

Case 1: One Variable (Population)

Assumptions	$\sigma$ is known	$\sigma$ is unknown	$n(p_0) > 5$ and $n(1 - p_0) > 5$	Data comes from Normal Population
Parameter of interest:	Mean, $\mu$	Mean, $\mu$	Proportion, $p$	Variance, $\sigma^2$
Confidence Interval Formula:	$\bar{x} \pm z(\alpha/2) \frac{\sigma}{\sqrt{n}}$	$\bar{x} \pm t(df, \alpha/2) \frac{s}{\sqrt{n}}$ with $df = n - 1$	$p' \pm z(\alpha/2) \sqrt{\frac{p'q'}{n}}$	$\frac{(n-1)s^2}{\chi^2(df, \alpha/2)} < \sigma^2 < \frac{(n-1)s^2}{\chi^2(df, 1 - \alpha/2)}$ with $df = n - 1$
Name of Hypothesis Test, $H_0$	One sample z-test, $H_0: \mu = \mu_0$	One sample t-test, $H_0: \mu = \mu_0$	One sample test of proportion $H_0: p = p_0$	One sample test for Variance $H_0: \sigma^2 = \sigma_0^2$
Test Statistic Formula:	$z^* = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}}$	$t^* = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}$ with $df = n - 1$	$z^* = \frac{p' - p_0}{\sqrt{\frac{p_0q_0}{n}}}$	$\chi^{2*} = \frac{(n-1)s^2}{\sigma_0^2}$ with $df = n - 1$
p-value:	$H_a: \mu > \mu_0$ , p-value= $P(z \geq z^*)$ $H_a: \mu < \mu_0$ , p-value= $P(z \leq z^*)$ $H_a: \mu \neq \mu_0$ , p-value= $2 \times P(z \geq  z^* )$	$H_a: \mu > \mu_0$ , p-value= $P(t(df) \geq t^*)$ $H_a: \mu < \mu_0$ , p-value= $P(t(df) \leq t^*)$ $H_a: \mu \neq \mu_0$ , p-value= $2 \times P(t(df) \geq  t^* )$	$H_a: p > p_0$ , p-value= $P(z \geq z^*)$ $H_a: p < p_0$ , p-value= $P(z \leq z^*)$ $H_a: p \neq p_0$ , p-value= $2 \times P(z \geq  z^* )$	$H_a: \sigma^2 > \sigma_0^2$ , p-value= $P(\chi^2(df) \geq \chi^{2*})$ $H_a: \sigma^2 < \sigma_0^2$ , p-value= $P(\chi^2(df) \leq \chi^{2*})$ $H_a: \sigma^2 \neq \sigma_0^2$ , p-value= $2 \times P(\chi^2(df) \geq \chi^{2*})$

Case 2: Two Numerical Variables (Populations)

	Dependent Samples (Paired Samples)	Independent Samples		Two Normal Populations Independent Samples
Parameter of interest:	Mean Difference, $\mu_d = \mu_1 - \mu_2$	Mean Difference, $\mu_1 - \mu_2$	Proportion Difference, $p_1 - p_2$	Ratio of variances, $\sigma_n^2 / \sigma_d^2$
Confidence Interval Formula:	$\bar{d} \pm t(df, \alpha/2) \frac{s_d}{\sqrt{n}}$  with $df = n - 1$  where $d = x_1 - x_2$	$(\bar{x}_1 - \bar{x}_2)$  $\pm t(df, \alpha/2) \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$  with $df = \min(n_1 - 1, n_2 - 1)$	$(p'_1 - p'_2)$  $\pm z(\alpha/2) \sqrt{\frac{p'_1 q'_1}{n_1} + \frac{p'_2 q'_2}{n_2}}$	$\frac{1}{F(df_n, df_d, \alpha/2)} \frac{s_n^2}{s_m^2} < \frac{\sigma_n^2}{\sigma_d^2}$  $< F(df_d, df_n, \alpha/2) \frac{s_n^2}{s_m^2}$  with $df_n = n_{num} - 1$ and $df_d = n_{den} - 1$
Name of Hypothesis Test, $H_0$	Paired samples $t$ -test, $H_0: \mu_1 = \mu_2$	Two independent samples $t$ -test, $H_0: \mu_1 = \mu_2$	Two sample test of proportion $H_0: p_1 = p_2$	Two sample test for variance $H_0: \sigma_n^2 = \sigma_d^2$
Test Statistic Formula:	$t^* = \frac{\bar{d}}{s_d / \sqrt{n}}$  with $df = n - 1$	$t^* = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$  with $df = \min(n_1 - 1, n_2 - 1)$	$z^* = \frac{p'_1 - p'_2}{\sqrt{p'_p q'_p \left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$  where $p'_p = \frac{x_1 + x_2}{n_1 + n_2}$ and $q'_p = 1 - p'_p$	$F^* = \frac{s_n^2}{s_m^2}$  with $df_n = n_{num} - 1$ and $df_d = n_{den} - 1$
p-value:	$H_a: \mu_1 > \mu_2$ , p-value= $P(t(df) \geq t^*)$ $H_a: \mu_1 < \mu_2$ , p-value= $P(t(df) \leq t^*)$ $H_a: \mu_1 \neq \mu_2$ , p-value= $2 \times P(t(df) \geq  t^* )$	$H_a: p_1 > p_2$ , p-value= $P(z \geq z^*)$ $H_a: p_1 < p_2$ , p-value= $P(z \leq z^*)$ $H_a: p_1 \neq p_2$ , p-value= $2 \times P(z \geq  z^* )$	$H_a: \sigma_n^2 > \sigma_d^2$ , p-value= $P(F(df_n, df_d) \geq F^*)$ $H_a: \sigma_n^2 \neq \sigma_d^2$ , p-value= $2 \times P(F(df_n, df_d) \geq F^*)$	

Case 3: More than Two Populations (Multinomial Experiment, Contingency Table, Test of Homogeneity - ANOVA)

	Multinomial Experiment, Contingency Table, Homogeneity		Analysis of Variance (ANOVA)
Parameter of interest:	Probability: $p_1, p_2, \dots, p_k$	Probability	Mean: $\mu_1, \mu_2, \dots, \mu_c$
$H_0$	$H_0: p_1 = p_{10}, \dots, p_k = p_{k0}$	$H_0$ : Independency (Homogeneity)	$H_0: \mu_1 = \mu_2 = \dots = \mu_c$
Test Statistic Formula:	$\chi^{2*} = \sum_{\text{all cells}} \frac{(O - E)^2}{E}$		$F^* = \frac{\text{MS(factor)}}{\text{MS(error)}} = \frac{\text{SS(factor)}/\text{df(factor)}}{\text{SS(error)}/\text{df(error)}}$
df and other items	$df = k - 1$ $E_i = n \times p_{i0}$	$df = (r - 1)(c - 1)$ $E_{ij} = \frac{R_i \times C_j}{n}$	$\text{df(factor)} = c - 1, \text{df(error)} = n - c$ $\text{SS(factor)} = \left( \frac{C_1^2}{k_1} + \frac{C_2^2}{k_2} + \dots + \frac{C_c^2}{k_c} \right) - \frac{(\sum x)^2}{n}$ $\text{SS(error)} = \sum (x^2) - \left( \frac{C_1^2}{k_1} + \frac{C_2^2}{k_2} + \dots + \frac{C_c^2}{k_c} \right)$
p-value:	p-value= $P(\chi^2(df) \geq \chi^{2*})$		p-value= $P(F(df_n, df_d) \geq F^*)$