Distribution	PDF	Mean	Variance	MGF
Binomial	$p(y)=\binom{n}{y}p^y(1-p)^{n-y}, y=0,1,...,n$	np	$np(1-p)$	$[pe^t+(1-p)]^n$
Geometric	$p(y)=p(1-p)^{y-1}, y=1,2,...$	$\frac{1}{p}$	$\frac{1-p}{p^2}$	$\frac{pe^t}{1-(1-p)e^t}$
Hypergeometric	$p(y)=\frac{\binom{r}{y}\binom{N-r}{n-y}}{Nn}, y=0,1,...$	$\frac{nr}{N}$	$n\frac{r}{N}\frac{N-r}{N}\frac{N-n}{N-1}$	DNE in closed form
Poisson	$p(y)=\frac{\lambda^y e^{-\lambda}}{y!}, y=0,1,2,..$	λ	λ	$e^{\lambda(e^t-1)}$
Negative Binomial	$p(y)=\binom{y-1}{r-1}p^r(1-p)^{y-r}, y=r,r+1,...$	$\frac{r}{p}$	$\frac{r(1-p)}{p^2}$	$\left[\frac{pe^t}{1-(1-p)e^t}\right]^t$
Uniform	$f(y)=\frac{1}{\theta_2-\theta_1}$	$\frac{\theta_1+\theta_2}{2}$	$\frac{(\theta_2-\theta_1)^2}{12}$	$\frac{e^{t\theta_2}-e^{t\theta_1}}{t(\theta_2-\theta_1)}$
Normal	$f(y)=\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-(y-\mu)^2}{2\sigma^2}}$	μ	σ^2	$e^{\mu t+\frac{t^2\sigma^2}{2}}$
Exponential	$f(y)=\frac{1}{\beta}e^{-y/\beta}$	β	β^2	$(1-\beta t)^{-1}$
Gamma	$f(y)=\frac{y^{\alpha-1}e^{-y/\beta}}{\Gamma(\alpha)\beta^\alpha}$	$\alpha\beta$	$\alpha\beta^2$	$(1-\beta t)^{-\alpha}$
Chi-square	$f(y)=\frac{y^{v/2-1}e^{-y/2}}{2^{v/2}\Gamma(v/2)}$	v	$2v$	(1-2t)$^{-v/2}$
Beta	$f(y)=\left[\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\right]y^{\alpha-1}(1-y)^{\beta-1}$	$\frac{\alpha}{\alpha+\beta}$	$\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$	DNE in closed form

Some Relevant Distribution Relationships Assume Y_i are i.i.d, i = 1, 2, ..., n, and $Y_i \sim$Normal(μ,σ^2)

$$\overline{Y}=\frac{1}{n}\sum_{i=1}^{n}Y_i,\qquad Z=\frac{\overline{Y}-\mu}{\sigma/\sqrt{n}}\sim \text{Normal}(0,1),\qquad \sum_{i=1}^{n}\left(\frac{Y_i-\mu}{\sigma}\right)^2\sim\chi^2_{(n)},\qquad \chi^2_{(n)}=\text{Gamma}(n/2,2)$$

$$\frac{(n-1)S^2}{\sigma^2}=\sum_{i=1}^{n}\frac{(Y_i-\overline{Y})^2}{\sigma^2}\sim\chi^2_{(n-1)},\qquad S^2=\frac{1}{n-1}\sum_{i=1}^{n}(Y_i-\overline{Y})^2$$

$$t_v=\frac{Z}{\sqrt{W/v}}\text{ where } Z\sim\text{Normal}(0,1), W\sim\chi^2_{(v)}, \text{ and } Z,W \text{ are independent}$$

$$F_{v1,v2}=\frac{W_1/v_1}{W_2/v_2}\text{ where } W_1\sim\chi^2_{(v_1)}, W_2\sim\chi^2_{(v_2)} \text{ and } W_1,W_2 \text{ are independent},\qquad F_{n_1-1,n_2-1}\sim\frac{S_1^2/\sigma_1^2}{S_2^2/\sigma_2^2}$$

$$\text{Exp}(\beta)=\text{Gamma}(\alpha=1,\beta),\qquad (\text{Normal}(0,1))^2=\chi^2_{(1)}=\text{Gamma}(1/2,2)$$

$$\mu=np,\sigma=\sqrt{np(1-p)}$$

$$Y_{(1)}=\min(Y_1,Y_2,...,Y_n)\quad f_{Y_{(1)}}(y)=n[1-F_{Y_i}(y)]^{n-1}f_{Y_i}(y),\qquad Y_{(n)}=\max(Y_1,Y_2,...,Y_n)\quad f_{Y_{(n)}}(y)=n[F_{Y_i}(y)]^{n-1}f_{Y_i}(y)$$

Derived Confidence Intervals

Large Sample C.I for p and μ:

$$\hat{p}\pm Z_{\alpha/2}\sqrt{\frac{\hat{p}(1-\hat{p})}{n}},\qquad \overline{Y}\pm Z_{\alpha/2}\frac{S}{\sqrt{n}}$$

Large Sample C.I for $\mu_1-\mu_2$ and p_1-p_2:

$$\overline{Y_1}-\overline{Y_2}\pm Z_{\alpha/2}\sqrt{\frac{S_1^2}{n_1}+\frac{S_2^2}{n_2}},\qquad (\hat{p_1}-\hat{p_2})\pm z_{\alpha/2}\sqrt{\frac{\hat{p_1}(1-\hat{p_1})}{n_1}+\frac{\hat{p_2}(1-\hat{p_2})}{n_2}}$$

Small Sample C.I for μ:

$$\overline{Y}\pm t_{\alpha/2}\left(\frac{S}{\sqrt{n}}\right)\quad\text{where t has}(n-1)\text{ df}$$

Small Sample C.I for $\mu_1-\mu_2$:

$$(\overline{Y}_1-\overline{Y}_2)\pm t_{\alpha/2}S_p\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}\quad\text{where t has }(n_1+n_2-2)\text{ df}\qquad S_p^2=\frac{(n_1-1)S_1^2+(n_2-1)S_2^2}{n_1+n_2-2}$$

C.I for σ^2:

$$\left(\frac{(n-1)S^2}{\chi^2_{\alpha/2}},\frac{(n-1)S^2}{\chi^2_{1-\alpha/2}}\right)\quad\text{where }\chi^2\text{ has }(n-1)\text{ df}$$

Large-Sample Test for Mean: $Z=\frac{\overline{Y}-\mu_0}{S/\sqrt{n}}$

	Alternative Hypothesis	Reject Region for Level α Test (Related to Standard Normal)
Upper-Tailed Test	$H_a:\mu>\mu_0$	$Z\geq Z_\alpha$
Lower-Tailed Test	$H_a:\mu<\mu_0$	$Z\leq -Z_\alpha$
Two-Tailed Test	$H_a:\mu\neq\mu_0$	$Z\geq Z_{\alpha/2}$ or $Z\leq -Z_{\alpha/2}$

Large-Sample Test for Proportion: $Z = \dfrac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}}$

	Alternative Hypothesis	Reject Region for Level α Test (Related to Standard Normal)
Upper-Tailed Test	$H_a : p > p_0$	$Z \geq Z_\alpha$
Lower-Tailed Test	$H_a : p < p_0$	$Z \leq -Z_\alpha$
Two-Tailed Test	$H_a : p \neq p_0$	$Z \geq Z_{\alpha/2}$ or $Z \leq -Z_{\alpha/2}$

Small-Sample Test for Mean: $T = \dfrac{\overline{Y} - \mu_0}{s/\sqrt{n}}$

	Alternative Hypothesis	Reject Region for Level α Test (Related to T-Distribution)
Upper-Tailed Test	$H_a : \mu > \mu_0$	$T \geq t_{\alpha,n-1}$
Lower-Tailed Test	$H_a : \mu < \mu_0$	$T \leq -t_{\alpha,n-1}$
Two-Tailed Test	$H_a : \mu \neq \mu_0$	$T \geq t_{\alpha/2,n-1}$ or $T \leq -t_{\alpha/2,n-1}$

Small-Sample Test Between 2 Means: $T = \dfrac{\overline{Y_1} - \overline{Y_2} - D_0}{S_p\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}, \qquad S_p = \sqrt{\dfrac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1+n_2-2}}$

	Alternative Hypothesis	Reject Region for Level α Test (Related to T-Distribution)
Upper-Tailed Test	$H_a : \mu_1 - \mu_2 > D_0$	$T \geq t_{\alpha,n_1+n_2-2}$
Lower-Tailed Test	$H_a : \mu_1 - \mu_2 < D_0$	$T \leq -t_{\alpha,n_1+n_2-2}$
Two-Tailed Test	$H_a : \mu_1 - \mu_2 \neq D_0$	$T \geq t_{\alpha/2,n_1+n_2-2}$ or $T \leq -t_{\alpha/2,n_1+n_2-2}$

Test for Variance: $\chi^2 = \dfrac{(n-1)S^2}{\sigma_0^2}$

	Alternative Hypothesis	Reject Region for Level α Test (Related to χ^2-Distribution)
Upper-Tailed Test	$H_a : \sigma^2 > \sigma_0^2$	$\chi^2 > \chi^2_{\alpha,n-1}$
Lower-Tailed Test	$H_a : \sigma^2 < \sigma_0^2$	$\chi^2 < \chi^2_{1-\alpha,n-1}$
Two-Tailed Test	$H_a : \sigma^2 \neq \sigma_0^2$	$\chi^2 > \chi^2_{\alpha/2,n-1}$ or $\chi^2 < \chi^2_{1-\alpha/2,n-1}$

Test for Equal Variances: $F = \dfrac{S_1^2}{S_2^2}$

	Alternative Hypothesis	Reject Region for Level α Test (Related to F-Distribution)
Upper-Tailed Test	$H_a : \sigma^2 > \sigma_0^2$	$F > F_{\alpha,n_1-1,n_2-1}$
Lower-Tailed Test	$H_a : \sigma^2 < \sigma_0^2$	$F < F_{1-\alpha,n_1-1,n_2-1}$
Two-Tailed Test	$H_a : \sigma^2 \neq \sigma_0^2$	$F > F_{\alpha/2,n_1-1,n_2-1}$ or $F < F_{1-\alpha/2,n_1-1,n_2-1}$

Least-Squares Estimators for the Simple Linear Regression Model:

$$\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}}, \quad \hat{\beta}_0 = \overline{y} - \hat{\beta}_1\overline{x}, \quad S_{xy} = \sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y}) = \sum_{i=1}^{n} x_i y_i - n(\overline{x})(\overline{y}) \quad S_{xx} = \sum_{i=1}^{n}(x_i - \overline{x})^2 = \sum_{i=1}^{n} x_i^2 - n\overline{x}^2,$$

$$V(\hat{\beta}_1) = \frac{\sigma^2}{S_{xx}}, \quad V(\hat{\beta}_0) = \sigma^2\left(\frac{1}{n} + \frac{\overline{x}^2}{S_{xx}}\right)$$

Linear Regression: Total Sum of Squares, Sum of Squares Error, Sum of Squares Regression

$$SSY = \sum_{i=1}^{n}(Y_i - \overline{Y})^2 = \sum_{i=1}^{n} Y_i^2 - n\overline{Y}^2, \quad SSE = \sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 = SSY - SS_{\text{reg}}, \quad SS_{\text{reg}} = \sum_{i=1}^{n}(\hat{Y}_i - \overline{Y})^2 = \hat{\beta}_1 S_{xy} = \hat{\beta}_1{}^2 S_{xx}$$

One Way ANOVA: Total Sum of Squares, Sum of Squares for Error, Sum of Squares for Treatments

$$n = \sum_{i=1}^{k} n_i, \quad \overline{Y_{i\bullet}} = \frac{1}{n_i}\sum_{i=1}^{n_i} Y_{ij} \quad \overline{Y} = \frac{1}{n}\sum_{i=1}^{k}\sum_{j=1}^{n_i} Y_{ij}, \quad \text{Total } SS = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(Y_{ij} - \overline{Y})^2 = \sum_{i=1}^{k}\sum_{j=1}^{n_i} Y_{ij}^2 - n\overline{Y}^2,$$

$$SSE = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(Y_{ij} - \overline{Y_{i\bullet}})^2 = \sum_{i=1}^{k}(n_i - 1)S_i^2 = \text{Total } SS - SST, \quad SST = \sum_{i=1}^{k} n_i(\overline{Y_{i\bullet}} - \overline{Y})^2 = \sum_{i=1}^{k} n_i\overline{Y_{i\bullet}}^2 - n\overline{Y}^2$$

$$MST = \frac{SST}{k-1}, \quad MSE = \frac{SSE}{n-k}, \quad F = \frac{MST}{MSE}$$