i (J-1) S_i^2 + \sum_i K_i^2 + \sigma^2$$

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-x^2/2\sigma^2)$$

$$SS_{\text{TOT}} = SS_A + SS_B + SS_{AB} + SS_E$$

The parametrization of a balanced three-way layout includes two-factor and three-factor interactions.

A two-factor interaction ($\alpha_i, \beta_j, \gamma_i$) represents the mean of a row, column, or depth of the matrix. While the three-factor interaction (δ_{ijk}) is interpreted as the residual within the cell.

$$20. Y_{ij} = \mu + A_i + E_{ij}; A_i = \text{Random}; E(A_i) = 0; \text{Var}(A_i) = \sigma_A^2; E_{ij} \text{ independent of } A_i$$

$$E(E_{ij}) = 0; \text{Var}(E_{ij}) = \sigma_E^2$$

$$a) \text{Show } E(MS_W) = \sigma_E^2; E(MS_B) = \sigma_E^2 + J\sigma_A^2; E(MS_W) = \frac{E(SS_{AB})}{(I-1)(J-1)} = \sigma^2 + \frac{1}{(I-1)(J-1)} \sum_i \sum_j \delta_{ijk}^2 = \sigma_E^2 + \sigma_A^2$$

$$E(MS_B) = \frac{E(SS_B)}{(J-1)} = \sigma_E^2 + \frac{I}{(J-1)} \sum_j \beta_j^2 = \sigma_E^2 + J\sigma_A^2$$

For dataset: Dye

Source	df	SS	MS	F
Samples	5	111.74	22.35	5.65
Error	5	113.65	22.73	-
Total	10	225.39	-	-

$$F = \frac{SS_B / (J-1)}{SS_W / [I(J-1)]} = 5.90.$$

b) The parameters of the model are estimated by the F-statistic because the stat incorporates

mean square error of multiple categories. The hypothesis ($H_0: \alpha_1 = \alpha_2 = \dots = \alpha_I = 0$) fails at a p-value of 0.05.

Two-Way Layout

$$\bar{Y}_{..} = \frac{1}{IJ} \sum_i \sum_j Y_{ij} : \text{Grand Average}$$

$\bar{Y}_{..i}$: Average over rows

$\bar{Y}_{.j}$: Average over columns

$$\hat{\alpha}_i = \bar{Y}_{..i} - \bar{Y}_{..} : \text{Differential row Average}$$

$$\hat{\beta}_j = \bar{Y}_{.j} - \bar{Y}_{..} : \text{Differential column Average}$$

$$\hat{\delta}_{ijk} = Y_{ijk} - \bar{Y}_{..i} - \bar{Y}_{.j} - \hat{\alpha}_i - \hat{\beta}_j : \text{Interaction of rows and columns}$$

$$Y_{ijk} = \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j + \hat{\delta}_{ijk} : \text{Additive Model}$$

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \delta_{ijk} + \epsilon_{ijk} : \text{Balanced}$$

Three-Way Layout

$$Y_{ijk} = \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j + \hat{\gamma}_k + \hat{\delta}_{ijk} + \epsilon_{ijk}$$

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-x^2/2\sigma^2)$$

$$l = -\frac{1}{2} \log 2\pi\sigma^2 - \epsilon^2/2\sigma^2$$

$$\frac{dl}{d\mu} = Y_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\gamma}_k - \hat{\delta}_{ijk} - H = 0$$

$$\frac{dl}{d\alpha_i} = Y_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\gamma}_k - \hat{\delta}_{ijk} - H = 0$$

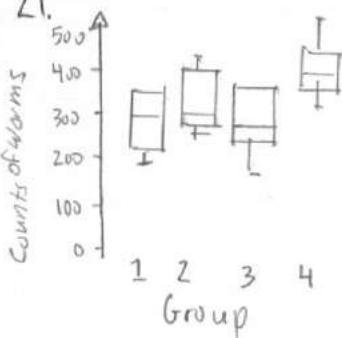
$$\frac{dl}{d\beta_j} = Y_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\gamma}_k - \hat{\delta}_{ijk} - H = 0$$

$$\frac{dl}{d\gamma_k} = Y_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\gamma}_k - \hat{\delta}_{ijk} - H = 0$$

$$\frac{dl}{d\delta_{ijk}} = Y_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\gamma}_k - \hat{\delta}_{ijk} - H = 0$$

$$\hat{\delta}_{ijk} = \bar{Y}_{ijk} - \bar{Y}_{..i} - \bar{Y}_{.j} - \bar{Y}_{..} + \bar{Y}_{...}$$

21. Parametric Technique



Nonparametric Technique:

Group	1	2	3	4
R	42	53	36	79

$$H = 6.2, df = 3, \chi^2_{0.90} = 7.8$$

Rejection of null hypothesis
at $p\text{-value} > 0.10$.

Both parametric and nonparametric tests demonstrate unequal amounts of variance per group.

22. Manufacturer #1

Source	df	SS	MS	F
Labs	6	0.125	0.021	5.66
Amount	63	0.231	0.004	
Total	69	0.356		

$$H_0: \bar{X}_1 = \bar{X}_2 = \bar{X}_3 = \bar{X}_4 = 0$$

 $H_1: \bar{X}_1 \neq \bar{X}_2 \neq \bar{X}_3 \neq \bar{X}_4 \neq 0$

$$F_{6,60} = 3.12$$

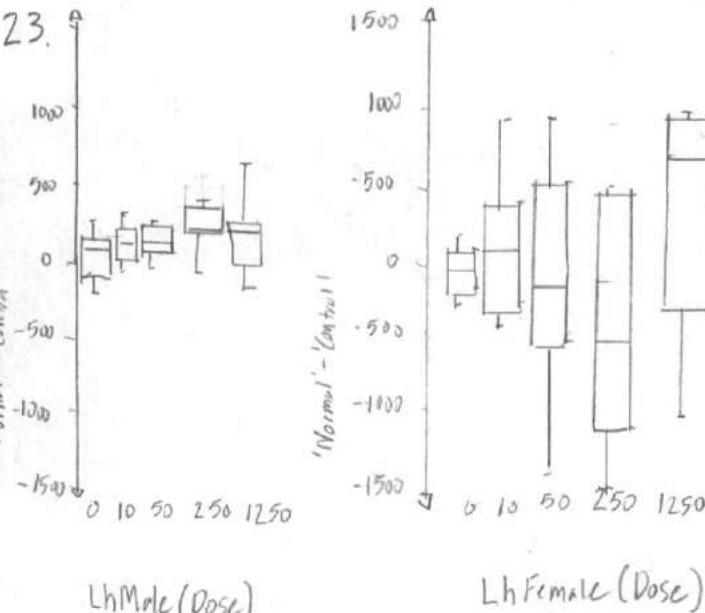
Rejection of the null hypothesis that lab data contains similar means and variances.

Manufacturer #2

Source	df	SS	MS	F
Labs	6	0.153	0.026	11.90
Amount	63	0.135	0.002	
Total	69	0.288		

Also, rejection of the null hypothesis with a $p\text{-value} > 0.01$.

23.



$$\chi^2(0.95) = 41.337, \chi^2 = 1040 \text{ Females' Normal - Constant}$$

$H_0: \bar{X} = \mu_0$ vs $H_1: \bar{X} \neq \mu_0$: Rejection of null hypothesis for females.
 There is indication of threshold dosage for Intensizing hormone.

Source	df	SS	MS	F
Posage	4	663.9701	165.9925	21.4
Lighter	1	950.6147	950.6447	122.4
Interaction	4	464.1765	116.0441	14.9
Error	50	388.3247	77.669	
Total	59	2467.1660		

24.

Source	SS	df	MS	F	p-value
Labs	33.1	11	3.0	6.7	3×10^{-3}
Cereal	3556.3	5	711.3	1453.5	2×10^{-12}
Interaction	30.3	55	0.55	1.1	0.29
Error	90.5	144	0.41		
Total	3690.2	215			

The first successful Two-Way ANOVA

by hand presents inconsistent data per lab and bran vs. cereal because of a p-value < 0.05. The error is consistent between data sets at 0.29.

The null hypothesis is rejected that the effect from Intensizing hormone generates a balanced result with increasing dosage for both men and women ($H_A: \bar{X}_i \neq \bar{X}_j$).

25. Null Hypothesis: $H_0: \mu_1 = \dots = \mu_i = 0$

Alternative Hypothesis: $H_1: \mu_1 \neq \dots \neq \mu_i \neq 0$

Source	SS	df	MS	F	p-value	Fcrit
Between	201.8	9	22.4	2.94	0.005	1.99
Within	710.4	90	7.9			
Total	912.2	99				

The data from magnesium samples, at glance, presents large chemical content in column #1. An One-way Anova describes error between the groups and Within at a p-value of 0.005, rejecting the null hypothesis of similar chemical content across samples and portions of the bar.

26. Parametric

Source	SS	df	MS	F	p-value	Fcrit
Dogs	0.52	9	0.057	0.349	0.95	2.39
Chemical	3.29	20	0.16			
Total	3.81	29				

Nonparametric

Dog

R

$$H = 0.87, \chi^2 = 1.73$$

1	2	3	4	5	6	7	8	9	10
37	60.5	67.5	38.5	45	43	40.5	55.5	44.5	25

The F-statistic concludes no difference per dog or chemical exposed, with a p-value > 0.95. A nonparametric Kruskall-Wallis test confirmed no differences as compared to a 9-degree chi-squared distribution. Blood plasma did not change as compared to exposure.

27. Bonferroni Method:

Comparison	Mean D.F.	CI
C7-AJ	177.3	69.4
C7-FZ	101.4	69.4
AJ-FZ	-75.9	69.4

The Bonferroni method confirms each group is drastically different as represented by their means; while, confidence intervals show errors of nearly double the comparator.

28. Parametric:

Source	SS	df	MS	F	p-value	Fcrit
Types(Between)	446.6	2	223.3	0.497	0.61	3.59
Types(Within)	762.3	17	44.80			
Total	9073.9	19				

Nonparametric:

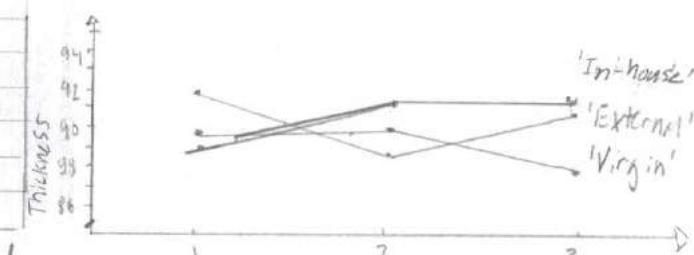
	Type I	Type II	Type III
R	76.5	78	55.5
n	9	6	5
H		2.15	

$$\chi^2 = 28.87$$

Both the parametric and nonparametric analysis confirmed the hypothesis ($H_0: \pi_1 = \pi_2 = \pi_3$).

29.

Source	SS	df	MS	F	p-value	Fcrit
Furnace	4.1	2	2.05	1.45	0.26	3.55
Wafer Type	5.9	2	2.95	2.07	0.16	3.55
Furnace and Wafer	21.3	4	5.34	3.76	0.02	2.93
Residual	25.6	18	1.42			
Total	56.9	26				



Noticeable differences exist between the furnace and wafer thickness, but the type and furnace individually are acceptable.

30. Tukey's Method:

$$q_{6,40}(0.05) = 4.23$$

$$S_p = 216.07$$

$$\sqrt{J} = 3.16$$

$$\text{Tukey CI} = 289.02$$

Plot Average

'3'	1263
'2'	1272.6
'5'	1306.4
'4'	1316.4
'6'	1331.4
'1'	1768.5

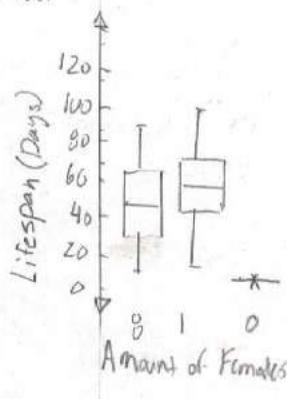
$$\max(\bar{Y}_i - \bar{Y}_j) = \text{Plot 3} - \text{Plot 1}$$

$$= 500.5$$

Tukey method's comparison of maximum average differences is not significant.

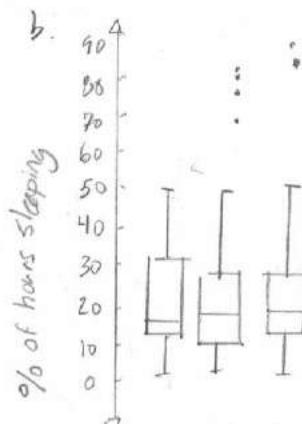
31. An additive model would provide a good fit to the dataset for secondary indication maximum windspeeds are variable

32. a.



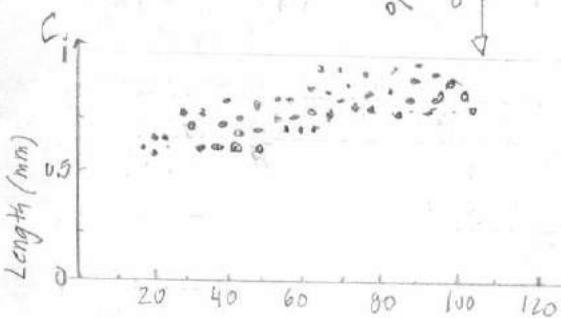
Amount of Females	Mean	Variance
0	63.6	259.8
1	60.8	240.73
0	51.0	323.6

The lifespan without females was drastically for male fruitflies.



Amount of Females	Mean	Variance
0	21.6	149.0
1	24.9	297.7
2	23.0	249.0

The hours slept were equivalent with or without a female fruitfly present.



a. Thorax, Lifespan (Days)

Source	df	MS	F	p-value	F-crit
Between	4	0.006	1.15	0.33	2.45
Within	120	6.006			
Total	124				

Lifespan

Source	df	MS	F	p-value	F-crit
Between	4	29.85	13.6	3.6e-10	2.45
Within	120	21.9			
Total	124				

Sleep

Source	df	MS	F	p-value	F-crit
Between	4	121.7	0.47	0.73	2.45
Within	120	256.5			
Total	124				

BonFerroni Method Lifespan : CI = 0.02

Comparison	9/10	9/11	9/30	9/31	10/11	10/30	10/31	11/30	11/31	12/31
Mean Difference	-2.2	6.8	0.2	24.3	9.0	1.4	26.1	-6.6	18.0	24.6

Thorax : CI = 3.21

Comparison	9/10	9/11	9/30	9/31	10/11	10/30	10/31	11/30	11/31	12/31
Mean Difference	0.01	0.00	0.00	0.04	-0.01	0.01	0.03	0.02	0.04	0.02

Sleep : CI = 3.21

Comparison	9/10	9/11	9/30	9/31	10/11	10/30	10/31	11/30	11/31	12/31
Mean Difference	-2.5	-4.2	-3.6	0.8	-1.7	-1.1	3.3	0.6	1.5	4.4

Sleep : CI = 0.02

Tukey Method:

Category	9/10,100	S _p	\sqrt{J}	CI	$\max(\bar{Y}_i - \bar{Y}_j)$
Thorax	5.32	3.05	2.3	7.2	0.04
Lifespan	9.32	0.02	2.3	0.04	26.08
Sleep	5.32	0.01	2.3	0.03	4.4

The lifespan is concluded as significant.

Confidence Interval.

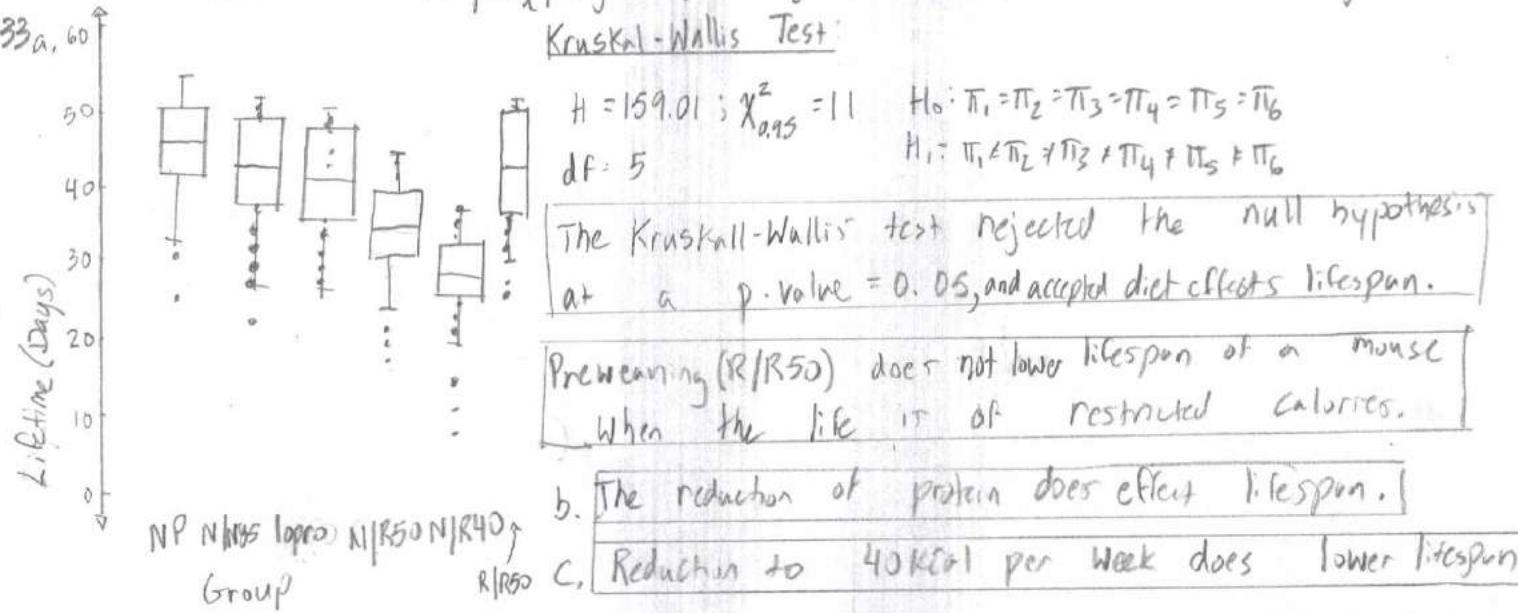
e. Kruskal-Wallis test:

Group	H	df	$\chi^2_{0.95}$
Lifespan	37.9	5	11.07
Thorax	5.6	5	11.07
Sleep	0.3	5	11.07

With another Nonparametric analysis, lifespan of the fruitfly is significant, and an outlier to the information collected.

f. The dataset of one, eight (pregnant, or virgin) females provides no change on sleep.

33. a. 60
Kruskal-Wallis Test:



34. a.

Source	SS	df	MS	F	p-value	Fcrit
Treatment	91.9	3	30.6	11.8	5.92×10^{-3}	3.0
Poison	105.1	5	21.0	8.1	0.0001	2.6
Treatment x Poison	39.2	15	2.6	1.01	0.43	2.1
Error	62.1	24	2.6			
Total	299.4	47				

The treatment and poison category show significance, but the interaction of the treatment x poison does not accept alternatives.

b.

Source	SS	df	MS	F	p-value	Fcrit
Treatment	0.20	3	0.07	23.6	2.41×10^{-7}	3.0
Poison	0.40	5	0.07	24.9	8.94×10^{-9}	2.6
Treatment x Poison	0.02	15	0.00	0.5	0.89	2.1
Error	0.07	24				
Total	0.65	47				

Bob and Cox (1964) analysis of reciprocal data conclude similar outcomes to particular Treatment x Poisons is not significant, and individual treatments or poisons are significant.

35. The interaction of dosage and serum were not important, indicating the culture produced similar amounts of estrogen relative to primary categories. Although, estrogen production did have significant differences for type of serum, in addition to increased dosage.

individual treatments or poisons are significant.

Source	SS	df	MS	F	p-value	Fcrit
Dosage	2.74×10^7	11	2.54×10^8	23.85	0.00	2.06
Treatment	6.30×10^8	2	3.15×10^8	29.60	0.00	3.76
Dosage x Treatment	3.98×10^8	22	1.41×10^7	1.70	0.07	1.85
Error	3.83×10^8	36	1.1×10^7			
Total	4.21×10^9	71				

e. $H_0: \beta_{1,\text{Male}} = \beta_{2,\text{Female}}$
 $H_1: \beta_{1,\text{Male}} \neq \beta_{2,\text{Female}}$

$$t = \frac{\beta_{1,\text{Male}} - \beta_{2,\text{Female}}}{S_{\beta_1 - \beta_2}} \sim S_{\beta_1 - \beta_2} = S_p \sqrt{\frac{1}{n} + \frac{1}{m}} = \sqrt{\frac{(n-1)S_x^2 + (m-1)S_y^2}{m+n-2} \left[\frac{1}{n} + \frac{1}{m} \right]} \\ = \sqrt{\frac{(65-1)1.039^2 + (64-1)1.316^2}{65+64-2} \left[\frac{1}{65} + \frac{1}{64} \right]} \\ = 7.13$$

Degrees of Freedom = 127

= 0.209

$t_{120}(0.95) < t$; An alternative hypothesis is acceptable; including male and female temperature vs heart rate are not related.

F. $H_0: \beta_{0,\text{Male}} = \beta_{0,\text{Female}}$
 $H_1: \beta_{0,\text{Male}} \neq \beta_{0,\text{Female}}$

$$t = \frac{\beta_{0,\text{Male}} - \beta_{0,\text{Female}}}{S_{\beta_0 - \beta_0}} \sim S_{\beta_0 - \beta_0} = \sqrt{\frac{(65-1)101.9^2 + (64-1)129.52^2}{65+64-2} \left[\frac{1}{65} + \frac{1}{64} \right]} \\ = \frac{-1233 + 871}{20.4} = 7.16$$

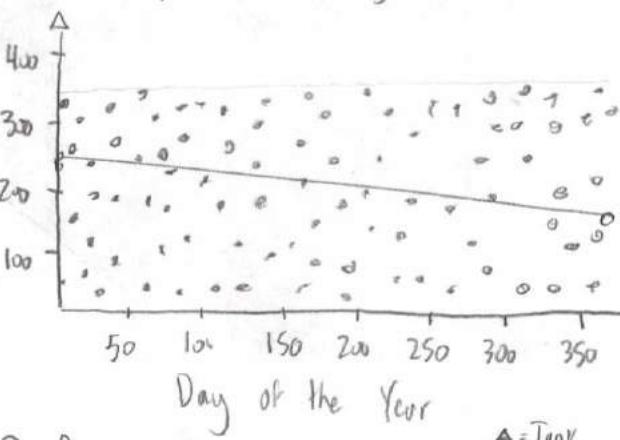
= 7.16

$t_{120}(0.95) < t$; An alternative hypothesis is acceptable.

53. Old faithful's interval between explosion is related to duration by a linear fit having an R^2 of 0.73.

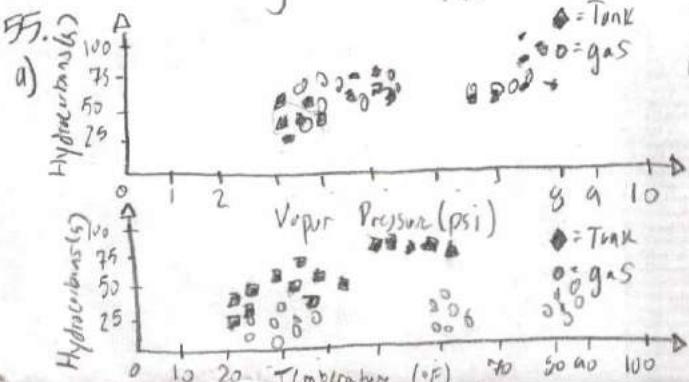
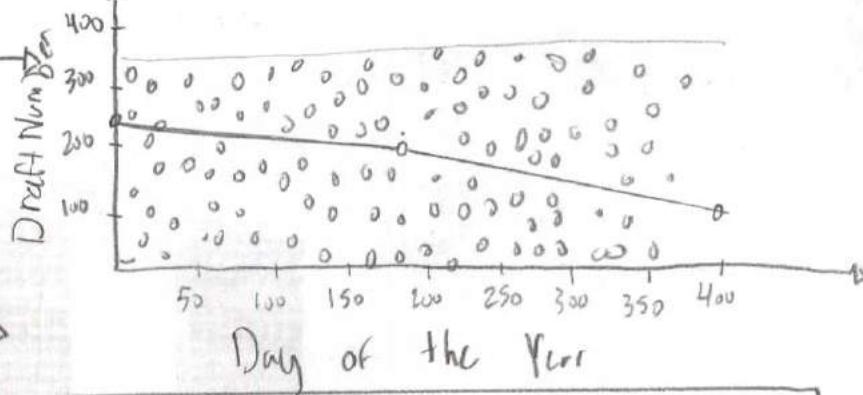
b) If the duration is 2 minutes, to predict a time until next eruption would require a function. Linear regression of $Y = 10.74 \cdot \text{Duration} + 33.83$ minutes is best fit and describes an interval till next eruption to be 55 min.

54. a) The plot of 'Day of the Year' vs 'Draft Number' shows lack of trend



b) The linear regression model $Y = -0.22X + 225$ is plotted in part a), but has an R^2 of 0.05.

c) Bandwidth = 180



The groupings (vapor pressure, temperature) are associated to hydrocarbon production by visual observations, especially vapor pressure.

b) The best fits are tank vapor pressure vs. hydrocarbon weight and gas vapor pressure vs. hydrocarbon weight.

c) Root mean square Prediction: $RMSPE = \sqrt{\frac{1}{40} \sum_{i=1}^{40} (Y_i - \hat{Y}_i)^2}$

Model: Gas Vapor Pressure vs. Hydrocarbon Weight

Coefficient	Estimate
β_0	6.62
β_1	5.56

$$RMSPE = \sqrt{\frac{1}{40} \sum_{i=1}^{40} (Y_i - 6.62 - 5.56 X_i)^2}$$

$$= 0.667$$

Model: Tank Vapor Pressure vs. Hydrocarbon weight

Coefficient	Estimate
β_0	3.59
β_1	6.34

$$RMSPE = \sqrt{\frac{1}{40} \sum_{i=1}^{40} (Y_i - 3.59 - 6.34 X_i)^2}$$

$$= 0.634$$

56. a) After examination of different combinations of data, insolation fits the upper ranges of oxidation, while wind speed, temperature, and humidity better fit oxidation when less than 30 ppm. Oxidation level maximums are modeled with insolation to a regression of $Y = 0.23X - 1.43$, but do have a squared multiple correlation coefficient (R^2) of 0.22.

b) Serial correlation (or experimental drift) appears in time-resolved data as increasing (or decreasing) residual error.

ABO System

Severity	O	A	AB	B
Moderate-Advanced	7	5	3	13
Minimal	27	32	8	18
Not Present	55	50	7	24

$$df = 6, \chi^2 = 20.20, \chi^2(0.995) = 18.55$$

O	A	AB	B
1.13	2.64	0.38	11.33
0.31	0.81	0.98	1.07
0.37	0.05	1.03	0.10

$$df = 4, \chi^2 = 12.05, \chi^2(0.995) = 14.86$$

INN System

Severity	MM	MN	NN
Moderate Advanced	21	6	1
Minimal	54	27	5
Not Present	74	51	11

MM	MN	NN
1.11	1.23	0.14
0.02	0.23	0.18
0.61	3.15	0.33

$$H_0: \pi_{ij} = \pi_{ii} \cdot \pi_{jj} \quad (\text{Independent Datasets})$$

Each of the datasets test $\chi^2 > \chi^2_{0.995}$ which implies disease severity is dependent on blood type.

	Male	Female	
Mentioned	86	55	141
Not Mentioned	283	360	643
	369	415	784

$$df = 1; \chi^2 = 13.38; \chi^2(0.995) = 7.88$$

5.81	5.17
1.27	1.13

$$H_0: \pi_{11} = \pi_{12}; H_1: \pi_{11} \neq \pi_{12}$$

The null hypothesis is rejected at a p-value < 0.005, that implies males and females do attribute differently.

Ethnic Origin	Yes	No	
Italian	76	47	125
Northern European	56	29	85
Other European	43	29	72
English	53	32	85
Irish	43	30	73
French Canadian	36	22	58
French	42	23	65
Portuguese	29	7	36
	380	219	599

$$df = 7, \chi^2 = 0.42$$

$$\chi^2_{0.005} = 0.989$$

$$H_0: \pi_{11} = \pi_{12}$$

$$H_1: \pi_{11} \neq \pi_{12}$$

The hypothesis is accepted at a p-value > 0.95, suggesting each ethnic origin equally responded 'yes' and 'no' to the questionnaire.

Chapter 13: The Analysis of Categorical Data

	Diabetic	Normal	
Bb/bb	12	4	16
BB	39	49	88
	51	53	104

$$p(Bb \text{ or } bb | \text{Diabetic}) = \frac{\left(\begin{array}{c} P(\text{Diabetic}) \\ P(Bb \text{ or } bb | \text{Diabetic}) \end{array} \right) \left(\begin{array}{c} P(BB) \\ P(BB | \text{Diabetic}) \end{array} \right)}{\left(\begin{array}{c} \text{Total} \\ P(\text{Diabetic}) \end{array} \right)}$$

$$= \frac{\left(\begin{array}{c} 61 \\ 12 \end{array} \right) \left(\begin{array}{c} 88 \\ 39 \end{array} \right)}{\left(\begin{array}{c} 104 \\ 51 \end{array} \right)} = 7.48 \times 10^{-5}$$

Fishers Exact Test

Yes, the probability of alleles (BB or bb) is less than a significance of $\alpha = 0.05$, which suggests an imbalance between the categories and acceptance of the alternative hypothesis ($p(Bb \text{ or } bb) \neq p(BB)$).

Chi-Square Test

	Diabetic	Non-Diabetic
BB/bb	2.99	0.214
BB	0.399	0.384

$$\chi^2 = \sum_{i=1}^2 \sum_{j=1}^2 \frac{(O_{ij} - E_{ij})^2}{E_{ij}} = \sum_{i=1}^2 \sum_{j=1}^2 \frac{(n_{ij} - n_i \cdot n_j / n_{..})^2}{n_i \cdot n_j / n_{..}}, \chi^2_{0.975} = 5.02$$

The outcome of comparing χ^2 -statistic was a p-value < 0.025, which agrees with Fishers exact statistic.

Week	Chinese	Jewish
-2	55	141
-1	33	145
1	70	139
2	49	161
	207	536
	196	743
	209	793

$$\chi^2 = 0.29 + 0.10 + 3.90 + 1.38 + 4.37 + 0.58 + 0.62 + 0.22 = 11.46, df = 3; \chi^2_{0.995} = 11.34$$

By leaving the data alone, a p-value < 0.005 was evaluated as a rejection of the null hypothesis.

Although, by combining the information before ceremony and weeks after into two groups,

χ^2 became 2.55 with $df = 1$, an acceptance of the

null hypothesis ($H_0: \text{Weeks Prior to Ceremony} = \text{Weeks after Ceremony}$) with a p-value > 0.10,

-2/-1	0.949	0.458	0.93
1/2	0.947	0.299	

0.949 0.458

Severely Advanced	0.299
Moderately Advanced	
Minimal	0.2755

Father's Activity	Female Offspring	Male Offspring
Flying Fighters	51	38
Flying Transports	14	16
Not Flying	38	46

89	0.756	0.779
30	0.931	0.101
94	0.501	0.526

103

100

203

$$\chi^2 = 3.64, df = 2, \chi^2_{0.90} = 4.61$$

$H_0: \Pi_{i1} = \Pi_{i2}$; $H_1: \Pi_{i1} \neq \Pi_{i2}$; The null hypothesis was accepted with this information at a p-value > 0.10, implying the offspring genders were independent of Father's activity.

Grade	Psychology	Biology	Other
A	8	15	13
B	14	19	15
C	15	4	7
D-F	3	1	4

1.45	0.81	0.10
1.32	0.62	0.05
4.34	2.45	0.30
0.03	1.02	0.695

$$df = 6, \chi^2 = 13.19$$

$$X^2_{0.975} = 14.45$$

$H_0: \Pi_{i1} = \Pi_{i2} = \Pi_{i3}$; $H_1: \Pi_{i1} \neq \Pi_{i2} \neq \Pi_{i3}$; The analysis of the data suggests a rejection of the null hypothesis in favor of the alternative, and grades

	# Patients	Incidence
Placebo	165	95
Chlorpromazine	152	52
Dimenhydrinate	85	52
Pentobarbital (10mg)	67	35
Pentobarbital (15mg)	85	37

0.53	1.09
1.64	3.36
0.53	1.09
0.03	0.07
0.12	0.24

 $df = 4$

$$\chi^2 = 8.69$$

$$X^2(0.95) = 9.49$$

$$df = 5, \chi^2 = 3.014$$

1.31	3.56
0.77	2.09
1.98	5.39
0.009	0.53
3.32	9.03
0.69	1.99

The null hypothesis is rejected at a p-value of 0.005.

Austen	Imitator
24	2
273	91
26	1
424	153
14	17
496	204

1247 458

$$X^2(0.995) = 16.75$$

$$H_0: \Pi_{i1} = \Pi_{i2}$$

$$H_1: \Pi_{i1} \neq \Pi_{i2}$$

Austen's Imitator did not write to similar standards as her original works.

10. Chi-Square Test of Independence:

Contingency Table:

$$\pi_{ij} = \sum \pi_{ij} ; \quad \pi_{i\cdot} = \pi_{i1}, \pi_{i\cdot} ; \quad H_0: \pi_{ij} = \pi_{i\cdot} \pi_{\cdot j} ; \text{ MLE } H_0: \hat{\pi}_{ij} = \hat{\pi}_{i\cdot} \hat{\pi}_{\cdot j} = \frac{n_{i\cdot}}{n} \times \frac{n_{\cdot j}}{n}$$

$$\pi_{\cdot j} = \sum \pi_{ij}$$

McNemars Test: $\hat{\pi}_{12} = \hat{\pi}_{21} = \frac{n_{12} + n_{21}}{2n}$

$$X^2 = \frac{(n_{12} - n_{21})^2}{n_{12} + n_{21}}$$

Derived From Multinomial:

$$lik(\pi_1, \pi_2, \dots, \pi_L) = \prod_{i=1}^L \binom{n_i}{n_{1i} n_{2i} \dots n_{Li}} \pi_1^{n_{1i}} \pi_2^{n_{2i}} \dots \pi_L^{n_{Li}}$$

$$I(\pi, \lambda) = \sum \log \left(\frac{n_{i\cdot}}{n_{1i} n_{2i} \dots n_{Li}} \right) + \sum_i n_{i\cdot} \log \pi_{i\cdot} + \lambda \left(\sum_i \pi_{i\cdot} - 1 \right)$$

11. a) Likelihood Ratio Test for Homogeneity:

$$\Lambda = \frac{P(\Theta | H_0)}{P(\Theta | H_1)} = \frac{P(\hat{\Theta})}{\hat{P}(\Theta)} = \frac{\frac{n!}{x_1! \dots x_m!} P_1(\hat{\Theta})^{x_1} \dots P_m(\hat{\Theta})^{x_m}}{\frac{n!}{x_1! \dots x_m!} P_1(\Theta)^{x_1} \dots P_m(\Theta)^{x_m}}$$

$$= \prod \left(\frac{P_i(\hat{\Theta})}{\hat{P}_i} \right)^{x_i}; \quad -2 \log \Lambda = -2n \sum p_i \log \left(\frac{P_i(\hat{\Theta})}{\hat{P}_i} \right) = 2 \sum \sum O_i \log \left(\frac{O_i}{E_i} \right) \quad \boxed{\pi_{i\cdot} = \frac{n_{i\cdot}}{n}}$$

$$(b) -2 \log \Lambda = 2 \sum \sum O_i \log \left(\frac{O_i}{E_i} \right) = 2 \sum \sum n_{ij} \cdot \log \left(\frac{n_{ij}}{n_{i\cdot} n_{\cdot j}} \right) =$$

c) Likelihood Ratio Test for Independence:

$$\Lambda_{ij} = \Lambda_i \cdot \Lambda_j = \frac{P(\theta_i | H_0)}{P(\theta_i | H_1)} \cdot \frac{P(\theta_j | H_0)}{P(\theta_j | H_1)} = \frac{\frac{n!}{x_1! \dots x_m!} P_1(\hat{\theta}_i)^{x_1} \dots P_m(\hat{\theta}_i)^{x_m}}{\frac{n!}{y_1! \dots y_m!} P_1(\hat{\theta}_j)^{y_1} \dots P_m(\hat{\theta}_j)^{y_m}} \cdot \frac{\frac{n!}{y_1! \dots y_m!} P_1(\hat{\theta}_j)^{y_1} \dots P_m(\hat{\theta}_j)^{y_m}}{\frac{n!}{y_1! \dots y_m!} P_1(\hat{\theta}_i)^{y_1} \dots P_m(\hat{\theta}_i)^{y_m}}$$

$$\Lambda_{ij} = \prod \left(\frac{P_i(\hat{\theta}_i)}{\hat{P}_i} \right)^{x_{ij}} \cdot \prod \left(\frac{P_j(\hat{\theta}_j)}{\hat{P}_j} \right)^{y_{ij}}$$

$$-2 \log \Lambda = 2 \sum O_{ij} \log \frac{O_{ij}}{E_{ij}} \quad ; \quad \hat{\pi}_{ij} = \frac{n_{i\cdot} n_{\cdot j}}{n^2} = \boxed{\frac{n_{ij}}{n^2}}$$

$$d) -2 \log \Lambda = 16.52 \quad \boxed{X^2 = 16.52}$$

12. McNemars Test:

$$\hat{\pi}_{11} = \frac{n_{11}}{n} ; \quad \hat{\pi}_{22} = \frac{n_{22}}{n} ; \quad \hat{\pi}_{12} = \hat{\pi}_{21} = \frac{n_{12} + n_{21}}{2n}$$

$$X^2 = \frac{(n_{12} - n_{21})^2}{n_{12} + n_{21}} ; \quad H_0: \pi_{12} = \pi_{21}$$

Example Dataset representing marks of 0/1

Test	value
McNemars	0
t-test	0

B.J/(J+1)

13. a) A test of independence would entail a hypothesis ($H_0: \pi_{12} = \frac{n_{12}}{n}$) and a chi-squared statistic of columns of younger vs older with rows of children.
 If $X^2 < X^2_{0.05}$, then the age of the sister is independent to number of children.
- b) A test of family size distribution for sisters is described by ($H_0: \pi_{11} = \pi_{12}$) with column of potentially number of children.

14. No high school Education.

Degrees of Interest	Under 45	Over 45
Great	71	217
Little	305	652

Some high school or more

Degrees of Interest	Under 45	Over 45
Great	305	180
Little	869	259

a. No high school Education: $\chi^2 = 5.5$; $\chi^2_{0.95} = 3.84$

Some high school Education: $\chi^2 = 34.3$; $\chi^2_{0.95} = 3.84$

Each analysis of political interest generated results to reject the null hypothesis and accept the alternative that age is an indicator for political interests.

b. H_0 : Given educational level, age, and degree of interest are unrelated.

H_1 : Given age, educational level and degree of interest are unrelated.

By adding the columns of educational level,

	No school	some school	χ^2
Great	288	485	17.12
Little	957	1128	

Reject H_0 ; $\pi_1 = \pi_2$.

By adding the rows of age,

	Under 45	over 45	χ^2
No school	376	869	513
some school	1174	439	

Reject H_0 , Accept H_1 .

15.

Source	χ^2	df	$\chi^2_{0.95}$	p-value
Incidence Among Males	13.54	4	9.49	0.02
Incidence Among Females	4.47	4	9.49	0.12

The number of females who grew a tumor was not significant because the expected values of predicted tumors correlated closely to the observed outcome. Male tumor data has a p-value of ~0.00

16. A chi-squared analysis ($\chi^2 = 27.29$, df=4) confirms rejection of the null hypothesis ($H_0: \pi_{1..} = \pi_{2..} = \pi_{3..}$) and accepts the alternative hypothesis ($H_1: \pi_{1..} \neq \pi_{2..} \neq \pi_{3..}$) at a significance level of $\alpha = 0.995$. There is a relationship between personality type and attitude toward small cars; extroverts have an unfavorable attitude.

17. London ($\chi^2 = 42.4$, df=1) and Manchester ($\chi^2 = 5.5$, df=1) data conclude different results upon the relationship between blood type and peptic ulcers. The city of London contains a relationship between blood type to disease, while Manchester does not. A p-value of <0.00 for London is a reason for investigation to the source.

Test	χ^2	df	$\chi^2_{0.95}$	H_0	H_1	Suggestion	p-value	Estrogen is correlated to cancer.
Matched Pair Design	75.03	1	3.84	$\pi_{12} = \pi_{21}$	$\pi_{12} \neq \pi_{21}$	Reject H_0	0.14	
Homogeneity	0.03	1	3.84	$\pi_{1..} = \pi_{2..}$	$\pi_{1..} \neq \pi_{2..}$	Accept H_0	1.00	

19. Fisher's Exact Test:

$$p(n_{11}) = \frac{(n_{11})(n_{21})}{\binom{n_{1+}}{n_{11}} \binom{n_{2+}}{n_{21}}}$$

n_{11}	$p(n_{11})$
5	0.03
6	0.06
7	0.09
8	0.12
9	0.12
10	0.10
11	0.06
12	0.03
13	0.01
14	0.000
15	0.000

The Fisher Exact Test presents no significant difference between the high and low anxiety groups at $N_n=12$.

20. Random Sample

$$\text{a) } P(D|X) = \frac{\pi_{11}}{\pi_{10} + \pi_{11}}$$

$$P(D|\bar{X}) = \frac{\pi_{10}}{\pi_{00} + \pi_{10}}$$

$$\Delta(X) = \frac{\text{odds}(D|X)}{\text{odds}(D|\bar{X})}$$

$$= \frac{P(D|X)}{1-P(D|X)} \cdot \frac{1-P(D|\bar{X})}{P(D|\bar{X})}$$

$$= \frac{\pi_{11}\pi_{00}}{\pi_{10}\pi_{10}}$$

Prospective Study

$$P(D|X) = \frac{n_{11}}{n_{10} + n_{11}}$$

$$P(D|\bar{X}) = \frac{n_{01}}{n_{00} + n_{01}}$$

$$\Delta = \frac{\text{odds}(D|X)}{\text{odds}(D|\bar{X})}$$

$$= \frac{P(D|X)}{1-P(D|X)} \cdot \frac{1-P(D|\bar{X})}{P(D|\bar{X})}$$

$$= \frac{n_{11}}{n_{01}} \cdot \frac{(n_{00})}{(n_{10})}$$

Retrospective Study

$$P(X|D) = \frac{n_{10}}{n_{10} + n_{01}}$$

$$P(X|\bar{D}) = \frac{n_{10}}{n_{00}}$$

$$\Delta = \frac{\text{odds}(D|X)}{\text{odds}(D|\bar{X})}$$

$$= \frac{P(D|X)}{1-P(D|X)} \cdot \frac{1-P(D|\bar{X})}{P(D|\bar{X})}$$

$$= \frac{n_{11}}{n_{01}} \cdot \frac{n_{00}}{n_{10}}$$

b) Method of Propagation Error: $\gamma = g(x) \approx g(\mu_x) + (x - \mu_x)g'(\mu_x)$

$$\pi_{11} + \pi_{10} + \pi_{01} + \pi_{00}$$

$$\mu_y = g(\mu_x)$$

$$\sigma_y^2 = \sigma_x^2 [g'(\mu_x)]^2$$

Retrospective Study

Random Sample

$$\log \Delta = \log \frac{\pi_{11}\pi_{00}}{\pi_{10}\pi_{01}}$$

$$\text{Var log}(\Delta) = \frac{\sum_i (x - \mu_x)^2}{n} \text{Var log}(\Delta) = \frac{\sum_i (x - \mu_x)^2}{n} \text{Var log}(\Delta) = \frac{\sum_i (x - \mu_x)^2}{n} \log \Delta$$

$$= \frac{\sum_i \sum_j (\pi_{ij} - \mu)^2}{m \cdot n} \cdot \frac{1}{\Delta^2}$$

$$= \frac{\sigma^2}{\Delta^2} = \sigma^2 \left(\frac{\pi_{10}\pi_{10}}{\pi_{11}\pi_{00}} \right)^2$$

$$P(D|X) = \frac{41}{31+41}; \quad \text{odds}(D|X) = \frac{41}{31}; \quad \Delta = \frac{41 \cdot 12}{31 \cdot 4} = \frac{12}{4} = 3$$

$$P(D|\bar{X}) = \frac{12}{12+4}; \quad \text{odds}(D|\bar{X}) = \frac{12}{12+4}; \quad \Delta = \frac{12}{4} = 3$$

The odds of being normal (Dominant) to Diabetic (Dominant-recessive) is 3.77:1.

21.

	Diabetic	Normal
Bb or bb	12	4
BB	39	49

Proportion of males advised to quit: $\frac{48}{48+47} = 50.6\%$

Proportion of females advised to quit: $\frac{80}{80+136} = 37.7\%$

Standard error of male proportion: 0.05

Standard error of female proportion: 1.91

Standard error of their difference: 0.05; Significant with t-test

	Advised	Not Advised
Male	48	47
Female	80	136

Proportion of Whites asked to quit: 43%

Proportion of African-Americans asked to quit: 41%

Standard error of White proportion: 0.6

Standard error of African-American proportion: 0.6; Significant t-test

	Advised	Not Advised
≤ 15	64	112
15-25	39	54
> 25	25	16

Proportion of smokers who smoke ≤ 15 , advised to quit: 36%
 Proportion of smokers, 15-25, advised to quit: 42%
 Proportion of smokers who smoke > 25 , advised to quit: 61%
 Standard error of smokers (≤ 15): 1.8
 Standard error of smokers (15-25): 0.77
 Standard error of smokers (> 25): 0.70

The differences in proportion are significant to an F-stat, one-sided.

	Advised	Not Advised
Male	73	94
Female	50	39

Proportion of male physicians who advised: 45%
 Proportion of female physicians who advised: 36%
 Standard error of male physicians who advised: 0.61
 Standard error of female physicians who advised: 1.65
 Standard error of the difference: 0.0; $t < t(0.95)$

F < F_{crit} | Significant results

	Advised	Not Advised
Smoker	13	37
Non-smoker	115	146

Proportion of smokers advised: 26%
 Proportion of non-smokers advised: 44%
 Standard error of smokers advised: 1.70
 Standard error of smokers not advised: 0.96
 Standard error of the difference: 0.0; $t < t(0.95)$ | Significant results

	Advised	Not Advised
≤ 30	33	123
30-39	23	37
> 39	12	19

Proportion of physicians age (≤ 30): 41%
 Proportion of physicians age (30-39): 43%
 Proportion of physicians age (> 39): 40%
 Standard error of physicians (≤ 30): 1.36
 Standard error of physicians (30-39): 0.56
 Standard error of physicians (> 39): 0.55
 Standard error of the difference: F-statistic = 17.07

Previous Day	Day of Infarction		
	Exertion	No Exertion	Total
Exertion	4	9	13
No exertion	50	1165	1215
Total	54	1174	1229

McNemar's Test:

$$H_0: \pi_{12} = \pi_{21}$$

$$H_1: \pi_{12} \neq \pi_{21}$$

$$\chi^2 = \frac{(n_{12} - n_{21})^2}{n_{12} + n_{21}} = 28.49, df=1; \chi^2_{0.95} = 3.84$$

F-crit = 9.55

| Not significant

Sport	Red	Blue
Boxing	148	120
Freestyle Wrestling	27	24
Greco Roman Wrestling	25	23
Tae Kwon Do	45	35

| The results by McNemar's Test are significant.
 Exertion is associated to infarction.

a. π_R = constant in red wins

$$= \frac{n_{12}}{n} = 0.55 \quad \bar{X}^2 = 0.30 \quad df = 3$$

$$H_0: \pi_R = \pi_L$$

$$H_1: \pi_R \neq \pi_L$$

| There appears to be no significant relationship between sport and color.

| The means of red and blue clothes are roughly equivalent.

- b. $H_0: \pi_{IR} = 1/2$ $\chi^2 = 0.30$; $\chi^2 = 7.81$
 $H_1: \pi_{IR} \neq 1/2$ df = 3 [Not significant between sports]
- c. Both of the tests are an equivalent argument with a chi-squared statistic.
- d. There is little evidence to suggest red is favorable to the wins of sports.
- e.

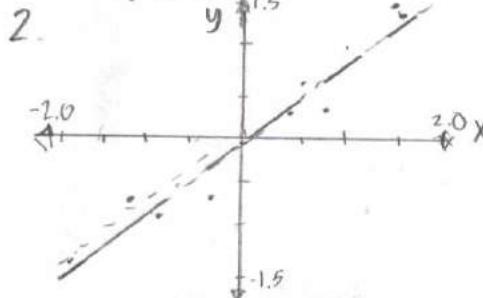
Sport	Red	Blue
Boxing	123	105
FreWrestling	23	39
GR Wrestling	25	34
Taekwondo	27	26

 $\bar{\chi}^2 = 0.59$ df = 3
 $\chi^2 = 7.81$ $\chi^2_{0.95} = 7.81$ Examination of larger datasets show a different conclusion; more specifically, color does effect the outcome of a match.
The means are significant across wrestling.
25. a. Individual analysis of aspirin's effects were conducted for myocardial infarction, and stroke. Myocardial disease ($\chi^2 = 1.38$, df = 1) results were not significant, but aspirin did effect a stroke ($\chi^2 = 30.65$, df = 1).
- b. Aspirin analysis significant results for lowering myocardial mortalities, but overall had no influence on death ($\chi^2 = 12.61$; df = 4).
26. McNemars Test evaluated DKA relationship to therapy. A chi-squared of 5.53, with one degree of freedom lists significant results for the relationship between side effects before and after therapy.
27. Upon examination, the defendant's race does not influence death penalty. By including the victim's race, the results could change the outcome, but not the analysis. The chi-square statistic ($\chi^2 = 15.92$, df = 3) does list significant results for a relationship of race to death penalty.
28. The chi-square test is independent to counts, frequency, or percent, and presents similar outcomes
29. Model: Satisfied Somewhat Dissatisfied Very Dissatisfied
A statistician should carry out a test of homogeneity, rather than a test for independence because of the workers being already independent to each other.

Chapter 14: Linear Least Squares

$$\frac{\sum x^2 - \sum x^2}{n} = \frac{1}{n}$$

1. a. $y = \frac{a}{(b+cx)}$; $\log y = \log a - \log(b+cx)$ b. $y = ae^{-bx}$; $\log y = -bx + \log a$ c. $y = ab^x$; $\log y = x \log b + \log a$
 d. $y = \frac{x}{(a+bx)}$; $\frac{1}{y} = \frac{a}{x} + b$; $\frac{1}{y} = k$; $\frac{1}{x} = j$; $k = aj + b$ e. $y = \frac{1}{1+e^{-bx}}$; $\log k - 1 = bx$ where $k = \frac{1}{y}$



$$\beta_0 = \frac{\sum x^2 \sum y - \sum x \sum xy}{n \sum x^2 - (\sum x)^2} = -0.03$$

$$\beta_1 = \frac{n \sum xy - \sum x \sum y}{n \sum x^2 - (\sum x)^2} = 0.904$$

b. $X = c + dy$; $c = -\frac{\beta_0}{\beta_1}$; $d = \frac{1}{\beta_1}$; c. The lines are equivalent graphically because the inverse is being plotted.

$$3. y = \mu + e_i; i=1\dots n; \text{ where } e_i = \text{independent errors } [\mu_e = 0, \sigma_e^2]$$

$$= \beta_0 + \beta_1 x + e_i = \beta_0 + e_i; \beta_0 = \frac{(\sum x^2)(\sum y) - (\sum x)(\sum xy)}{n \sum x^2 - (\sum x)^2} = \frac{\mu (\sum x^2 - (\sum x)^2)}{\sum x^2 - (\sum x)^2} \frac{n}{n} = \mu$$

$$4. \text{ LPM: } Y_i = \beta_0 + \beta_1 x_i + e_i, i=1, 2..n$$

Model: $Y_f = I_F(i)\beta_F + I_m(i)\beta_m + \beta_3 x_i + e_i$; where $I_F(i)$ and $I_m(i)$ are indicator variables that are 0/1 for male or female.

Design Matrix: $\mathbb{X} = \begin{pmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{pmatrix}$

$$5. p_1 < p_2 < p_3$$

a. $\mathbb{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix}$ b. $\mathbb{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \\ Y_5 \end{bmatrix}$ c. $\mathbb{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \\ Y_5 \\ Y_6 \end{bmatrix}$

$$\mathbb{X} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & -1 & 0 \\ 1 & 0 & -1 \\ 0 & 1 & -1 \end{bmatrix} \quad \beta = (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \mathbb{Y}$$

6. w_1 and w_2

1) Object 1 Weighed by itself, 3g; 2) a) $\mathbb{X} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -1 & -1 \\ 1 & 1 \end{bmatrix}$ b) $\mathbb{Y} = \begin{bmatrix} 3 \\ 3 \\ 1 \\ 7 \end{bmatrix}$

3) Objects 1 and object 2, $\Delta w = 1g$.

4) $\sum w = 7g$
 b) $S(\beta_0, \beta_1) = \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$; $S(w_1, w_2) = \sum_{i=1}^4 (y_i - w_1 - w_2 x_i)^2 = (3-w_1)^2 + (3-w_2)^2 + (1-w_1+w_2)^2 + (7-w_1-w_2)^2$

$$\frac{dS}{dw_1} = -2(3-w_1) - 2(1-w_1+w_2) - 2(7-w_1-w_2) = 0 \Rightarrow 11-3w_1 = 0; w_1 = \frac{11}{3}$$

$$\frac{dS}{dw_2} = -2(3-w_2) + 2(1-w_1+w_2) + 2(7-w_1-w_2) = 0; 9-3w_2 = 0; w_2 = 3$$

c) $s^2 = \frac{1}{n-2} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$; $s^2 = \frac{1}{4-2} [(3-\frac{11}{3})^2 + (3-3)^2 + (1-\frac{11}{3}+3)^2 + (7-\frac{11}{3}-3)^2] = 5^2 = 1/3$

$$d. \sigma_s^2 = (w_1 - w_2)^2 = \frac{2}{3} \cdot \frac{1}{3} = \boxed{\frac{2}{9}} \quad f. H_0: w_1 = w_2 \text{ } \pm 6.95 > t ; 2.353 > \sqrt{2}; \text{ Accept null hypothesis.}$$

$$e. t = \frac{w_1 - w_2}{\sqrt{\sigma_s^2}} = \frac{2/3}{\sqrt{2/9}} = \boxed{\sqrt{2}}$$

$$7. y_i = \beta_0 + \beta_1 x_i + e_i; \text{Var}(e_i) = p_i^2 \sigma^2; \hat{p}_i y_i = \hat{p}_i \beta_0 + \hat{p}_i \beta_1 x_i + \hat{p}_i e_i \text{ or } z_i = u_i \beta_0 + v_i \beta_1 + \delta_i \\ \text{where } u_i = \hat{p}_i^{-1}; v_i = \hat{p}_i^{-1} x_i; \delta_i = \hat{p}_i^{-1} e_i$$

$$a. Z_i = u_i \beta_0 + v_i \beta_1 + \delta_i; \frac{y_i}{p_i} = \frac{\beta_0}{p_i} + \frac{x \beta_1}{p_i} + \frac{e_i}{p_i}; y_i = \beta_0 + x \beta_1 + e_i$$

$$b. S(\beta_0, \beta_1) = \sum_{i=1}^n (z_i - u_i \beta_0 - v_i \beta_1 - \delta_i)^2; \frac{\partial S}{\partial \beta_0} = -2 \sum u_i (z_i - u_i \beta_0 - v_i \beta_1 - \delta_i) = 0; \sum z_i = \beta_0 \sum u_i + \beta_1 \sum v_i \\ \frac{\partial S}{\partial \beta_1} = -2 \sum v_i (z_i - u_i \beta_0 - v_i \beta_1 - \delta_i) = 0; \sum v_i z_i = (\beta_0 \sum u_i + \beta_1 \sum v_i) v_i$$

$$\sum z_i = \frac{\beta_0 n}{p_i} + \frac{\beta_1}{p_i} \sum x_i; p_i \sum z_i = n \beta_0 + \beta_1 \sum x_i \\ \sum v_i z_i = \beta_0 \sum v_i + \beta_1 \sum v_i^2; p_i \sum v_i z_i = \beta_0 \sum x + \beta_1 \sum x^2$$

$$\boxed{\begin{aligned} \beta_0 &= \frac{p_i \sum x_i^2 \cdot \sum y_i - p_i \sum x_i \sum x_i y_i}{n \sum x_i^2 - (\sum x_i)^2} \\ \beta_1 &= \frac{n p_i \sum x_i y_i - p_i (\sum x_i)(\sum y_i)}{n \sum x_i^2 - (\sum x_i)^2} \end{aligned}}$$

$$c. \frac{d}{d \beta_0} \sum (y_i - \beta_0 - \beta_1 x_i)^2 p_i^{-2} = -2 \sum (y_i - \beta_0 - \beta_1 x_i) \cdot p_i^{-2} = 0; \beta_0 = \frac{\sum x_i^2 \sum y_i - \sum x_i \sum x_i y_i}{n \sum x_i^2 - (\sum x_i)^2}$$

$$d. \boxed{\text{Var}(\beta_0) = \frac{\sigma^2 \sum x_i^2 \cdot p_i^2}{n \sum x_i^2 - (\sum x_i)^2}, \text{Var}(\beta_1) = \frac{n \sigma^2 p_i^2}{n \sum x_i^2 - (\sum x_i)^2}}, \boxed{\beta_1 = \frac{n \sum x_i y_i - (\sum x_i)(\sum y_i)}{n \sum x_i^2 - (\sum x_i)^2}}$$

$$8. \mathbb{X} = Q \cdot R \text{ where } Q^T Q = I; \text{ Show } \hat{\beta} = (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T Y \text{ is } \hat{\beta} = R^{-1} Q^T Y$$

$$(n \times p) \cdot (n \times p) \cdot (p \times p) \quad R = (r_{ij} = 0, i > j) \quad Y = \mathbb{X} \beta; \mathbb{X}^T Y = (\mathbb{X}^T \mathbb{X}) \beta; (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T Y = \hat{\beta}$$

The last equation $(R \hat{\beta} = Q^T Y)$ may be solved by back-substitution because there are p variables for p equations.

$$\begin{aligned} &= (Q^T R^T Q R) Q^T R^T Y \\ &= (Q^T R^T Q)^{-1} \cdot R^T Q^T R^T Y \\ &= R^{-1} Q^T Y \end{aligned}$$

$$9. \text{Cholesky Decomposition } \mathbb{X}^T \mathbb{X} = R^T R \text{ where } R = (r_{ij} = 0, i > j)$$

Show $R^T Y = \mathbb{X}^T Y$; $R \hat{\beta} = V$; Show $R^T V = \mathbb{X}^T Y$ is solved with Back-substitution because of the dimensions $(p \times p) \cdot (p \times 1)$, indicating p variables and p equations, which is similar to $R \hat{\beta} = V$.

$$\boxed{\hat{\beta} = \mathbb{X}^T Y}$$

$$10. \hat{\beta}_0 = \bar{y} - \beta_1 \bar{x} \text{ and } \beta_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}; \bar{y} = \beta_0 + \beta_1 \bar{x}; |\beta_0| = |\bar{y} - \beta_1 \bar{x}|$$

$$11. \text{Corr}(\beta_0, \beta_1) = \frac{\text{Cov}(\beta_0, \beta_1)}{\sqrt{\text{Var}(\beta_1) \cdot \text{Var}(\beta_0)}}$$

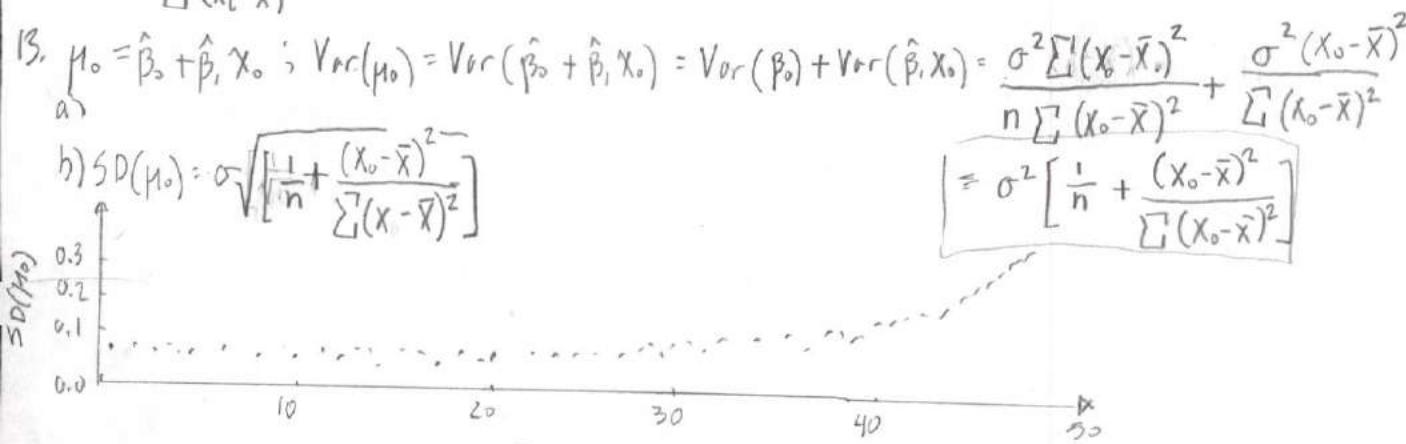
$$= \frac{-\sigma^2 \sum x_i}{n \sum x_i^2 - (\sum x_i)^2}$$

$\sqrt{\frac{\sigma^2 \sum x_i^2}{n \sum x_i^2 - (\sum x_i)^2} \frac{n \sigma^2}{n \sum x_i^2 - (\sum x_i)^2}}$

$$12. \hat{\beta}_0 = \bar{y} - \beta_1 \bar{x}$$

$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$

$\text{@ } (\bar{x}, \bar{y}) : \boxed{\bar{y} = \beta_0 + \beta_1 \bar{x} = \hat{\beta}_0 + \hat{\beta}_1 \bar{x} = \bar{y} : \beta_1 \bar{x} + \hat{\beta}_1 \bar{x} = \bar{y}}$



$$14. Y_0 = \beta_0 + \beta_1 x_0 + e_0 \text{ by the estimator } \hat{Y}_0 = \hat{\beta}_0 + \hat{\beta}_1 x_0$$

a) $\text{Var}(\hat{Y}_0 - Y_0) = \text{Var}(\hat{\beta}_0 + \hat{\beta}_1 x_0 - \beta_0 - \beta_1 x_0 - e_0) = \text{Var}(\hat{\beta}_0 - \beta_0) + \text{Var}[(\hat{\beta}_1 - \beta_1)x_0] - \text{Var}(e_0)$

$= \text{Var}(\hat{\beta}_0 - \beta_0) + \text{Var}[(\hat{\beta}_1 - \beta_1)x_0]$

$= (\hat{\sigma}^2 - \sigma^2) \left[\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum (x_i - \bar{x})^2} \right]$

b) $\boxed{(\hat{Y} - Y_0) \pm \sqrt{(\hat{\sigma}^2 - \sigma^2) \left[\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum (x_i - \bar{x})^2} \right]} \cdot t_{n-2}(x/2)}$

$$15. Y = \beta x \text{ to points } (x_i, y_i) \text{ where } i=1\dots n$$

$$\beta = (X^T X)^{-1} X^T y \text{ or } S = \sum (\hat{y}_i - \beta x_i)^2; \frac{dS}{d\beta} = -2 \sum x_i (y_i - \beta x_i) = 0; \sum x_i y_i - \beta \sum x_i^2 = 0; \boxed{\beta = \frac{\sum x_i y_i}{\sum x_i^2}}$$

16. a) $y = \beta_0 x + \beta_1 x^2$; $X^T X = \begin{pmatrix} x & x^2 \end{pmatrix} \quad (X^T X)^{-1} = \frac{1}{\sum x^2 \sum x^4 - (\sum x^3)^2} \begin{pmatrix} \sum x^4 - \sum x^3 & -\sum x^3 \sum x^2 \\ -\sum x^3 \sum x^2 & \sum x^2 \sum x^4 \end{pmatrix}$

$\boxed{\beta = \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix} = \frac{\left(\begin{matrix} \sum x^2 y & \sum x^3 y \\ \sum x^3 y & \sum x^4 y \end{matrix} \right)}{\sum x^2 \sum x^4 - (\sum x^3)^2}}$

$\boxed{Y = \beta X^2}$

$\boxed{= \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix} \begin{pmatrix} x & x^2 \\ x^2 & x^4 \end{pmatrix}^{-1} \begin{pmatrix} x^2 & x^3 \\ x^3 & x^4 \end{pmatrix} \begin{pmatrix} \sum x^2 y & \sum x^3 y \\ \sum x^3 y & \sum x^4 y \end{pmatrix}}$

$$\begin{pmatrix} \sum x^4 \sum x^3 y - \sum x^3 y \sum x^3 & \sum x^4 \sum x^3 y - \sum x^3 \sum x^4 y \\ \sum x^4 \sum x^3 y - \sum x^3 \sum x^4 y & \sum x^3 \sum x^3 y + \sum x^2 \sum x^4 y \end{pmatrix} = \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix}$$

$$\sum x^2 \sum x^4 - (\sum x^3)^2$$

$$\beta_0 = \frac{\sum x^4 \sum x^3 y - \sum x^3 y \sum x^3 + \sum x^4 \sum x^3 y - \sum x^3 \sum x^4 y}{\sum x^2 \sum x^4 - (\sum x^3)^2}$$

$$\beta_1 = \frac{\sum x^4 \sum x^3 y - \sum x^3 \sum x^4 y + \sum x^3 \sum x^3 y + \sum x^2 \sum x^4 y}{\sum x^2 \sum x^4 - (\sum x^3)^2}$$

$$\frac{2 \sum x^4 \sum x^3 y - \sum x^3 (\sum x^3 y - \sum x^4 y)}{\sum x^2 \sum x^4 - (\sum x^3)^2}$$

$$\frac{2 \sum x^3 y (\sum x^4 + \sum x^3) + (\sum x^2 - \sum x^3) \sum x^4 y}{\sum x^2 \sum x^4 - (\sum x^3)^2}$$

b. $\text{Cov}(\beta_0, \beta_1) = \frac{\sum x^4 \sum x^3 y - \sum x^3 \sum x^4 y}{\sum x^2 \sum x^4 - (\sum x^3)^2} \sigma^2$

17. $E(X) = \mu_X \quad E(Y) = \mu_Y \quad a) E(Y - \hat{Y})^2 = E(Y^2) - 2E(Y\hat{Y}) + E(\hat{Y}^2) = \mu_Y^2 - 2E(Y(\kappa + \beta X)) + E((\kappa + \beta X)^2)$
 $\text{Var}(X) = \sigma_X^2 \quad \text{Var}(Y) = \sigma_Y^2 \quad = \mu_Y^2 - 2\kappa\mu_Y - 2\beta \text{Cov}(X, Y) + E(\kappa)^2 + 2E(X\beta X) + E(\beta^2 X^2)$
 $\frac{dE(Y - \hat{Y})^2}{d\kappa} = \mu_Y^2 - 2\kappa\mu_Y - 2\beta \sigma_{XY} + \kappa^2 + 2\kappa\beta\mu_X + \beta^2\sigma_X^2 = 0 ; \kappa = \mu_Y - \beta\mu_X$
 $\frac{dE(Y - \hat{Y})^2}{d\beta} = -2\sigma_{XY} + \beta\sigma_X^2 ; \beta = \frac{\sigma_{XY}}{\sigma_X^2}$

b. Prove $\frac{\text{Var}(Y) - \text{Var}(Y - \hat{Y})}{\text{Var}(Y)} = n \frac{\sigma_{XY}^2}{\sigma_Y^2} ; \frac{\text{Var}(Y) - \text{Var}(Y - \hat{Y})}{\text{Var}(Y)} = \frac{\sigma_Y^2 - \sigma_Y^2 + \sigma_{XY}^2 + \beta^2 \sigma_X^2}{\text{Var}(Y)} = \frac{\sigma_{XY}^2}{\text{Var}(Y) \text{Var}(X)}$

18. $Y_i = \beta_0 + \beta_1 X_i + e_i$ where $i=1\dots n$, $e_i \sim N(\mu=0, \sigma^2)$; Find the mle's of β_0 and β_1 .

 $\mathcal{L}(\beta_0, \beta_1) = \sum (y_i - \beta_0 - \beta_1 x_i + e_i)^2 ; \frac{d\mathcal{L}}{d\beta_1} = -2 \sum (y_i - \beta_0 - \beta_1 x_i + e_i) \sum x_i = 0 ; \sum x_i y_i - \beta_0 \sum x_i - \beta_1 (\sum x_i^2) = 0$
 $\sum x_i y_i = \beta_0 \sum x_i + \beta_1 (\sum x_i^2)$
 $\frac{d\mathcal{L}}{d\beta_0} = -2 \sum (y_i - \beta_0 - \beta_1 x_i + e_i) = 0 ; \sum y_i = n\beta_0 + \beta_1 \sum x_i$
 $n \sum x_i y_i = \sum x \sum y - \beta_1 (\sum x_i)^2 + n \beta_1 \sum x_i^2 = \sum x \sum y + \beta_1 (\sum x_i^2 - (\sum x_i)^2)$
 $\beta_1 = \frac{n \sum x_i y_i - \sum x \sum y}{n \sum x_i^2 - (\sum x_i)^2}$

$$\sum y_i = n \beta_0 \sum x_i^2 - (\sum x_i)^2 + n \sum x \sum xy - \sum x_i^2 \sum y_i$$

$$\frac{n \sum y_i \sum x_i^2 - \sum y_i (\sum x_i)^2}{n \sum x_i^2 - (\sum x_i)^2} = \beta_0$$

19. a. Vector of Residuals: $\hat{e} = Y - \hat{Y} = (I - P)Y$

$$\hat{e}^T X^T = \begin{vmatrix} Y_1 - X_1\beta \\ Y_2 - X_2\beta \end{vmatrix}^T [X_1 \ X_2]^T = Y_1 X_1 - X_1 X_2 \beta + Y_2 X_2 - X_2 X_2 \beta$$

$$= Y_1 X_1 - Y_1 X_1 + Y_2 X_2 - Y_2 X_2$$

$$= 0$$

b. $\sum_{i=1}^2 e_i = Y_1 - X_1\beta + Y_2 - X_2\beta = Y - \hat{Y} = 0$

20. Assume X, X_1, X_2 are orthogonal; that is $X_i^T X_j = 0$ for $i \neq j$

If $X = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix}$, covariance matrix of a least squares estimate:

21. $VN(\beta_1) = \frac{\sigma^2}{\sum (x_i - \bar{x})^2}$

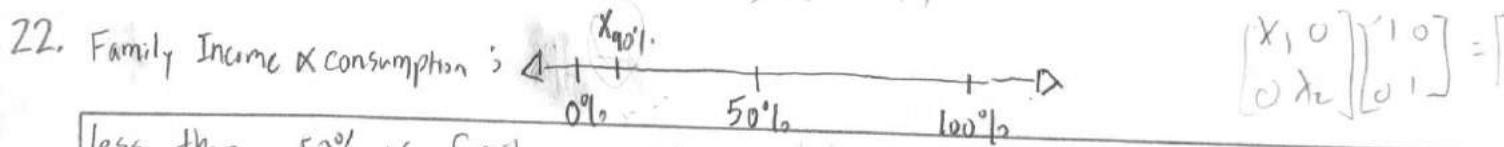
$$\Sigma_{\beta\beta} = \sigma^2 (X^T X)^{-1} = \sigma^2 \left(\begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \right)^{-1} = \sigma^2 \begin{bmatrix} X_1^2 & 0 \\ 0 & X_2^2 \end{bmatrix}^{-1}$$

$$= \sigma^2 \begin{bmatrix} \frac{1}{X_1^2} & 0 \\ 0 & \frac{1}{X_2^2} \end{bmatrix}$$

$$A^T A = A$$

To minimize the variance of β_1 , the average value

Should be close to zero.



Less than 5.0% of families would be at the 90% percentile of consumption
When the total proportion is above the 90% of family income.

23a. $P = \frac{\text{cov}(\text{Exam, midterm})}{\sqrt{\text{Var}(\text{Exam})} \sqrt{\text{Var}(\text{Midterm})}} = 0.5$; $\bar{X} = \frac{\text{Exam} + \text{midterm}}{2} = 75$; $\sigma = \sqrt{\frac{(\text{Exam} - 75)^2 + (\text{midterm} - 75)^2}{2}} = 10$

If student scores 95 on the midterm, what is the final exam?

$$\frac{95+75}{2} = 85$$

b. If a student scored 95 on the final, what would you guess her score on the midterm was?

$$\frac{85+75}{2} = 80$$

24. $\hat{Y} = X\beta = KX\beta = [X_1 \ X_2 \ \dots \ X_n] \begin{bmatrix} X_1 & 0 & 0 \\ 0 & X_2 & 0 \\ 0 & 0 & X_n \end{bmatrix} [\beta_1 \ \beta_2 \ \dots \ \beta_n] = \begin{bmatrix} K_1 X_1 & 0 & 0 \\ 0 & K_2 X_2 & 0 \\ 0 & 0 & K_n X_n \end{bmatrix} [\beta_1 \ \beta_2 \ \dots \ \beta_n] = U\beta$

The linear least squares constant β does not change

25. Y_{11}, Y_{12} are regressive mean responses to a linear least squares because the process is independent of grouping data points.

26. Z_1, Z_2, Z_3, Z_4 are random variables with $\text{Var}(Z_i) = 1$ and $\text{Cov}(Z_i, Z_j) = 0$ for $i \neq j$. Prove $Z_1 + Z_2 + Z_3 + Z_4$ is uncorrelated with $Z_1 + Z_2 - Z_3 - Z_4$.

IF $Y_1 = Z_1 + Z_2 + Z_3 + Z_4$ and $Y_2 = Z_1 + Z_2 - Z_3 - Z_4$

$$\begin{aligned} \text{Cov}(Y_1, Y_2) &= \text{Var}(Z_1) + \text{Cov}(Z_1, Z_2) - \text{Cov}(Z_1, Z_3) - \text{Cov}(Z_1, Z_4) + \text{Var}(Z_2) - \text{Cov}(Z_2, Z_3) \\ &\quad - \text{Cov}(Z_2, Z_4) - \text{Var}(Z_3) - \text{Cov}(Z_3, Z_4) + \text{Cov}(Z_4, Z_1) + \text{Cov}(Z_4, Z_2) \\ &\quad - \text{Cov}(Z_4, Z_3) - \text{Var}(Z_4) + \text{Cov}(Z_2, Z_1) + \text{Cov}(Z_3, Z_1) + \text{Cov}(Z_3, Z_2) \end{aligned}$$

$$\Rightarrow 1 + 1 - 2 = 0$$

27. $\sigma^2 I = \sum_{i=1}^n \hat{Y}_i \hat{Y}_i^T + \sum_{i=1}^n \hat{e}_i \hat{e}_i^T$; Prove $n\sigma^2 = \sum_{i=1}^n \text{Var}(Y_i) + \sum_{i=1}^n \text{Var}(e_i)$ (100)

$$\sum_{i=1}^n Y_i Y_i^T = \sigma^2 I \quad (\because \sum_{i=1}^n e_i e_i^T = \sigma^2 I) \quad \sum_{i=1}^n Y_i Y_i^T + \sum_{i=1}^n e_i e_i^T = \sigma^2 I$$

$$n\sigma^2 = n(\sum_{i=1}^n Y_i Y_i^T + \sum_{i=1}^n e_i e_i^T) = \sum_{i=1}^n \text{Var}(Y_i) + \sum_{i=1}^n \text{Var}(e_i)$$

28. $Y = \sum a_i X_i$; $\text{Var}(Y) = \sigma^2$; $\bar{X} = \mu_i$; $\sum_{i=1}^n Y_i = A \sum_{i=1}^n X_i$; $Z = BX$; $\sum_{i=1}^n Y_i Z_i = A \sum_{i=1}^n X_i B^T$

a) If $Z = \sum b_i X_i$; Use theorem D; $Y = AX$; $Z = BX$; $\sum_{i=1}^n Y_i Z_i = A \sum_{i=1}^n X_i B^T = \sum a_i \sum_{i=1}^n b_i \sigma_{ij}$

b) Theorem C of 14.4.1

$$E(X^T A X) = \text{trace}(A\Sigma) + \mu^T A \mu$$

$$E(X_i X_j) = \sigma_{ij} + \mu_i \mu_j$$

$$E(\sum_i \sum_j X_i X_j a_{ij}) = \sum_i \sum_j \sigma_{ij} a_{ij} + \sum_i \sum_j \mu_i \mu_j a_{ii} \\ = \text{trace}(A\Sigma) + \mu^T A \mu$$

$$E\left(\sum_{i=1}^n \sum_{j=1}^n X_i X_j\right) = \sigma_{ij} + \mu_i \mu_j \\ = \sigma + \mu^2$$

29. $\text{Cov}(X_1, X_2) = 0$; $\text{Var}(X_1) = \text{Var}(X_2) = \sigma^2$; Use matrix methods to show $Y = X_1 + X_2$; $Z = X_1 - X_2$

Find $\sum_{i=1}^n Y_i Z_i = \text{Cov}(Y, Z) = \text{Cov}(X_1 + X_2, X_1 - X_2) \\ = \text{Var}(X_1) - \text{Cov}(X_1, X_2) + \text{Cov}(X_2, X_1) - \text{Var}(X_2) \boxed{= 0}$

30. X_1, \dots, X_n ; $\text{Var}(X_i) = \sigma^2$; $\text{Cov}(X_i, X_j) = \rho \sigma^2$ for $i \neq j$; Find $\text{Var}(\bar{X})$:

$$\text{Var}(\bar{X}) = \text{Var}\left(\frac{X_1 + \dots + X_n}{n}\right) = \frac{1}{n^2} \text{Var}(X_1 + \dots + X_n) = \frac{1}{n^2} [\text{Var}(X_1) + \dots + \text{Var}(X_n)] = \boxed{\frac{\sigma^2}{n}}$$

31. $Z_{1,2,3,4}$; $\sum_{i=1}^4 Z_i = \sigma^2 I$; Let $V = Z_1 + Z_2 + Z_3 + Z_4$ and $Z = (Z_1 + Z_2) - (Z_3 + Z_4)$

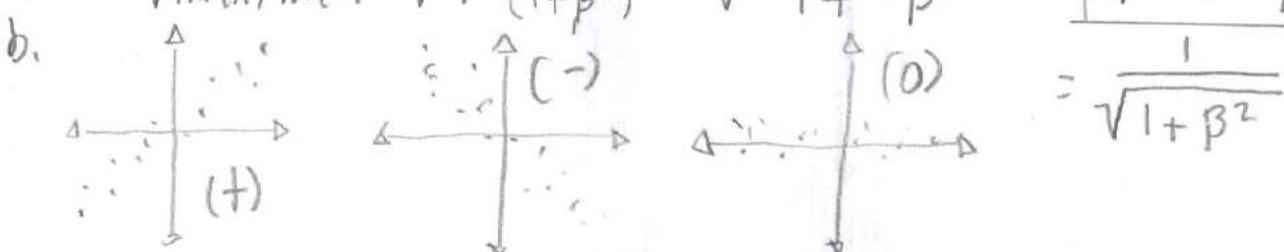
Find $\text{Cov}(V, Z) = \text{Cov}(Z_1 + Z_2 + Z_3 + Z_4, (Z_1 + Z_2) - (Z_3 + Z_4)) \\ = \text{Var}(Z_1) + \text{Cov}(Z_1, Z_2) - \text{Cov}(Z_1, Z_3) - \text{Cov}(Z_1, Z_4) + \text{Var}(Z_2) + \text{Cov}(Z_2, Z_3) \\ - \text{Cov}(Z_2, Z_4) + \text{Cov}(Z_3, Z_1) + \text{Cov}(Z_3, Z_2) - \text{Var}(Z_3) \\ - \text{Cov}(Z_3, Z_4) + \text{Cov}(Z_4, Z_1) + \text{Cov}(Z_4, Z_2) - \text{Cov}(Z_4, Z_3) - \text{Var}(Z_4) \\ = 2\text{Cov}(Z_1, Z_2) - 2\text{Cov}(Z_3, Z_4) \boxed{= 0}$

32. $Y_1 = X_1$, $Y_i = X_i - X_{i-1}$, $i = 1, 2, \dots, n$

a. $\sum_{i=1}^n Y_i Y_i^T = \sum_{i=1}^n X_i X_i^T - \sum_{i=1}^n X_{i-1} X_{i-1}^T = \sigma^2 I \quad$ b. $\sum_{i=1}^n Y_i Y_i^T = \sum_{i=1}^n Y_i^2 = \sigma^2 I$

33. $X \sim N(0, 1)$ and $E \sim N(0, 1)$, let $Y = X + \beta E$

a. $r_{XY} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = \frac{\text{Var}(X-\bar{X})(Y-\bar{Y})}{\sqrt{1 \cdot (1+\beta^2)}} = \frac{\text{Var}(X-\bar{X})(X+\beta E - 0 + 0)}{\sqrt{1 + \beta^2}} = \frac{\text{Var}(X) - \beta^2 \text{Var}(X) - \text{Var}(X) - \text{Var}(X\beta E)}{\sqrt{1 + \beta^2}}$



34,

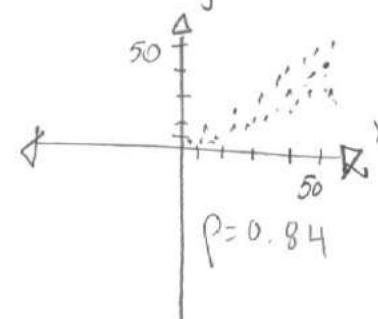
x	y
1	0.94
2	2.09
3	2.05
4	3.13
5	7.03
6	5.96
7	4.04
8	9.78
9	6.78
10	5.94
11	19.42
12	11.77
13	13.90
14	13.77
15	24.25
16	0.72
17	11.28
18	10.36
19	10.04
20	10.88
21	23.99
22	15.37
23	19.51
24	11.56
25	21.99
26	32.89
27	20.91
28	13.53
29	25.76
30	20.94
31	40.26
32	30.91
33	35.75
34	25.18
35	24.26
36	53.21
37	23.70
38	23.65
39	36.63
40	37.53
41	40.62
42	19.44
43	63.42
44	36.17
45	46.04
46	47.43
47	74.14
48	43.41
49	24.127462
50	26.30
X	1275
y	1205
Σx^2	47975
Σxy	41073

	B_0	-1.22
	B_1	0.99
	P_{xy}	0.94

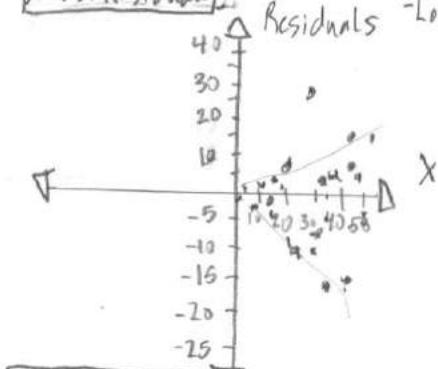
$$y = -1.22 + 0.99x$$

x	$y - \hat{y}$
1	0.16
2	1.76
3	2.30
4	1.02
5	3.20
6	2.39
7	11.54
8	9.38
9	11.76
10	10.01
11	13.98
12	10.06
13	10.04
14	9.84
15	19.00
16	16.56
17	4.45
18	20.68
19	26.74
20	32.59
21	14.77
22	16.87
23	16.88
24	21.67
25	32.37
26	14.22
27	24.29
28	35.85
29	21.17
30	24.33
31	16.95
32	13.45
33	22.14
34	55.78
35	25.24
36	21.97
37	28.49
38	34.31
39	22.23
40	20.47
41	53.70
42	36.51
43	48.14
44	54.55
45	42.24
46	49.99
47	27.06
48	24.55
49	61.49
50	41.57

Scatter plot

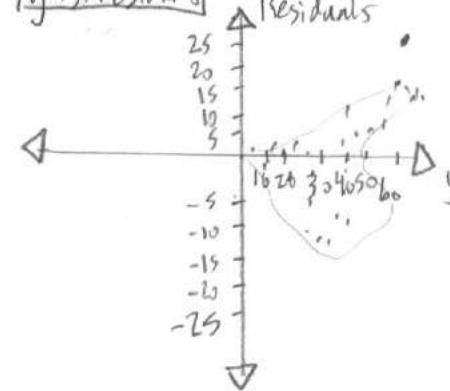


X vs. Residuals



Not to scale
Lost my ruler

Y vs. Residuals

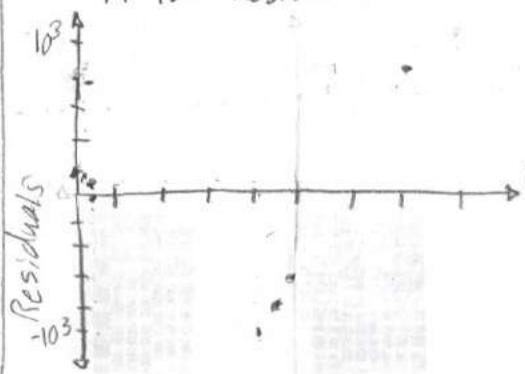


$$35. X_3 = X_1 + X_2$$

$$X = \begin{pmatrix} 1 & X_1 \\ 1 & X_2 \\ 1 & X_3 \end{pmatrix} = \begin{pmatrix} 1 & X_1 \\ 1 & X_2 \\ 1 & X_2 - X_1 \end{pmatrix} \xrightarrow{\text{RREF}} \begin{pmatrix} 1 & X_1 \\ 1 & X_2 \\ 2 & X_2 \end{pmatrix} \xrightarrow{\text{RREF}} \begin{pmatrix} 1 & X_1 \\ 1 & X_2 \\ 1 & 0 \end{pmatrix} \xrightarrow{-1} \begin{pmatrix} 0 & X_1 \\ 0 & X_2 \\ 1 & 0 \end{pmatrix} \xrightarrow{\text{RREF}} \begin{pmatrix} 0 & X_1 \\ 0 & X_2 \\ 0 & 0 \end{pmatrix}$$

	Σx	14393
	Σy	448764
	Σxy	19512852
	Σx^2	39764174
B_0	24818	
B_1	-8.49	

X vs. Residuals.



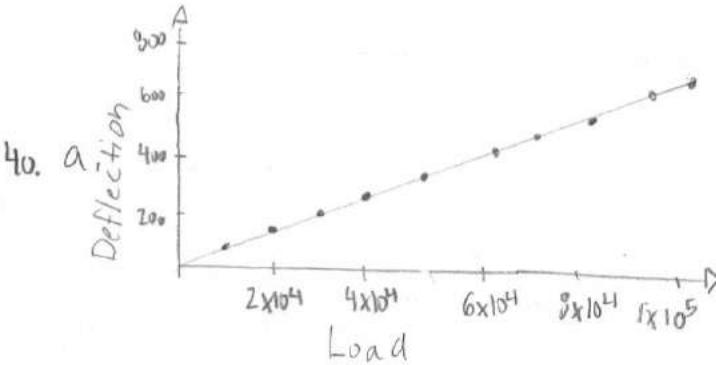
The residuals demonstrate the fit wasn't an exact approximation. Separately, an analysis of variance demonstrated an F-statistic that accepted the alternative.

$$\beta_2 = \frac{[\sum xy - \frac{1}{n} \sum x \sum y][\sum x^2 - \frac{1}{n} (\sum x)^2] - [\sum xy - \frac{1}{n} \sum x \sum y][\sum x^2 - \sum x \sum x^2/n]}{[\sum x^2 - (\sum x)^2/n][\sum x^4 - \frac{1}{n} (\sum x^2)^2] - (\sum x^3 - \sum x \sum x^2/n)^2}$$

B2

$$\beta_1 = \frac{[\sum xy - \sum x \sum y/n][\sum x^4 - (\sum x^2)^2/n] - [\sum x^2 y - \sum x^2 \sum y/n][\sum x^3 - \sum x \sum x^2/n]}{[\sum x^2 - (\sum x)^2/n][\sum x^4 - \frac{1}{n} (\sum x^2)^2] - (\sum x^3 - \sum x \sum x^2/n)^2}$$

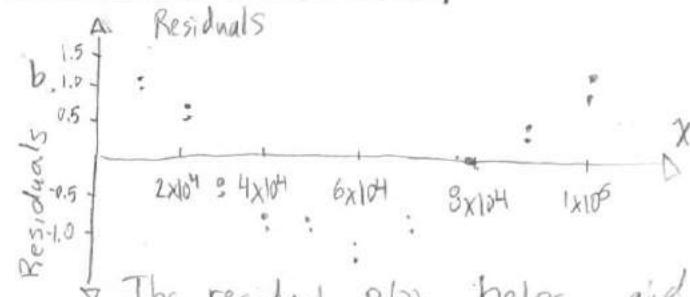
$$\beta_0 = \frac{\sum y}{n} - \beta_1 \left[\frac{\sum x}{n} \right] - \beta_2 \left[\frac{\sum x^2}{n} \right]$$



The plot resembles a linear function.

Coefficient	Estimate
β_0	-205
β_1	2164
β_2	83.19

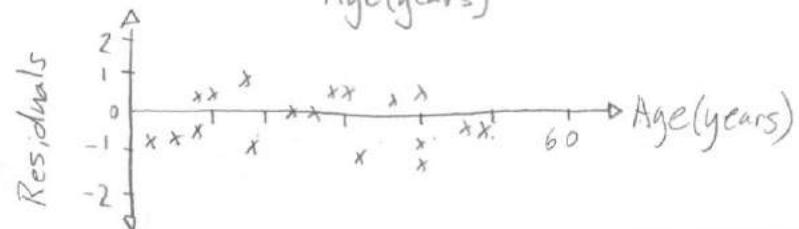
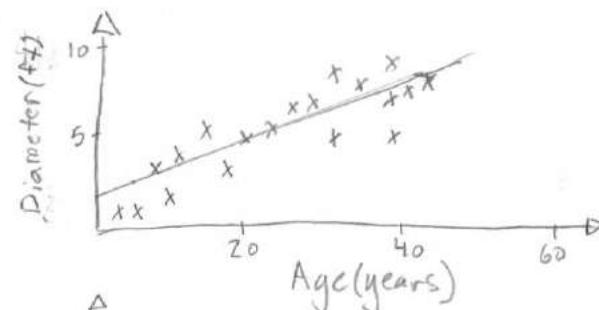
The fit is slightly better but negligible to linear.



The residual plot helps aid the recognition of regions that over or under fit.

Coefficient	Estimate	Standard Error
β_0	0.1362	0.073
β_1	0.0069	3.04×10^{-6}
β_2	7.29×10^{10}	2.69×10^{-11}

41.



I thought a better fit of Age vs Diameter required Age vs. $(\text{Diameter})^2$, but the book reasons $\sqrt{\text{Age}}$ vs Diameter.

42. The residuals of velocity vs $\sqrt{\text{Distance}}$ were 10x smaller than residuals extracted from velocity vs Distance.

A reason to explain the difference is the second-order differential equation $m\ddot{x} = mg - kv^2$, in which re-arranged is

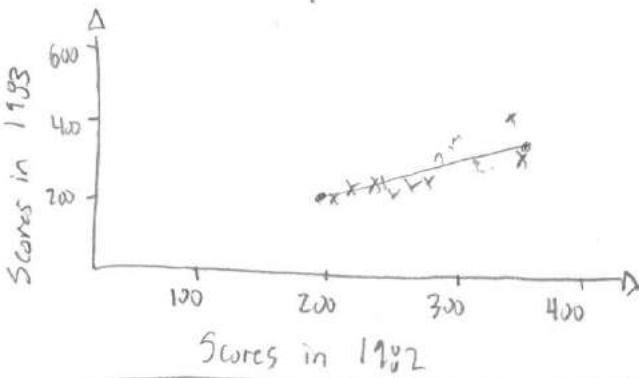
$$v = \sqrt{\frac{mg}{k} \left(1 - \frac{\Delta \text{Distance}}{\Delta \text{time}} \right)}$$

Coefficient	Estimate	Standard Error
β_0	23.86	0.83
β_1	-0.17	0.13
β_2	0.07	0.15
β_3	-0.45	0.18

43. The information provided of cyst diameters as a function of temperature looks to be quadratic.

44. A correlation coefficient ($\rho = -0.37$) signifies weak correlation for the asthma dataset, and similar insignificance for the cystfibr dataset having a correlation of ($\rho = -0.27$). The F-statistic for asthma ($F_{0.95}(40,1) = 0.01 < 6.57$) and Cystfibr ($F_{0.95}(22,1) = 0.20 < 1.75$) also say no significance. A plot of either datasets' fits were unresolved, having no confidence, "Yes!"

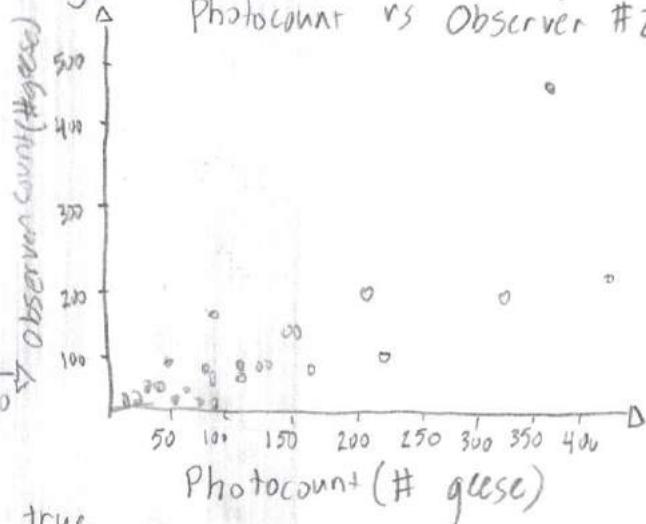
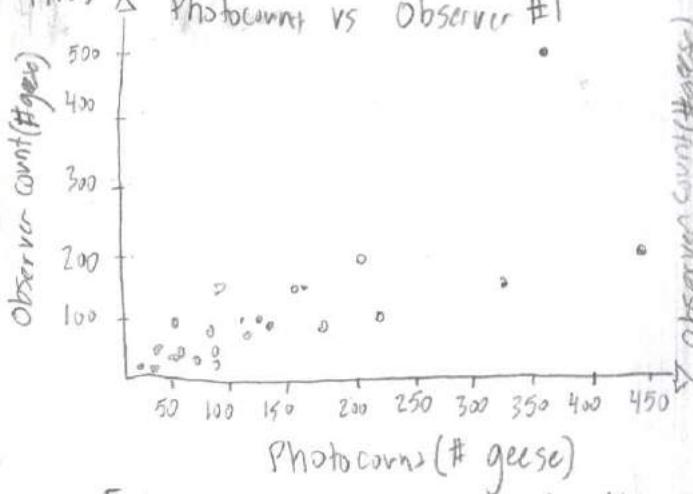
45. The relationship of student reading scores exists from year-to-year.



Coefficient	Estimate	Standard Error
B_0	57.54	24.89
B_1	0.80	0.09

46. Phase Contrast Microscopy (PCM) Fit Scanning Electron Microscopy (SEM) with an R^2 of 0.37. The residuals of data points were as large as the magnitude of the datapoint, but generally, do present a positive correlation.

47. a) Photocount vs Observer #1



Each plot comparison of the true photocount to the observer looks to be linear.

Coefficient	Estimate	Standard Error
B_0	-4.93	9.31
B_1	0.85	0.07

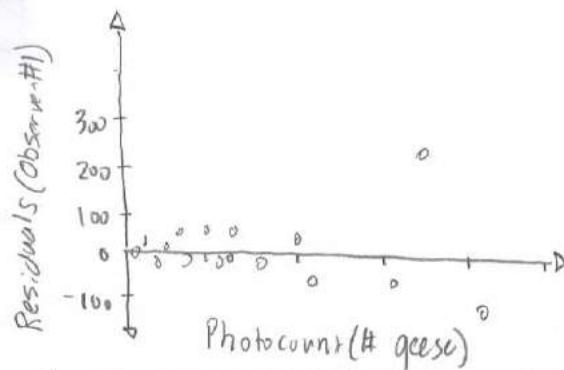
standard Residual Error: 1815

Coefficient	Estimate	Standard Error
B_0	-4.15	9.71
B_1	1.11	0.07

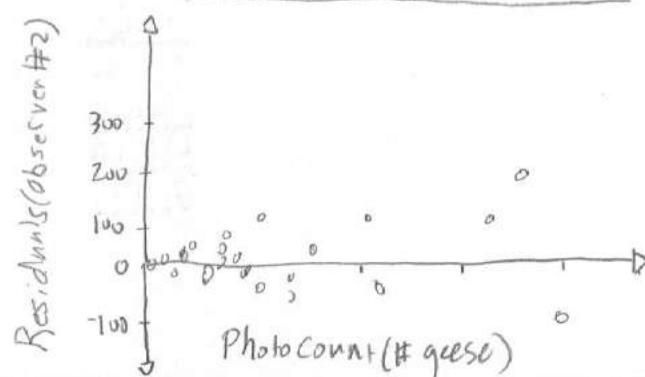
standard Residual Error: 1584

The coefficients and standard residual error for each plot demonstrate similarities.

Residuals of Observer #1:



Residuals of Observer #2:



C. Square rooting the photocount did not stabilize variance, and increased the errors across sampled datasets.

D. Again, the original fit was appropriate to the analysis.

E. Both observers either over- or under-estimated the number of geese by 15%.

Coefficients	Estimate	Standard Error
β_0	-57.99	8.64
β_1	4.71	0.26
β_2	0.34	0.13

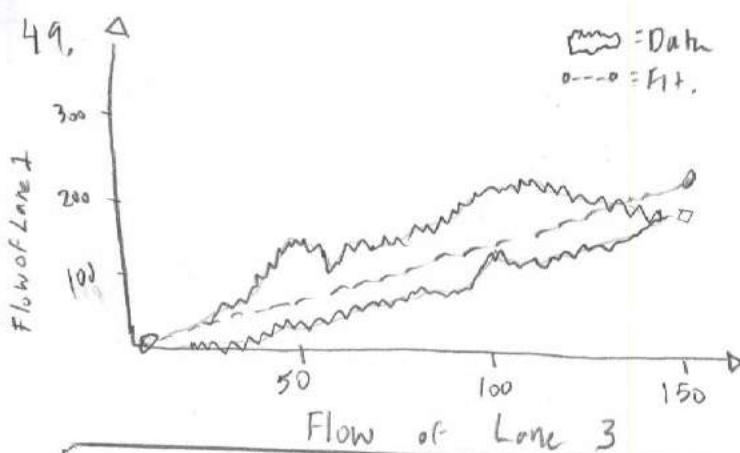
$$\text{Model : } Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

where $X_1 = \text{height}$, $X_2 = \text{Diameter}$.

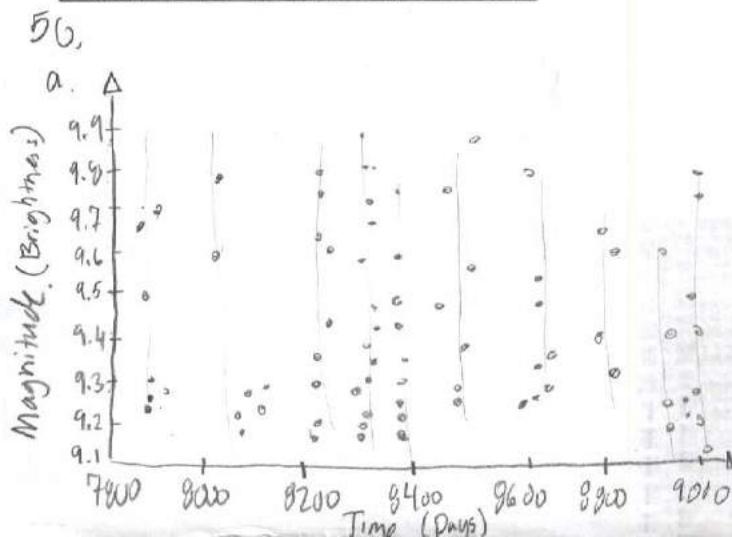
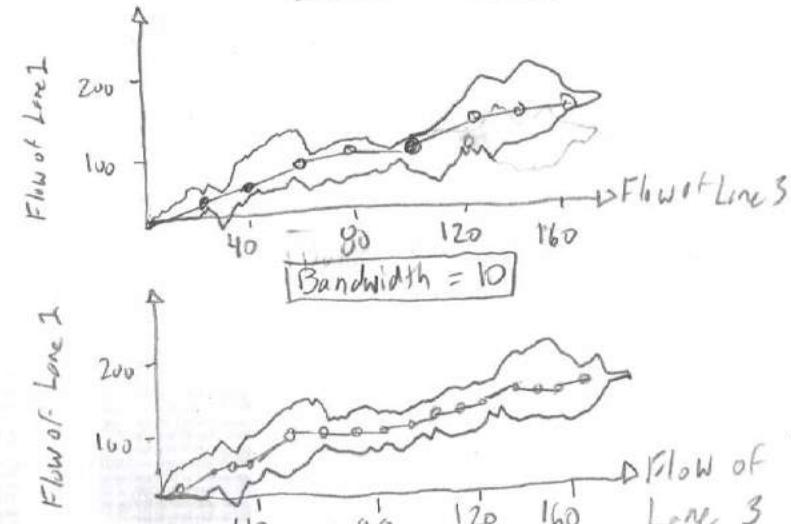
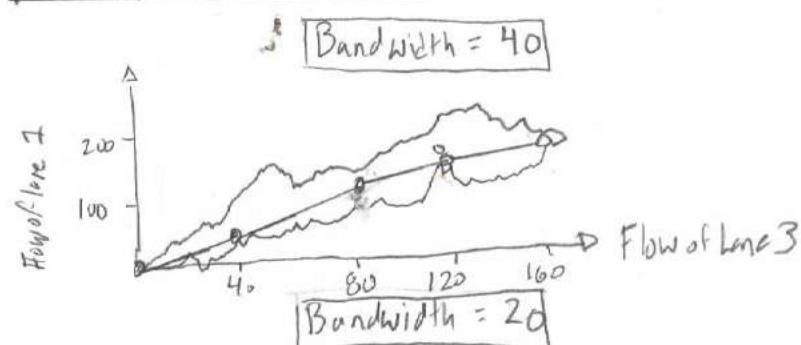
$Y = \text{Volume}$.

The relationship $\text{volume} = \pi \left(\frac{\text{Diameter}}{2} \right)^2 \times \text{Height}$ did not fit well.

A linear regression of Lane 1 vs Lane 3 flow is justified by observation and tabulated data.

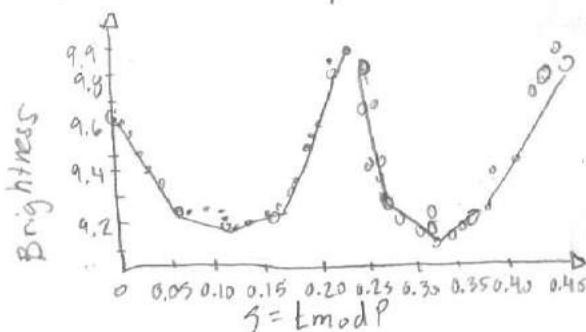


The best balance between a small bandwidth (10) and large (160) became a $w(X_i - \bar{X}) = 40$. My perspective is only by observation and not numerical determinations.



The structure of time vs brightness seems to be measurements near the same time.

b. $P = 0.407524$ days; $s = t \bmod P$ c. See part b.)



d) As the modular period changes, the graph becomes less periodic. The true period could be estimated with a sinusoidal wave.

The structure seems to be periodic from the $s = t \bmod P$ transformation.

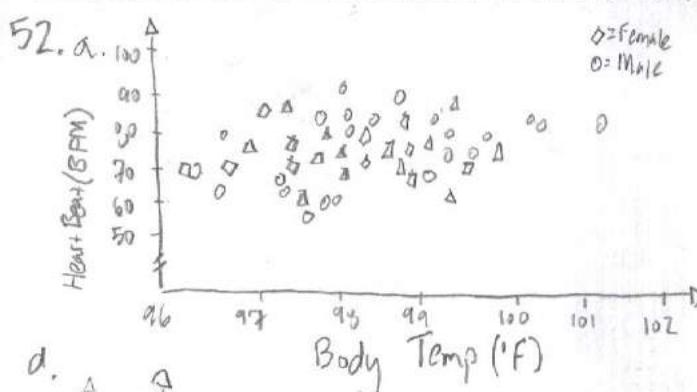
51. Model: Disney = $\beta_0 + \beta_1 \cdot \text{MacDonalds} + \beta_2 \cdot \text{Schumberger} + \beta_3 \cdot \text{Haliburton}$.

Coefficient	Estimate	Standard Error
β_0	0.0938	0.0981
β_1	-0.8812	1.1045
β_2	1.3151	1.9877
β_3	-0.1717	1.3442

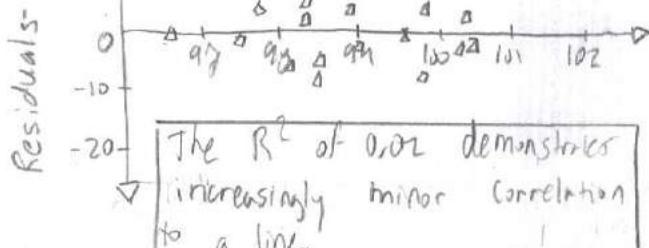
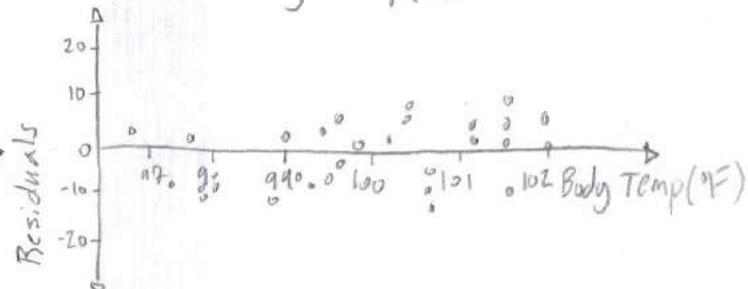
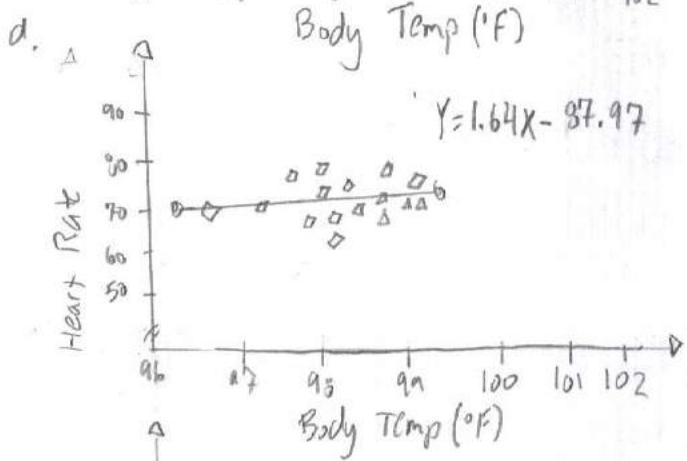
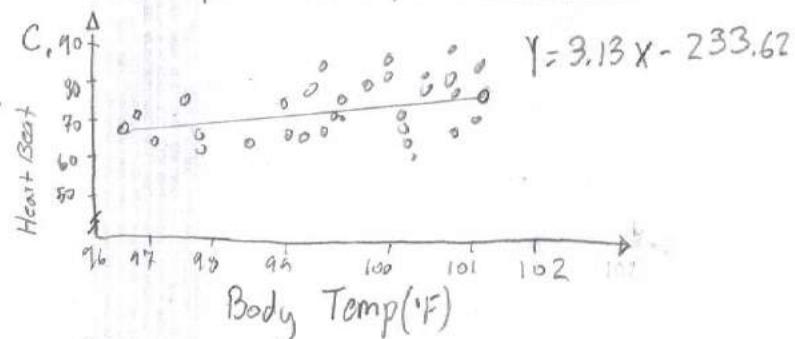
Standard Deviation of Residuals = 0.056
 R^2 of Fit = 0.6293.

The fitted errors of multiple linear regression
 $S = \sum (y_i - \beta_0 - \beta_1 x_1 - \beta_2 x_2 - \beta_3 x_3)^2$
 has a standard deviation of 0.022.

The comparison of monthly returns from 1998 to 1999 coefficient estimates of different values. The fundamental model has three independent variables that represent individual stock price.



b. Male vs female data do relate through a positive correlation.
 $r_{male} = 0.28$, $r_{female} = 0.20$.



Male body temperature is regressed to a linear fit with a standard error of 7.70 for residuals. The R^2 of 0.09 may indicate a slightly positive relationship to body measurements.