1. Expected values and standard errors of common point ESTIMATORS

| $\bar{Y}$ | $\mu$ | $\frac{\sigma}{\sqrt{n}}$ |
| :---: | :---: | :---: |
| $\hat{p}=Y / n$ | $p$ | $\sqrt{\frac{\bar{p}}{n}}$ |
| $\bar{Y}_{1}-\bar{Y}_{2}$ | $\mu_{1}-\mu_{2}$ | $\sqrt{\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}}$ |
| $\hat{p}_{1}-\hat{p}_{2}$ | $p_{1}-p_{2}$ | $\sqrt{\frac{p_{1} q_{1}}{n_{1}}+\frac{p_{2} q_{2}}{n_{2}}}$ |

2. SMALL-SAMPLE NORMAL POPULATION CONFIDENCE INTERVAL SUMMARY

| parameter | confidence interval | Notes |
| :---: | :---: | :---: |
| $\mu$ | $\bar{Y} \pm t_{\alpha / 2, \nu}$ | $\nu=$ degrees of freedom $=n-1$ |
| $\mu_{1}-\mu_{2}$ | $\bar{Y}_{1}-\bar{Y}_{2} \pm t_{\alpha / 2, \nu} S_{p} \sqrt{\frac{1}{n_{1}}+\frac{1}{n_{2}}}$ | $\nu=n_{1}+n_{2}-2$ |

note: $S_{p}^{2}=\frac{\left(n_{1}-1\right) S_{1}^{2}+\left(n_{2}-1\right) S_{2}^{2}}{n_{1}+n_{2}+1}$
3. Confidence interval for $\sigma^{2}$

$$
\left(\frac{(n-1) S^{2}}{\chi_{\alpha / 2, n-1}^{2}}, \frac{(n-1) S^{2}}{\chi_{1-\alpha / 2, n-1}^{2}}\right)
$$

4. Fisher information, large sample distribution of MAXIMUM LIKELIHOOD STATISTICS

If $Y_{1}, \ldots, Y_{n}$ is a random sample from a distribution with density $f(y)$ depending on parameter $\theta$, the Fisher information $I(\theta)$ is defined as:

$$
I(\theta)=\left[n E\left(-\frac{\partial^{2} \ln f(y)}{\partial \theta^{2}}\right)\right]^{-1}
$$

If $t$ is a differentiable function of the parameter $\theta$ then under the usual regularity conditions, for large sample sizes

$$
Z=\frac{t(\hat{\theta})-t(\theta)}{\sqrt{\left[\frac{\partial t(\theta)}{\partial \theta}\right]^{2} I(\theta)}}
$$

has an approximately standard normal distribution.

## 5. Hypothesis tests for means

$$
\begin{array}{lcccl}
\text { type } & H_{0} & H_{a} & \text { test statistic } & \text { rejection region } \\
\hline \text { large sample } & \theta=\theta_{0} & \theta \neq \theta_{0} & z=\frac{\hat{\theta}-\theta_{0}}{\sigma / \sqrt{n}} & |z|>z_{\alpha / 2} \\
\text { small sample } & \theta=\theta_{0} \quad \theta \neq \theta_{0} & t=\frac{\hat{\theta}-\theta_{0}}{S / \sqrt{n}} & |t|>t_{\alpha / 2, n-1}
\end{array}
$$

## 6. Large sample distribution of likelihood ratio test STATISTIC

If $\lambda$ is the test statistic for a likelihood ratio test of

$$
H_{0}: \theta \in \Omega_{0} \quad \text { versus } \quad H_{a}: \theta \in \Omega
$$

where the number of free parameters specified by the statement $\theta \in \Omega$ is one, then $-2 \ln \lambda$ is approximately distributed as a $\chi^{2}$ random variable with one degree of freedom.

## 7. LINEAR MODELS

For the linear model

$$
Y=X \beta+e
$$

where the $e_{i}$ are IID $N\left(0, \sigma_{e}^{2}\right)$, the least squares estimates $\hat{\beta}$ of the parameters $\beta$ are given by:

$$
\hat{\beta}=\left(X^{\prime} X\right)^{-1} X^{\prime} Y
$$

where the columns of $X$ are linearly independent. Furthermore, the vector of 'fitted values' is given by

$$
X \hat{\beta}=X\left(X^{\prime} X\right)^{-1} X^{\prime} Y
$$

and the vector of residuals is given by

$$
e=Y-X \hat{\beta}=\left[I-X\left(X^{\prime} X\right)^{-1} X^{\prime}\right] Y
$$

## 8. MISCELLANEOUS FORMULAS

If $Y$ is a vector of random variables, $\mu$ is the vector of expected values of the $Y_{i}$, that is, $E(Y)=\mu$, and $V$ is the variance-covariance matrix of $Y$, then if $t$ is a vector and $A$ is a matrix,

$$
E\left(t^{\prime} Y\right)=t^{\prime} \mu \quad V\left(t^{\prime} y\right)=t^{\prime} V t \quad E\left(A^{\prime} Y\right)=A^{\prime} \mu \quad V\left(A^{\prime} Y\right)=A^{\prime} V A
$$

Suppose $Y$ has a multivariate normal distribution with mean vector 0 and variance-covariance matrix $I$ (i.e, $Y$ is a vector of IID $N(0,1)$ random variables). Then:

1) The quadratic form $Y^{\prime} A Y$ has a chi-square distribution with degrees of freedom equal to the rank of $A$ if and only if $A$ is idempotent, that is, $A^{2}=A$.
2) The quadratic forms $Y^{\prime} A Y$ and $Y^{\prime} B Y$ are independently distributed if $A B=0$

## 9. CRITICAL VALUES

If $z$ is a $N(0,1)$ random variable, then

$$
P(-1.96<z<1.96)=0.95
$$

If $t$ has a $t$-distribution with $n$ degrees of freedom, then:

$$
\begin{array}{ll}
\text { If } n=8 & P(-2.306<t<2.306)=0.95 \\
\text { If } n=9 & P(-2.262<t<2.262)=0.95 \\
\text { If } n=10 & P(-2.228<t<2.228)=0.95 \\
\text { If } n=11 & P(-2.201<t<2.201)=0.95
\end{array}
$$

If $x$ has a $\chi^{2}$ distribution with one degree of freedom, then

$$
P(x>0.00393)=.95
$$

