

$$E(X) = G'(1) \qquad \text{Var}(X) = G''(1) + G'(1) - (G'(1))^2$$

$$\text{Bernoulli} \qquad F(x) = p^x (1-p)^{1-x} \qquad G(x) = qs^0 + ps^1$$

$$\text{Binomial} \qquad p(k) = \binom{n}{k} p^k (1-p)^{n-k} \qquad G(x) = (q + ps)^n$$

$$\text{Geometric} \qquad p(k) = (1-p)^{k-1} p \qquad G(x) = \frac{p}{1-qs}$$

$$\text{Negative Binomial} \qquad p(k) = \binom{n-1}{k-1} p^r (1-p)^{k-r} \qquad G(x) = \left( \frac{p}{1-qs} \right)^r$$

$$\text{Poisson} \qquad p(k) = \frac{\lambda^k e^{-\lambda}}{k!} \qquad G(x) = e^{\lambda(s-1)}$$

$$\text{Uniform} \qquad f(x) = \frac{1}{b-a}, a \leq x \leq b$$

$$\text{Exponential} \qquad f(x) = \lambda e^{-\lambda x}, x \geq 0$$

$$\text{Gamma} \qquad g(t) = \frac{\lambda^\alpha t^{\alpha-1} e^{-\lambda t}}{\Gamma(\alpha)} \quad \text{for } \alpha = 1, \text{ it tends to exponential distribution}$$

$$\text{Normal} \qquad \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Let us assume that  $X_1, X_2, \dots, X_n$  are independent random variables with the common cdf  $F$  and density  $f$ . Let  $U$  denote the maximum of the  $X_i$  and  $V$  the minimum.

$$f_U(u) = [F(u)]^n \qquad f_U(u) = nf(u)[F(u)]^{n-1}$$

$$f_V(v) = 1 - [1 - F(v)]^n \qquad f_V(v) = nf(v)[1 - F(v)]^{n-1}$$

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

If there are  $p$  experiments and the first has  $n_1$  possible outcomes, the second  $n_2, \dots$ , and the  $p$ th  $n_p$  possible outcomes, then there are a total of  $n_1 \times n_2 \times \dots \times n_p$  possible outcomes for the  $p$  experiments

For a set of size  $n$  and a sample of size  $r$ , there are  $n^r$  different ordered samples with replacement and  $n(n-1)(n-2) \dots (n-r+1)$  different ordered samples without replacement.

The number of unordered samples of  $r$  objects selected from  $n$  objects without replacement is  $\binom{n}{r}$ .

The number of ways that  $n$  objects can be grouped into  $r$  classes with  $n_i$  in the  $i^{\text{th}}$  class is

$$\binom{n}{n_1 n_2 \dots n_r} = \frac{n!}{n_1! n_2! \dots n_r!}$$

$$\text{CDF} = \int_{-\infty}^x \text{PDF} \qquad \text{CDF} = F_X(x) = P(X \leq x)$$

If  $X \sim N(\mu, \sigma^2)$  and  $Y = aX + b$ , then  $Y \sim N(a\mu + b, a^2\sigma^2)$ .

$$\text{Let } X \text{ have } f(x) \text{ and let } Y = g(X) \qquad f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right|$$

**PROPOSITION C** \qquad Let  $Z = F(X)$ ; then  $Z$  has a uniform distribution on  $[0,1]$ .

**PROPOSITION D** \qquad Let  $U$  be uniform on  $[0,1]$ , and let  $X = F^{-1}(U)$ . Then the cdf of  $X$  is  $F$ .

$$E(X) = \sum_i x_i p(x_i) \text{ or } E(X) = \int_{-\infty}^{\infty} xf(x)dx \qquad \text{Suppose that } Y = g(X), \text{ replace } x = g(x)$$

**THEOREM A** \qquad Markov's Inequality

If  $X$  is a random variable with  $P(X \geq 0) = 1$  and for which  $E(X)$  exists, then  $P(X \geq t) \leq \frac{E(X)}{t}$

If  $X_1, \dots, X_n$  are jointly distributed random variables with expectations  $E(X_i)$  and  $Y$  is a linear function

$$\text{of the } X_i, Y = a + \sum_{i=1}^n b_i E(X_i), \quad \text{then } E(Y) = a + \sum_{i=1}^n b_i E(X_i)$$

$$\text{Var}(X) = E(X^2) - [E(X)]^2 \quad \text{or} \quad \text{Var}(X) = E\{[X - E(X)]^2\}$$

If  $\text{Var}(X)$  exists and  $Y = a + bX$ , then  $\text{Var}(Y) = b^2 \text{Var}(X)$ .

**THEOREM C**      *Chebyshev's Inequality*

Let  $X$  be a random variable with mean  $\mu$  and variance  $\sigma^2$ . Then, for any  $t > 0$ ,

$$P(|X - \mu| > t) \leq \frac{\sigma^2}{t^2}$$

**COROLLARY A**      If  $\text{Var}(X) = 0$ , then  $P(X = \mu) = 1$ .

*A Model for Measurement Error*

$$X = x_0 + \beta + \varepsilon \quad E(X) = x_0 + \beta \quad \text{and} \quad \text{Var}(X) = \sigma^2 \quad \beta \text{ is bias}$$

$$\text{MSE} = E[(X - x_0)^2] = \beta^2 + \sigma^2$$

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y)$$

$$\text{Cov}(a + X, Y) = \text{Cov}(X, Y)$$

$$\text{Cov}(aX, bY) = ab \text{Cov}(X, Y)$$

$$\text{Cov}(X, Y + Z) = \text{Cov}(X, Y) + \text{Cov}(X, Z)$$

$$\text{Cov}(aW + bX, cY + dZ) = ac \text{Cov}(W, Y) + bc \text{Cov}(X, Y) + ad \text{Cov}(W, Z) + bd \text{Cov}(X, Z)$$

$$U = a + \sum_{i=1}^n b_i X_i \quad \text{and} \quad V = c + \sum_{j=1}^n d_j Y_j, \quad \text{then} \quad \text{Cov}(U, V) = \sum_{\substack{1 \leq i \leq n \\ 1 \leq j \leq n}} b_i d_j \text{Cov}(X_i, Y_j)$$

$$\text{Var}\left(a + \sum_{i=1}^n b_i X_i\right) = \sum_{\substack{1 \leq i \leq n \\ 1 \leq j \leq n}} b_i b_j \text{Cov}(X_i, X_j)$$

$$\text{Var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \text{Var}(X_i) \quad \text{if } X_i \text{ are independent}$$

$$\text{Correlation } \rho = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X) \text{Var}(Y)}}$$

$-1 \leq \rho \leq 1$ . Furthermore,  $\rho = \pm 1$  if and only if  $P(Y = a + bX) = 1$  for some constants  $a$  and  $b$ .

$$\binom{n}{k} = \binom{n-1}{r-1} + \binom{n-1}{r}$$

$$|A_1 \cup A_2 \cup \dots \cup A_p| = \sum_{1 \leq i \leq p} |A_i| - \sum_{1 \leq i_1 < i_2 \leq p} |A_{i_1} \cap A_{i_2}| +$$

$$\sum_{1 \leq i_1 < i_2 < i_3 \leq p} |A_{i_1} \cap A_{i_2} \cap A_{i_3}| - \dots + (-1)^{p-1} |A_1 \cap A_2 \cap \dots \cap A_p|,$$

**Inclusion Exclusion**

$$\text{Derangement} \quad n! \left(1 - \frac{1}{1!} + \frac{1}{2!} - \frac{1}{3!} + \dots + (-1)^n \frac{1}{n!}\right) = n! \sum_{r=0}^n (-1)^r \frac{1}{r!}$$

$$\text{Law of large numbers: } - \bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \quad E[\bar{X}_n] = \mu \quad \text{Var}[\bar{X}_n] = \frac{\sigma^2}{n} \quad \hat{I}(f) = \frac{1}{n} \sum_{i=1}^n f(X_i)$$

$$\text{Central limit theorem: } - \text{MGF} = \int_{-\infty}^{\infty} e^{tx} f(x) dx \quad P(a > Y > b) = \Phi\left(\frac{Y-b}{\sigma}\right) - \Phi\left(\frac{Y-a}{\sigma}\right) \\ E[Y] = nE[X] \quad \text{Var}[Y] = n^2 \text{Var}(X)$$

$$\text{Continuity Correction: } - P(A) = P\left(l - \frac{1}{2} \leq Y \leq u + \frac{1}{2}\right)$$

$$\text{Chi Square Distribution: } - \chi_n = U_1 + U_2 + \dots + U_n \quad \text{where } U = Z^2, \quad Z \text{ is Standard Normal Distribution}$$

$$\text{It is gamma distribution } \frac{\lambda^\alpha t^{\alpha-1} e^{-\lambda t}}{\Gamma(\alpha)} \quad \text{with } \alpha = \frac{n}{2} \quad \text{and } \lambda = \frac{1}{2} \quad \text{for DOF} = n \quad \text{MGF} = (1 - 2t)^{-\frac{n}{2}}$$

$$t \text{ Distribution: } - \frac{Z}{\sqrt{\frac{U}{n}}} \quad f(x) = \frac{\frac{\Gamma(n+1)}{2} \pi^{-\frac{n}{2}}}{\sqrt{n} \Gamma(\frac{n}{2})} \left(1 + \frac{x^2}{n}\right)^{-\frac{n+1}{2}} \quad f(x) = f(-x)$$

$$\text{Sample Mean } \bar{X} = \sum_{i=1}^n X_i \quad \text{Sample Variance } s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 \quad \text{or} \quad s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i^2 - n \bar{X}^2) \\ \frac{(n-1)s^2}{\sigma^2} \rightarrow \text{chi square with } (n-1) \text{ DOF} \quad \frac{\bar{X} - \mu}{\frac{s}{\sqrt{n}}} \rightarrow t \text{ distribution with } t_{n-1}$$

For Simple Random Sampling

Population Parameter	Estimate	Variance of Estimate	Estimated Variance
$\mu$	$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$	$\sigma_{\bar{X}}^2 = \frac{\sigma^2}{n} \left(\frac{N-n}{N-1}\right)$	$s_{\bar{X}}^2 = \frac{s^2}{n} \left(1 - \frac{n}{N}\right)$
$p$	$\hat{p} = \text{sample proportion}$	$\sigma_{\hat{p}}^2 = \frac{p(1-p)}{n} \left(\frac{N-n}{N-1}\right)$	$s_{\hat{p}}^2 = \frac{\hat{p}(1-\hat{p})}{n-1} \left(1 - \frac{n}{N}\right)$
$\tau$	$T = N\bar{X}$	$\sigma_T^2 = N^2 \sigma_{\bar{X}}^2$	$s_T^2 = N^2 s_{\bar{X}}^2$
$\sigma^2$	$\left(1 - \frac{1}{N}\right) s^2$		

$$\text{where } s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2.$$

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i \quad \tau = N\mu \quad \sigma^2 = s^2 \quad \text{Var}(\bar{X}) \text{ with replacement} = \frac{\sigma^2}{n}$$

For Stratified Random Sampling

$$L \text{ stratas have pop elements } l = N_l, \quad N = N_1 + N_2 + \dots + N_L, \quad \text{population mean and variance } \mu_l \text{ and } \sigma_l^2$$

$$W_l = \frac{N_l}{N}, \quad x_{il} \rightarrow i^{\text{th}} \text{ pop in } l^{\text{th}} \text{ stratum}, \quad \mu = \sum_{l=1}^L W_l \mu_l$$

$$\text{Sample mean } \bar{X}_l = \frac{1}{n_l} \sum_{i=1}^{n_l} X_{il} \quad \text{Startified estimate } \bar{X}_s = \sum_{l=1}^L W_l \bar{X}_l \quad \text{Population total } T_s = N \bar{X}_s$$

$$\text{Variance of startified mean } \text{Var}(\bar{X}_s) = \sum_{l=1}^L W_l^2 \left(\frac{1}{n_l}\right) \left(1 - \frac{n_l-1}{N_l-1}\right) \sigma_l^2$$

$$s_l^2 = \frac{1}{n_l-1} \sum_{i=1}^{n_l} (X_{il} - \bar{X}_l)^2 \quad s_{\bar{X}_s}^2 = \sum_{l=1}^L W_l^2 \left(\frac{1}{n_l}\right) \left(1 - \frac{n_l}{N_l}\right) s_l^2$$

$$\text{Neyman Allocation } n_l = n \frac{W_l \sigma_l}{\sum_{k=1}^L W_k \sigma_k} \quad \text{proportional allocation } n_l = n \frac{N_l}{N}$$

$$Var(\bar{X}_{sp}) = \frac{1}{n} (\sum_{l=1}^L W_l \sigma_l^2)^2 \quad Var(\bar{X}_{so}) = \frac{1}{n} \sum_{l=1}^L W_l \sigma_l^2 \quad Var(\bar{X}_{sp}) - Var(\bar{X}_{so}) = \sum_{l=1}^L W_l (\sigma_l - \bar{\sigma})^2$$

$$MLE \ l(\theta) = \sum_{i=1}^n \log(f(X_i|\theta)) \quad MLE \ multinomial \ Cell \ Probabilities \ f(x_i | p_m) = \frac{n!}{\sum x_m!} \sum (p_m)^{x_m}$$

*Confidence intervals for MLE*

$$P\left(\bar{X} - \frac{s}{\sqrt{n}} t_{n-1}\left(\frac{\alpha}{2}\right) \leq \mu \leq \bar{X} + \frac{s}{\sqrt{n}} t_{n-1}\left(\frac{\alpha}{2}\right)\right) = 1 - \alpha$$

$$P\left(\frac{n \hat{\sigma}^2}{\chi_{n-1}^2\left(\frac{\alpha}{2}\right)} \leq \sigma^2 \leq \frac{n \hat{\sigma}^2}{\chi_{n-1}^2\left(\frac{1-\alpha}{2}\right)}\right) = 1 - \alpha$$

*Hypothesis Testing*

*Null Hypothesis ( $H_0$ )      Alternate Hypothesis ( $H_A$ )*

*$P(\text{reject } H_0 | H_0) = P(X > c | H_0) \rightarrow \text{Type I error } (\alpha) \quad \text{Significance Level} = \alpha$*

*$P(\text{accept } H_0 | H_1) = p(X \leq c | H_1) \rightarrow \text{Type II error } (\beta) \quad \text{Power} = 1 - \beta$*

$$Z(\alpha) = \frac{x_0 - \mu_0}{\frac{\sigma}{\sqrt{n}}} \quad Z(\alpha) = \frac{\bar{X} - \mu_0}{\frac{s}{\sqrt{n}}}$$

*Likelihood Ratio Tests*

$$\hat{p}_i = \frac{x_i}{n} \quad \Lambda = \prod_{i=1}^m \left(\frac{P_i(\hat{\theta})}{\hat{P}_i}\right)^{x_i} \quad x_i = \text{observed count in } m \text{ cells, } \hat{\theta} = \text{MLE of } \theta$$

*$p_i(\hat{\theta}) = \text{corresponding probabilities}$*

$$-2 \log \Lambda = 2 \sum_{i=1}^m O_i \log\left(\frac{O_i}{E_i}\right) \quad O_i = n \hat{p}_i \quad \text{and} \quad E_i = n p_i(\hat{\theta})$$

$$\text{Pearson's chi - square statistic} \quad \chi^2 = \sum \frac{[x_i - n p_i(\hat{\theta})]^2}{n p_i(\hat{\theta})}$$