

# TMA4275 LIFETIME ANALYSIS

## Slides 3: Parametric families of lifetime distributions

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For a lifetime  $T$  we define

$$MTTF = E(T) = \int_0^{\infty} tf(t)dt = \int_0^{\infty} R(t)dt$$

*(The last equality can be proven by partial integration, noting that  $R'(t) = -f(t)$ . Try to do it! You will need that  $\lim_{t \rightarrow \infty} t R(t) = 0$  which holds if  $E(T) < \infty$ . )*

$$\begin{aligned} \text{Var}(T) &= \int_0^{\infty} (t - E(T))^2 f(t)dt \\ &= \int_0^{\infty} t^2 f(t)dt - (E(T))^2 \\ &= E(T^2) - (E(T))^2 \end{aligned}$$

$$\text{SD}(T) = (\text{Var}(T))^{1/2}$$

## EXAMPLE: EXPONENTIAL DISTRIBUTION

Let  $T$  be exponentially distributed with density  $f(t) = \lambda e^{-\lambda t}$ . Then you may check the following computations:

$$\begin{aligned}E(T) &= \int_0^{\infty} t \lambda e^{-\lambda t} dt = \int_0^{\infty} e^{-\lambda t} dt = \frac{1}{\lambda} \\ \text{Var}(T) &= E(T^2) - (E(T))^2 = \frac{2}{\lambda^2} - \frac{1}{\lambda^2} = \frac{1}{\lambda^2} \\ \text{SD}(T) &= \frac{1}{\lambda}\end{aligned}$$

Thus: For a component with exponentially distributed lifetime,

$$\text{MTTF} = 1/\text{failure rate}$$

**NOTE:** We will mainly use the parameterization  $f(t) = \frac{1}{\theta} e^{-t/\theta}$ , so that

$$R(t) = e^{-t/\theta}, \quad E(T) = \theta, \quad \text{SD} = \theta$$

The lifetime  $T$  is Weibull-distributed with *shape* parameter  $\alpha > 0$  and *scale* parameter  $\theta > 0$ , written  $T \sim \text{Weib}(\alpha, \theta)$ , if

$$R(t) = e^{-\left(\frac{t}{\theta}\right)^\alpha}$$

From this we can derive:

$$Z(t) = \left(\frac{t}{\theta}\right)^\alpha$$

$$z(t) = \frac{\alpha}{\theta} \left(\frac{t}{\theta}\right)^{\alpha-1}$$

$$f(t) = z(t)e^{-Z(t)} = \frac{\alpha}{\theta} \left(\frac{t}{\theta}\right)^{\alpha-1} e^{-\left(\frac{t}{\theta}\right)^\alpha}$$

$\alpha = 1$  corresponds to the exponential distribution;

$\alpha < 1$  gives a decreasing failure rate (DFR);

$\alpha > 1$  gives an increasing failure rate (IFR).

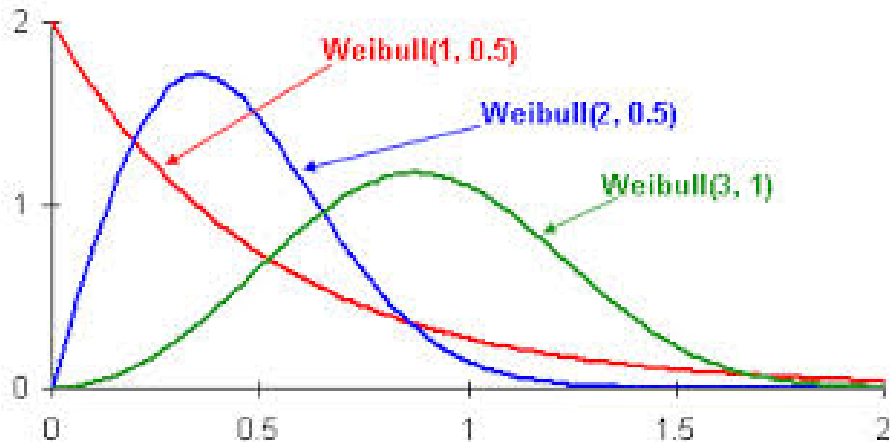
$$E(T) = \int_0^{\infty} R(t)dt = \int_0^{\infty} e^{-(\frac{t}{\theta})^\alpha} dt = \dots = \theta \cdot \Gamma\left(\frac{1}{\alpha} + 1\right)$$

where  $\Gamma(\cdot)$  is the gamma-function defined by  $\Gamma(a) = \int_0^{\infty} u^{a-1} e^{-u} du$ .

$$\text{Var}(T) = \theta^2 \left( \Gamma\left(\frac{2}{\alpha} + 1\right) - \Gamma^2\left(\frac{1}{\alpha} + 1\right) \right)$$

$$SD(T) = \theta \left( \Gamma\left(\frac{2}{\alpha} + 1\right) - \Gamma^2\left(\frac{1}{\alpha} + 1\right) \right)^{1/2}$$

# WEIBULL DISTRIBUTION (CONT.)



Standard normal distribution,  $Z \sim N(0, 1)$ :

$$f_Z(z) = \phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$$

$$F_Z(z) = \Phi(z) = \int_{-\infty}^z \phi(w) dw$$

Now Let  $Y \sim N(\mu, \sigma)$ . Then it is well known that

$$F_Y(y) = P(Y \leq y) = \Phi\left(\frac{y - \mu}{\sigma}\right)$$

$$M_Y(t) = E(e^{tY}) = e^{\mu t + \frac{1}{2}\sigma^2 t^2} \quad (\text{moment generating function})$$

Further, if we let  $Z = \frac{Y - \mu}{\sigma} \sim N(0, 1)$ , then  $Y = \mu + \sigma Z$ .

**Thus:** The model  $Y \sim N(\mu, \sigma)$  is a **location–scale family**, defined by the standardized random variable  $Z$ , with *location parameter*  $\mu$  and *scale parameter*  $\sigma$ .

- 1 Consider  $Y = \mu + \sigma Z$  where  $Z \sim N(0, 1)$ . What is the distribution of  $Y$ ? Why are the names *location* parameter and *scale* parameter appropriate for, respectively,  $\mu$  and  $\sigma$ ?
- 2 The normal distribution is sometimes used as a lifetime distribution (in fact it is a possible choice in MINITAB). What is a possible problem with this distribution?



The lifetime  $T$  has a lognormal distribution with parameters  $\mu$  and  $\sigma$  if  $Y \equiv \ln T$  is normally distributed,  $Y \sim N(\mu, \sigma)$ .

We can hence write

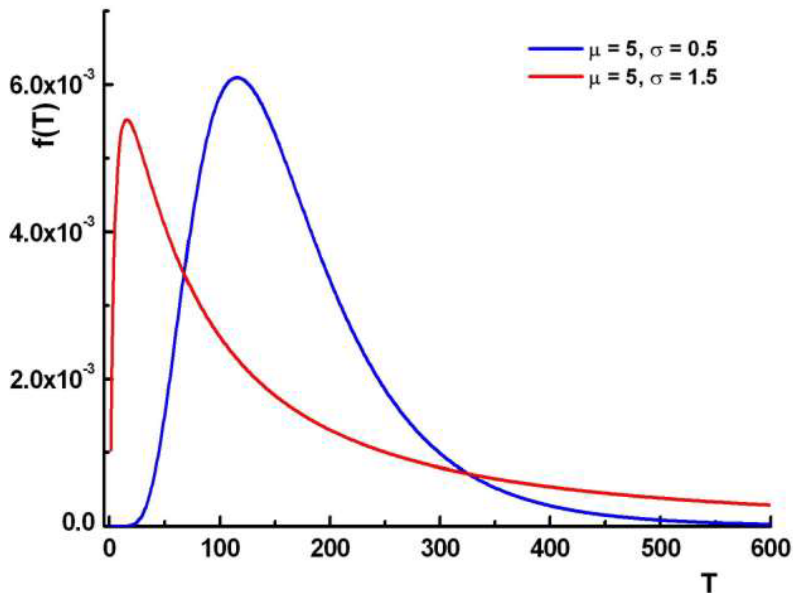
$$Y = \ln T = \mu + \sigma Z \quad (*)$$

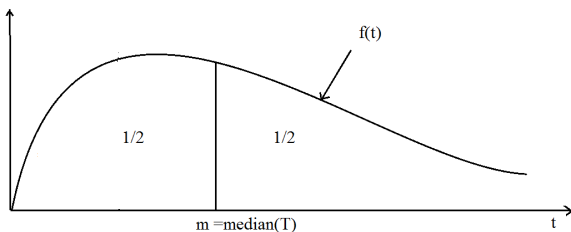
where  $Z \sim N(0, 1)$ .

Here  $\mu$  is called the *location parameter* and  $\sigma$  is called the *scale parameter* of the lognormal distribution.

Because of (\*) we say that the lognormal distribution is a **log-location-scale family** of distributions, meaning that the log of  $T$  defines a *location-scale* family.

# LOGNORMAL DISTRIBUTION (CONT.)





$m = \text{median}(T)$  is defined by  $F(m) = R(m) = 1/2$ .

Compute the median  $m$  when  $T$  is

- 1 Exponentially distributed with parameter  $\theta$ , i.e.  $T \sim \text{Expon}(\theta)$
- 2  $T \sim \text{Weib}(\alpha, \theta)$
- 3  $T \sim \text{lognormal}(\mu, \sigma)$

Recall:

$$T \sim \text{lognormal}(\mu, \sigma) \iff \ln T \sim N(\mu, \sigma)$$

Thus

$$\begin{aligned} R(t) &= P(T > t) = P(\ln T > \ln t) \\ &= 1 - \Phi\left(\frac{\ln t - \mu}{\sigma}\right) \end{aligned}$$

and

$$\begin{aligned} f(t) &= -R'(t) = \phi\left(\frac{\ln t - \mu}{\sigma}\right) \cdot \frac{1}{t\sigma} \\ &= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sigma} \cdot \frac{1}{t} e^{-\frac{(\ln t - \mu)^2}{2\sigma^2}} \text{ for } t > 0 \end{aligned}$$

$$z(t) = \frac{f(t)}{R(t)} = \frac{\phi\left(\frac{\ln t - \mu}{\sigma}\right) / (t\sigma)}{1 - \Phi\left(\frac{\ln t - \mu}{\sigma}\right)}$$

Let  $T \sim \text{lognormal}(\mu, \sigma)$ . Then  $Y = \ln T \sim N(\mu, \sigma)$ , and hence

$$M_Y(t) = E(e^{tY}) = e^{\mu t + \frac{1}{2}\sigma^2 t^2}$$

Thus:

$$\begin{aligned} E(T) &= E(e^Y) = M_Y(1) = e^{\mu + \frac{1}{2}\sigma^2} \\ E(T^2) &= E(e^{2Y}) = M_Y(2) = e^{2\mu + 2\sigma^2} \\ \text{Var}(T) &= e^{2\mu + 2\sigma^2} - e^{2\mu + \sigma^2} = e^{2\mu + \sigma^2} (e^{\sigma^2} - 1) \end{aligned}$$

On the other hand,

$$\text{median}(T) = e^\mu$$

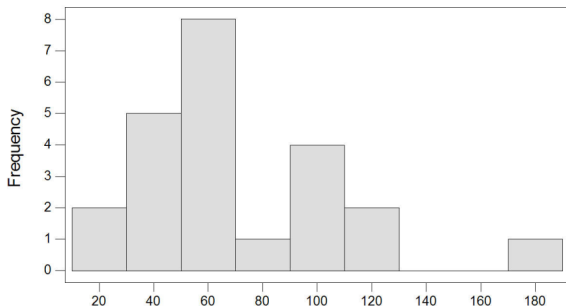
since  $P(T \leq e^\mu) = P(\ln T \leq \mu) = P(Y \leq \mu) = 1/2$ .

# RECALL BALL BEARING FAILURE DATA

17,88	28,92	33,00	41,52	42,12	45,60	48,40	51,84
51,96	54,12	55,56	67,80	68,64	68,64	68,88	84,12
93,12	98,64	105,12	105,84	127,92	128,04	173,40	

**Question:** *How can we fit a parametric lifetime model to these data?*

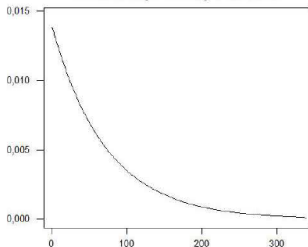
Histogram of Revolutions



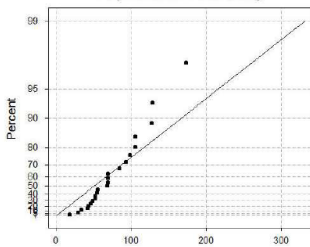
## Ball Bearings Failure Data

ML Estimates - Complete Data

Probability Density Function



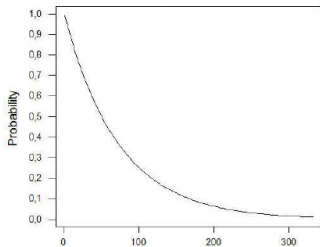
Exponential Probability



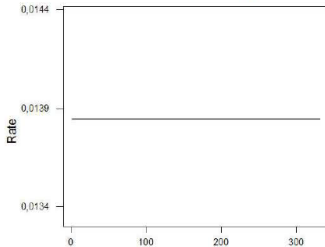
Shape	1
Scale	72,22
MTTF	72,22
Failure	23
Censor	0

Goodness of Fit  
AD\* 3,341

Survival Function



Hazard Function

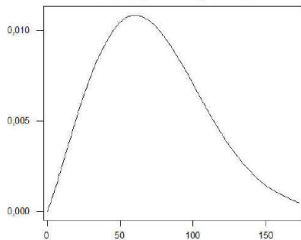




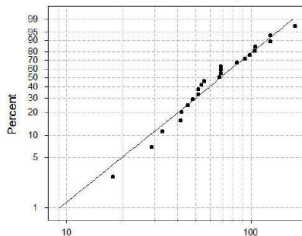
## Ball Bearings Failure Data

ML Estimates - Complete Data

Probability Density Function



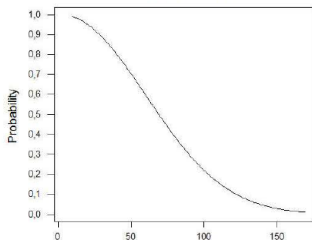
Weibull Probability



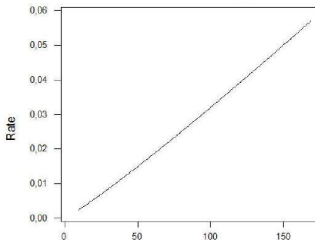
Shape 2,1018  
 Scale 81,875  
 MTTF 72,515  
 Failure 23  
 Censor 0

Goodness of Fit  
 AD\* 0,802

Survival Function



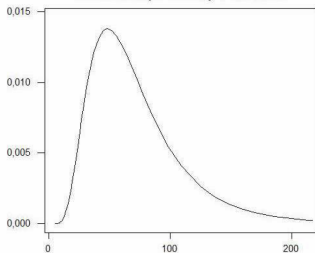
Hazard Function



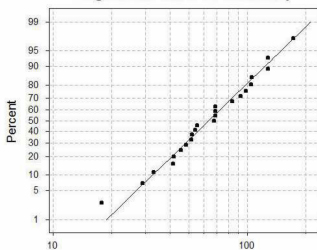
## Ball Bearings Failure Data

ML Estimates - Complete Data

Probability Density Function



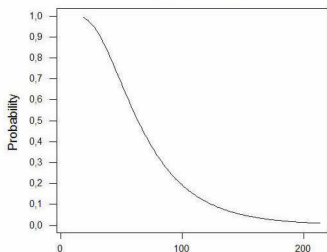
Lognormal base e Probability



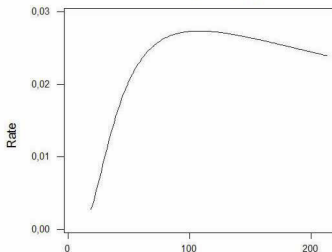
Location	4,1504
Scale	0,5217
MTTF	72,709
Failure	23
Censor	0

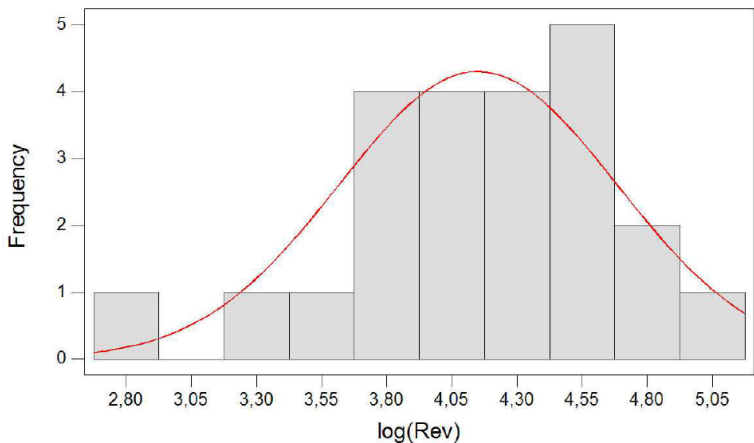
Goodness of Fit	
AD*	0,647

Survival Function

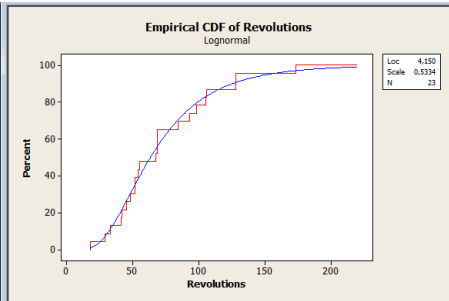
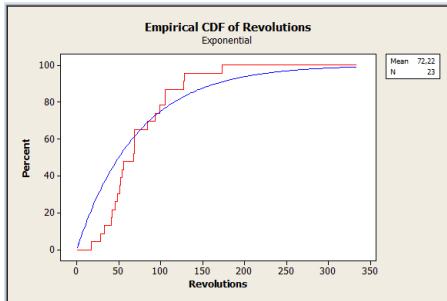


Hazard Function



Histogram of  $\log(\text{Rev})$ , with Normal Curve

# BB-DATA: EMPIRICAL DISTRIBUTION COMPARED TO PARAMETRIC FITS



# BB-DATA: SUMMARY OF ESTIMATION RESULTS

Model	$\widehat{\text{MTTF}}$	$\widehat{\text{STD}}(T)$	$\widehat{\text{med}}(T)$	$\hat{\alpha}$	$\hat{\theta}$	$\hat{\mu}$	$\hat{\sigma}$
Exp	72.221	72.221	50.060		72.221		
Weib	72.515	36.250	68.773	2.102	81.875		
Logn	72.710	40.664	63.458			4.150	0.522
Norm	72.221	36.667	72.221			72.221	36.667

*Method: Maximum likelihood.*

- Simplest distribution used in the analysis of reliability data.
- Has the important characteristic that its hazard function is constant (does not depend on time  $t$ ).
- Popular distribution for some kinds of electronic components (e.g., capacitors or robust, high-quality integrated circuits).
- Might be useful to describe failure times for components that exhibit physical wearout only after expected technological life of the system, in which the component would be replaced.

- The theory of extreme values shows that the Weibull distribution can be used to model the minimum of a large number of independent positive random variables from a certain class of distributions.
  - Failure of the weakest link in a chain with many links with failure mechanisms (e.g. fatigue) in each link acting approximately independently.
  - Failure of a system with a large number of components in series and with approximately independent failure mechanisms in each component.
- The more common justification for its use is empirical: the Weibull distribution can be used to model failure-time data with a decreasing or an increasing hazard function.

- The lognormal distribution is a common model for failure times.
- It can be justified for a random variable that arises from the product of a number of identically distributed independent positive random quantities (remember central limit theorem for sum of normals).
- It has been suggested as an appropriate model for failure time caused by a degradation process with combinations of random rates that combine multiplicatively.
- Widely used to describe time to fracture from fatigue crack growth in metals.



- Definition of
  - $MTTF = E(T)$
  - $\text{Var}(T)$
  - $SD(T) = \sqrt{\text{Var}T}$
- Presentation of distributions:
  - *Weibull-distribution*,  $\text{Weib}(\alpha, \theta)$
  - *Normal distribution*,  $N(\mu, \sigma)$
  - *Lognormal distribution*,  $\text{lognormal}(\mu, \sigma)$
- Definition of
  - *location-scale family*, e.g.  $N(\mu, \sigma)$
  - *log-location-scale family*, e.g.  $\text{lognormal}(\mu, \sigma)$