

# Statistics Formulas

## Means and Variances

	Mean	Variance
<b>Sample</b> (of size $n$ )	$\bar{x} = \frac{1}{n} \sum_i x_i$	$s^2 = \frac{1}{n-1} \sum_i (x_i - \bar{x})^2$
<b>Random variable <math>X</math></b>		
<b>discrete <math>X</math></b>		
General	$E(X) = \sum_x x f_X(x)$	$\text{Var}(X) = \sum_x (x - \mu_X)^2 f_X(x)$ $= E([X - E(X)]^2)$ $= E(X^2) - [E(X)]^2$
$X \sim \text{Binom}(n, \pi)$	$E(X) = n\pi$	$\text{Var}(X) = n\pi(1 - \pi)$
$X \sim \text{Hyper}(m, n, k)$	$E(X) = \frac{km}{m+n}$	$\text{Var}(X) = k \left( \frac{m}{m+n} \right) \left( \frac{n}{m+n} \right) \left( \frac{m+n-k}{m+n-1} \right)$
<b>continuous <math>X</math></b>		
General	$E(X) = \int_{-\infty}^{\infty} x f_X(x) dx$	$\text{Var}(X) = \int_{-\infty}^{\infty} [x - E(X)]^2 f_X(x) dx$ $= E([X - E(X)]^2)$ $= E(X^2) - [E(X)]^2$
$X \sim \text{Unif}(a, b)$	$E(X) = \frac{1}{2}(a + b)$	$\text{Var}(X) = \frac{1}{12}(b - a)^2$
$X \sim \text{Exp}(\lambda)$	$E(X) = 1/\lambda$	$\text{Var}(X) = 1/\lambda^2$
$X \sim \text{Norm}(\mu, \sigma)$	$E(X) = \mu$	$\text{Var}(X) = \sigma^2$

## 100(1 - $\alpha$ )% Confidence Intervals

For  $T \sim t(\nu)$  choose  $t_{\beta, \nu}$  so that  $P(T > t_{\beta, \nu}) = \beta$ . The 2-sided 100(1 -  $\alpha$ )% CI is

$$(\text{estimate}) \pm t^*(\text{std. error}),$$

with  $t^* = t_{\alpha/2, \nu}$ , and the degrees of freedom  $\nu$  chosen appropriately (see below).

What estimating?	Sample size	Estimate	std. error	$\nu$
$\mu_X$	$n$	$\bar{x}$	$\frac{s}{\sqrt{n}}$	$n - 1$
$\mu_X - \mu_Y$	$m, n$ (resp.)	$\bar{x} - \bar{y}$	$\left( \frac{s_X^2}{m} + \frac{s_Y^2}{n} \right)^{1/2}$	$\frac{\left( \frac{s_X^2}{m} + \frac{s_Y^2}{n} \right)^2}{\frac{(s_X^2/m)^2}{m-1} + \frac{(s_Y^2/n)^2}{n-1}}$
$\beta_1$	$n$	$b_1$	$s_{b_1} = \sqrt{\frac{\text{MSE}}{\sum_i (x_i - \bar{x})^2}}$	$n - 2$