Description	*Model*	*Parameter of Interest*	*Point Estimate*	*Standard Error*	*Test Statistic*	*Sampling Distribution*
Single Proportion	$X \sim Binom(n, p)$ *Assumptions: BINS*	p, the true population proportion	$\widehat{p_{AC}} = \frac{X+2}{n+4}$ (Only make AC adjustment for confidence intervals.)	$\sqrt{\frac{\widehat{p_{AC}}(1-\widehat{p_{AC}})}{n+4}}$	X, the observed number of successes	For confidence intervals: $N(0,1)$. For hypothesis testing: $X \sim Binom(n, p_0)$ where p_0 is the value of p under the null hypothesis.
Difference in Proportions	$X \sim Binom(n_1, p_1)$ $Y \sim Binom(n_2, p_2)$ *Assumptions: BINS within each group*	$p_1 - p_2$, the difference in true population proportions	$\widehat{p_{1AC}} - \widehat{p_{2AC}}$ $\widehat{p_{1AC}} = \frac{X_1+1}{n_1+2}$ $\widehat{p_{2AC}} = \frac{X_2+1}{n_2+2}$ (Only make AC adjustment for confidence intervals.)	For confidence intervals: $\sqrt{\frac{\widehat{p_{1AC}}(1-\widehat{p_{1AC}})}{n_1+2} + \frac{\widehat{p_{2AC}}(1-\widehat{p_{2AC}})}{n_2+2}}$ For hypothesis testing: $\sqrt{\frac{\bar{p}(1-\bar{p})}{n_1} + \frac{\bar{p}(1-\bar{p})}{n_2}}$ where $\bar{p} = (X_1 + X_2)/(n_1 + n_2)$	$Z = \frac{(\widehat{p_1} - \widehat{p_2}) - p_{diff,null}}{SE(\widehat{p_1} - \widehat{p_2})}$ where $p_{diff,null}$ is the value of $p_1 - p_2$ under the null hypothesis (often 0).	$Z \sim N(0,1)$
Single Mean	$X_i \sim D(\mu, \sigma)$, for $i = 1, \dots, n$ where D is an arbitrary distribution, μ is the mean and σ is the std. dev. of D. *Assumptions: Independence*	μ, the true population mean	$\bar{x}$	$\frac{s}{\sqrt{n}}$ where s is the sample standard deviation.	$T = \frac{\bar{x} - \mu_{null}}{SE(\bar{x})}$ where μ_{null} is the value of μ under the null hypothesis.	$T \sim t(df = n-1)$
Difference in Means	$X_i \sim D_x(\mu_x, \sigma_x)$ $Y_i \sim D_y(\mu_y, \sigma_y)$ See above for definitions. *Assumptions: Independence*	$\mu_x - \mu_y$, the difference in true population means	$\bar{x} - \bar{y}$	$\sqrt{\frac{{s_x}^2}{n_x} + \frac{{s_y}^2}{n_y}}$	$T = \frac{(\bar{x} - \bar{y}) - \mu_{diff,null}}{SE(\bar{x} - \bar{y})}$ where $\mu_{diff,null}$ is the value of $\mu_x - \mu_y$ under the null hypothesis (often 0).	$T \sim t(df = W)$ $W = \frac{(\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y})^2}{\left(\frac{s_x^2}{n_x}\right)^2/(n_x-1) + \left(\frac{s_y^2}{n_y}\right)^2/(n_y-1)}$ (provided in t.test() output)
Linear Regression	$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$, $\varepsilon_i \sim N(0, \sigma)$ *Assumptions: Linear form (1), errors are normally distributed around 0 (2), with constant variance (3)*	β_1, the true population slope	$\widehat{\beta_1} = r * \frac{s_y}{s_x}$ (provided in lm() output)	$\sqrt{\frac{\sum(y_i - \hat{y}_i)^2/(n-2)}{\sum(x_i - \bar{x})^2}}$ (provided in lm() summary output)	$T = \frac{\widehat{\beta_1} - \beta_{1,null}}{SE(\widehat{\beta_1})}$ where $\beta_{1,null}$ is the value of β_1 under the null hypothesis (often 0).	$T \sim t(df = n-2)$

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Hypothesis Testing

$$test\ statistic\ = \frac{point\ estimate - null\ value}{standard\ error}.$$

Confidence Intervals

Point Estimate $\pm$ Quantile Confidence Score * Standard Error