

Introduction to Probability and Statistics  
for Engineers and Scientists  
*Sheldon M Ross*  
Solutions

Anirudh Krishnan

October 11, 2021

# Contents

<b>1</b>	<b>Life Testing</b>	<b>2</b>
1.1	Introduction . . . . .	2
1.2	Hazard rate functions . . . . .	2
1.3	Exponential distributions in life testing . . . . .	3
1.4	Two-sample problem . . . . .	7
1.5	Weibull distribution in life testing . . . . .	8
<b>2</b>	<b>Life Testing</b>	<b>10</b>

# Chapter 1

## Life Testing

“Ch14 Quote here.”

### 1.1 Introduction

The general problem being considered here is a population of independent items having some common underlying distribution of lifetimes, which is known but for a single parameter.

The concept of a hazard rate is used in engineering to analyze this problem and the most common choice of *a-priori* distribution assumed is an exponential RV.

### 1.2 Hazard rate functions

Consider a positive RV  $X$  with some CDF ( $F$ ) and PDF ( $f$ ). The *failure rate* (also called *hazard rate*) function of  $F$  is now defined as

$$\lambda(t) = \frac{f(t)}{1 - F(t)} \quad (0.1)$$

$\lambda(t)$  represents the conditional probability that an item of age  $t$  will fail imminently.

$$P\{X \in (t, t + dt) \mid X > t\} \approx \frac{f(t)}{1 - F(t)} dt \quad (0.2)$$

For an underlying exponential distribution, which is memoryless,  $\lambda(t) = \lambda$  constant equal to its rate. The rate function is uniquely able to determine an the underlying CDF for a positive continuous RV.

$$\lambda(s) = \frac{d F(s)}{ds} \frac{1}{1 - F(s)} = \frac{d}{ds} -\log [1 - F(s)] \quad (0.3)$$

$$1 - F(t) = \exp \left[ - \int_0^t \lambda(s) ds \right] \quad (0.4)$$

A special case of  $\lambda(t) = bt$  is called the *Rayleigh* density function. A linear relationship between death rates between two conditions leads to a power law relationship between the probability of both conditions surviving to the same age.

$$\begin{aligned} \lambda_y &= n\lambda_x \\ \implies P\{Y > b \mid Y > a\} &= P\{X > b \mid X > a\}^n \end{aligned} \quad (0.5)$$

Where  $b > a$  are some ages and  $X, Y$  are two categories being compared.

## 1.3 Exponential distributions in life testing

*Stopping at the  $r^{th}$  failure* : Consider a population of  $n$  items which are all IID using an exponential distribution with unknown mean  $\theta$ . A problem of great interest is to attempt to estimate  $\theta$  using observations about the time taken for  $r$  out of  $n$  simultaneously initialized items to fail.

The observed data takes the form of an ascending ordered set of failure times  $\{x_1, \dots, x_r\}$  along with a set of indices for the failing items  $\{i_1 \dots i_r\}$ . If the lifetime of component  $i_j$  is denoted by  $X_{i_j}$ , then the independence of components gives

$$f_{X_{i_j}} = \frac{1}{\theta} \exp[-x_j/\theta] \quad (0.6)$$

$$f_{X_{i_1} \dots X_{i_r}} = \prod_{j=1}^r \frac{1}{\theta} \exp[-x_j/\theta] \quad (0.7)$$

Additionally, the probability of the rest of the  $(n-r)$  components having a lifetime larger than  $x_r$  is

$$P\{\text{rest of the components lasting longer}\} = [\exp(-x_r/\theta)]^{n-r} \quad (0.8)$$

Defining a likelihood function  $\mathcal{L}$  as the product of the two expression above and finding an MLE  $\hat{\theta}$  of the unknown mean  $\theta$  and defining  $X_{(j)}$  as the time at which the  $j^{\text{th}}$  failure occurs,

$$\hat{\theta} = \frac{1}{r} \left[ \sum_{j=1}^r X_{(j)} + (n-r)X_{(r)} \right] = \frac{\tau}{r} \quad (0.9)$$

$\tau$  is called the *total time-on-test* statistic, because it represents the sum of lifetimes of all  $r$  failing items as well as all  $n-r$  surviving items.

For an interval estimate of  $\theta$ , consider a set of RVs  $\{Y_j\}$  which measure the additional time on test contributed by the time interval between the  $(i-1)^{\text{th}}$  and  $i^{\text{th}}$  failures

$$Y_j = (n-j+1) (X_{(j)} - X_{(j-1)}) \quad (0.10)$$

$$\tau = \sum_{j=1}^r Y_j \quad (0.11)$$

$$Y_j \sim \text{Expon}(1/\theta) \quad \text{and} \quad \tau \sim \text{Gamma}(r, 1/\theta) \quad (0.12)$$

Using the relation  $\text{Gamma}(n/2, 1/2) \equiv \chi_n^2$ , the confidence interval for  $\theta$  can be defined as

$$\frac{2\tau}{\theta} \sim \chi_{2r}^2 \quad (0.13)$$

$$\theta \in \left( \frac{2\tau}{\chi_{\alpha/2, 2r}^2}, \frac{2\tau}{\chi_{1-\alpha/2, 2r}^2} \right) \quad (0.14)$$

The length of the test  $X_{(r)}$  is itself the sum of many exponential functions, with

$$\mathbb{E}[X_{(r)}] = \sum_{j=1}^r \frac{\theta}{n-j+1} \quad \cong \theta \log \left[ \frac{n}{n-r+1} \right] \quad (0.15)$$

$$\text{Var}(X_{(r)}) = \sum_{j=1}^r \left( \frac{\theta}{n-j+1} \right)^2 \quad \cong \theta^2 \left[ \frac{r-1}{n(n-r+1)} \right] \quad (0.16)$$

*Sequential Testing* : If an infinite supply of IID items (each exponentially distributed with mean  $\theta$ ) are put to test one by one instead of simultaneously, with the test ending at some fixed time  $T$ .

The observations at the end of such a test is a set of lifetimes  $\{x_j\}$  with  $j \in 1, \dots, r$  for the total number of items  $r$  that failed within time  $T$ .

In order for the total number of failed items to be exactly  $r$ , the inequality

$$\sum_{i=1}^r x_i < T < \sum_{i=1}^r x_i + X_{r+1} \quad (0.17)$$

Once again defining a likelihood function  $\mathcal{L}$  and finding the MLE  $\hat{\theta}$ ,

$$\mathcal{L}(r, x_1, \dots, x_r \mid \theta) = \frac{1}{\theta^2} \exp[-T/\theta] \quad (0.18)$$

$$\hat{\theta} = \frac{T}{r} \quad (0.19)$$

Once again, the interval estimate for  $\theta$  involves relating **Gamma** and  $\chi^2$  RVs

$$\frac{2T}{\theta} \sim \chi_{2r}^2 \quad (0.20)$$

$$\theta \in \left( \frac{2T}{\chi_{\alpha/2, 2r}^2}, \frac{2T}{\chi_{1-\alpha/2, 2r}^2} \right) \quad (0.21)$$

*Simultaneous testing with fixed time stop:* Consider the earlier simultaneous test case except that the test stops either at a fixed time  $T$  or when all  $n$  items fail, whichever is sooner.

If  $r$  out of the  $n$  items, indexed by the set  $\{i_j\}$  have failed by time  $T$ , with respective fail times  $\{x_j\}$ , then the likelihood of such a set of observations is

$$f(\{i_j\}, \{x_j\}) = \frac{1}{\theta^r} \exp \left[ -\frac{\sum_{i=1}^r x_i}{\theta} - \frac{(n-r)T}{\theta} \right] \quad (0.22)$$

If  $R$  items fail by time  $T$ , with the ordered set of failure times  $\{X_{(j)}\}$ , the MLE of  $\theta$  is give by

$$\hat{\theta} = \frac{1}{R} \left( \sum_{i=1}^r X_{(i)} + (n-R)T \right) = \frac{\tau}{R} \quad (0.23)$$

Note the resemblance of the above expression to the result from the simultaneous testing method. Since  $\tau$  and  $R$  above are both random and dependent on each other, finding an interval estimate of  $\theta$  is too complex to pursue here.

*Bayesian approach :* For a set of IID items being tested with common unknown mean  $(1/\lambda)$ , the likelihood function is given by

$$f(\text{data} \mid \lambda) = K \lambda^r e^{-\lambda t} \quad (0.24)$$

with  $t$  being the summed time on test of items that do and don't fail and  $r$  the number of failing items.

Assuming a prior distribution  $g(\lambda)$  and applying Bayes' theorem,

$$f(\lambda \mid \text{data}) = \frac{f(\text{data} \mid \lambda) g(\lambda)}{\int f(\text{data} \mid \lambda) g(\lambda) d\lambda} \quad (0.25)$$

$$g(\lambda) \sim \text{Gamma}(b, a) \implies f(\lambda \mid \text{data}) \sim \text{Gamma}(b + R, a + \tau) \quad (0.26)$$

The Bayes estimator of  $\lambda$  for the special case of a gamma-RV as prior distribution is simply

$$\mathbb{E}[\lambda \mid \text{data}] = \frac{b + R}{a + \tau} \quad (0.27)$$

## 1.4 Two-sample problem

Consider two sets of items produced using different processes, whose lifetimes are exponentially distributed with mean  $\theta_1, \theta_2$  respectively. Let samples of size  $(n, m)$  be used to test lifetimes resulting in the set of observations  $\{X_i\}, \{Y_j\}$ .

Testing the hypothesis  $\theta_1 = \theta_2$ , involves the sample mean lifetimes  $\bar{X}, \bar{Y}$ , and the relation between exponential and gamma RVs

$$\begin{aligned} \bar{X} &\sim \text{Gamma}(n, 1/\theta_1) \\ \frac{2}{\theta_1} \bar{X} &\sim \chi_{2n}^2 \end{aligned} \quad (0.28)$$

Rearranging the  $\chi^2$ -RVs into an F-RV yields the test statistic for the above hypothesis tests along with a p-value and rejection criterion



$$H_0 : \theta_1 = \theta_2 \quad \text{vs} \quad H_1 : \theta_1 \neq \theta_2 \quad (0.29)$$

$$F_{n,m} \sim \frac{2\bar{X}/\theta_1}{2n} \frac{2m}{2\bar{Y}/\theta_2} \quad (0.30)$$

$$\begin{aligned} \text{reject } H_0 \text{ if } & P_{H_0}\{F \leq \nu\} \leq \frac{\alpha}{2} \quad \text{or} \quad P_{H_0}\{F \geq \nu\} \leq \frac{\alpha}{2} \\ \text{accept } H_0 & \quad \text{otherwise} \end{aligned} \quad (0.31)$$

$$p \text{ value} = 2 \times \min(P\{F \leq \nu\}, 1 - P\{F \leq \nu\}) \quad (0.32)$$

## 1.5 Weibull distribution in life testing

Moving away from the simplistic constant value of hazard rate function, a commonly encountered real-world functional form for  $\lambda(t)$  is

$$\lambda(t) = \alpha\beta t^{\beta-1} \quad \alpha, \beta, t > 0 \quad (0.33)$$

$$F(t) = 1 - \exp[-\alpha t^\beta] \quad (0.34)$$

$$f(t) = \alpha\beta t^{\beta-1} \exp[-\alpha t^\beta] \quad (0.35)$$

*Parameter estimation by maximum likelihood :* Consider  $n$  IID Weibull RVs  $\{X_1, \dots, X_n\}$  being used to estimate the parameters  $\alpha, \beta$  of the Weibull distribution. The MLE approach yields

$$\hat{\alpha} = \frac{n}{\sum x_i^{\hat{\beta}}} \quad n + \hat{\beta} \log \left( \prod x_i \right) = \frac{n\hat{\beta} \sum x_i^{\hat{\beta}} \log x_i}{\sum x_i^{\hat{\beta}}} \quad (0.36)$$

The MLE estimators are unfortunately not closed-form and need to be solved for numerically.

*Parameter estimation by least squares :* Given  $n$  IID Weibull RVs, and an ordered set of sample values  $X_{(i)}$ ,

$$F(x) = 1 - \exp \left[ -\alpha x^\beta \right] \quad (0.37)$$

$$\log \log \left[ \frac{1}{1 - F(x)} \right] = \beta \log x + \log \alpha \quad (0.38)$$

If the LHS above can be approximated using  $y_i$ , then a linear regression problem can be set up to yield approximate values  $\hat{\alpha}$ ,  $\hat{\beta}$ . Multiple methods of estimating  $y_i$  exist, with no real winner in terms of computation time or accuracy.

# Chapter 2

## Life Testing

1 Weibull RV with parameters  $\alpha, \beta$

$$\begin{aligned} F(t) &= 1 - \exp \left[ -\alpha t^\beta \right] & t \geq 0 \\ \lambda(t) &= \frac{f(t)}{1 - F(t)} = \frac{\alpha \beta t^{\beta-1} \exp \left[ -\alpha t^\beta \right]}{\exp \left[ -\alpha t^\beta \right]} \\ &= \alpha \beta t^{\beta-1} \end{aligned} \tag{1.1}$$

2 Two RVs  $X, Y$  with respective failure rate functions  $\lambda_x(t), \lambda_y(t)$ . Their minimum is  $Z$

$$\begin{aligned} Z &\equiv \min(X, Y) \\ P\{Z > t\} &= P\{X > t\} \times P\{Y > t\} \end{aligned} \tag{2.1}$$

$$\begin{aligned} [1 - F_z(t)] &= [1 - F_x(t)] [1 - F_y(t)] \\ f_z(t) &= \frac{d}{dt} F_z(t) = f_x(t) [1 - F_y(t)] + f_y(t) [1 - F_x(t)] \end{aligned} \tag{2.2}$$

$$\lambda_z(t) = \lambda_x(t) + \lambda_y(t) \tag{2.3}$$

3 Given failure rate function  $\lambda(t)$ ,

$$\lambda(t) = 0.027 + 0.025 \left( \frac{t-40}{10} \right)^4 \quad (3.1)$$

$$\begin{aligned} F(t) &= 1 - \exp \left[ - \int_0^t \lambda(s) \, ds \right] \\ &= 1 - \exp \left[ -0.027t - 0.05 \left( \frac{t-40}{10} \right)^5 \right] \end{aligned}$$

$$P\{t \geq 50 \mid t > 40\} = \frac{1 - F(50)}{1 - F(40)} = 72.6\% \quad (3.2)$$

$$P\{t \geq 60 \mid t > 40\} = 11.7\% \quad (3.3)$$

$$P\{t \geq 70 \mid t > 40\} = 0.0002\% \quad (3.4)$$

$$(3.5)$$

4 Given  $\lambda(t) = t^3$

$$\begin{aligned} 1 - F(2) &= \exp \left[ - \int_0^2 \lambda(s) \, ds \right] = \exp \left[ \left( \frac{t^4}{4} \right) \Big|_2^0 \right] \\ &= 1.83\% \end{aligned} \quad (4.1)$$

$$F(1.4) - F(0.4) = 99.36\% - 38.27\% = 61.09\% \quad (4.2)$$

$$\begin{aligned} \mathbb{E}[T] &= \int_0^\infty [1 - F(t)] \, dt = \frac{1}{4} (-0.25^{-0.25}) \Gamma(1/4) \\ &= 1.28 \end{aligned} \quad (4.3)$$

$$P\{t \geq 2 \mid t > 1\} = 2.35\% \quad (4.4)$$

5 Failure rate is non-decreasing in  $t$ , called IFR

$$f(t) = \lambda e^{-\lambda t} (\lambda t)^{\alpha-1}$$

$$\lambda(t) = \frac{\lambda e^{-\lambda t} (\lambda t)^{\alpha-1}}{\int_t^{\infty} \lambda e^{-\lambda s} (\lambda s)^{\alpha-1} ds} \quad (5.1)$$

$$= \left[ \int_t^{\infty} e^{-\lambda(s-t)} (s/t)^{\alpha-1} ds \right]^{-1} \quad (5.2)$$

$$= \left[ \int_0^{\infty} e^{-\lambda v} (1 + v/t)^{\alpha-1} dv \right]^{-1} \quad (5.3)$$

The above integrand is decreasing in  $t$  if  $\alpha - 1 > 0$ . This implies an IFR for  $\alpha > 1$ . The first expression is a special case of  $\alpha = 2$  and is thus also IFR.

6 Uniform RV on  $[a, b]$  is IFR

$$f(t) = \frac{1}{(b-a)} \quad \forall x \in (a, b)$$

$$\lambda(t) = \frac{1}{(b-t)} \quad \forall t \in (a, b) \quad (6.1)$$

$$(6.2)$$

Clearly, since  $t < b$ , the failure rate is increasing in  $t$

7 Consider the bar chart to be composed of horizontal bars first  $\{h_j\}$  and then vertical bars  $\{v_k\}$

$$h_1 = n \times [X_{(1)} - X_{(0)}]$$

$$h_r = (n - r + 1) \times [X_{(r)} - X_{(r-1)}]$$

$$\text{Area under curve} = \sum_j h_j \quad (7.1)$$

$$v_1 = X_{(1)}$$

$$v_k = X_{(r)} \quad \forall k \geq r$$

$$\text{Area under curve} = \sum_k v_k \quad (7.2)$$

$$(7.3)$$

The area under the curve is thus equal to both  $\sum_{j=1}^r X_{(j)} + (n-r)X_{(r)}$  and also to  $\tau$ .

**8** Performing the simultaneous start test and stopping at  $r$  failures,

Stopping at $r$ failures	
Total items ( $n$ )	30
Number failed ( $r$ )	10
Total time on test ( $\tau$ )	1541.50
MLE of mean ( $\hat{\theta}$ )	154.15
Stop time ( $T$ )	62.20
$p$ value %	0.00

Confidence interval of 0.95 % for the mean lifetime is [90.23, 321.45]

Hypothesis test for  $\theta_0 = 7.5$  is rejected

Lower confidence interval of 95 % for the mean lifetime is  $(-\infty, 284.13]$

**9** Placeholder P9

**10** Performing the simultaneous start test and stopping at  $r$  failures,

Hypothesis test for  $\theta_0 = 10$  is accepted

Stopping at $r$ failures	
Total items ( $n$ )	20
Number failed ( $r$ )	8
Total time on test ( $\tau$ )	44.31
MLE of mean ( $\hat{\theta}$ )	5.54
Stop time ( $T$ )	2.72
$p$ value %	16.20

**11** Using the exact formula for the mean and variance of the testing period  $T$

Statistics of testing period	
Total items ( $n$ )	20
Number failed ( $r$ )	10
Mean lifetime ( $\theta$ )	10.00
Test Period mean (exact)	6.69
Test Period variance (exact)	4.64

**12** Using the approximate formula for the mean testing period

$$\mathbb{E}[X_{(r)}] \cong \log \left( \frac{n}{n-r+1} \right) \quad (12.1)$$

$$3 = \theta \log \left( \frac{n}{n-9} \right)$$

$$9/n = 1 - \exp(-3/20)$$

$$n = 64.6 \quad (12.2)$$

A minimum of 65 items need to be tested simultaneously.

**13** Performing the sequential test,

Confidence interval of 95 % for the mean lifetime is [12.13, 32.8]

Hypothesis test for  $\theta_0 = 20$  is accepted

Stopping at fixed time	
Number failed ( $r$ )	16
Total time on test ( $T$ )	300.00
MLE of mean ( $\hat{\theta}$ )	18.75
$p$ value %	86.38

**14** Inter arrival times are IID exponential RVs. The resulting process is a Poisson RV

Using the results from sequential testing with fixed stopping time  $T$

$$P\{N(x/2) \geq n\} = P\{X_1 + \dots + X_n \leq x/2\} \quad (14.1)$$

The sum of the first  $n$  inter-arrival times have to be smaller than  $x/2$  for the Poisson process to yield an integer not smaller than  $n$  after time  $x/2$  elapses.

$$\sum_{j=1}^n X_j \sim \text{Gamma}(n, 1/\theta)$$

$$\sim \frac{\theta}{2} \chi_{2n}^2$$

$$P\{N(x/2) \geq n\} = P\left\{ \frac{\theta}{2} \chi_{2n}^2 \leq x/2 \right\} \quad (14.2)$$

Thus, the RHS can be rearranged to be the CDF of a  $\chi^2$  RV with  $2n$  DOF.

**15** First consider the case when time  $T$  elapses and the test stops before  $r$  failures. Let the number of failures be  $k < r$ . The observations  $\{x_i\}$  indicate the failure times.

The differences between successive elements of  $\{x_i\}$  are the lifetimes of each item.

$$\mathcal{L}(x_1, \dots, x_r \mid \theta) = \prod_{i=1}^k \frac{1}{\theta} \exp \left[ \frac{-(x_i - x_{i-1})}{\theta} \right] \times P \{x_{k+1} > T\} \quad (15.1)$$

$$= \frac{1}{\theta^k} \exp \left[ \frac{-(x_k - x_0)}{\theta} \right] \times \exp \left[ \frac{-(T - x_k)}{\theta} \right] \quad (15.2)$$

$$= \theta^{-k} \exp \left\{ \frac{-T}{\theta} \right\} \quad (15.3)$$

$$\frac{d}{d\theta} \log(\mathcal{L}) = 0 = \frac{-k}{\theta} + \frac{T}{\theta^2}$$

$$\hat{\theta} = T/k = \frac{\text{total duration of test}}{\text{number of failures}} \quad (15.4)$$

Next consider the case where the test stops because all  $r$  items have failed before time  $T$

$$\mathcal{L}(x_1, \dots, x_r \mid \theta) = \prod_{i=1}^r \frac{1}{\theta} \exp \left[ \frac{-(x_i - x_{i-1})}{\theta} \right] \quad (15.5)$$

$$= \frac{1}{\theta^r} \exp \left[ \frac{-(x_r - x_0)}{\theta} \right] \quad (15.6)$$

$$= \theta^{-r} \exp \left\{ \frac{-x_r}{\theta} \right\} \quad (15.7)$$

$$\frac{d}{d\theta} \log(\mathcal{L}) = 0 = \frac{-r}{\theta} + \frac{x_r}{\theta^2}$$

$$\hat{\theta} = x_r/k = \frac{\text{total duration of test}}{\text{number of failures}} \quad (15.8)$$

In both cases the general formula does hold, as seen in the last step.

**16** Find MLE given likelihood function



$$\mathcal{L} = \frac{K}{\theta^r} \exp \left[ \frac{-1}{\theta} \left( \sum_{i=1}^r x_i + \sum_{j=1}^s y_j \right) \right] \quad (16.1)$$

$$= \frac{K}{\theta^r} \exp \left[ \frac{-\tau}{\theta} \right] \quad (16.2)$$

$$\frac{d}{d\theta} \log(\mathcal{L}) = 0 = \frac{-r}{\theta} + \frac{\tau}{\theta^2}$$

$$\hat{\theta} = \frac{\tau}{r} = \frac{1}{r} \left( \sum_{i=1}^r x_i + \sum_{j=1}^s y_j \right) \quad (16.3)$$

17 Performing the sequential test with panel size 5

Stopping at fixed time	
Number failed ( $r$ )	9
Total time on test ( $T$ )	764.00
MLE of mean ( $\hat{\theta}$ )	84.89

18 Using the general rule for the MLE of  $\theta$

$$\begin{aligned} \hat{\theta} &= \frac{\text{total time on test}}{\text{number of failures}} \\ &= \frac{702}{12} = 58.57 \end{aligned} \quad (18.1)$$

19 Data from Problem 17, Prior distribution is **Gamma**(1, 100)

$$g(\lambda) = \text{Gamma}(a, b) \quad (19.1)$$

$$\begin{aligned} \mathbb{E}[\lambda \mid \text{data}] &= \frac{b + R}{a + \tau} \\ &= \frac{100 + 9}{1 + 764} = 0.1425 \end{aligned} \quad (19.2)$$

**20** Data from Problem 18, Prior distribution is  $\text{Expon}(\lambda = 30)$

$$\begin{aligned}
 f(\lambda \mid \text{data}) &= \frac{\lambda^r e^{-\lambda t} g(\lambda)}{\int \lambda^r e^{-\lambda t} g(\lambda) \, d\lambda} \\
 &= \frac{\lambda^r e^{-(\lambda)t}}{\int \lambda^r e^{-(\lambda)t} \, d\lambda} \\
 &= \frac{(t)^{r+1} \lambda^r e^{-\lambda t}}{(r)!} \\
 &= \text{Gamma}(r + 1, t)
 \end{aligned} \tag{20.1}$$

$$\mathbb{E}[f(\lambda \mid \text{data})] = \frac{r + 1}{t} = 0.0185 \tag{20.2}$$

$$\lambda_b = 54.08 \tag{20.3}$$

**21** Performing the two sample test for equality of the exponential RV means, null hypothesis is accepted

Two sample problem	
Sample A size ( $n$ )	7
Sample B size ( $m$ )	7
Mean Lifetime A ( $\bar{X}$ )	123.17
Mean Lifetime B ( $\bar{Y}$ )	89.51
Test Statistic (F Test)	1.38
$p$ vlaue %	68.43