Expected Value
$E[c] = c$
$E[cX] = cE[X]$
$E[X_1 + X_2 ... X_n] = \Sigma E[X_i]$

$E[g(X)] = \Sigma g(x) \cdot pmf(x)$
$E[g(X)] = \int g(x) \cdot pdf(x) dx$

$E[g(X,Y)] = \Sigma\Sigma g(x,y) \cdot pmf(x,y)$
$E[g(X,Y)] = \int\int g(x,y) \cdot pdf(x,y) dxdy$

Given $X_1, ..., X_n$ are independent then
$E[(X_1)(...)(E_n)] = (E[X_1])(...)(E[X_n])$

Marginal
$f_x = \int f(X,Y)dy$
$f(X|Y) = \frac{f(X,Y)}{f_y(Y)}$
Given X and Y are independent then
$...f(X,Y) = f_x(X) \cdot f_y(Y)$

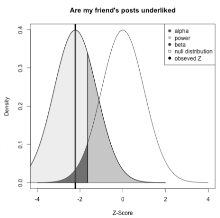
$\boxed{(n-1)\frac{S^2}{\sigma^2} \approx \chi^2}$

Chebyshev's inequality
Within k Standard Deviations
there is at least $1 - \frac{1}{k^2}$ of the data

Conditional Expectation
$E[g(X)|Y=y)] = \int g(X) f(X|Y) dx$
$E[g(X)|Y=y)] = \Sigma g(X) f(X|Y)$

Sampling Distribution
$\bar{Y} = \frac{1}{n}\Sigma y_i$
$E[\bar{Y}] = \mu$ and $V[\bar{Y}] = \frac{\sigma^2}{n}$
If Y's are taken from a normal, then $\bar{Y}$ is normal. Else n must be large to be normal
$Z = \frac{\bar{Y} - \mu_{\bar{Y}}}{\frac{\sigma_{\bar{Y}}}{\sqrt{n}}} = \sqrt{n}(\frac{\bar{Y}-\mu}{\sigma})$

Likelyhood
$L(\theta|y_1 ... y_2)$
$\Pi pdf(y_i)$



Confidence Interval
$\hat{\theta} \pm Z * StandardError$
$SE = \sqrt{Var}$
Z can sometimes be T

Variance
$Var[c] = 0$
$Var[cX] = c^2 Var[X]$
$Var[X_1 + X_2 ... X_n] = \Sigma\Sigma Cov(X_i, X_j)$
$.... = \Sigma Var[X_i] + 2(\Sigma\Sigma Cov(X_i, X_j)$
If $X_1, ..., X_n$ are independent then
$Var[X_1, ..., X_n] = \Sigma Var[X_i]$

$Var = \sigma^2 = E[X^2] - E[X]^2$
$SE =$ Standard Error $= \sqrt{Var}$

CoVariance
$cov(X,Y) = E[(X - E[X])(Y - E[Y])]$
$.....= E[XY] - E[X]E[Y]$
It follows that cov(X, X)=Var(X)
And that if X and Y are independent
$cov(X,Y) = 0$

$\boxed{S_p^2 = \frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1+n_2-2} \text{ and } p_p = \frac{n_1p_1 + n_2p_2}{n_1+n_2}}$

Correlation
$\rho = \frac{cov(X,Y)}{\sqrt{var(X) \cdot var(Y)}}$ and $-1 \le \rho \le 1$

Order Statistics
If $Y_1 ... Y_n$ iid with CDF F and pdf f then
$g_{(k)} = \frac{n!}{(k-1)!(n-k)!} F(y)^{k-1}(1-F(y))^{n-k} f(y)$
$G_{(n)}(y) = P(.....Y_{n-1} \le y, Y_n \le y)$
$G_{(1)}(y) = P(y \le Y_1, y \le Y_2.....)$

Don't Forget!
$P(Y \le y) = CDF(y)$
$P(y \le Y) = 1 - CDF(y)$

Bias
$B[\hat{\theta}] = E[\hat{\theta}] - \theta$
$MSE[\hat{\theta}] = E[(\hat{\theta} - \theta)^2]$
$MSE[\hat{\theta}] = V[\hat{\theta}] - B[\hat{\theta}]^2$
$error = \int_{\theta-b}^{\theta+b} pmf(\hat{\theta}) d\hat{\theta}$ which is then bounded using distributions
Unbiased if $E[\hat{\theta}] = \theta$

Consistent
Consistient if $\lim_{n\to\infty} V[\theta] = 0$

Suffiency
θ is a sufficient statistic for u if $L(\theta|y_1 ... y_2)$ can be written as
$g(u,\theta) * f(y_1, ... y_n)$

MLE
Find Likelyhood
Find the minimum of this
If it is not obvious take the log
Set to 0
Solve for θ and call it $\hat{\theta}$

Neyman–Pearson Lemma
$\frac{L(\theta_0)}{L(\theta_a)} < k$ so $RR: \{y < k^*\}$
where k^* is found in
$\alpha lph\alpha = P(Y < k^*|\theta = \theta_a)$

Type	pmf	mean	variance	mgf
Binomial	$\binom{n}{x}p^x(1-p)^{n-x}$	np	$np(1-p)$	$((1-p)+pe^t)^n$
Negative	$\binom{Y-1}{r-1}p^r(1-p)^{Y-r}$	$\frac{r(1-p)}{p}$	$\frac{r(1-p)}{p^2}$	$\left(\frac{P}{1-(1-p)e^t}\right)^r$
Hyper	$\frac{\binom{y}{r}\binom{N-r}{n-y}}{\binom{N}{n}}$	$\frac{nr}{N}$	$(\frac{nr}{N})(\frac{(N-r)(N-n)}{N(N-1)})$	DNE
Geometric	$p(1-p)^{x-1}$	$\frac{1}{p}$	$\frac{1-p}{p^2}$	$\frac{pe^t}{1-(1-p)e^t}$
Poisson	$e^{-\lambda}\frac{\lambda^y}{y!}$	λ	λ	$e^{\lambda(e^t-1)}$

Type	pdf	mean	variance	mgf
Chi-Square	$\frac{y^{\frac{v}{2}-1}e^{\frac{-y}{2}}}{2^{v/2}\Gamma(\frac{v}{2})}$	v	$2v$	$(1-2t)^{\frac{-v}{2}}$
Exponential	$\frac{1}{\theta}e^{\frac{-x}{\theta}}$	θ	θ^2	$\frac{1}{1-\theta t}$
Gamma	$\frac{1}{\Gamma(\alpha)\beta^\alpha}x^{\alpha-1}e^{\frac{-x}{\beta}}$	$\alpha\beta$	$\alpha\beta^2$	$\left(\frac{1}{1-\beta t}\right)^\alpha$
Uniform	$\frac{1}{b-a}$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$	$\frac{e^{bt}-e^{at}}{(b-a)t}$
Normal	$\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-(x-\mu)^2}{2\sigma^2}}$	μ	σ^2	$e^{\mu t + \frac{\sigma^2 t^2}{2}}$

Point	Estimators			
Parameter	Sample Size	$\hat{\theta}$	$E[\hat{\theta}]$	SE
μ	n	$\bar{Y}$	μ	$\frac{\sigma}{\sqrt{n}}$
p	n	$\hat{p} = \frac{Y}{n}$	p	$\sqrt{\frac{pq}{n}}$
$\mu_1 + \mu_2$	$n_1 + n_2$	$\bar{Y_1} - \bar{Y_2}$	$\mu_1 - \mu_2$	$\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$
$p_1 - p_2$	$n_1 + n_2$	$\hat{p_1} - \hat{p_2}$	p_1	$\sqrt{\frac{p_1q_1}{\sqrt{n_1}} + \frac{p_2q_2}{\sqrt{n_2}}}$

Hypothesis	Testing	
Hypothesis	Sample Stat	Distribution
$H_0: \mu_0 = \mu_a$ $H_a: \mu_0 \ne \mu_a$	$\bar{x}$	$Z = \frac{\bar{x}-\mu_a}{s\sqrt{n}}$
$H_0: \mu_1 = \mu_2$ $H_a: \mu_1 \ne \mu_2$	$\bar{x}_1 - \bar{x}_2$	$Z = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$
$H_0: p_0 = p_a$ $H_a: p_0 \ne p_a$	$\hat{p}$	$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$
$H_0: p_1 = p_2$ $H_a: p_1 \ne p_2$	$\hat{p}_1 - \hat{p}_2$	$Z = \frac{(\hat{p}_1 - \hat{p}_2) - (p_1 - p_2)}{\sqrt{p_p(1-p_p)\frac{1}{n_1} + \frac{1}{n_2}}}$