Mean (Expected Value) of a Discrete Random Variable:  \[ \mu = \sum_j x_j p_j = \sum_j x_j P(x_j) \]

Variance of a Discrete Random Variable:  \[ \sigma^2 = \sum_j (x_j - \mu)^2 p_j = \left[ \sum_j x_j^2 p_j \right] - \mu^2 \]

Linear combination of independent random variables:  

\[ E(\sum_j X_j) = \sum_j E(X_j) \]  
\[ \text{Var}(\sum_j X_j) = \sum_j \text{Var}(X_j) \]

Summary Measures for Samples:

\[ \bar{X} = \frac{\sum_j x_j}{n} \]
\[ S^2 = \frac{\sum_j (x_j - \bar{x})^2}{n-1} = \frac{1}{n-1} \left[ \sum_j x_j^2 - \frac{(\sum_j x_j)^2}{n} \right] \]

\[ \text{Cov}(X,Y) = S_{xy} = \frac{\sum_j (x_j - \bar{x})(y_j - \bar{y})}{n-1} = \frac{1}{n-1} \left[ \sum_j x_j y_j - \frac{(\sum_j x_j)(\sum_j y_j)}{n} \right] \]  
\[ r_{xy} = \frac{S_{xy}}{S_x S_y} \]

Binomial:  
\[ P(X = x) = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x} \]
\[ \mu_x = np \]
\[ \sigma_x = \sqrt{np(1-p)} \]

Conversion to Standard Normal for any Normal Random Variable:  
\[ Z = \frac{\text{value} - \mu}{\text{stddev}} \]

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Distribution</th>
<th>Mean</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>( X = # ) successes in ( n ) trials</td>
<td>Binomial, but can be approximated with Normal if ( np ) and ( n(1-p) \geq 5 )</td>
<td>( \mu_x = np )</td>
<td>( \sigma_x = \sqrt{np(1-p)} )</td>
</tr>
<tr>
<td>( \hat{p} = \frac{X}{n} )</td>
<td>Same as ( X ) above</td>
<td>( \mu_{\hat{p}} = p )</td>
<td>( \sigma_{\hat{p}} = \sqrt{\frac{p(1-p)}{n}} )</td>
</tr>
<tr>
<td>( \bar{X} = ) sample average</td>
<td>Depends on population. If the population is Normal, then ( \bar{X} ) is exactly Normal. If the population is not Normal, but ( n ) is sufficiently large, ( \bar{X} ) is approximately Normal.</td>
<td>( \mu_{\bar{X}} = \mu )</td>
<td>( \sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}} ) \text{ Or sometimes } \sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}} \sqrt{\frac{N-n}{N-1}}</td>
</tr>
<tr>
<td>( \bar{X}_1 - \bar{X}_2 )</td>
<td>Depends on the populations. But if the populations are Normal, then ( \bar{X}_1 - \bar{X}_2 ) is exactly Normal. If the populations are not Normal, but ( n_1 ) and ( n_2 ) are both sufficiently large, ( \bar{X}_1 - \bar{X}_2 ) is approximately Normal.</td>
<td>( \mu_{\bar{X}_1 - \bar{X}_2} = \mu_1 - \mu_2 )</td>
<td>( \sigma_{\bar{X}_1 - \bar{X}_2} = \sqrt{\frac{\sigma_1^2 + \sigma_2^2}{n_1 + n_2}} )</td>
</tr>
</tbody>
</table>

Inference about \( \mu \) when \( \sigma \) is known:

\( (1-\alpha)\% \) Confidence Interval:
\[ \bar{x} \pm Z_{\alpha/2} \left( \frac{\sigma}{\sqrt{n}} \right) \]

Sampling Error or Margin of Error:
\[ W = |\bar{x} - \mu| = Z_{\alpha/2} \left( \frac{\sigma}{\sqrt{n}} \right) \]

Test Statistic:
\[ Z_{\text{obs}} = \frac{\bar{x} - \mu_0}{\sigma_{\bar{X}}} \]

\( P(\text{Type II Error}) = \beta = P(\text{Do not reject } H_0 / H_0 \text{ is false}) \)