

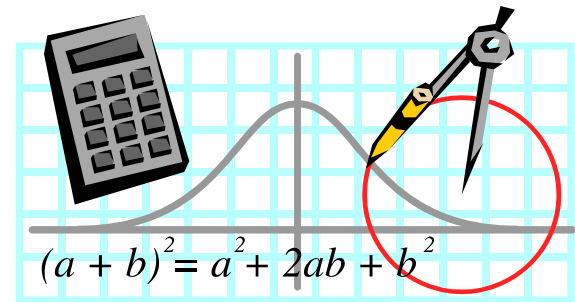


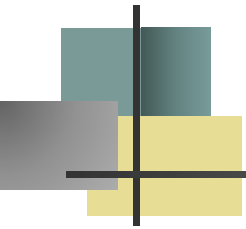
Chapter 15

Identifying Failure & Repair Distributions

Parameter Estimation

- maximum likelihood estimator





Maximum Likelihood Estimation (MLE)

Find estimates for the distribution parameters which will maximize the probability of obtaining the observed sample times.

$$\text{Max } f(t_1) f(t_2) \dots f(t_r)$$




Why MLE's????

1. MLE's are invariant: $y = h(\theta)$ then $\hat{y} = h(\hat{\theta})$

2. MLE's are Consistent:

$$\text{as } n \rightarrow \infty, \hat{\theta} \rightarrow \theta$$

3. MLE's are (best) asymptotically normal:


$$\sigma_{\hat{\theta}}^2 \leq \sigma_{\tilde{\theta}}^2$$

4. Required for certain tests such as the Chi-Square GOF test.

5. Has an intuitive appeal.

6. Can accommodate censored data



MLE - Geometric Distribution

Let X = a discrete random variable, the number of trials necessary to obtain the first failure. Assume the probability of a failure remains a constant p and each trial is independent, then:

$$\text{Prob}\{X=x\} = f(x) = (1-p)^{x-1} p, \quad x = 1, 2, \dots, n$$

$$f_{x_1, \dots, x_n}(x_1, x_2, \dots, x_n) = f(x_1)f(x_2)\dots f(x_n)$$

$$= (1-p)^{x_1-1} p (1-p)^{x_2-1} p \dots (1-p)^{x_n-1} p$$

$$= p^n (1-p)^{\sum_{i=1}^n (x_i - 1)}$$



Geometric Distribution

Max

$$0 \leq p \leq 1 \quad g(p) = p^n (1-p)^{\sum_{i=1}^n (x_i - 1)}$$

$$\ln g(p) = n \ln p + \left[\sum_{i=1}^n (x_i - 1) \right] \ln(1-p) = 0$$

$$\frac{n}{p} + \frac{\sum_{i=1}^n (x_i - 1)}{1-p} (-1) = 0$$

$$\hat{p} = \frac{n}{n + \sum_{i=1}^n (x_i - 1)} = \frac{n}{\sum_{i=1}^n x_i}$$



Example 15.13

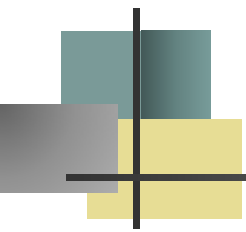
The following data was collected on the number of production runs which resulted in a failure which stopped the production line: 5, 8, 2, 10, 7, 1, 2, 5. Therefore, X = the number of production runs necessary to obtain a failure.

$$\hat{p} = \frac{n}{\sum_{i=1}^n x_i} = \frac{8}{40} = .2$$

$$Prob[X = x] = f(x) = .8^{(x-1)} \quad (.2)$$

$$\text{Mean} = 1/p = 40/8 = 5$$

$$\Pr\{X = 3\} = .8^2 (0.2) = 0.128$$



Likelihood Function

$$L(\theta_1, \dots, \theta_k) = \prod_{i=1}^n f(t_i / \theta_1, \dots, \theta_k)$$

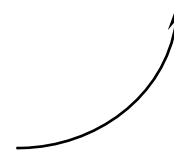
maximize the log of the likelihood function:

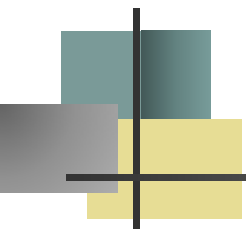
$$\frac{\partial \ln L(\theta_1, \dots, \theta_k)}{\partial \theta_i} = 0 \quad ; \quad i = 1, 2, \dots, k$$

for Type I (right censored) data:

$$L(\theta_1, \dots, \theta_k) = \prod_{i=1}^r f(t_i / \theta_1, \dots, \theta_k) [R(t_*)]^{n-r}$$

for Type II, t_r





Exponential MLE - Type II data

$$f(t_j) = \lambda e^{-\lambda t_j}, \quad j = 1, 2, \dots, r$$

$$P[T_j > t_r \text{ for all } j > r] = (e^{-\lambda t_r})^{n-r}$$

$$L(t_1, \dots, t_r) = \prod_{j=1}^r \lambda e^{-\lambda t_j} (e^{-\lambda t_r})^{n-r}$$

$$= \lambda^r \exp \left\{ -\lambda \sum_{j=1}^r t_j - \lambda(n-r) t_r \right\}$$

Exponential MLE - Type II data

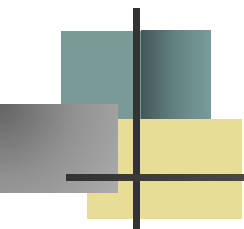
$$L = \lambda^r \exp \left\{ -\lambda \sum_{j=1}^r t_j - \lambda(n-r) t_r \right\}$$

$$\ln L = r \ln \lambda - \lambda \sum_{j=1}^r t_j - \lambda(n-r) t_r$$

$$\frac{d \ln L}{d\lambda} = \frac{r}{\lambda} - \sum_{j=1}^r t_j - (n-r)t_r = 0$$

$$\hat{\lambda} = \frac{r}{\sum_{j=1}^r t_j + (n-r)t_r} = \frac{r}{T}$$

—Type I, use t_*



Total Time on Test - CFR

n = nbr on test

r = nbr failures

k = nbr multiply censors

t_i = failure time

t_i^+ = censor time

t_* = test time (Type I)

t_r = test time (Type II)

$$MTTF = T / r$$

Complete: $\sum_{i=1}^n t_i; r = n$

Type I: $\sum_{i=1}^n t_i + (n - r)t_*$

Type II: $\sum_{i=1}^n t_i + (n - r)t_r$

Type I multiply: $\sum_{i=1}^n t_i^+ + (n - r - k)t_*$

Type II multiply: $\sum_{i=1}^n t_i^+ + (n - r - k)t_r$

Type I replacement: nt_*

Type II replacement: nt_r



Weibull MLE - Type II Data

$$L(\theta, \beta) = \prod_{i=1}^r f(t_i) R(t_r)^{n-r} = \left[\prod_{i=1}^r \frac{\beta}{\theta} \left(\frac{t_i}{\theta} \right)^{\beta-1} e^{-\left(\frac{t_i}{\theta} \right)^{\beta}} \right] \left[e^{-\left(\frac{t_r}{\theta} \right)^{\beta}} \right]^{n-r}$$

$$\ln L = r \ln \beta - \beta r \ln \theta + \sum_{i=1}^r (\beta - 1) \ln t_i - \sum_{i=1}^r \left(\frac{t_i}{\theta} \right)^{\beta} - (n - r) \left(\frac{t_r}{\theta} \right)^{\beta}$$

$$\frac{\partial \ln L}{\partial \theta} = -\beta r + \frac{\beta}{\theta^{\beta}} \sum_{i=1}^r t_i^{\beta} + \frac{(n - r) \beta}{\theta^{\beta}} t_r^{\beta} = 0$$

$$\frac{\partial \ln L}{\partial \beta} = \frac{r}{\beta} + \sum_{i=1}^r \ln t_i - r \ln \theta + r \ln \theta - \frac{r \sum_{i=1}^r t_i^{\beta} + (n - r) t_r^{\beta} \ln t_r}{\sum_{i=1}^r t_i^{\beta} + (n - r) t_r^{\beta}} = 0$$



Weibull MLE - singly censored

$$g(\hat{\beta}) = \frac{\sum_{i=1}^r \hat{t}_i^{\hat{\beta}} \ln t_i + (n-r) \hat{t}_s^{\hat{\beta}}}{\sum_{i=1}^r \hat{t}_i^{\hat{\beta}} + (n-r) \hat{t}_s^{\hat{\beta}}} - \frac{1}{\hat{\beta}} - \frac{1}{r} \sum_{i=1}^r \ln t_i = 0$$

$$\hat{\theta} = \left\{ \frac{1}{r} \left[\sum_{i=1}^r \hat{t}_i^{\hat{\beta}} + (n-r) \hat{t}_s^{\hat{\beta}} \right] \right\}^{\frac{1}{\hat{\beta}}}$$

$$\text{where } t_s = \begin{cases} 1 & \text{for complete data} \\ t^* & \text{for type I data} \\ t_r & \text{for type II data} \end{cases}$$



Newton-Raphson Method

$$\hat{\beta}_{j+1} = \hat{\beta}_j - \frac{\hat{g}(\hat{\beta}_j)}{\hat{g}'(\hat{\beta}_j)}$$

where $g'(x) = \frac{d g(x)}{dx}$



Normal & Lognormal MLEs complete data

NORMAL

$$\hat{\mu} = \bar{x}$$

$$\hat{\sigma}^2 = \frac{(n-1)s^2}{n}$$

recall:

$$s^2 = \sum_{i=1}^n \frac{(t_i - \hat{MTTF})^2}{n-1}$$

LOGNORMAL

$$\hat{\mu} = \sum_{i=1}^n \frac{\ln t_i}{n}$$

$$\hat{t}_{MED} = e^{\hat{\mu}}$$

$$\hat{s} = \sqrt{\frac{\sum_{i=1}^n (\ln t_i - \hat{\mu})^2}{n}}$$



Example 15.16

Ex. 15.8: 47.1, 84.8, 151.9, 122.5, 218.2, 99.6, 59.8, 138.8,
213.5, 53.4, 102.4, 100.8, 230.1, 104.6, 61.5, 122.1, 186.2,
498.4, 77.0, 78.7, 112.3, 44.0, 151.3, 151.3, 222.8

L-S estimates: $t_{\text{med}} = 116$ and $s = .613$

$$\mu = (\ln 44 + \ln 47.1 + \dots + \ln 498.4)/25 = 118.8/25 = 4.752$$

$$t_{\text{med}} = e^{4.753} = 115.932$$

$$s^2 = [(\ln 44 - 4.752)^2 + (\ln 47.1 - 4.752)^2 + \dots + (\ln 498.4 - 4.752)^2]/25 = .31798$$
$$s = .5639.$$

MLE with Multiply Censored Data

prob of failure
occurring at time t_i

prob of failure
occurring after time t_i^+

$$L(\theta) = \prod_{i \in F} f(t_i; \theta) \prod_{i \in C} R(t_i^+; \theta)$$

F = set of indices for failure times

C = set of indices for censored times
(including singly censored times)

MLE Exponential - multiply censored data

$$L(\lambda) = \prod_{i \in F} \lambda e^{-\lambda t_i} \prod_{i \in C} e^{-\lambda t_i^+} = \lambda^r e^{-\lambda \sum_{i \in F} t_i} e^{-\lambda \sum_{i \in C} t_i^+}$$

$$\ln L(\lambda) = r \ln \lambda - \lambda \sum_{i \in F} t_i - \lambda \sum_{i \in C} t_i^+$$

$$\frac{d \ln L(\lambda)}{d\lambda} = \frac{r}{\lambda} - \sum_{i \in F} t_i - \sum_{i \in C} t_i^+ = 0$$

$$\hat{\lambda} = \frac{r}{\sum_{i \in F} t_i + \sum_{i \in C} t_i^+}$$

T

MLE Weibull multiply censored data

$$L(\theta, \beta) = \prod_F f(t_i) \prod_C R(t_i) = \left[\prod_F \frac{\beta}{\theta} \left(\frac{t_i}{\theta} \right)^{\beta-1} e^{-\left(\frac{t_i}{\theta} \right)^\beta} \right] \prod_C \left[e^{-\left(\frac{t_i}{\theta} \right)^\beta} \right]$$

$$\ln L = \sum_F \left[\ln \beta - \beta \ln \theta + (\beta - 1) \ln t_i - \left(\frac{t_i}{\theta} \right)^\beta \right] - \sum_C \left(\frac{t_i}{\theta} \right)^\beta$$

$$\frac{\partial L}{\partial \theta} = \sum_F \left[\frac{-\beta}{\theta} + \frac{\beta}{\theta} \left(\frac{t_i}{\theta} \right)^\beta \right] + \sum_C \left[\frac{\beta}{\theta} \left(\frac{t_i}{\theta} \right)^\beta \right] = 0$$

$$\frac{\partial L}{\partial \beta} = \sum_F \frac{1}{\beta} + \ln \left(\frac{t_i}{\theta} \right) - \left(\frac{t_i}{\theta} \right)^\beta \ln \left(\frac{t_i}{\theta} \right) - \sum_C \left(\frac{t_i}{\theta} \right)^\beta \ln \left(\frac{t_i}{\theta} \right) = 0$$

MLE Weibull - multiply censored data

$$\sum_{i \in F} \frac{\ln t_i}{r} = \sum_{\text{all } i} t_i^\beta \ln t_i \sum_{\text{all } i} (t_i^\beta)^{-1} - \frac{1}{\beta}$$

solve
numerically

monotonically
increasing RHS

$$\hat{\theta} = \left[\sum_{\text{all } i} \frac{t_i^{\hat{\beta}}}{r} \right]^{\frac{1}{\hat{\beta}}}$$



Example 15.17

Fifteen units were placed on test for 500 hours. The following failure times and censor times were observed prior to concluding the test:

34 136 145+ 154 189 200+ 286 287 334 353 380+

For the exponential,

$T = 34 + 136 + 145 + 154 + 189 + 200 + 286 + 287 + 334 + 353 + 380 + 4(500)$
 $= 4498$ and the MLE for the MTTF $= T/r = 4498/8 = 562.25$.

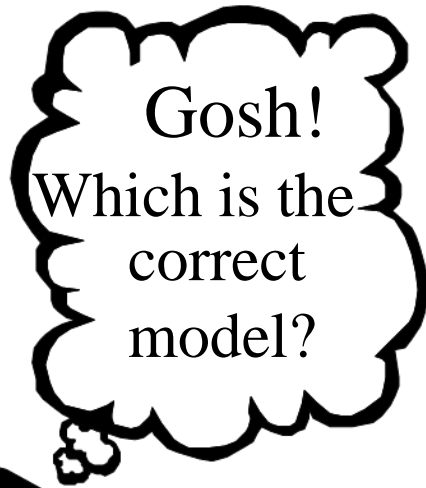
For the Weibull, the 4 units which had not failed by the end of the test are assigned censored times of 500 hours. The left hand side of MLE Eq. equals 5.21385. Beginning with $\beta = .1$ and increasing β in the right hand side by .01 until it exceeds 5.21, results in $\beta = 1.43$. Then $\theta = 491$.



Example 15.17

exponential:

$$R(t) = e^{-t/562.25} \quad R(100) = .837$$



Weibull:

$$R(t) = e^{-\left(\frac{t}{491}\right)^{1.43}} \quad R(100) = .902$$





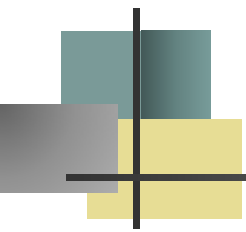
Normal Distribution - Censored Data

$$L(\mu, \sigma) = \prod_{i \in F} f(t_i) \prod_{i \in C} R(t_i^+)$$

$$\ln L(\mu, \sigma) = \sum_{i=1}^r \ln \left[\frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{1}{2} \frac{(t-\mu)^2}{\sigma^2}} \right]$$

Maximize using a
Numerical search algorithm

$$+ \sum_{i=1}^{n-r} \ln \left[\int_t^{\infty} \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt' \right]$$



Minimum Extreme Value Distribution

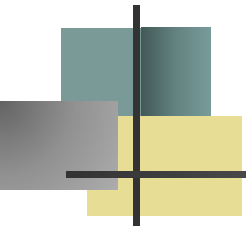
Complete or right censored data

Likelihood function:

$$L(\alpha, \mu) = \prod_{i=1}^r \left(\frac{1}{\alpha} \right) e^{\frac{(t_i - \mu)}{\alpha}} e^{-e^{\frac{(t_i - \mu)}{\alpha}}} \prod_{i=r+1}^n e^{-e^{\frac{(t_s^+ - \mu)}{\alpha}}}$$

$$\ln L(\alpha, \mu) = -r \ln \alpha + \sum_{i=1}^r \frac{(t_i - \mu)}{\alpha} - \sum_{i=1}^r e^{\frac{(t_i - \mu)}{\alpha}} - (n - r) e^{\frac{(t_s^+ - \mu)}{\alpha}}$$

$$\text{where } t_s = \begin{cases} 1 & \text{for complete data} \\ t_* & \text{for Type I data} \\ t_r & \text{for Type II data} \end{cases}$$

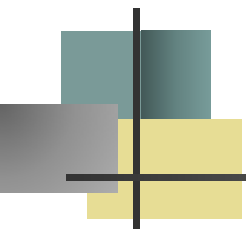


Minimum Extreme Value Distribution

$$\frac{\partial \ln L(\alpha, \mu)}{\partial \alpha} = \frac{\partial \ln L(\alpha, \mu)}{\partial \mu} = 0$$

$$-\hat{\alpha} - \frac{1}{r} \sum_{i=1}^r t_i + \frac{\sum_{i=1}^r t_i e^{t_i/\hat{\alpha}} + (n-r)t_s^+ e^{t_s^+/\hat{\alpha}}}{\sum_{i=1}^r e^{t_i/\hat{\alpha}} + (n-r)e^{t_s^+/\hat{\alpha}}} = 0$$

$$\hat{\mu} = \hat{\alpha} \ln \left[\frac{1}{r} \sum_{i=1}^r e^{t_i/\hat{\alpha}} + \left(\frac{n-r}{r} \right) e^{t_s^+/\hat{\alpha}} \right]$$



Minimum Extreme Value Distribution

Complete data

Method of Moments:

$$m_1 = \sum_{i=1}^n t_i / n; \quad m_2 = \sum_{i=1}^n t_i^2 / n$$

$$m_1 = \mu - \gamma\alpha; \quad m_2 = \frac{\alpha^2 \pi^2}{6} + (\mu - \gamma\alpha)^2$$

solving:

$$\tilde{\alpha} = \sqrt{\frac{6(m_2 - m_1^2)}{\pi^2}}; \quad \tilde{\mu} = m_1 + \gamma\tilde{\alpha}; \quad \gamma \approx .577215665$$



Gamma Distribution

Complete data, likelihood function:

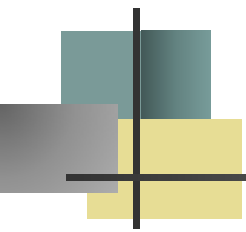
$$L(t_i, i = 1, \dots, n \mid \gamma, \alpha) = \prod_{i=1}^n \frac{t_i^{\gamma-1} e^{-t_i/\alpha}}{\alpha^\gamma \Gamma(\gamma)}$$

$$\ln L = (\gamma - 1) \sum_{i=1}^n \ln t_i - \frac{1}{\alpha} \sum_{i=1}^n t_i - n\gamma \ln \alpha - n \ln \Gamma(\gamma)$$

$$\frac{\partial \ln L(\alpha, \gamma)}{\partial \alpha} = 0 \text{ and solving for } \alpha : \hat{\alpha} = \frac{1}{n\gamma} \sum_{i=1}^n t_i$$

Substituting for α : $\ln L(\gamma) = (\gamma - 1) \sum_{i=1}^n \ln t_i - n\gamma - n\gamma \ln \left(\frac{1}{n\gamma} \sum_{i=1}^n t_i \right) - n \ln \Gamma(\gamma)$

Maximize directly



Gamma Distribution

Complete data

Method of Moments:

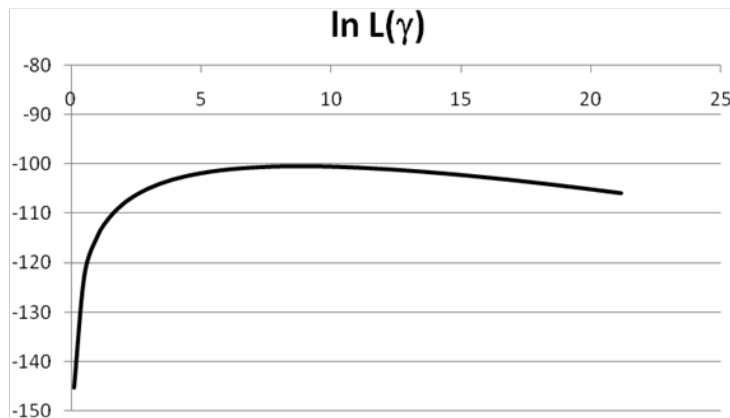
$$m_1 = \alpha\gamma; \quad m_2 = \gamma\alpha^2 + (\gamma\alpha)^2$$

$$\tilde{\gamma} = \frac{m_1^2}{m_2 - m_1^2}; \quad \tilde{\alpha} = \frac{m_2 - m_1^2}{m_1}$$

EXAMPLE 15.20

Twenty units believed to have a gamma distribution were placed on an accelerated life test with failures in days occurring at the times shown: 152 152 115 109 137 88 94 77 160 165 125 40 128 123 136 101 62 153 83 69. Using Excel Solver,

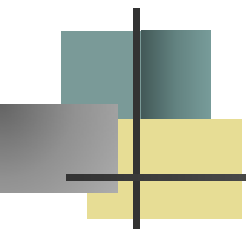
$$\underset{\gamma}{\text{Max}} \ln L(\gamma) = 93.469281(\gamma - 1) - 20\gamma - 20\gamma \ln\left(\frac{2269}{20\gamma}\right) - 20 \ln \Gamma(\gamma)$$



$$\hat{\gamma} = 8.7992 \quad \hat{\alpha} = 12.893$$

The corresponding method of moments estimators are

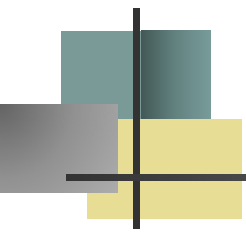
$$\tilde{\gamma} = 10.5773 \text{ and } \tilde{\alpha} = 10.7258$$



Parameter Estimation for Interval Data

n_j , is the number of failures that occur within the interval (a_{j-1}, a_j) where $j = 1, \dots, k$. Any right censored units are counted in the interval (a_k, ∞) . The likelihood function can be stated as

$$L(\boldsymbol{\theta}) = \prod_{j=1}^{k+1} \left[R(a_{j-1} | \boldsymbol{\theta}) - R(a_j | \boldsymbol{\theta}) \right]^{n_j}$$



EXAMPLE 15.21 (Weibull)

Monthly failures of fifty units in operation were recorded over a six month period with the following results:

Month	Upper bound in days	Number of Failures
1	30.0	10
2	60.0	11
3	90.0	7
4	120.0	4
5	150.0	3
6	180.0	2

$$L(\theta, \beta) = \prod_{j=1}^{k+1} \left[e^{-\left(\frac{a_{j-1}}{\theta}\right)^\beta} - e^{-\left(\frac{a_j}{\theta}\right)^\beta} \right]^{n_j} \longrightarrow \ln L(\theta, \beta) = \sum_{j=1}^{k+1} n_j \ln \left[e^{-\left(\frac{a_{j-1}}{\theta}\right)^\beta} - e^{-\left(\frac{a_j}{\theta}\right)^\beta} \right] \longrightarrow$$



EXAMPLE 15.21 (Weibull)

Using Excel Solver, maximize

$$\begin{aligned} \ln L(\theta, \beta) = \ln L(\theta, \beta) = & 10 \ln \left[1 - e^{-\left(\frac{30}{\theta}\right)^\beta} \right] + 11 \ln \left[e^{-\left(\frac{30}{\theta}\right)^\beta} - e^{-\left(\frac{60}{\theta}\right)^\beta} \right] + 7 \ln \left[e^{-\left(\frac{60}{\theta}\right)^\beta} - e^{-\left(\frac{90}{\theta}\right)^\beta} \right] \\ & + 4 \ln \left[e^{-\left(\frac{90}{\theta}\right)^\beta} - e^{-\left(\frac{120}{\theta}\right)^\beta} \right] + 3 \ln \left[e^{-\left(\frac{120}{\theta}\right)^\beta} - e^{-\left(\frac{150}{\theta}\right)^\beta} \right] + 2 \ln \left[e^{-\left(\frac{150}{\theta}\right)^\beta} - e^{-\left(\frac{180}{\theta}\right)^\beta} \right] + 13 \ln \left[e^{-\left(\frac{180}{\theta}\right)^\beta} \right] \end{aligned}$$

$$\hat{\beta} = .9486 \text{ and } \hat{\theta} = 125.612$$



Next Time



Chapter 16

Goodness-of-Fit Testing

The Chi-Square test



Testing for
Chi-squares