

Population - all sample - same, simple random - equal and independent, minimized bias makes possible to reduce sampling error  
 Simple random - easily accessible researcher, without bias - difference between volunteers  
 categorical - category, group, no magnitude or numerical scale, nominal = order, ordinal = no order  
 numerical - has magnitude and quantitative continuous any value, discrete = indivisible  
 predict response variable from explanatory variable  
 dependent independent  
 probability distributions - distribution of variables on whole population  
 pseudoreplication = displaying inappropriate for data, hypotheses - not independent  
 experimental - assigns, observational - nature assigns

Bar graph, histogram - numerical variable, cumulative frequency distribution - fraction of observations  $\leq$  that measurement  
 grouped bar graph categorical, mosaic categorical area  
 bell curve

symmetric, asymmetric, skewed, mode, bimodal  
 quantile = Xth percentile =  $X/100$  quantile, eg 10th percentile = .1 quantile  
 Scatter plot - numerical   
 (3) Identifying data  
 Shykeren - average of measurements in sample sample s.d. = spread of distribution  
 variance =  $\frac{\sum (y_i - \bar{y})^2}{n-1}$  mean sd =  $\sqrt{\text{variance}}$   
 coefficient of variation =  $\frac{sd}{\text{mean}} \times 100\%$   
 types: 2 categorical (grouped bar graph, mosaic, grouped histograms, cum. freq. dist., bar plot), 2 numerical (scatter plot, map)

ZQR = 25% - 50% (med) - 75% (3rd quartile)  
 Inequality: population parameters vs sample estimates  
 $\mu, \sigma, p$  vs  $\bar{y}, s, \hat{p}$   
 sampling distribution = probability distribution of values for a statistic - use might obtain when we sample  
 confidence intervals = range of values surrounding sample estimate  
 sample space - all possible outcomes of trial

(5) Probability  
 random trial = 2 or more outcomes where occurrence not predicted  
 mutually exclusive - can't occur simultaneously  
 independent = occurrence of one does not affect other  
 probability distributions = list of all possibilities of all mutually exclusive outcomes of trials  
 discrete = each; continuous = probability density - graph  
 Bayes theorem:  $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$

(6) Hypothesis testing  
 null hypothesis - nothing, a default - change  
 two-sided / two-tailed - alternative hypothesis includes values on both sides of value specified by  $H_0$   
 test statistic - quantity calculated from data used to evaluate how compatible the results of the test are with null hypothesis  
 null distribution: sampling distribution of outcomes for test statistic when null hypothesis is true  
 p-value: probability of obtaining data (or data showing  $\geq$  null hypothesis) if null hypothesis were true  
 statistical significance level = probability used as criterion to reject null hypothesis.  $p \leq \alpha$  = reject  
 $\alpha$  = probability of type I error  
 $\beta$  = probability random sample  $\Rightarrow$  reject false null hypothesis - Type II error =  $P(\text{reject } H_0 | H_0 \text{ true})$   
 hypothesis = sufficient evidence?  
 95% confidence interval  $\Rightarrow \alpha = 0.05$

(7) Binomial distribution - probability dist. for data success in trials when prob. same on each trial.  
 add up probabilities  $P(A \text{ or } B) = P(A) + P(B)$   
 $p' = 2 \sqrt{\frac{p(1-p)}{n}}$   $98\%, z = 1.96$   $p' = \frac{1.96 \times 2}{n}$   
 $99\%, z = 2.58$   $p' = \frac{2.58 \times 2}{n}$

(8) Wald  $\hat{p} - 2SE\hat{p} < p < \hat{p} + 2SE\hat{p}$   
 $P(X \text{ successes}) = \binom{n}{x} p^x (1-p)^{n-x} = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}$   
 $p = \text{prob}, x = \text{# successes}, n = \text{trials } SE\hat{p} = \sqrt{\frac{p(1-p)}{n}}$   
 goodness of fit: compares frequency data to model selected by null hypothesis  $\chi^2 = \text{measures discrepancy between observed & expected frequencies}$   
 critical value = value of test statistic that marks boundary of specified  $\alpha$  in tail(s) of sampling distribution model

(9) Contingency analysis = goodness of fit tests for association between 2+ categorical variables  
 $\chi^2$  contingency test. Some assumptions: 68.3, 95, 99.5  $P(\text{blue hand} < 22 \text{ yellow}) = P(Z < 2.2)$   
 normal distribution - continuous probability dist. derived from bell curve. standard normal distribution = normal dist. w/  $\mu = 0$  and  $\sigma = 1$   $P(Z > 2.2)$   
 Central Limit Theorem: sum of large # of normally distributed variables approx. normal dist. if dist. skewed  
 It variable  $X$  has normal dist. in pop, then dist. of means  $\bar{y}$  also normal. Sampled from non-normal population approx. normal dist. if dist. skewed

(10) 2-sample t-test paired - distributions to compare  
 2 sample - each treatment represented by independent sample of units  
 paired - control to single measurement, making difference self-comparison

$sd = \sqrt{\frac{\sum (Y_i - \bar{Y})^2}{n-1}}$   $se = \sigma_Y - \frac{\sigma}{\sqrt{n}} \Rightarrow SE_{\bar{Y}} = \frac{s}{\sqrt{n}}$   $\hat{p} = \frac{x}{n}$   $SE_{\hat{p}} = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$

Agresti-Coull:  $(p' - 2\sqrt{\frac{p'(1-p')}{n+4}}) < p < (p' + 2\sqrt{\frac{p'(1-p')}{n+4}})$   $p' = \frac{x+2}{n+4}$   $z = 1.96$  for 95%  $x = \text{success}, n = \text{trials}$

$P = 2(\sum_{i=x}^n Pr(i \text{ successes}))$  for  $\frac{x}{n} > p_0$  or  $P = 2(\sum_{i=0}^x Pr(i \text{ successes}))$  for  $\frac{x}{n} < p_0$

$\chi^2 = \sum \frac{(observed - expected)^2}{expected}$   $df = \# \text{ categories} - 1 - \# \text{ of parameters estimated from data}$

odds  $O = \frac{p}{1-p} = \frac{\hat{p}}{1-\hat{p}}$   $OR = \frac{O_1}{O_2} = \text{odds ratio}$   $SE[\ln OR] = \sqrt{\frac{1}{a+b} + \frac{1}{c+d}}$

$\chi^2 = \sum_{\text{column}} \sum_{\text{row}} \frac{[observed(\text{column, row}) - expected(\text{column, row})]^2}{expected(\text{column, row})}$   $df = (r-1)(c-1)$

normal  $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$   $z = \frac{Y-\mu}{\sigma} = \frac{\bar{Y}-\mu}{\sigma_{\bar{Y}}} = \frac{\sigma}{s/\sqrt{n}}$

$n\hat{p}$ , binomial prob. dist  $\Rightarrow$   $np, sd = \sqrt{np(1-p)}$

normal approx to binomial dist:  $Pr[X \geq \text{observed}] = Pr[Z > \frac{\text{observed} - np}{\sqrt{np(1-p)}}$

$n\hat{p}, n(1-\hat{p}) \geq 5$  continuity correction for normal approx to binom. dist

$Pr[X \geq \text{observed}] = Pr[Z > \frac{\text{observed} - \frac{1}{2} - np}{\sqrt{np(1-p)}}]$   $Pr[X \leq \text{observed}] = Pr[Z \leq \frac{\text{observed} + \frac{1}{2} - np}{\sqrt{np(1-p)}}]$

$t$ -test  $z = \frac{\bar{Y}-\mu}{\sigma_{\bar{Y}}}$   $SE_{\bar{Y}} = \frac{s}{\sqrt{n}}$   $t = \frac{\bar{Y}-\mu_0}{s/\sqrt{n}}$   $df = n-1$

$-t_{0.05/2, df} < \frac{\bar{Y}-\mu}{SE_{\bar{Y}}} < t_{0.05/2, df} \Rightarrow \bar{Y} - t_{0.05/2, df} SE_{\bar{Y}} < \mu < \bar{Y} + t_{0.05/2, df} SE_{\bar{Y}}$

$\bar{Y} - t_{2(2), df} SE_{\bar{Y}} < \mu < \bar{Y} + t_{2(2), df} SE_{\bar{Y}}$   $P = Pr[t < y] + Pr[t > y]$

$\chi^2 = (n-1) \frac{s^2}{\sigma^2}$   $\frac{df s^2}{\chi^2_{\frac{\alpha}{2}, df}} < \sigma^2 < \frac{df s^2}{\chi^2_{1-\frac{\alpha}{2}, df}}$   $\Rightarrow$  confidence interval for variance, or not normal

2-sample  $t$ -test  $t = \frac{\bar{d} - \mu_{d0}}{SE_{\bar{d}}}$   $P = Pr[t_y < -t] + Pr[t_y > t] = 2Pr[t > t]$

assumptions: each of the two samples is a random sample the merge variable is normally distributed  $Jd + \text{variance}$  is same in both pop.  $t$ -test  $\rightarrow$  Welch's  $t$ -test

normal - approx - normal dist  $\Rightarrow$   $Pr[X \geq \text{observed}] = Pr[Z > \frac{\text{observed} - np}{\sqrt{np(1-p)}}$

Ch 10 simulation - use computer to create 1 sample pop w/ null 2) calculate test statistic 3) repeat 4) normal distribution 5) compare test statistics

Factorial - categorical - response, randomized else 1) randomize 2) calculate statistic 3) repeat

bootstrap - resamples to create sampling distribution 1) randomize 2) estimate 3) repeat 4) sample distribution = standard deviation

Ch 11 F measures improvement in fit model to determine for describing explanatory variable included

Ch 13 transformations - arcsin, sqrt, square, reciprocals, properties, counts labels left

Man-Whitney U test - looks  $u_1 = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1$   $u_2 = n_1 n_2 + \frac{n_2(n_2+1)}{2} - R_2$

Ch 10 binomial, replication, confidence, confidence, randomization, holmes block, hypothesis =  $n = \frac{4p(kp)}{margin^2}$

| Ch 15 ANOVA SS                                 | df    | mean squares                      | F ratio                          |
|--|-------|-----------------------------------|----------------------------------|
| groups $SS = \sum n_i (\bar{y}_i - \bar{y})^2$ | $k-1$ | $\frac{SS_{groups}}{df_{groups}}$ | $\frac{MS_{groups}}{MS_{error}}$ |
| error $SS = \sum s_i^2 (n_i - 1)$              | $N-k$ | $\frac{SS_{error}}{df_{error}}$   |                                  |

$n = \text{style size}$   
 $k = \text{# of groups}$

$$p^2 = \frac{SS_{groups}}{SS_{total}}$$

Ch 16:

$$SS_{prod} = -\sum (x - \bar{x})(y - \bar{y}) = \sum (xy) - \frac{\sum x \sum y}{n}$$

$$SS_{squares} = \sum (x - \bar{x})^2 = \sum (x^2) - \frac{(\sum x)^2}{n}$$

$$Covariance(x, y) = \frac{\sum (x - \bar{x})(y - \bar{y})}{n}$$

$$correl. coefficient = r = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2} \sqrt{\sum (y - \bar{y})^2}} \quad df = n - 2$$

pop correlation - random sample  $r = 2 \cos \theta$   $\sigma = \sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}$

$$r = 0.5 \ln \left( \frac{1+r}{1-r} \right) \quad \sigma = \sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}$$

for future interval =  $n - 2$   $df$   $t = \frac{r}{SE_r} \quad SE_r = \sqrt{\frac{1-r^2}{n}}$

Ch 17 regression slope =  $\beta_1$   $b_1$   $b_2$

t-test for slope  $t = \frac{b_1 - \beta_0}{SE}$

$$R^2 = \frac{SS_{regression}}{SS_{total}}$$

| ANOVA      | SS                         | df    | mean squares                    | F ratio                       |
|------------|----------------------------|-------|---------------------------------|-------------------------------|
| regression | $\sum (x_i - \bar{x})^2$   | 1     | $\frac{MS_{reg}}{df_{reg}}$     | $\frac{MS_{reg}}{MS_{resid}}$ |
| residual   | $\sum (y_i - \hat{y}_i)^2$ | $n-2$ | $\frac{MS_{resid}}{df_{resid}}$ |                               |

$$MS_{resid} = \frac{\sum (y_i - \hat{y}_i)^2 - b \sum (x_i - \bar{x})(y_i - \bar{y})}{n-2}$$

Likelihood

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

$\theta_p / \ln \theta$

$$\frac{x^2}{2} = 1.92$$

$$2 \ln \left( \frac{Lik_{alt}}{Lik_{null}} \right)$$