Population distribution	$X\sim ???(\mu \ , \sigma)$	$\mu$ normal	θ bernouli	$\mu$ normal
Repeatedly take samples of size <i>n</i> and calculate	$\overline{X}$	$\overline{X}$	$p = \frac{\sum x}{n} = \text{proportion}$	$\frac{(n-1)s^2}{\sigma^2}$
The distribution of those sample statistics will approximate	$( if n is large and \sigma is known )$	$\frac{1}{\text{(if } \sigma \text{ is known)}}$	normal	k chi-square
with parameters	$\mu_{\overline{X}} = \mu$ $\sigma_{\overline{X}} = \frac{\sigma}{\sqrt{n}}$	$\mu_{\overline{X}} = \mu$ $\sigma_{\overline{X}} = \frac{\sigma}{\sqrt{n}}$	$\mu_p = \frac{\sum x}{n}$ $\sigma_p = \sqrt{\frac{p(1-p)}{n}}$	k = n - 1 $\mu = k$ $\sigma = 2k$
Other notes:	If $\sigma$ must be estimated from the data, then the distribution is: $\mu \qquad df_1$ $\frac{df_1}{t \text{ distrib.}}$ where $\mu_{\bar{X}} = \mu$ $\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}}$ $df = n - 1$	If $\sigma$ must be estimated from the data, then the distribution is: $\mu \qquad df_1$ $\frac{df_1}{t \text{ distrib.}}$ where $\mu_{\overline{X}} = \mu$ $\sigma_{\overline{X}} = \frac{\sigma}{\sqrt{n}}$ $df = n - 1$		Notice that this only holds when the population follows a normal distribution.

Population distributions	$egin{aligned} X_1 &\sim ??? ig( oldsymbol{\mu}_1 \ , \ \sigma_1 ig) \ X_2 &\sim ??? ig( oldsymbol{\mu}_2 \ , \ \sigma_2 ig) \end{aligned}$	θ bernouli X <sub>1</sub> X <sub>2</sub>	$\frac{\mu_{normal}}{X_1} \qquad \frac{\mu_{normal}}{X_2}$
Repeatedly take samples of size <i>n</i> and calculate	$\overline{X}_1 - \overline{X}_2$	$p_1 - p_2$	$rac{\sigma_{ ext{bigger}}^2}{\sigma_{ ext{smaller}}^2}$
The distribution of those sample statistics will approximate	normal (if n values are large and $\sigma$ values are known)	normal (if n values are large)	df <sub>1</sub> , df <sub>2</sub> F dist.
with parameters	$\mu_{\bar{X}_{1}-\bar{X}_{2}} = \mu_{1} - \mu_{2}$ $\sigma_{\bar{X}_{1}-\bar{X}_{2}} = \sqrt{\frac{\sigma_{1}^{2}}{n_{1}} + \frac{\sigma_{2}^{2}}{n_{2}}}$	$\mu_{p_1-p_2} = p_1 - p_2$ $\sigma_{p_1-p_2} = \sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right) \left(\frac{n_1 p_1 + n_2 p_2}{n_1 + n_2}\right) \left(1 - \frac{n_1 p_1 + n_2 p_2}{n_1 + n_2}\right)}$	$df_1 = n_1 - 1$ $df_2 = n_2 - 1$
Other notes:	If $\sigma$ must be estimated from the data, then the distribution is: $\mu \int_{\underline{\mu}} df_1$ where $\mu_{\bar{X}_1 - \bar{X}_2} = \mu_1 - \mu_2$ $\sigma_{\bar{X}_1 - \bar{X}_2} = \sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right) \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}}$ $df = n_1 + n_2 - 2$		