

<p>Ch. 3: Descriptive Statistics</p>	<p>Ch. 7: Confidence Intervals (one population)</p>
$\bar{x} = \frac{\sum x}{n} \text{ Mean}$ $\bar{x} = \frac{\sum f \cdot x}{\sum f} \text{ Mean (frequency table)}$ $s = \sqrt{\frac{\sum (x - \bar{x})^2}{n - 1}} \text{ Standard deviation}$ $s = \sqrt{\frac{n(\sum x^2) - (\sum x)^2}{n(n - 1)}} \text{ Standard deviation (shortcut)}$ $s = \sqrt{\frac{n[\sum (f \cdot x^2)] - [\sum (f \cdot x)]^2}{n(n - 1)}} \text{ Standard deviation (frequency table)}$ <p>variance = s^2</p>	$\hat{p} - E < p < \hat{p} + E \text{ Proportion}$ <p>where $E = z_{\alpha/2} \sqrt{\frac{\hat{p}\hat{q}}{n}}$</p> <hr/> $\bar{x} - E < \mu < \bar{x} + E \text{ Mean}$ <p>where $E = z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$ (σ known)</p> <p>or $E = t_{\alpha/2} \frac{s}{\sqrt{n}}$ (σ unknown)</p> <hr/> $\frac{(n - 1)s^2}{\chi_R^2} < \sigma^2 < \frac{(n - 1)s^2}{\chi_L^2} \text{ Variance}$
<p>Ch. 4: Probability</p>	<p>Ch. 7: Sample Size Determination</p>
<p>$P(A \text{ or } B) = P(A) + P(B)$ if A, B are mutually exclusive</p> <p>$P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$ if A, B are not mutually exclusive</p> <p>$P(A \text{ and } B) = P(A) \cdot P(B)$ if A, B are independent</p> <p>$P(A \text{ and } B) = P(A) \cdot P(B A)$ if A, B are dependent</p> <p>$P(\bar{A}) = 1 - P(A)$ Rule of complements</p> ${}_n P_r = \frac{n!}{(n - r)!} \text{ Permutations (no elements alike)}$ $\frac{n!}{n_1! n_2! \cdots n_k!} \text{ Permutations (} n_1 \text{ alike, } \dots \text{)}$ ${}_n C_r = \frac{n!}{(n - r)! r!} \text{ Combinations}$	$n = \frac{[z_{\alpha/2}]^2 \cdot 0.25}{E^2} \text{ Proportion}$ $n = \frac{[z_{\alpha/2}]^2 \hat{p}\hat{q}}{E^2} \text{ Proportion (} \hat{p} \text{ and } \hat{q} \text{ are known)}$ $n = \left[\frac{z_{\alpha/2} \sigma}{E} \right]^2 \text{ Mean}$
<p>Ch. 5: Probability Distributions</p>	<p>Ch. 9: Confidence Intervals (two populations)</p>
$\mu = \sum x \cdot P(x) \text{ Mean (prob. dist.)}$ $\sigma = \sqrt{\sum [x^2 \cdot P(x)] - \mu^2} \text{ Standard deviation (prob. dist.)}$ $P(x) = \frac{n!}{(n - x)! x!} \cdot p^x \cdot q^{n-x} \text{ Binomial probability}$ $\mu = n \cdot p \text{ Mean (binomial)}$ $\sigma^2 = n \cdot p \cdot q \text{ Variance (binomial)}$ $\sigma = \sqrt{n \cdot p \cdot q} \text{ Standard deviation (binomial)}$ $P(x) = \frac{\mu^x \cdot e^{-\mu}}{x!} \text{ Poisson distribution}$ <p>where $e \approx 2.71828$</p>	$(\hat{p}_1 - \hat{p}_2) - E < (p_1 - p_2) < (\hat{p}_1 - \hat{p}_2) + E$ <p>where $E = z_{\alpha/2} \sqrt{\frac{\hat{p}_1 \hat{q}_1}{n_1} + \frac{\hat{p}_2 \hat{q}_2}{n_2}}$</p> <hr/> $(\bar{x}_1 - \bar{x}_2) - E < (\mu_1 - \mu_2) < (\bar{x}_1 - \bar{x}_2) + E \text{ (Indep.)}$ <p>where $E = t_{\alpha/2} \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$ (df = smaller of $n_1 - 1, n_2 - 1$)</p> <p>(σ_1 and σ_2 unknown and not assumed equal)</p> <hr/> $E = t_{\alpha/2} \sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}$ <p>(df = $n_1 + n_2 - 2$)</p> $s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{(n_1 - 1) + (n_2 - 1)}$ <p>(σ_1 and σ_2 unknown but assumed equal)</p> <hr/> $E = z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$ <p>(σ_1, σ_2 known)</p> <hr/> $\bar{d} - E < \mu_d < \bar{d} + E \text{ (Matched pairs)}$ <p>where $E = t_{\alpha/2} \frac{s_d}{\sqrt{n}}$ (df = $n - 1$)</p>
<p>Ch. 6: Normal Distribution</p>	
$z = \frac{x - \bar{x}}{s} \text{ or } \frac{x - \mu}{\sigma} \text{ Standard score}$ $\mu_{\bar{x}} = \mu \text{ Central limit theorem}$ $\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}} \text{ Central limit theorem (Standard error)}$	

Ch. 8: Test Statistics (one population)	Ch. 10: Linear Correlation/Regression
$z = \frac{\hat{p} - p}{\sqrt{\frac{pq}{n}}}$ Proportion—one population	$\text{Correlation } r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2} \sqrt{n(\sum y^2) - (\sum y)^2}}$ where $z_x = z$ score for x $z_y = z$ score for y
$z = \frac{\bar{x} - \mu}{\sigma/\sqrt{n}}$ Mean—one population (σ known)	or $r = \frac{\sum(z_x z_y)}{n - 1}$
$t = \frac{\bar{x} - \mu}{s/\sqrt{n}}$ Mean—one population (σ unknown)	Slope: $b_1 = \frac{n\sum xy - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2}$
$\chi^2 = \frac{(n - 1)s^2}{\sigma^2}$ Standard deviation or variance— one population	or $b_1 = r \frac{s_y}{s_x}$
Ch. 9: Test Statistics (two populations)	
$z = \frac{(\hat{p}_1 - \hat{p}_2) - (p_1 - p_2)}{\sqrt{\frac{\hat{p}\hat{q}}{n_1} + \frac{\hat{p}\hat{q}}{n_2}}}$ Two proportions $\bar{p} = \frac{x_1 + x_2}{n_1 + n_2}$	$y\text{-Intercept: } b_0 = \bar{y} - b_1 \bar{x} \quad \text{or} \quad b_0 = \frac{(\sum y)(\sum x^2) - (\sum x)(\sum xy)}{n(\sum x^2) - (\sum x)^2}$
$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$ df = smaller of $n_1 - 1, n_2 - 1$	$\hat{y} = b_0 + b_1 x$ Estimated eq. of regression line
↑ Two means—dependent; σ_1 and σ_2 unknown, and not assumed equal.	$r^2 = \frac{\text{explained variation}}{\text{total variation}}$
$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}}$ (df = $n_1 + n_2 - 2$) $s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$	$s_e = \sqrt{\frac{\sum(y - \hat{y})^2}{n - 2}} \quad \text{or} \quad \sqrt{\frac{\sum y^2 - b_0 \sum y - b_1 \sum xy}{n - 2}}$
↑ Two means—dependent; σ_1 and σ_2 unknown, but assumed equal.	$\hat{y} - E < y < \hat{y} + E$ Prediction interval
$z = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$ Two means—dependent; σ_1, σ_2 known.	$\text{where } E = t_{\alpha/2, s_e} \sqrt{1 + \frac{1}{n} + \frac{n(x_0 - \bar{x})^2}{n(\sum x^2) - (\sum x)^2}}$
$t = \frac{\bar{d} - \mu_d}{s_d/\sqrt{n}}$ Two means—matched pairs (df = $n - 1$)	<b style="background-color: #ADD8E6;">Ch. 12: One-Way Analysis of Variance
$F = \frac{s_1^2}{s_2^2}$ Standard deviation or variance— two populations (where $s_1^2 \geq s_2^2$)	Procedure for testing $H_0: \mu_1 = \mu_2 = \mu_3 = \dots$ <ol style="list-style-type: none"> 1. Use software or calculator to obtain results. 2. Identify the P-value. 3. Form conclusion: <ul style="list-style-type: none"> If $P\text{-value} \leq \alpha$, reject the null hypothesis of equal means. If $P\text{-value} > \alpha$, fail to reject the null hypothesis of equal means.
Ch. 11: Goodness-of-Fit and Contingency Tables	
$\chi^2 = \sum \frac{(O - E)^2}{E}$ Goodness-of-fit (df = $k - 1$)	<b style="background-color: #ADD8E6;">Ch. 12: Two-Way Analysis of Variance
$\chi^2 = \sum \frac{(O - E)^2}{E}$ Contingency table [df = $(r - 1)(c - 1)$] where $E = \frac{(\text{row total})(\text{column total})}{(\text{grand total})}$	Procedure: <ol style="list-style-type: none"> 1. Use software or a calculator to obtain results. 2. Test H_0: There is no interaction between the row factor and column factor. 3. Stop if H_0 from Step 2 is rejected. If H_0 from Step 2 is not rejected (so there does not appear to be an interaction effect), proceed with these two tests: <ul style="list-style-type: none"> Test for effects from the row factor. Test for effects from the column factor.
$\chi^2 = \frac{(b - c - 1)^2}{b + c}$ McNemar's test for matched pairs (df = 1)	