

# ECE 510 Lecture 8

## Acceleration, Maximum Likelihood

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# Acceleration Concept

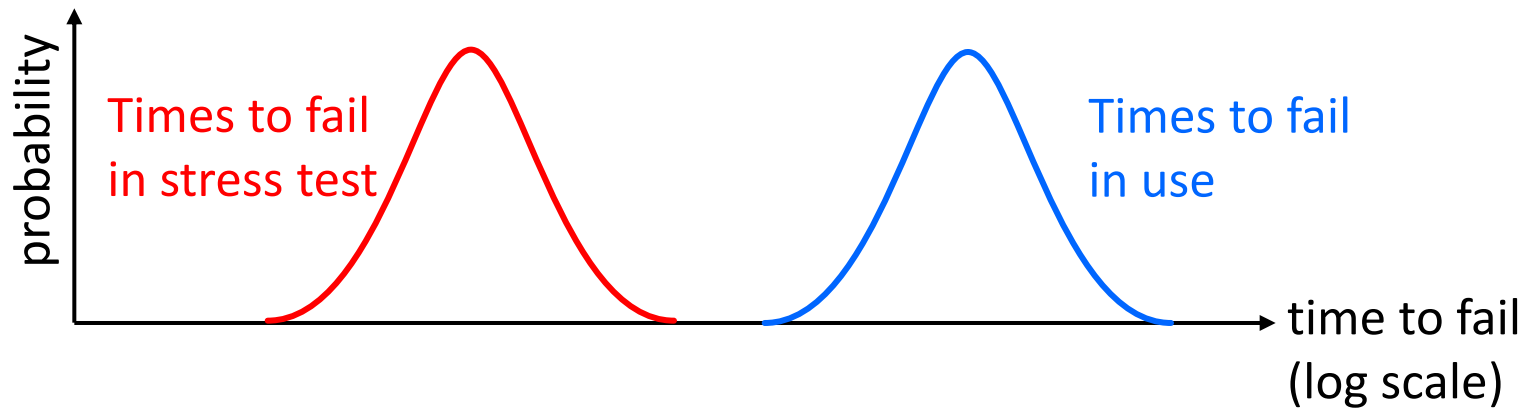
# Stress and Failure

- How long is our product going to last?
- We can't wait until it fails to see
  - that takes too long!
- We need to identify the stresses that cause it to fail
  - ...and then apply them harder to make our parts fail in a reasonable amount of time
- Our stresses include
  - Voltage
  - Temperature
  - Current
  - Humidity
  - Mechanical stress
  - ...and others



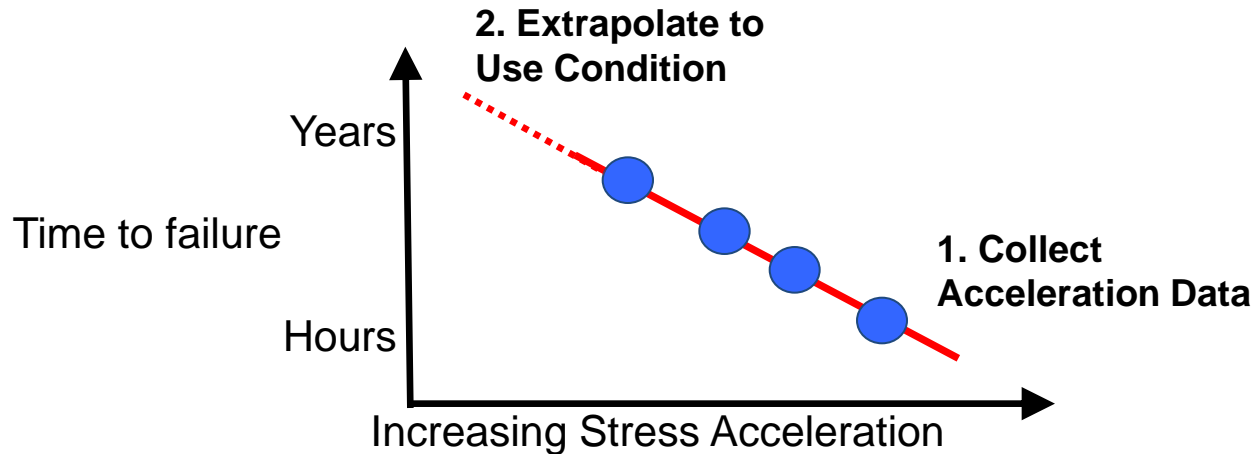
# Reliability Models

Probability distributions of times-to-fail at two stress conditions



- Knowledge-based qual based on a *reliability model*
  - Model is built at one test condition
  - It can be scaled (“*accelerated*”) to other use conditions
- Models are built from data from reliability tests

# Accelerated Test



- Accelerated test increases one or more conditions (e.g., T, V, etc.) to reduce times to failure
  - Life Test (years) → Accelerated Test (hours)
- Intention is to accelerate a mechanism without inducing new mechanisms

# Semiconductor Failure Mechanisms

Category	Mechanism	Cause	Stress
Constant	Electrical Overstress	ESD and Latchup	V, I
IM	Infant Mortality	Extrinsic Defects	V, T
Wearout	Hot Carrier	e- Impact ionization	V, I
Wearout	Neg. Bias-T Instability	Gate dielectric damage	V, T
Wearout	Electromigration	Atoms move by e- wind	I, T
Wearout	Time-Dep Diel. B'down	Gate dielectric leakage	V, T
Wearout	Stress Migration	Metal diffusion, voiding	T
Wearout	Interlayer Cracking	Interlayer stress	$\Delta T$
Wearout	Solder Joint Cracking	Atoms move w/ stress	$\Delta T$
Wearout	Corrosion	Electrochemical reaction	V, T, RH
Constant	Soft Error	n & $\alpha$ e-h pair creation	radiation

V = Voltage, I = Current, T = Temperature,  $\Delta T$  = Temp cycle, RH = Relative Humidity

# Reliability Tests

Name	Count	Time and Stress	Mechanisms
Infant Mortality Experiment	~10,000 units	48 hr at hi-V, hi-T	Latent reliability defects (IM)
Extended Life Test	~300 units	500 hr at hi-V, hi-T	Wearout (oxide, PBT, Fmax, Vccmin)
Test structure stress tests	100's of devices	Hours at hi-V, hi-T	Oxide breakdown, PMOS bias-temp, electromigration, other silicon mechs
Bake	~300 units	100's of hours at hi-T	TIM degradation, cracking and delaminating
Highly Accelerated Stress Test (HAST)	~300 units	50-150 hr at hi-T, hi-RH	Metal migration, adhesion fail
Temperature Cycling	~300 units	~1000 cycles -55C to 125C	Cracks anywhere, TIM degradation

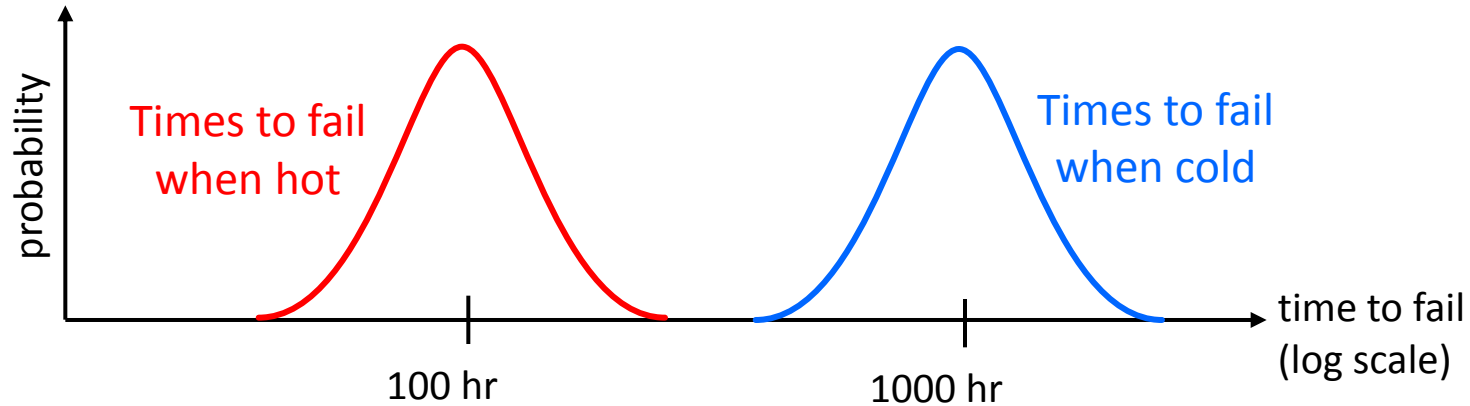
# Accelerated Testing Pitfalls

- Different mechanisms might accelerate differently
- No universal test:
  - Stress tests are idealizations of real life
  - Some mechanisms might get too much acceleration
  - Single stress does not stimulate all relevant behaviors
  - May not comprehend effects like materials creep
- The most accurate data is the most difficult or unrealistic to acquire:
  - Long test times are required at low acceleration conditions



# Acceleration Calculation

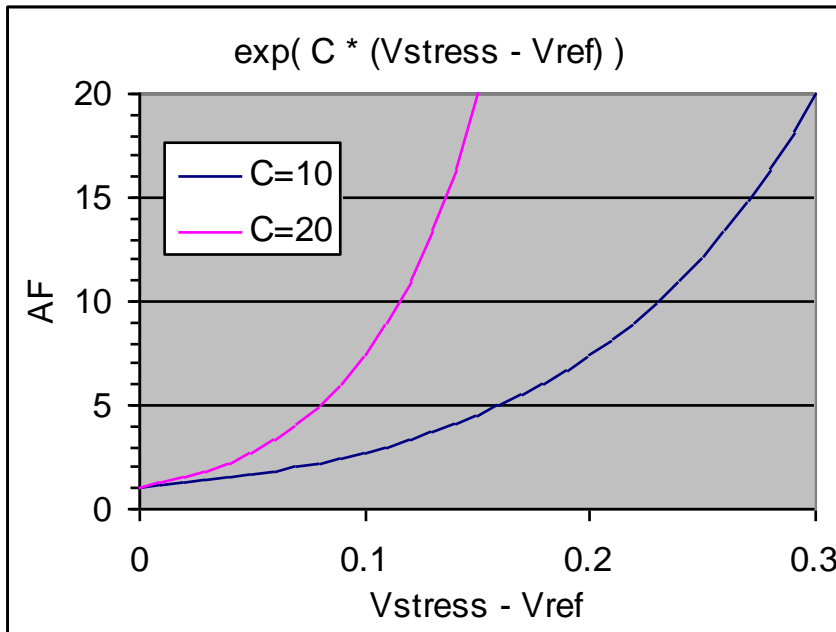
# Acceleration Factor



$$AF = \frac{t_{cold}}{t_{hot}} = \frac{1000\text{hr}}{100\text{hr}} = 10$$

- An acceleration factor describes how much a particular stress accelerates degradation or failure

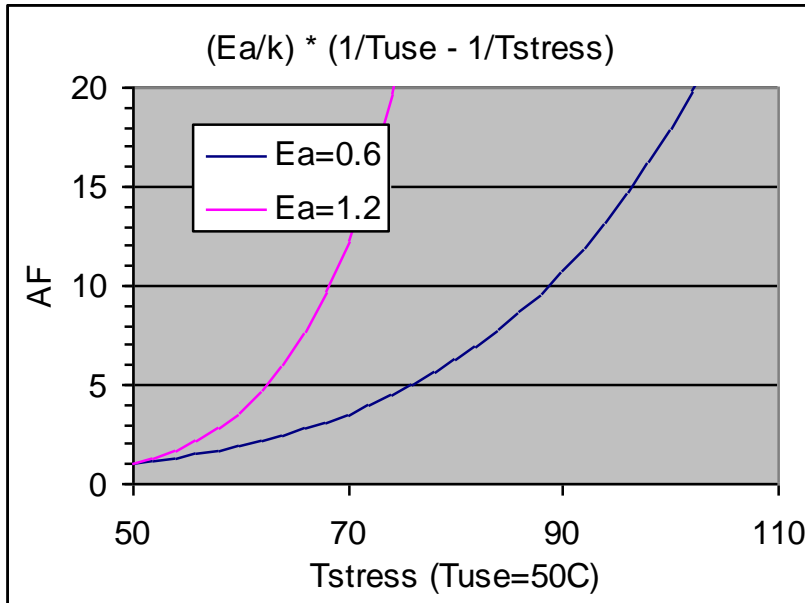
# Voltage Acceleration Model



$$AF = \exp \{ C \times (V_{stress} - V_{use}) \}$$

- Acceleration models are determined empirically
- Voltage acceleration is usually exponential, like this example

# Temperature Acceleration Model

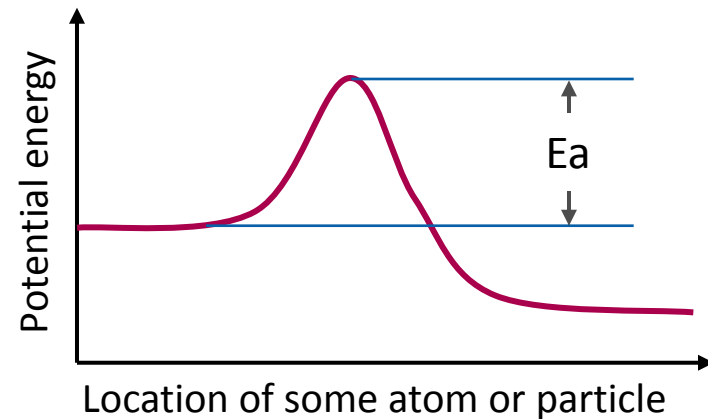


Activation energy

Must be Kelvin

$$AF = \exp \left\{ \left( \frac{E_a}{k} \right) \times \left( \frac{1}{T_{use}} - \frac{1}{T_{stress}} \right) \right\}$$

Boltzmann constant  
k = 8.62 × 10<sup>-5</sup> eV/K



- Temperature acceleration is usually like a chemical reaction
  - Arrhenius model with an energy barrier

# Exercise 8.1

If two samples of devices give these MTTFs:

- 1943 hours at 1.2V
- 286 hours at 1.4 V

find the

- Voltage Acceleration Factor (VAF)
- Constant C in the an exponential voltage acceleration model

# Solution 8.1

V1	1.2	V
V2	1.4	V
MTTF 1	1943	hr
MTTF 2	286	hr
VAF	6.793706	6.793706
C	9.579983	

$=C7/C8$  →

$=EXP(C11*(C6-C5))$  →

$=LN(C10) / (C6-C5)$  →

# Exercise 8.2

If two samples of devices give these MTTFs:

- 905 hours at 80 deg C
- 201 hours at 120 deg C

find the

- Temperature Acceleration Factor (TAF)
- Activation energy  $E_a$  in the an Arrhenius temperature acceleration model

# Solution 8.2

T1	80	deg C
T2	120	deg C
MTTF 1	905	hr
MTTF 2	201	hr
k	8.62E-05	eV/K
VAF	4.502488	4.502488
C	0.449687	

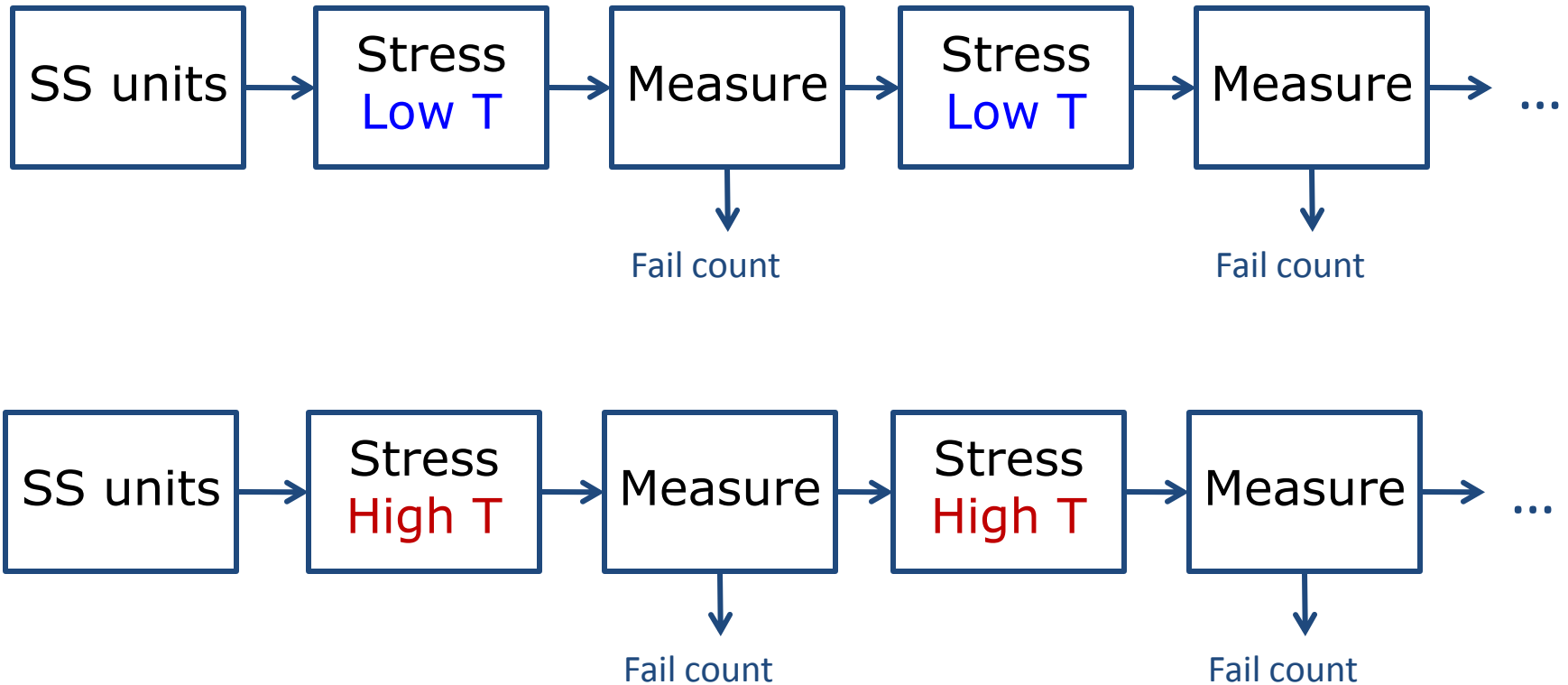
$=C7/C8$

$=EXP(C12/C9 * (1/(C5+273) - 1/(C6+273)))$

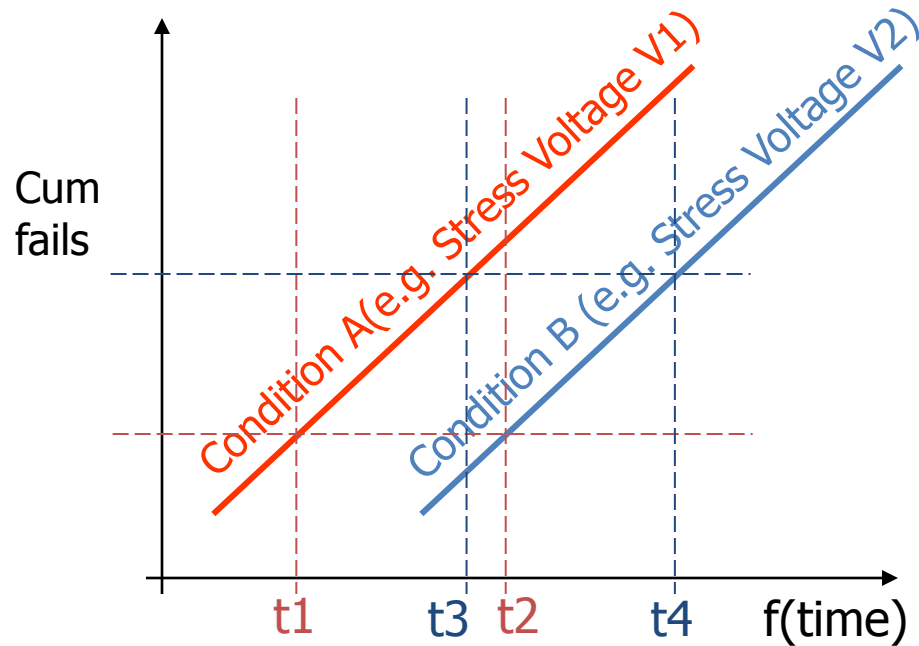
$=LN(C11)*C9 / (1/(C5+273) - 1/(C6+273))$



# Acceleration Experiment



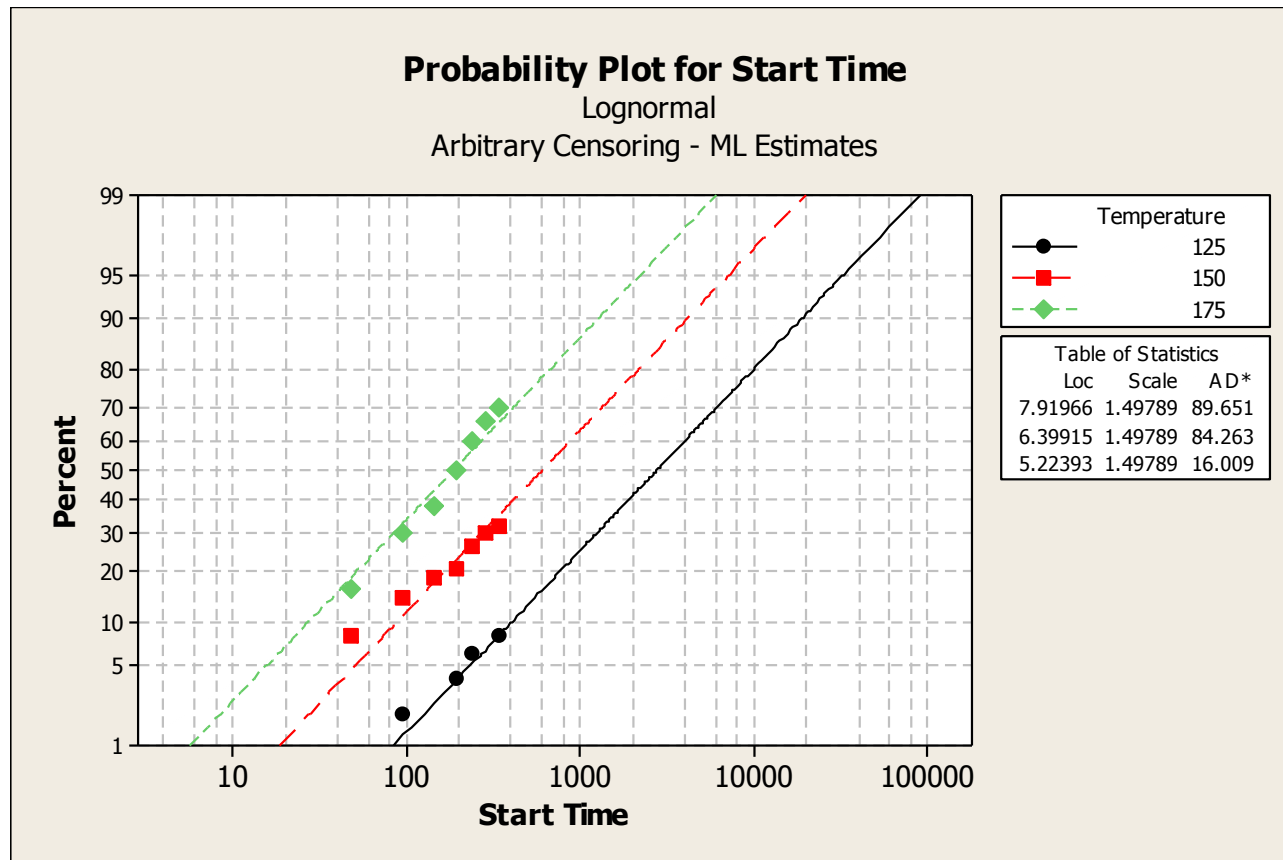
# Acceleration Concept



$$AF = \frac{t2}{t1} = \frac{t4}{t3}$$

- Distributions at both conditions must match for acceleration concept to make sense

# Acceleration Example



A temperature acceleration experiment showing the same distribution shape (slope) at each stress temp

# Accelerated Stress Testing

- Special-purpose equipment accelerates various fail mechanisms



An LCBI burn-in system gives V and T stress to accelerate Si fail mechanisms



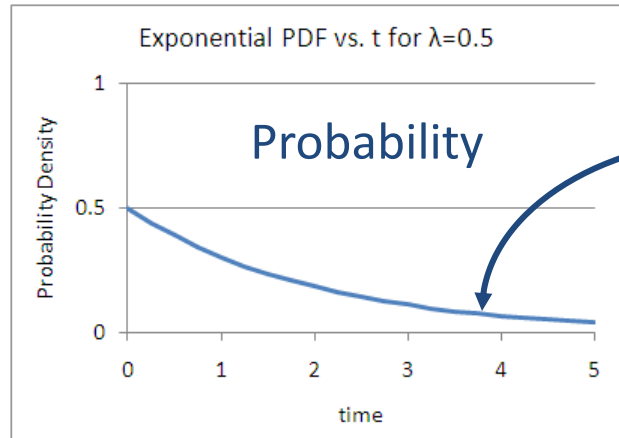
A HAST system gives pressure and humidity along with V and T to accelerate package fail mechanisms

# Maximum Likelihood Method and the Exponential Distribution

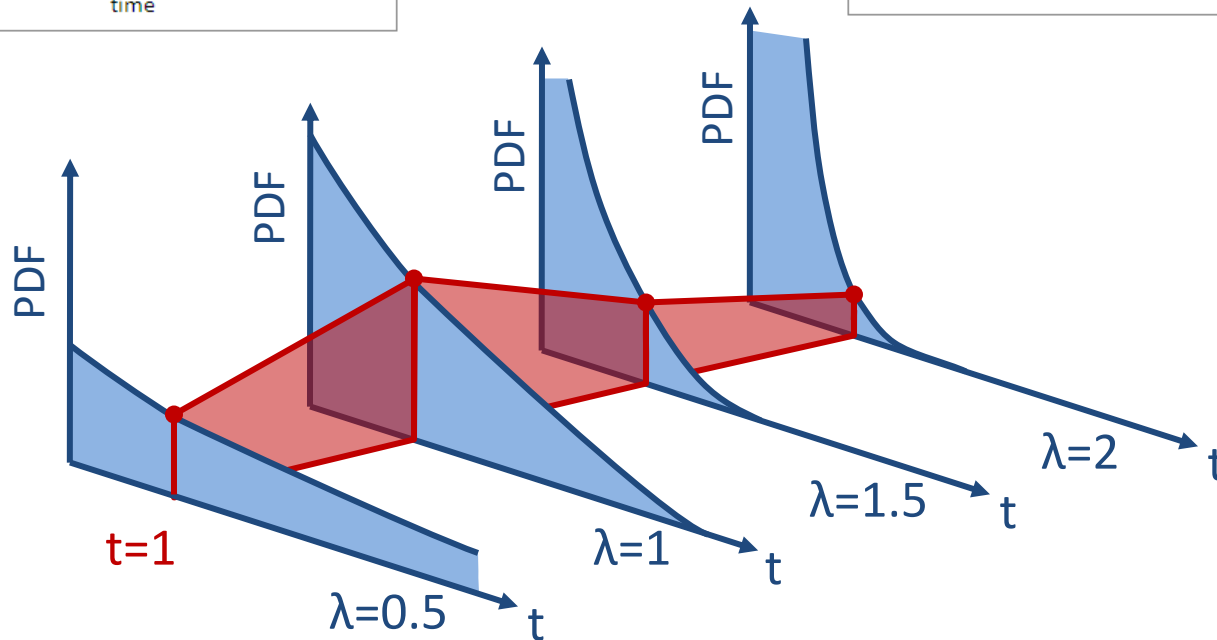
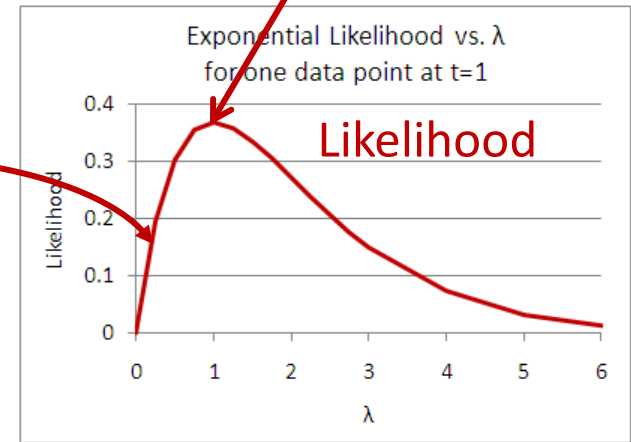
# MLE

- Maximum Likelihood Estimation (MLE) is a fitting technique that is good for any model
- Principle
  - We can't ask: What is the most likely model?
    - Because we don't have some well-defined space of possible models
  - We can ask: Given this model, how likely is this data set?
  - (This is a fairly Bayesian approach. We are usually frequentists.)

# Probability vs. Likelihood



$$\lambda e^{-\lambda t}$$



# MLE

- Likelihood for each point
  - For exact values (exact times to fail), use the PDF
  - For ranges (failed between two readout times), use CDF delta
  - Multiply all together (or add logs)
- Use
  - Choose a model functional form with adjustable parameters
  - Adjust the parameters to maximize the likelihood



# MLE for Exponential Data

- For a complete set of times to fail, likelihood is the PDF:

$$PDF_i = \lambda e^{-\lambda t_i}$$

- Take log of PDF:

$$\ln PDF_i = \ln \lambda - \lambda t_i$$

- Add up likelihood for each data point:

$$L = \sum_i \ln PDF_i = \sum_i (\ln \lambda - \lambda t_i) = N \ln \lambda - \lambda \sum_i t_i$$

Device hours =  $\sum_i t_i$



- Then choose  $\lambda$  to maximize  $L$

Sample Size =  $N$

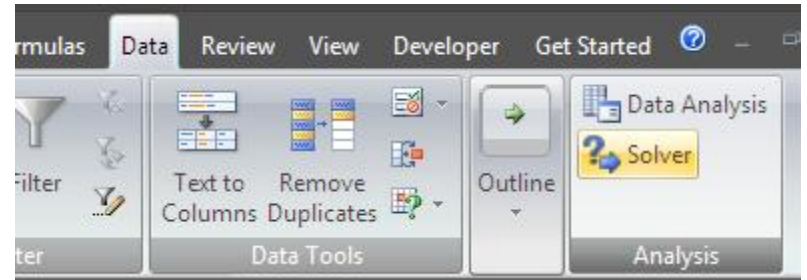


# Ex 8.3a – MLE for Exponential

Maximum likelihood:			
	lambda	likelihood	Log LR
UCL			
estimate	0.03248	-221.357	
LCL			

guess

$$= \$C\$3 * LN(F8) - F8 * \$C\$4$$



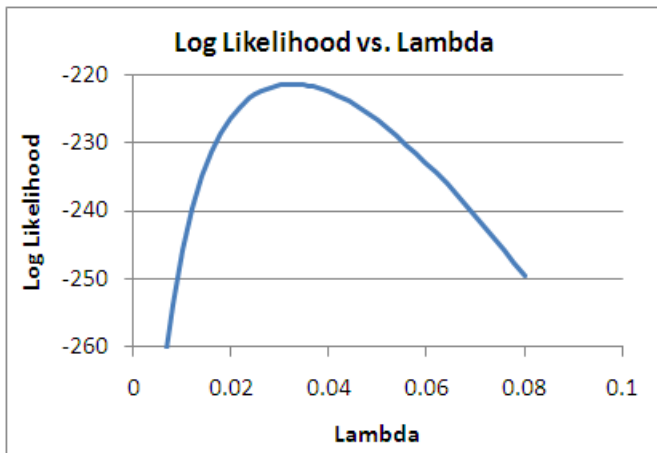
**Solver Parameters**

Set Target Cell:

Equal To:  Max  Min  Value of:

By Changing Cells:

Subject to the Constraints:



# Solution 8.3a

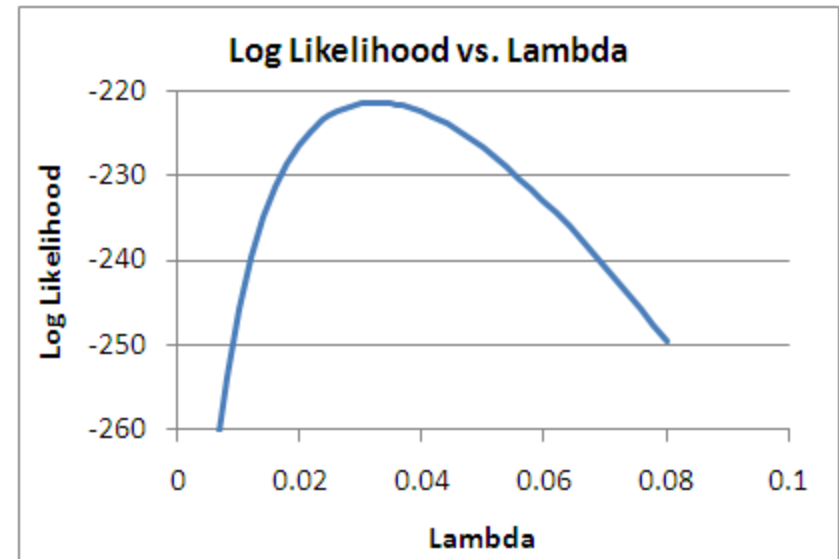
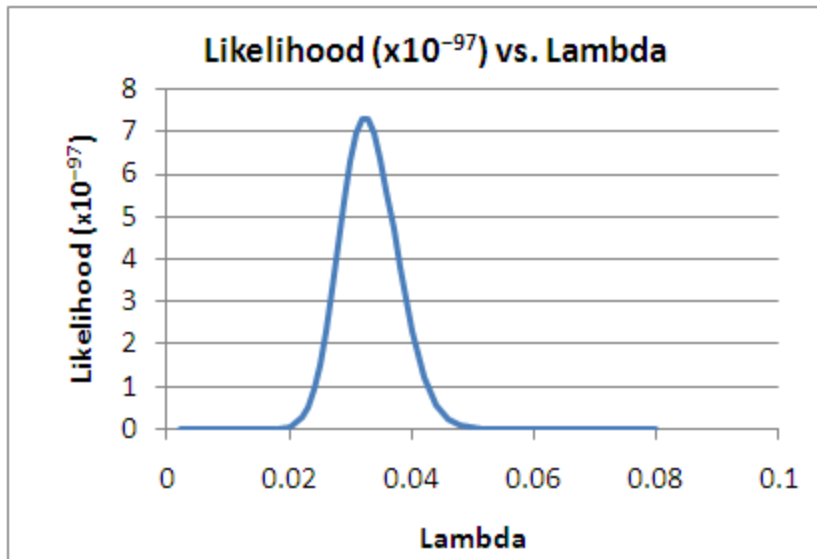
Maximum likelihood:			
	lambda	likelihood	Log LR
UCL			
estimate	0.03248	-221.357	
LCL			

$\lambda = 0.032$  per hour = 3.2% per hour

MTTF =  $1/\lambda = 30.8$  hours

# Graphs of Likelihood vs. Lambda

Maximum likelihood:			
	lambda	likelihood	Log LR
UCL			
estimate	0.03248	-221.357	
LCL			



# Analytic $\lambda$


- For exponential, can maximize analytically:

$$L = N \ln \lambda - \lambda \sum_i t_i$$

$$\frac{dL}{d\lambda} = \frac{N}{\lambda} - \sum_i t_i = 0$$

$$\lambda = \frac{N}{\sum_i t_i} = \frac{\text{Number of fails}}{\text{Total device hours}}$$

Even works for  
type I censored  
data



# Exercise 8.3b

- Calculate  $\lambda$  for the Ex 8.3 data set using the analytic expression and compare it to what you got from the MLE technique

# Solution 8.3b

- Same as MLE technique

Analytic

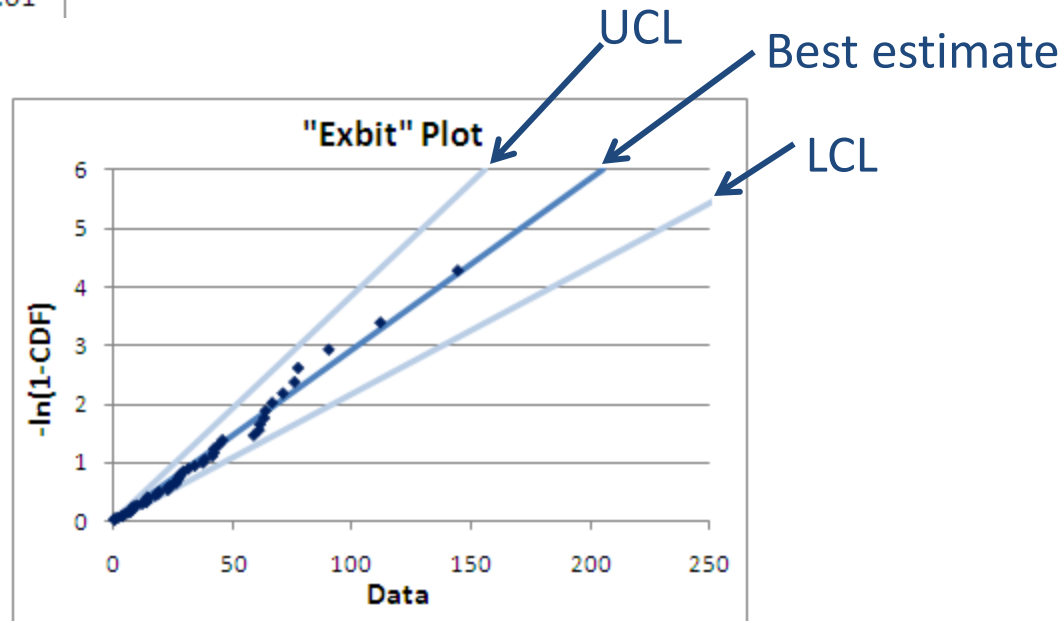
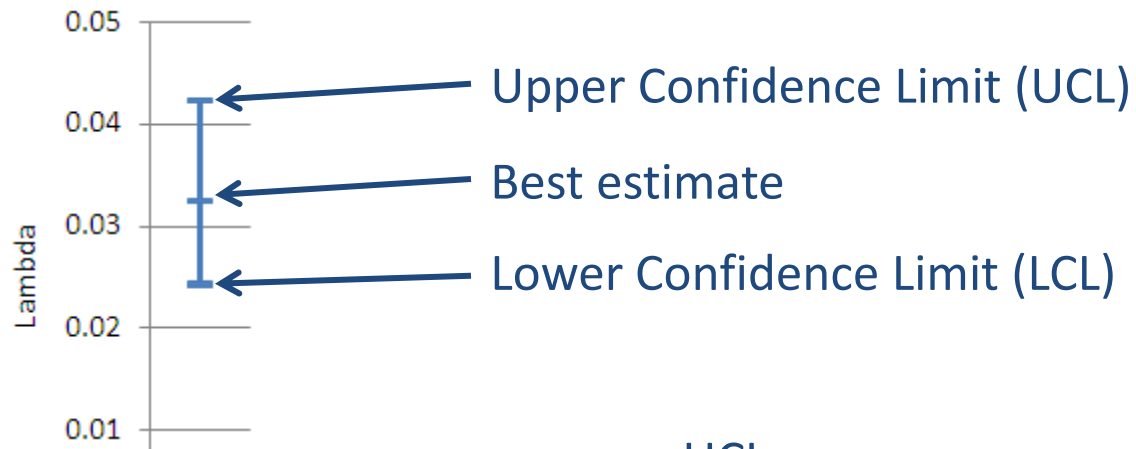
fail count	50
device hours	1539.413
lambda (fails / dev hrs)	0.03248

MLE

Maximum likelihood:			
	lambda	likelihood	Log LR
UCL			
estimate	0.03248	-221.357	
LCL			

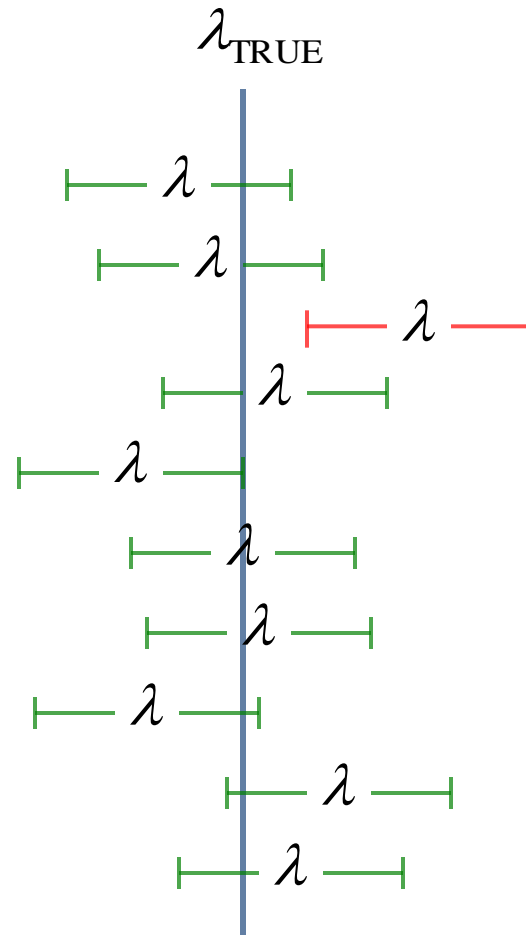


# Uncertainty Range of Lambda



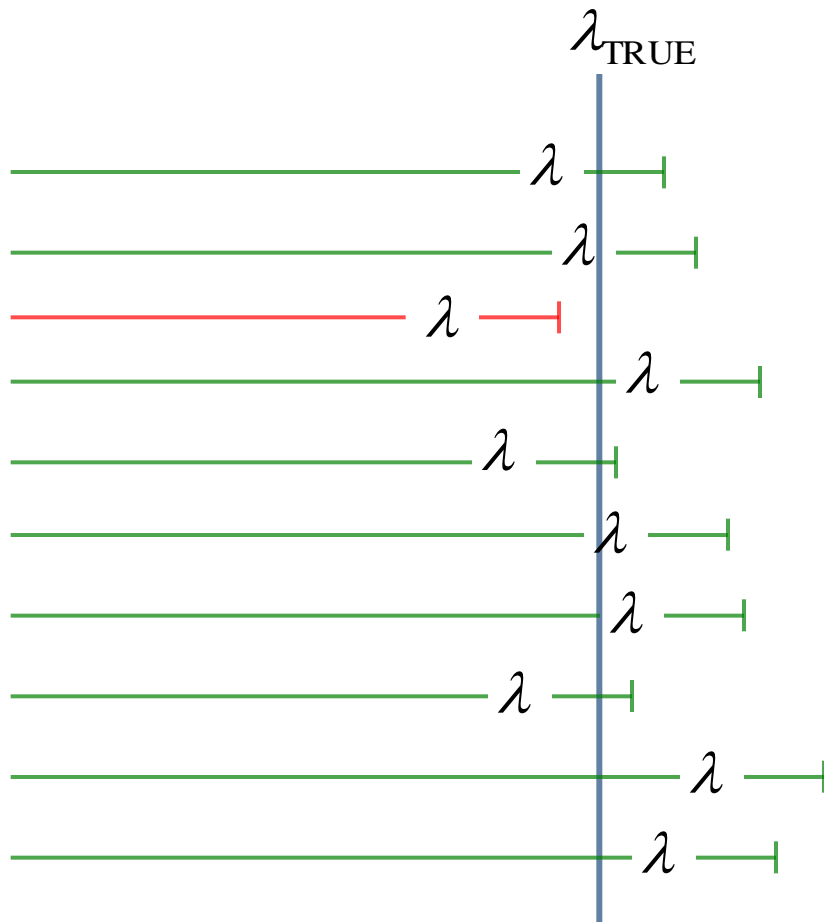


# Confidence Interval (2-Sided)



- 90% of random sample  $\lambda$ 's with this confidence interval include the true population  $\lambda$

# Confidence Interval (1-Sided)

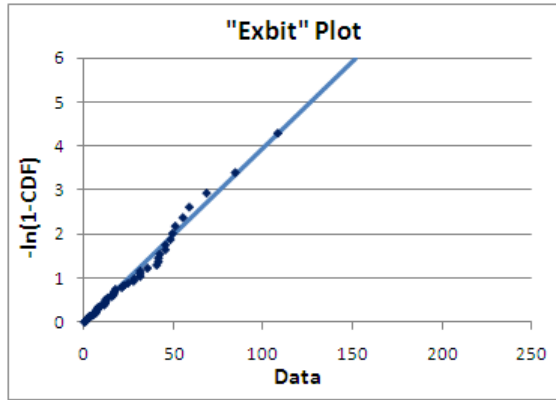


# Uncertainties on Parameters

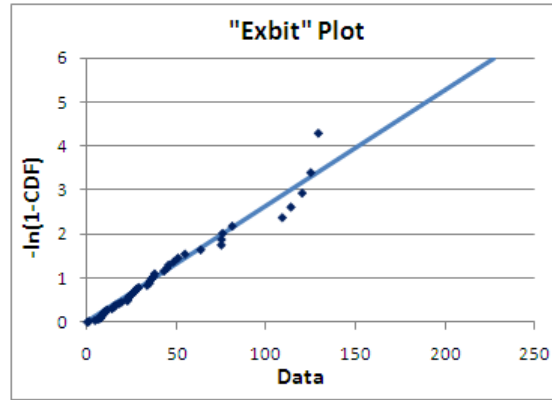
To calculate:

- Monte Carlo
- Likelihood ratio
- Analytic

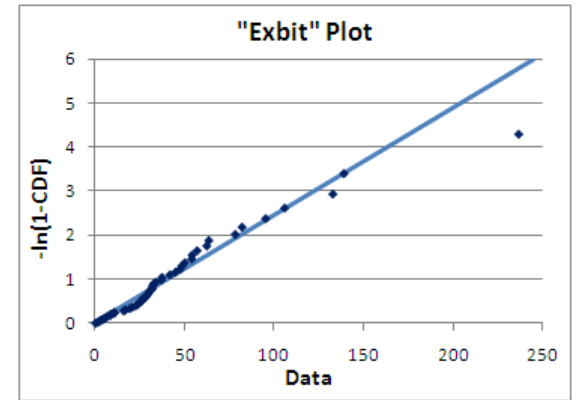
# Recall Monte Carlo Lambda Uncertainty



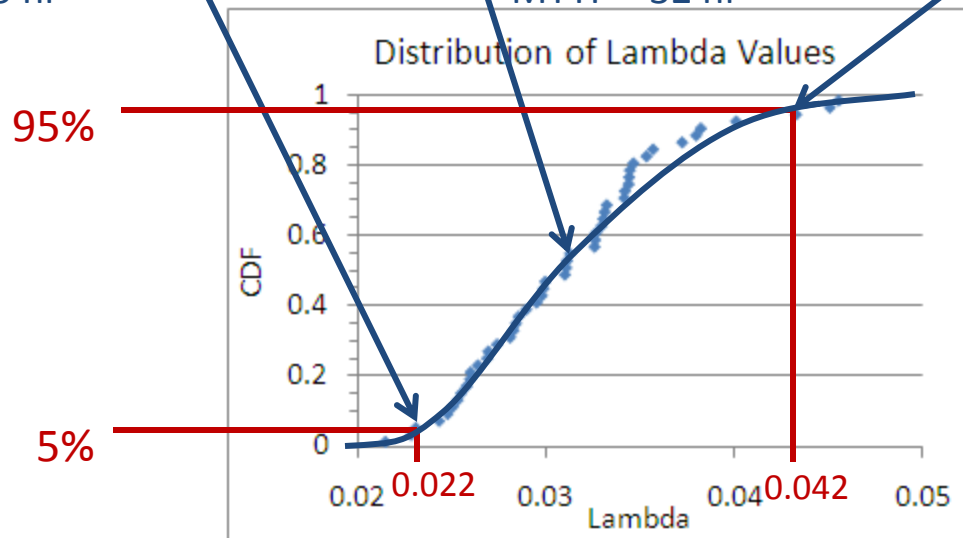
$\lambda=0.022$   
MTTF = 45 hr



$\lambda=0.031$   
MTTF = 32 hr

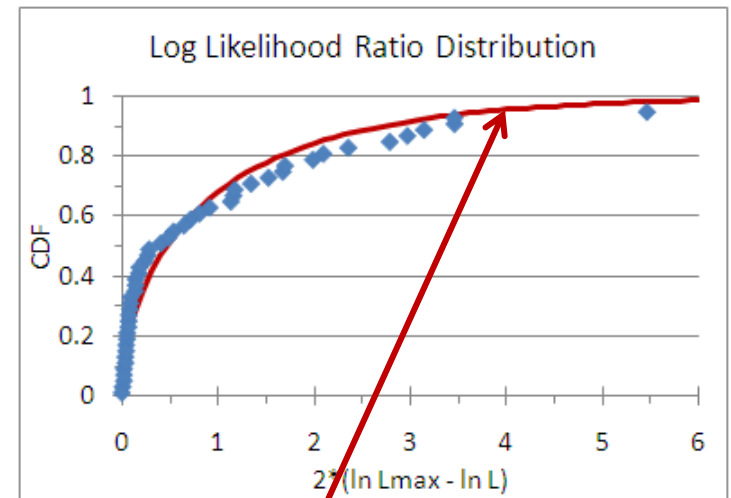
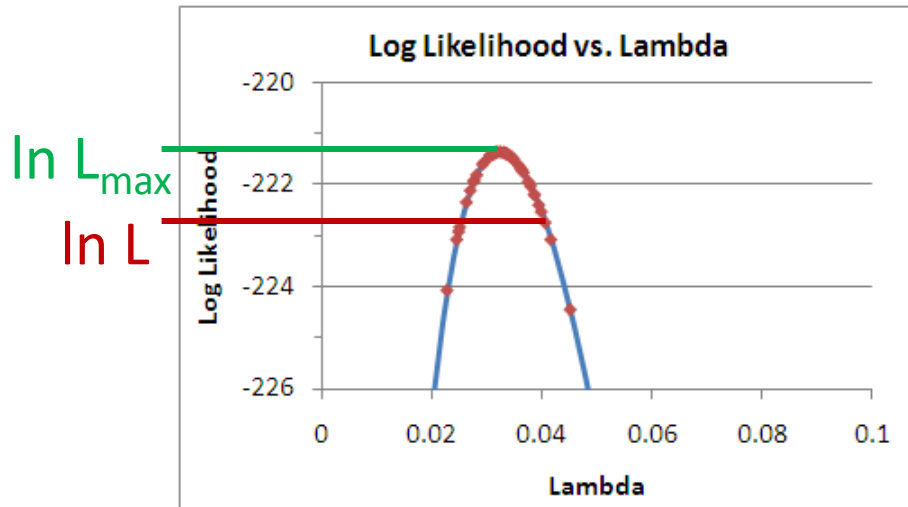
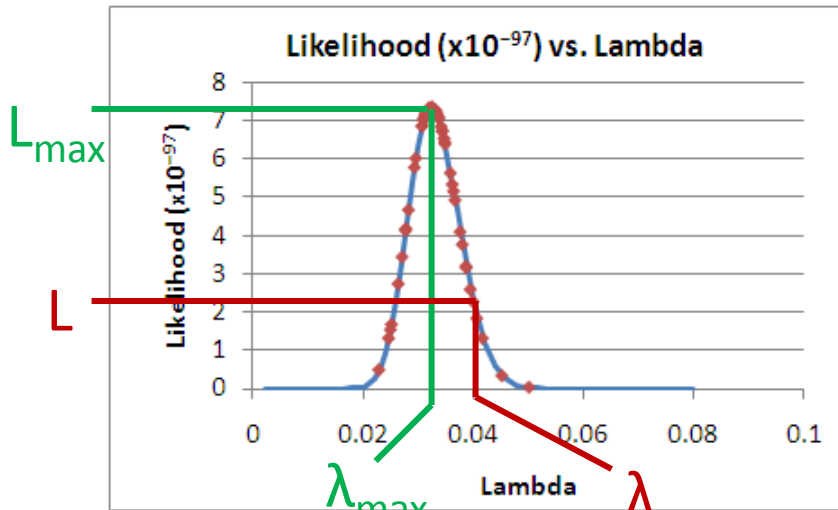


$\lambda=0.042$   
MTTF = 24 hr



# Likelihood Ratio Lambda Uncertainty

$$\ln \left( \frac{L_{\max}}{L} \right)^2 = 2 \times (\ln L_{\max} - \ln L)$$



$$1 - \text{CHIDIST}(\text{Log LR}, 1)$$

Number of parameters in model (=1 for exponential)

# Exercise 8.3c

- Calculate UCL and LCL for lambda:
  - Calculate Log LR for each (below)
  - Choose lambda for each to set Log LR = 0.1
    - Do by hand first, then use Solver to fine-tune

Maximum likelihood:			
	lambda	likelihood	Log LR
UCL	0.040632	-222.709	0.100001
estimate	0.03248	-221.357	1
LCL	0.025499	-222.709	0.100001

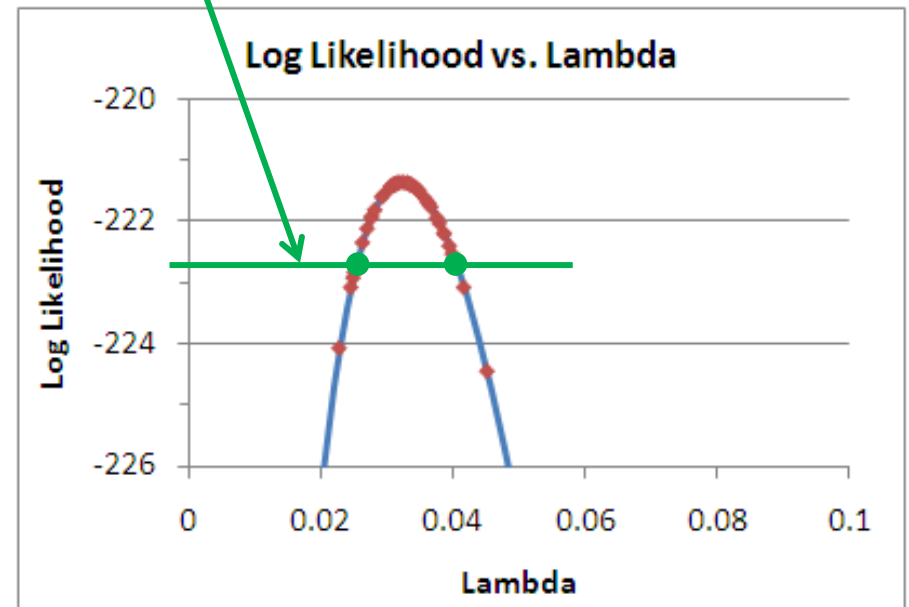
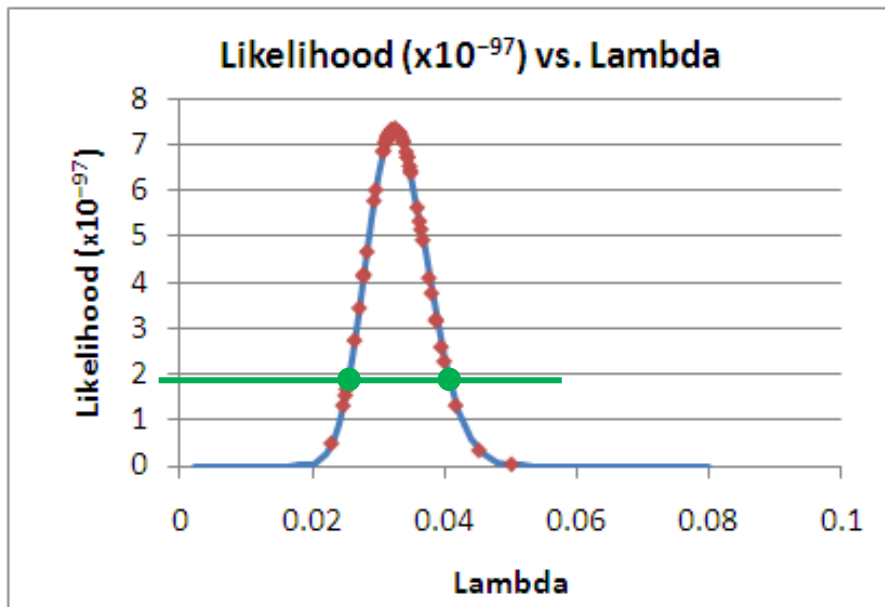
Likelihood of best estimate

Likelihood of UCL

$$=CHIDIST(2*(\$G\$8-G7), 1)$$

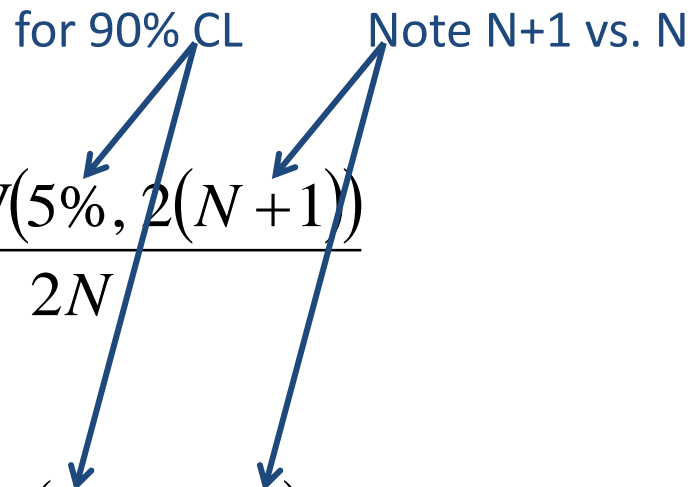
# Solution 8.3c

Maximum likelihood:			
	lambda	likelihood	Log LR
UCL	0.040632	-222.709	0.100001
estimate	0.03248	-221.357	1
LCL	0.025499	-222.709	0.100001



# Analytic Lambda Uncertainty

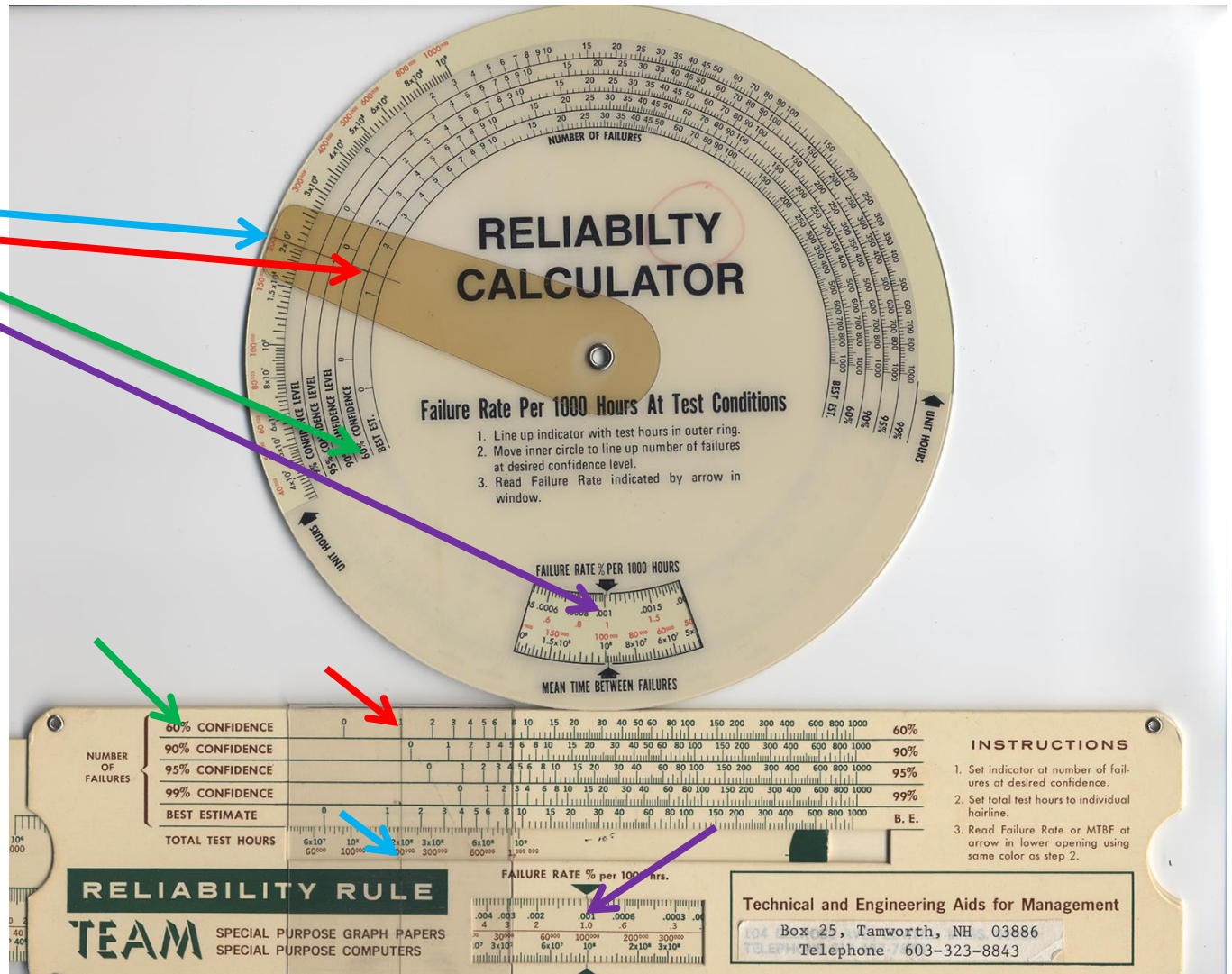
for 90% CL      Note N+1 vs. N

$$\lambda_{UCL} = \lambda_{BE} \frac{\text{CHIINV}(5\%, 2(N+1))}{2N}$$
$$\lambda_{LCL} = \lambda_{BE} \frac{\text{CHIINV}(95\%, 2N)}{2N}$$




# Venerable Calculation

Reliability Calculator	
Device hours	200
Fails	1
Confidence	60%
Fail rate (%/hr)	1.01%

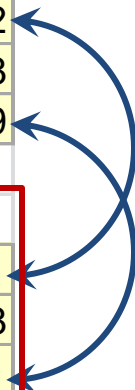


# Exercise 8.3d

- Calculate lambda UCL and LCL analytically

# Solution 8.3d

Maximum likelihood:	
	lambda
UCL	0.040632
estimate	0.03248
LCL	0.025499
Analytic:	
UCL	0.041111
estimate	0.03248
LCL	0.025311



# Exercise 8.4

- This is Tobias & Trindade problem 3.1
- How many units do we need to verify a 500,000 hr MTTF with 80% confidence, given that we can run a test for 2500 hours and 2 fails are allowed?
- Hint: you can do this by trial and error. Calculate the UCL on  $\lambda$  as a function of sample size  $SS$  and then adjust  $SS$  until the UCL equals the target  $\lambda$ .

# Solution 8.4

## Find sample size to meet a MTTF target

How many units do we need to verify a 500,000 hr MTTF with 80% confidence, given that we can run a test for 2500 hours and 2 fails are allowed?

1. Note that the target lambda as  $1/\text{MTTF}$ .
2. Note that all lambda values below are multiplied by 1,000,000 to make them easier to evaluate.
3. Guess at a sample size SS (>1) and list all other givens.
4. Calculate the point (best) estimate lambda\_BE as  $\text{fails} / (\text{hours} * \text{SS})$
5. Calculate the upper confidence value lambda\_UCL as  $\text{CHIINV}(1-\text{CL}, 2 * (\text{fails} + 1)) / (2 * \text{hours} * \text{SS})$
6. By trial and error, adjust SS until lambda\_UCL is as close as you can get to the target

MTTF	500000	
confidence level	80%	
hr	2500	
fails	2	
SS	855	=CHIINV(1-C12, 2*(C14+1))/(2*C13*C15) *1000000
lambda_target	2 / 1,000,000	=1/MTTF *10^6
lambda_BE	0.935673 / 1,000,000	=fails/(hours*SS) *10^6
lambda_UCL	2.001885 / 1,000,000	=CHIINV(1-CL, 2*(fails+1))/(2*hours*SS) *10^6

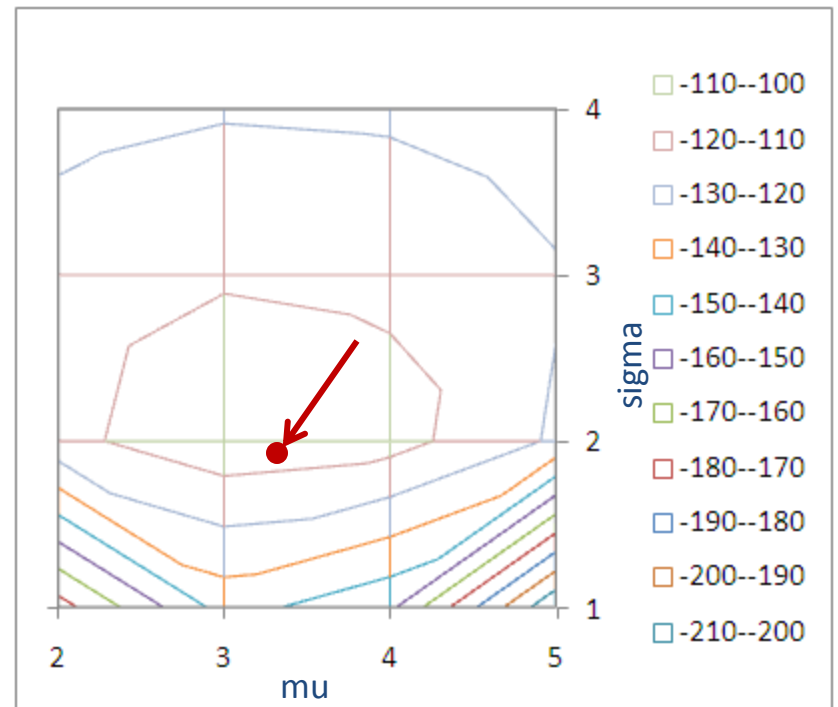
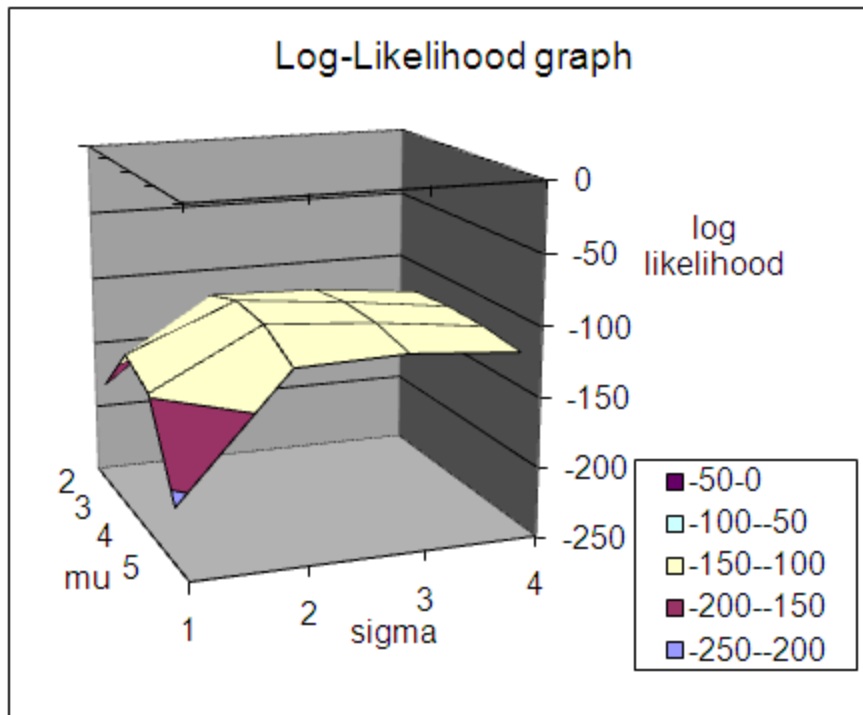
# Normal Distribution

## MLE and Analytic

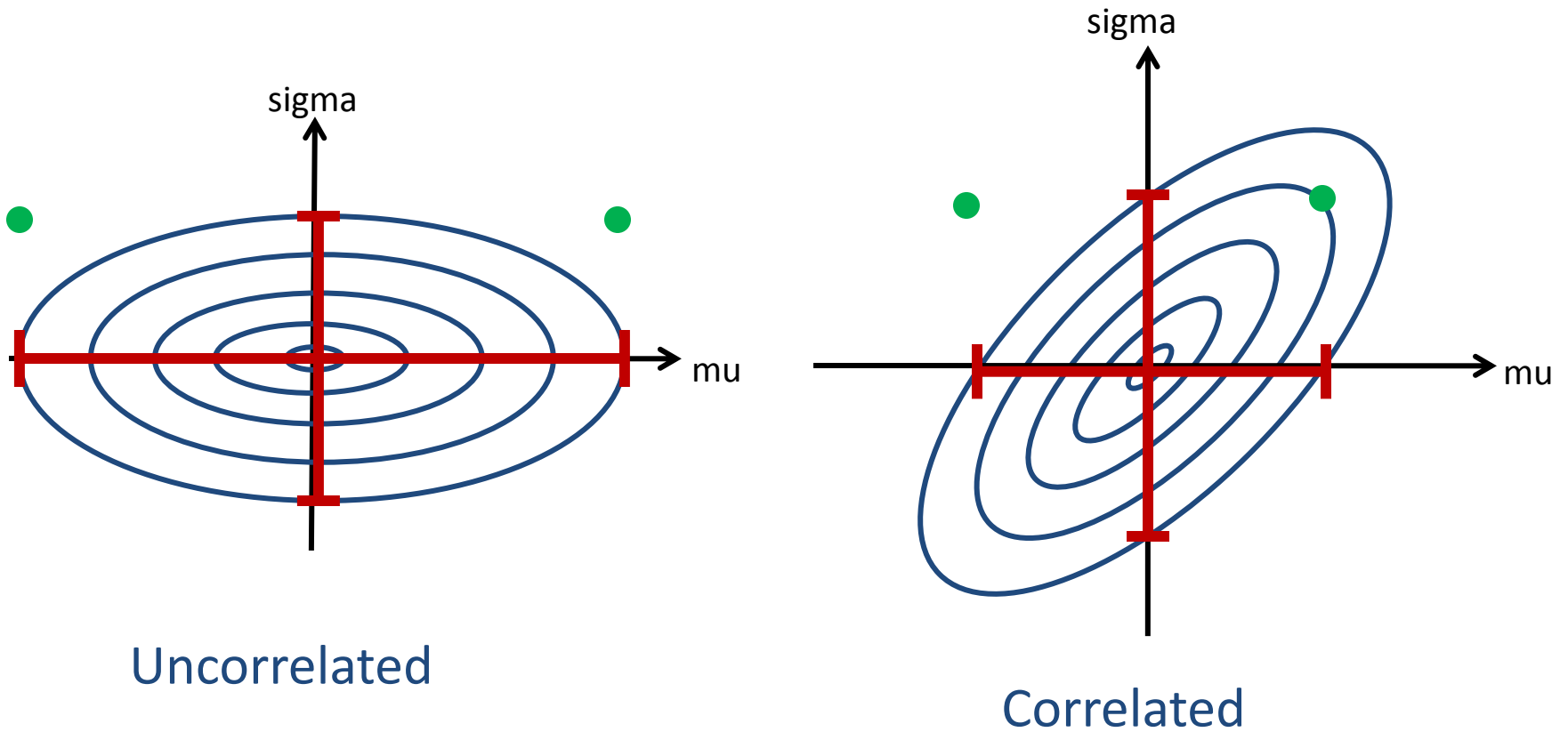
# MLE for the Normal

$$L_i = \ln(\text{NORMDIST}(\text{data}_i, \mu, \sigma, \text{false}))$$

↓ ↓



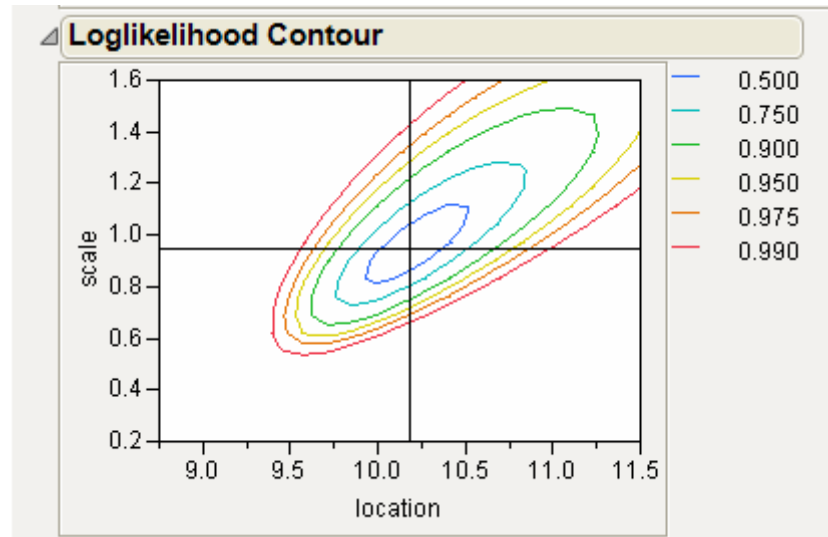
# 2D MLE



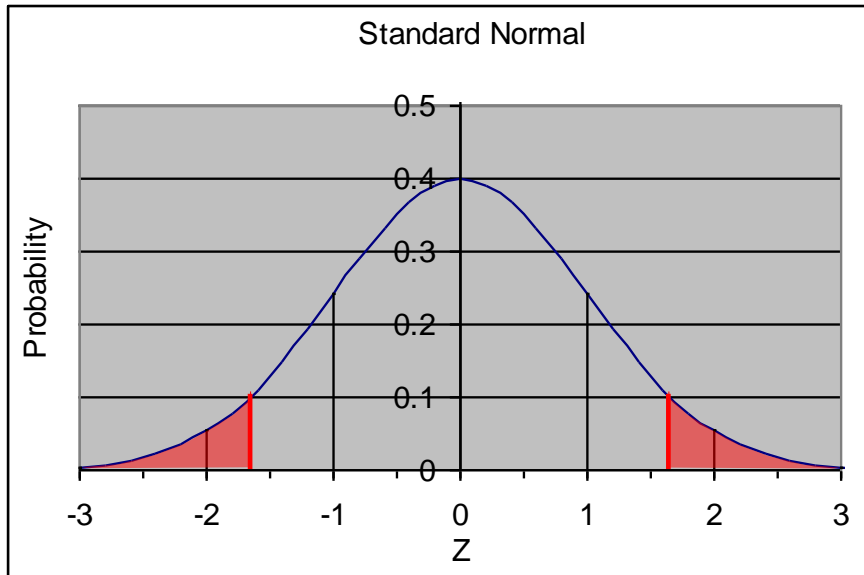
Described by covariance matrix



# JMP MLE Correlations



# Analytic Uncertainty of Mean



Z-statistic:

$$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}}$$

$\bar{X}$  = sample mean

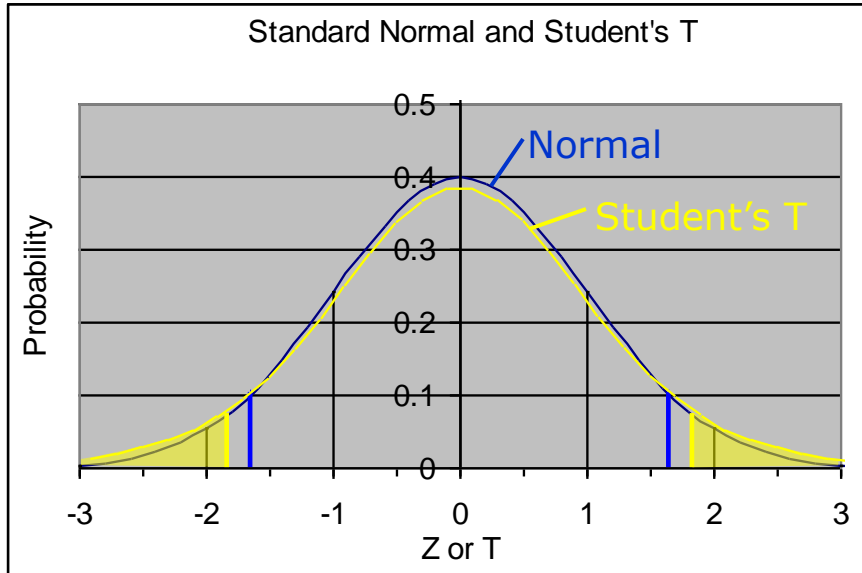
$\mu$  = population mean

$\sigma$  = population stdev

$n$  = sample size

- Using a *Z-statistic* is exactly equivalent to the previous slides
  - Gives error in  $\bar{X}$  in units of  $\sigma/\sqrt{n}$
- (Note that we need the true population standard deviation)

# Analytic Uncertainty of Mean



T-statistic:

$$T = \frac{\bar{X} - \mu}{S/\sqrt{n}}$$

$\bar{X}$  = sample mean

$\mu$  = population mean

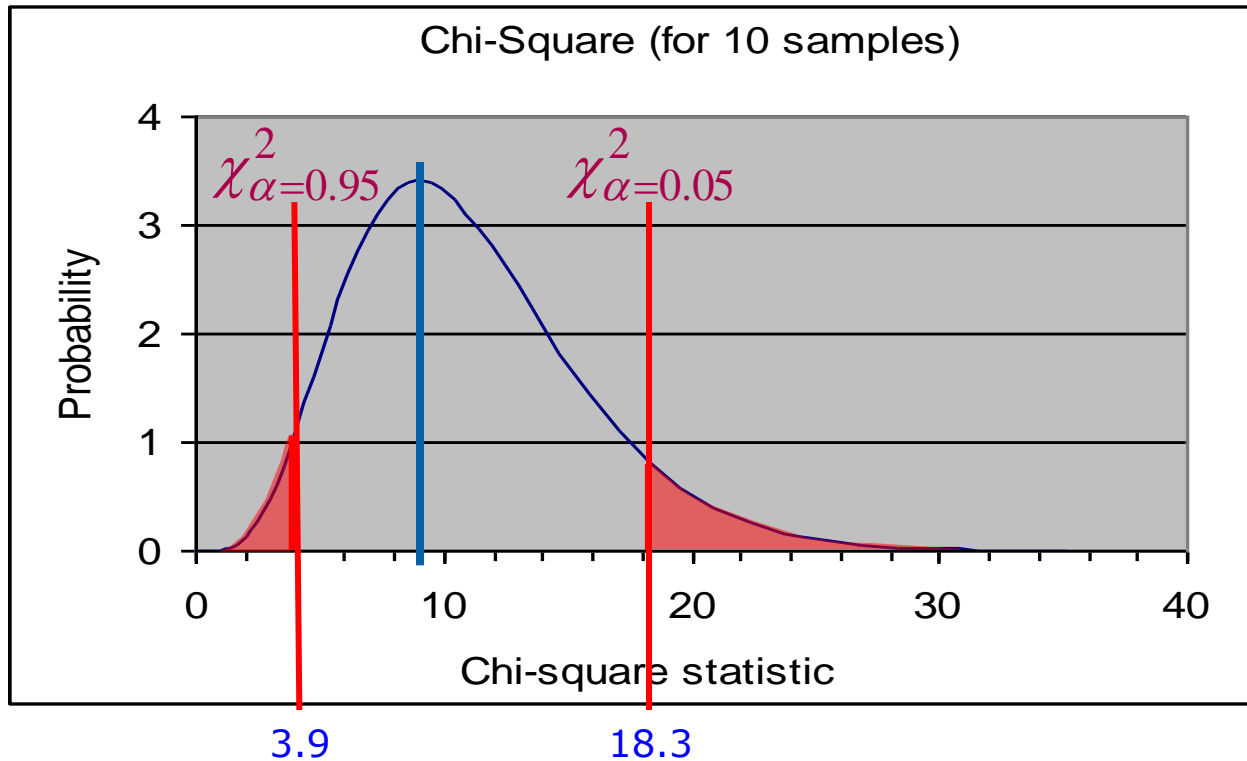
$S$  = sample stdev

$n$  = sample size

- Similar to *Z-statistic* but
  - Gives error in  $\bar{X}$  in units of  $S/\sqrt{n}$
- Preferred over *Z* because true  $\sigma$  is usually not known
- Calculate  $\mu$  range from:

$$\bar{X} - \frac{t_{\alpha/2, n-1} S}{\sqrt{n}} \leq \mu \leq \bar{X} + \frac{t_{\alpha/2, n-1} S}{\sqrt{n}}$$

# Analytic Uncertainty of Standard Deviation



Chi<sup>2</sup> statistic:

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

$S$  = sample stdev

$\sigma$  = population stdev

$n$  = sample size

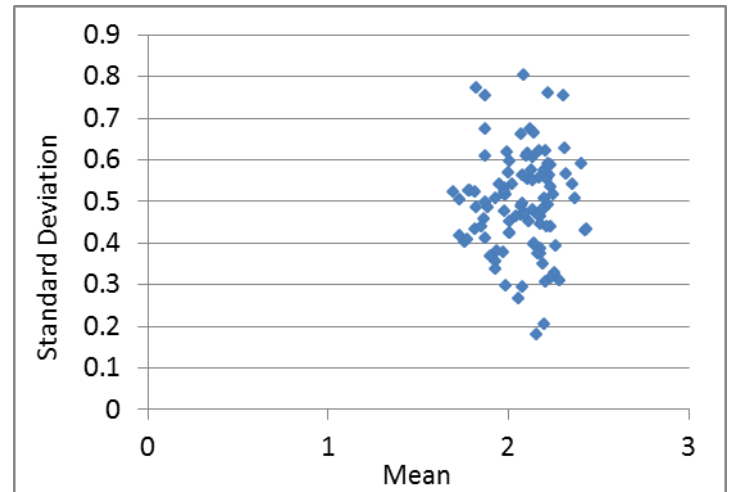
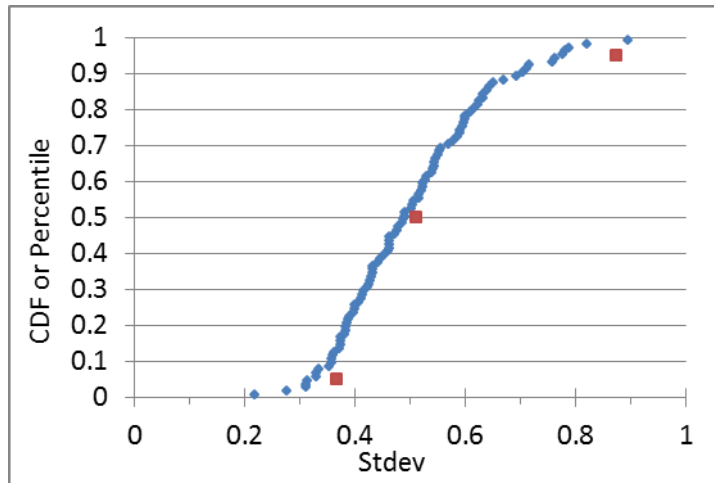
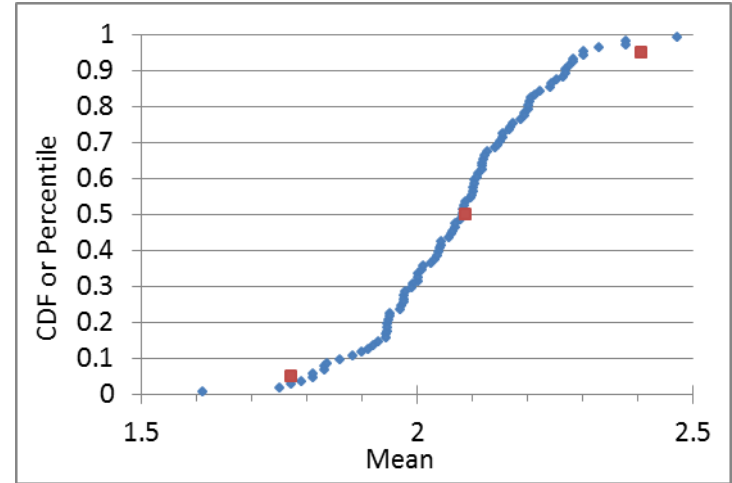
- Gives error as ratio of sample variance / pop variance (times n-1)
- Distribution of chi<sup>2</sup> statistic follows a chi<sup>2</sup> distribution
- Calculate  $\sigma^2$  range from: 
$$\frac{(n-1)S^2}{\chi_{\alpha/2, n-1}^2} \leq \sigma^2 \leq \frac{(n-1)S^2}{\chi_{1-\alpha/2, n-1}^2}$$

# Exercise 8.5a

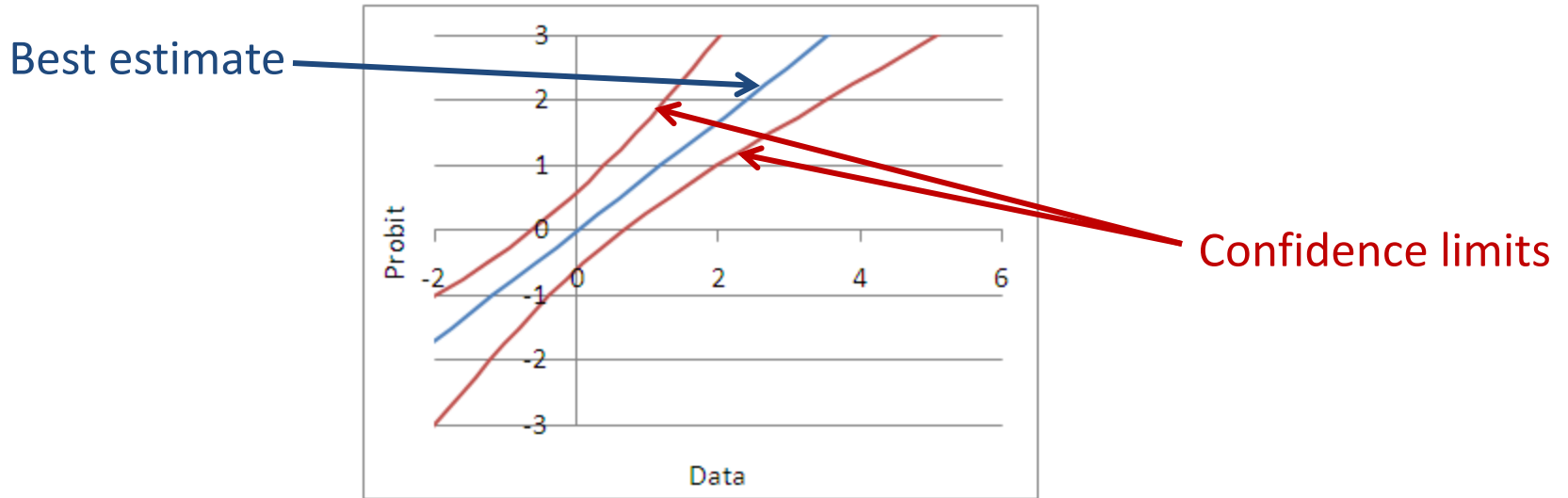
- For the 9 data points given, extract  $\mu$ ,  $\sigma$ , and their 95% confidence intervals.

# Solution 8.5a

Mean	$=G7 + T.INV(C4, C5-1) * G13 / SQRT(C5)$	
Name	Percentile	Value
UCL	95%	2.40531
Best Est	50%	2.088376
LCL	5%	1.771442
$=SQRT((\$C\$5-1) * \$G\$13^2 / CHIINV(F12, \$C\$5-1))$		
Standard Deviation		
Name	Percentile	Value
UCL	95%	0.874856
Best Est	50%	0.511308
LCL	5%	0.367248



# Normal Distribution Uncertainties



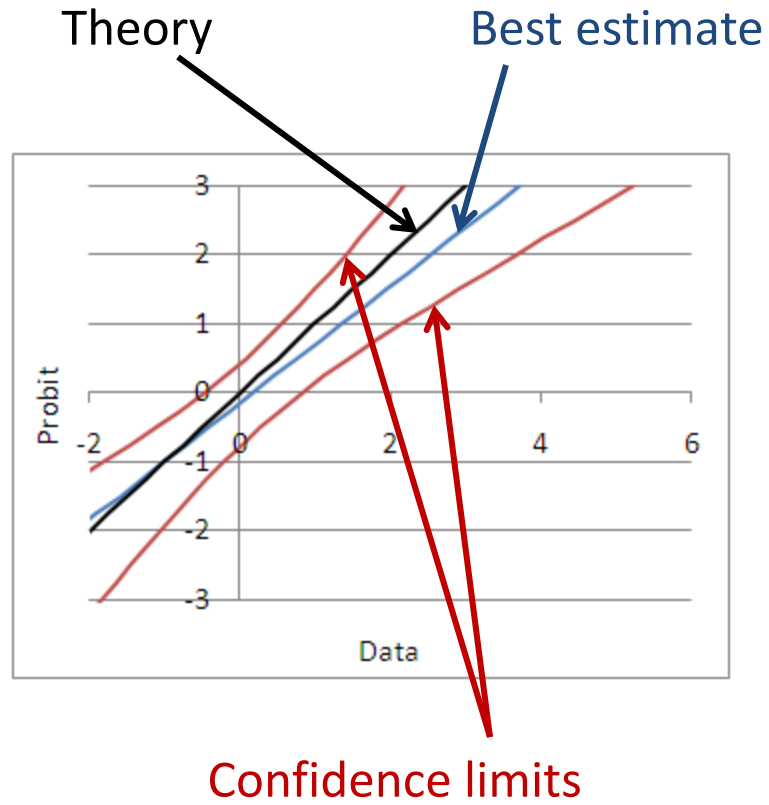
	Best estimate	Uncertainty
Mean $\mu$	$\mu = \text{AVERAGE}(\text{data})$	$m = \text{NORMSINV}(\text{CL}) * \sigma / \text{SQRT}(N)$
Stdev $\sigma$	$\sigma = \text{STDEV}(\text{data})$	$s = \sigma * (\text{SQRT}(\text{CHIINV}(1-\text{CL}, N-1) / (N-1)) - 1)$
Percentil e	$\mu + z * \sigma$	$\text{UCL} = \mu + z * \sigma + \text{SQRT}(m^2 + z^2 * s^2)$ $\text{LCL} = \mu + z * \sigma - \text{SQRT}(m^2 + z^2 * s^2)$

CL = confidence level (e.g., 95%)

z = probit value at which to evaluate distribution (e.g., -2)

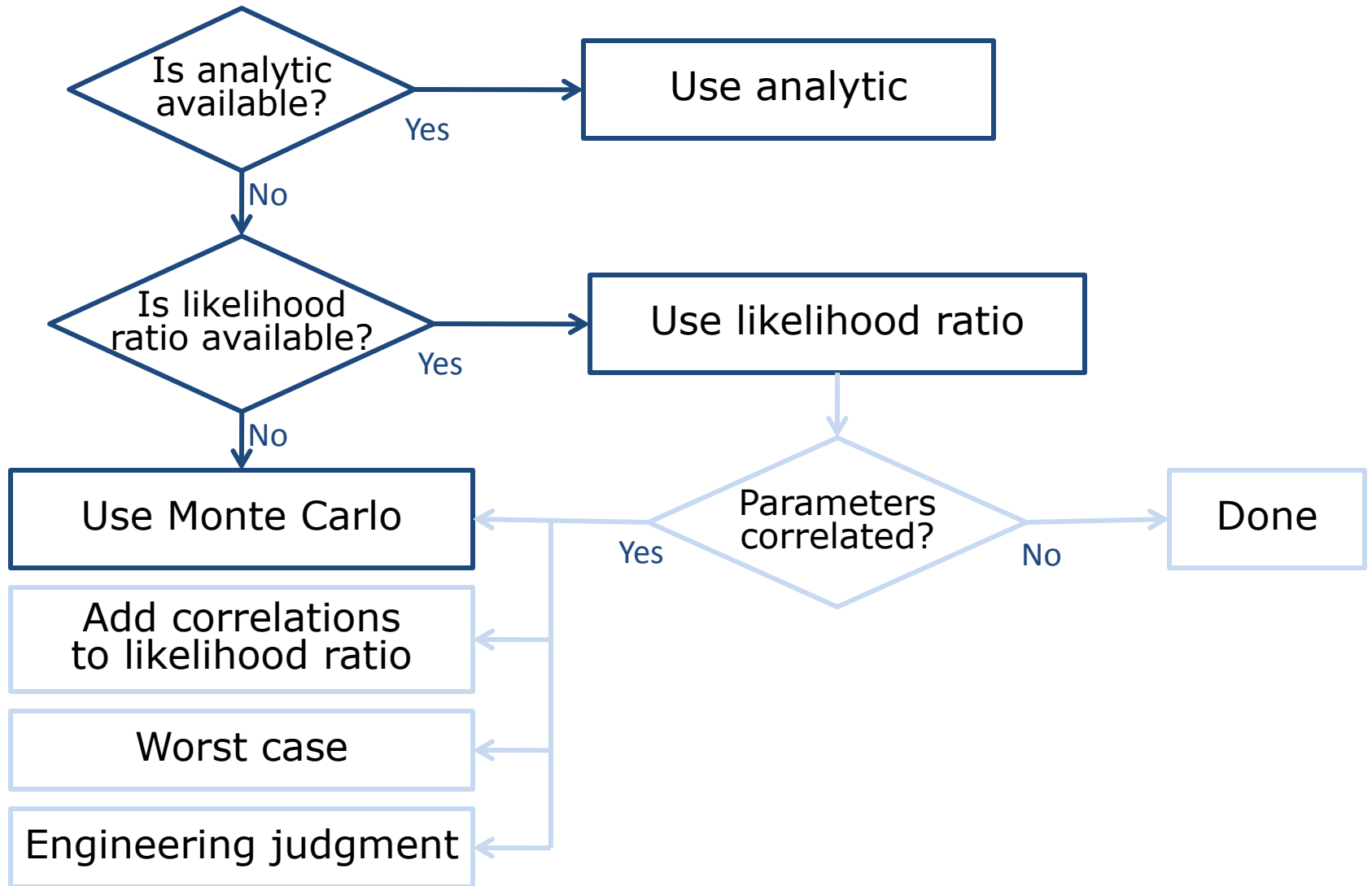
N = number of samples in data set

# Exercise 8.5b



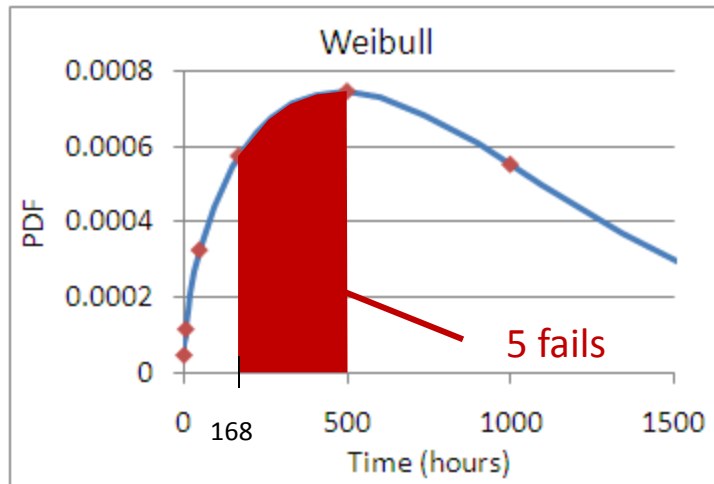


# Calculation Method Flowchart



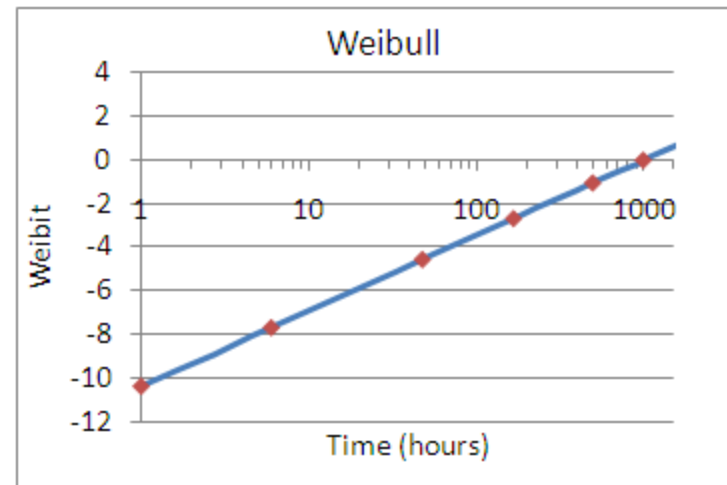
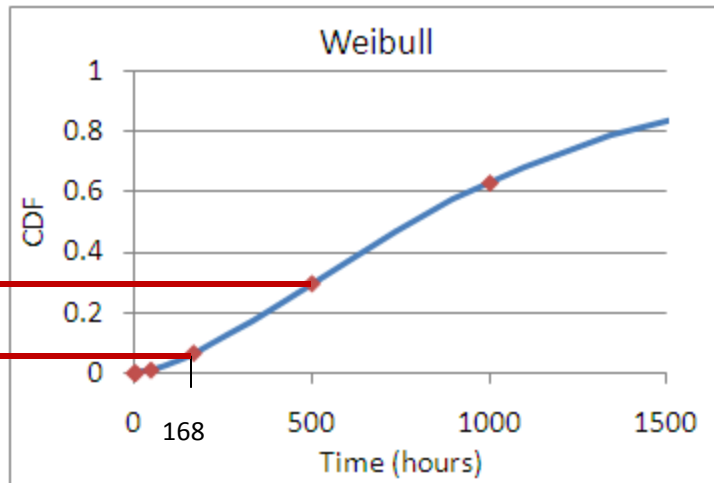
# Weibull MLE with Readout Data

# Weibull Readout Data



$$LIK = [F(500) - F(168)]^5$$

$$L = 5 \cdot \ln[F(500) - F(168)]$$

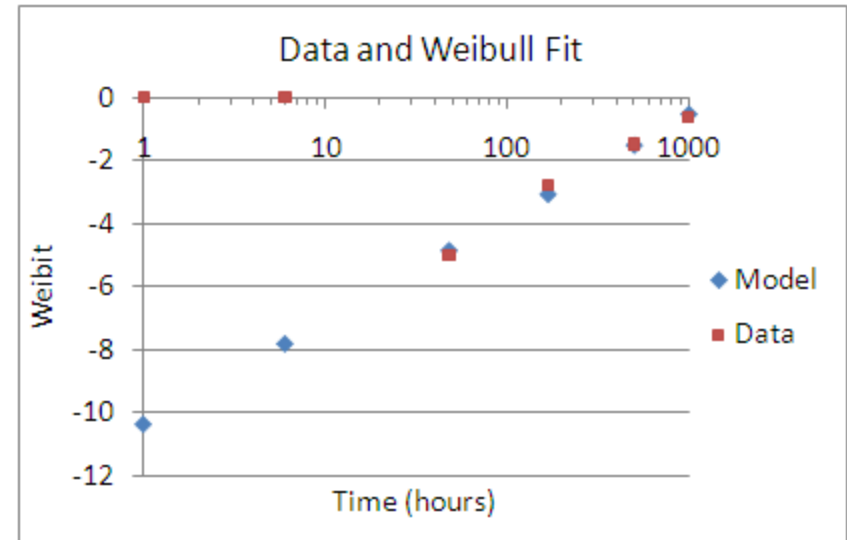


# MLE for Weibull

Vary these to maximize this

shape	1.2
lifetime	1500
SS	300

time	fails	model F	L
0		0	
1	0	0.000154	0
6	0	0.001325	0
48	2	0.015948	-8.45037
168	16	0.069736	-46.763
500	43	0.234771	-77.4687
1000	63	0.459218	-94.1294
survivors	176	0.540782	-108.194
		Ltotal	-335.006



$$L = \sum_{r=1}^R [n_r \cdot \ln \{F(t_r) - F(t_{r-1})\} + d_r \cdot \ln S(t_r)] + s_R \ln S(t_R)$$

$$F(t) = 1 - \exp \left\{ - \left( \frac{t}{\alpha} \right)^\beta \right\}$$

$$S(t) = \exp \left\{ - \left( \frac{t}{\alpha} \right)^\beta \right\}$$

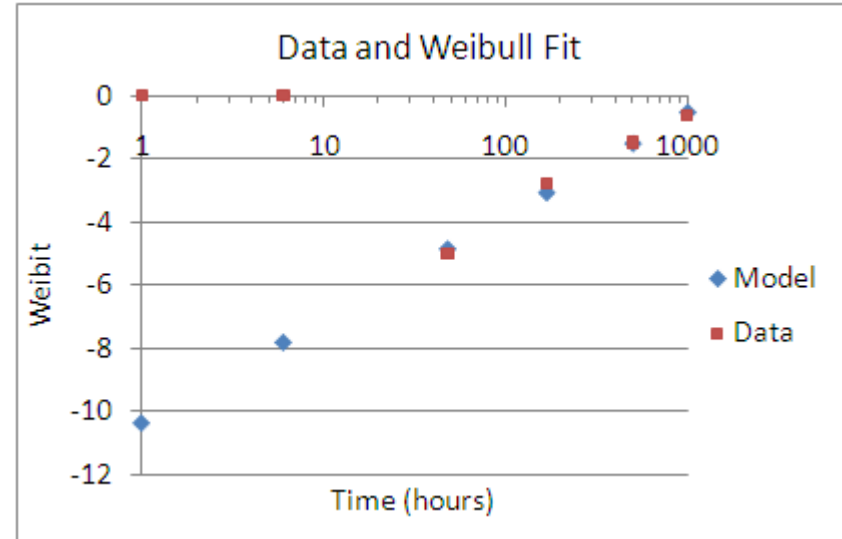
# Exercise 8.6a

- Use MLE to determine Weibull fit parameters for the readout data given below and on the Ex16 tab.
- Also, find (separate) 90% confidence intervals for each parameter using the likelihood ratio technique. (That is the confidence where the  $LR=0.1$ .)

time	fails
0	
1	0
6	0
48	2
168	16
500	43
1000	63

# Solution 8.6a

		LCL	Best	UCL		
shape	1.260344	1.117712	1.260344	1.413664		
lifetime	1642.709	1464.712	1642.709	1852.951		
SS	300					
					Weibits	
time	fails	model F	L	data F	Data	Model
0		0				
1	0	8.86E-05	0	0	#NUM!	-9.331715
6	0	0.000847	0	0	#NUM!	-7.073482
48	2	0.01158	-9.06888	0.006667	-5.00729	-4.45267
168	16	0.054921	-50.2186	0.06	-2.78263	-2.873758
500	43	0.200137	-82.9697	0.203333	-1.4814	-1.499171
1000	63	0.414306	-97.0824	0.413333	-0.62867	-0.625567
survivors	176	0.585694	-94.1526	0.586667		
		Ltotal	-333.492			



# Exercise 8.6b

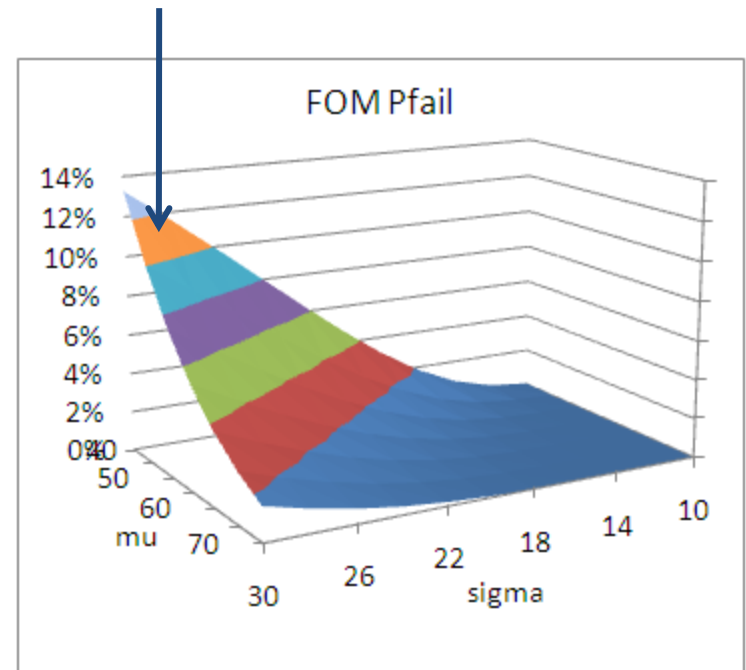
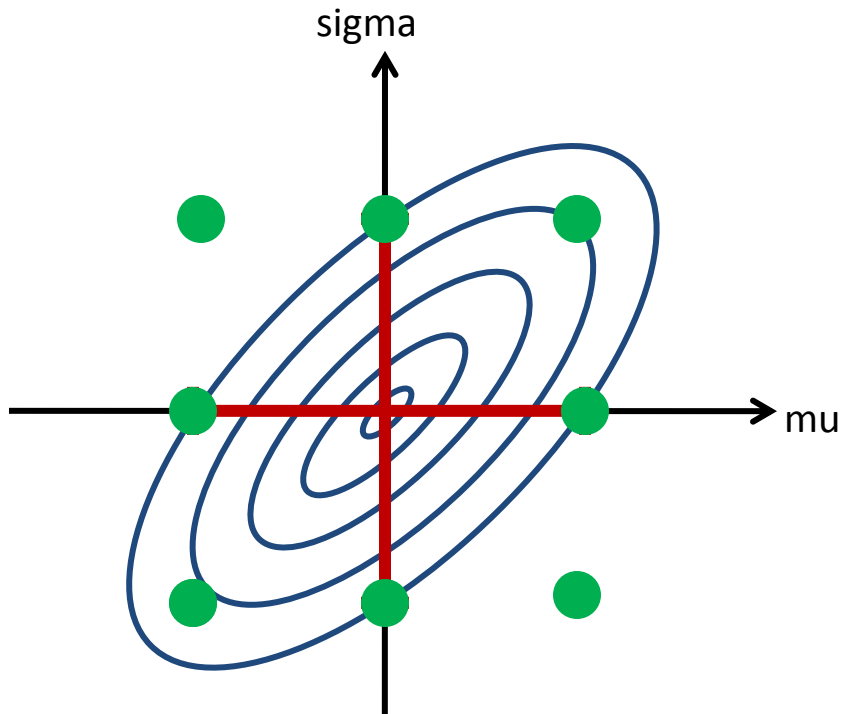
- Add a chi-square goodness-of-fit test to your fit from part (a). Recall that the bins should have more than about 5 fails each, so you will need to combine the first few readouts into 1 bin. So we do things the same way, combine the first 3 readouts into 1 bin, even though they only have 2 total fails.

# Solution 8.6b

time	fails	model F	L	data F	Weibits		Goodness of fit test		
					Data	Model	pred fails	chi-sq stat	
0		0							
1	0	8.86E-05	0	0	#NUM!	-9.331715			
6	0	0.000847	0	0	#NUM!	-7.073482			
48	2	0.01158	-9.06888	0.006667	-5.00729	-4.45267	3.473957	0.625382	
168	16	0.054921	-50.2186	0.06	-2.78263	-2.873758	13.0022	0.691176	
500	43	0.200137	-82.9697	0.203333	-1.4814	-1.499171	43.56502	0.007328	
1000	63	0.414306	-97.0824	0.413333	-0.62867	-0.625567	64.25062	0.024343	
survivors	176	0.585694	-94.1526	0.586667			175.7082	0.000485	
		Ltotal	-333.492				chi-sq	1.348713	
							dof	2	
							p-value	0.509484	pass



# Confidence and Figures of Merit



# Exercise 8.6c

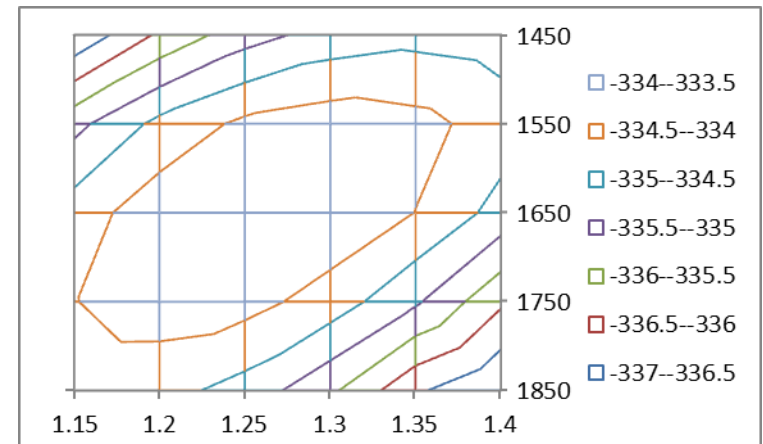
- Use the pfail at 2000 hours as the FOM for the Weibull model of 8.6. Evaluate this pfail as a function of the shape and lifetime parameters.
- Try various corners of the “space” of shape and lifetime values and find the worst case corner. Report these values as your worst case shape and lifetime values.

# Solution

		LCL	Best	UCL		Worst case		FOM time	2000
shape	1.413664	1.117712	1.260344	1.413664		1.4136642		FOM pfail	0.788438
lifetime	1464.712	1464.712	1642.709	1852.951		1464.7121			0.722
SS	300								

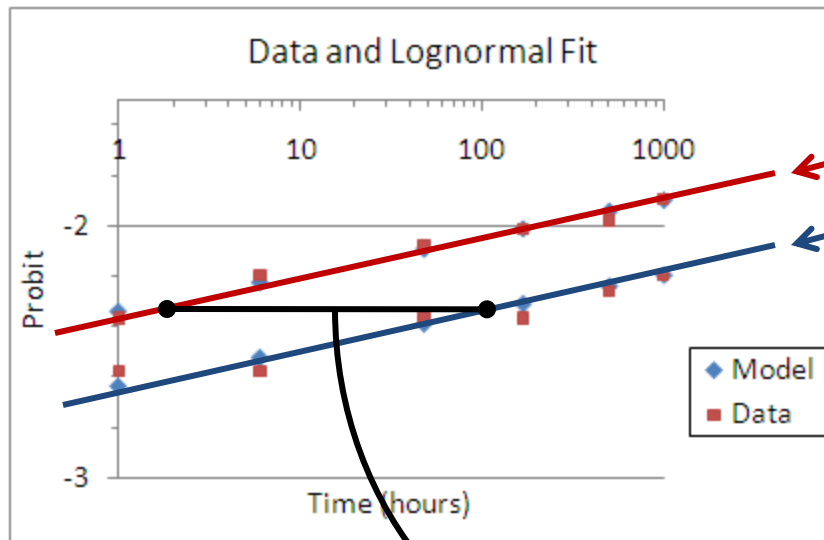
Ltotal	-334.69
best L	-333.492
LR p-value	0.121738

	1.15	1.2	1.25	1.3	1.35	1.4
1450	-336.92	-335.908	-335.208	-334.798	-334.656	-334.764
1550	-335.151	-334.357	-333.889	-333.724	-333.84	-334.218
1650	-334.247	-333.702	-333.497	-333.606	-334.008	-334.684
1750	-334.016	-333.741	-333.817	-334.22	-334.926	-335.915
1850	-334.314	-334.321	-334.691	-335.397	-336.417	-337.728



# Acceleration Calculations

# Acceleration



$F(t)$  at high  $T$  ( $T_{stress}$ )

$F(t)$  at low  $T$  ( $T_{use}$ )

$$AF = \exp \left\{ \left( \frac{E_a}{k} \right) \times \left( \frac{1}{T_{use}} - \frac{1}{T_{stress}} \right) \right\}$$

# Acceleration MLE

Now vary these

3

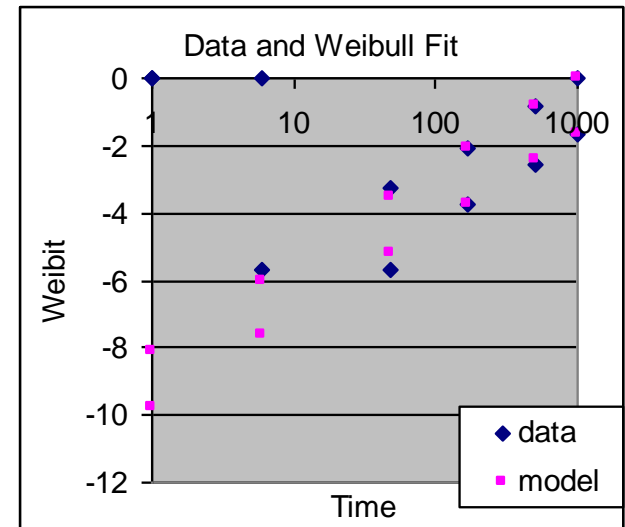
shape	1.176941
lifetime	4036.87
Ea	0.797264
Tref	80
SS	300

$$AF = \exp \left\{ \left( \frac{E_a}{k} \right) \times \left( \frac{1}{T_{ref} + 273} - \frac{1}{T + 273} \right) \right\}$$

$$t_{eff} = AF \times t_{clock}$$

	T	time_clock	fails	time_eff	model F	log-likelihood
leg1	80	0	0	0	0	-614.108115
	80	1	0	1	5.7E-05	0
	80	6	0	6	0.000469	0
	80	48	1	48	0.005413	-5.3096733
	80	168	6	168	0.023432	-24.0978516
	80	500	15	500	0.08203	-42.5559058
	80	1000	31	1000	0.175945	-73.3263981
leg2	100	0	0	0	0	-614.108115
	100	1	0	4.072326	0.000298	0
	100	6	1	24.43396	0.002449	-6.14171667
	100	48	10	195.4716	0.02794	-36.6941477
	100	168	24	684.1508	0.116439	-58.1942923
	100	500	72	2036.163	0.360369	-101.583041
	100	1000	84	4072.326	0.635907	-108.27857
leg1	80		survivors	247	0.824055	-47.7988956
leg2	100		survivors	109	0.364093	-110.127623

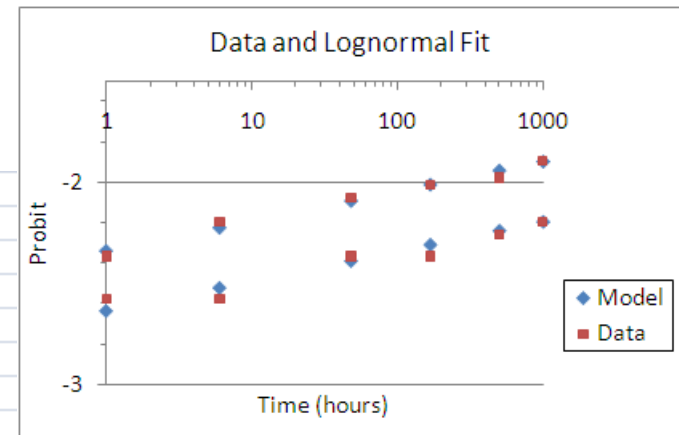
$$F(t) = 1 - \exp \left\{ - \left( \frac{t_{eff}}{\alpha} \right)^\beta \right\}$$



# Exercise

- Do an MLE to get the 3 parameters ( $\mu$ ,  $\sigma$ , and  $E_a$ ) for a lognormal model of times to fail with an Arrhenius temperature acceleration for the data in tab Ex17.
- Also do a goodness-of-fit test to see if the lognormal is a good fit to the data.
- Also determine 90% confidence limits on all 3 parameters (separately).
- Use a FOM of 1 year at  $T=75$  and find what the conservative combination of confidence limits is.

# Solution



			-278.701						
		LCL	Best	UCL		FOM time	8760		
mu	41.15301	39.57157	41.15301	42.81081		FOM T	75		
sigma	15.59689	14.84208	15.59689	16.39438		FOM t_eff	517.0626		
Ea	1.267126	0.695541	1.267126	1.808363		FOM pfail	0.012613		
Tref	100								
SS	1000		LR p-value	0.999834					

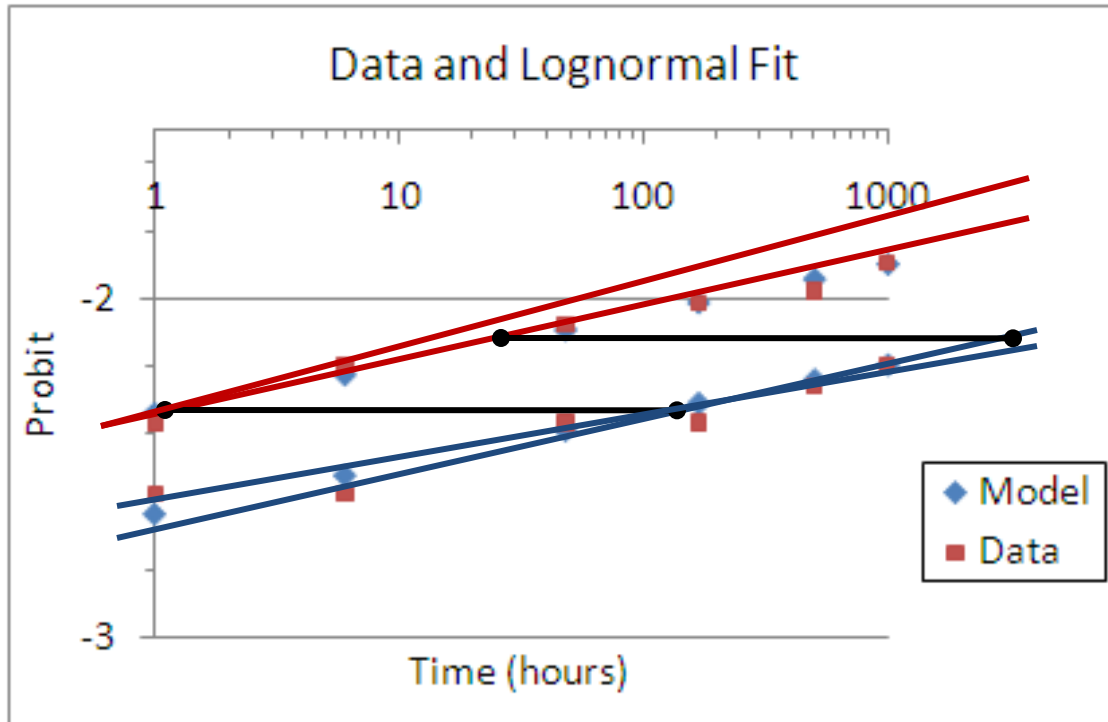
					-278.701	Probits		Goodness of fit test		
T	time_clock	fails	time_eff	model F	L	data F	Data	Model	pred fails	chi-sq stat
leg1	0		0	0						
100	1	5	1	0.004163	-27.4074	0.005	-2.57583	-2.63854	4.163201	0.168196
100	6	0	6	0.005807	0	0.005	-2.57583	-2.52366		
100	48	4	48	0.008416	-23.7944	0.009	-2.36562	-2.39034	4.25328	0.015083
100	168	0	168	0.010444	0	0.009	-2.36562	-2.31001		
100	500	3	500	0.012543	-18.499	0.012	-2.25713	-2.24009		
100	1000	2	1000	0.014059	-12.9833	0.014	-2.19729	-2.19565	5.642151	0.073085
leg2										
150	1	9	105.2628	0.009642	-41.7745	0.009	-2.36562	-2.33999	9.642155	0.042767
150	6	5	631.5765	0.013037	-28.4276	0.014	-2.19729	-2.22511	3.394783	0.759025
150	48	5	5052.612	0.018229	-26.3033	0.019	-2.07485	-2.09179	5.191912	0.007094
150	168	3	17684.14	0.022138	-16.6331	0.022	-2.01409	-2.01146	3.90937	0.211531
150	500	2	52631.38	0.026097	-11.0639	0.024	-1.97737	-1.94154	3.958352	0.968874
150	1000	5	105262.8	0.028908	-29.371	0.029	-1.8957	-1.8971	2.811069	1.704482
leg1	survivors	986		0.985941	-13.9602				985.9414	3.49E-06
leg2	survivors	971		0.971092	-28.483				971.0924	8.78E-06

		LCL	Best	UCL		FOM time	8760		
mu	39.57157	39.57157	41.15301	42.81081		FOM T	75		
sigma	16.39438	14.84208	15.59689	16.39438		FOM t_eff	1853.156		
Ea	0.695541	0.695541	1.267126	1.808363		FOM pfail	0.025306	0.0126	

chi-sq	3.950149
dof	7
p-value	0.785501



# Is Acceleration Valid?



# Likelihood Ratio Test

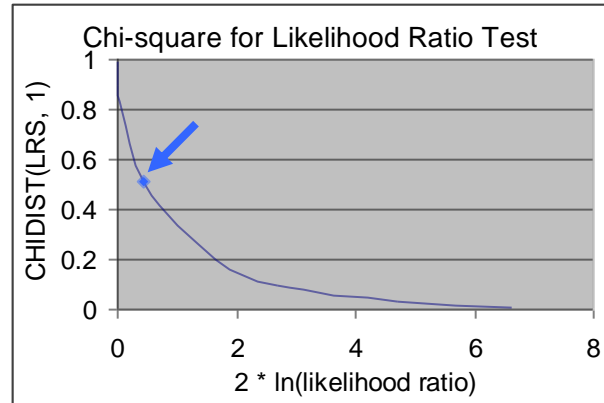
Likelihood ratio statistic:

$$LR = 2 \times (\ln L_1 - \ln L_2)$$

Chi-square distributed:

$$\begin{aligned} CHIDIST(LR, \Delta DoF) \\ = CHIDIST(0.43, 1) = 0.51 \text{ (likely)} \end{aligned}$$

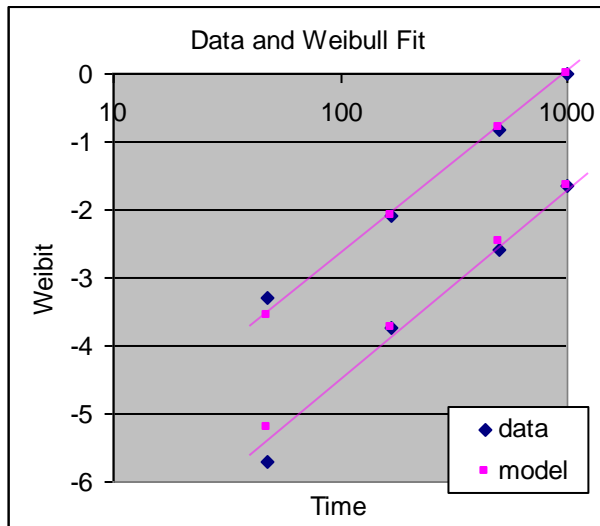
p-value



Acceleration is valid

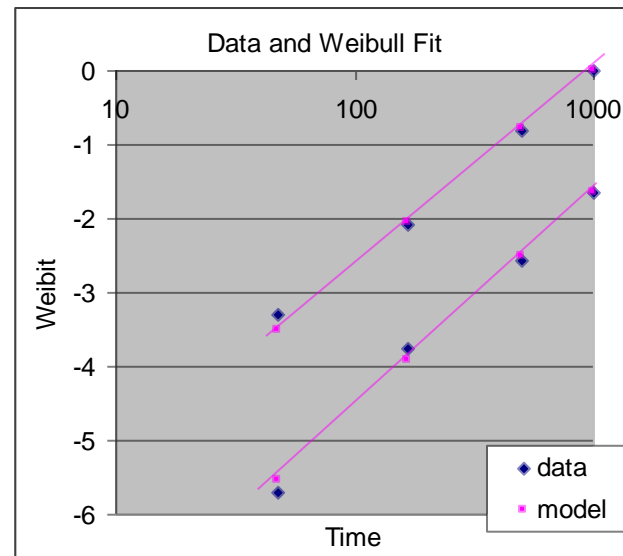
## Case 1: One Distribution

shape	1.176943	log L <sub>1</sub> =	-614.108
lifetime	4036.862		
Ea	0.797262		



## Case 2: Separate Distributions

leg1	shape	1.281392	-192.912	Leg1
	lifetime	3592.847	-420.981	Leg2
leg2	shape	1.154944	log L <sub>2</sub> = -613.893	
	lifetime	4071.605		



# Likelihood Ratio Test

Likelihood ratio statistic:

$$LR = 2 \times (\ln L_1 - \ln L_2)$$

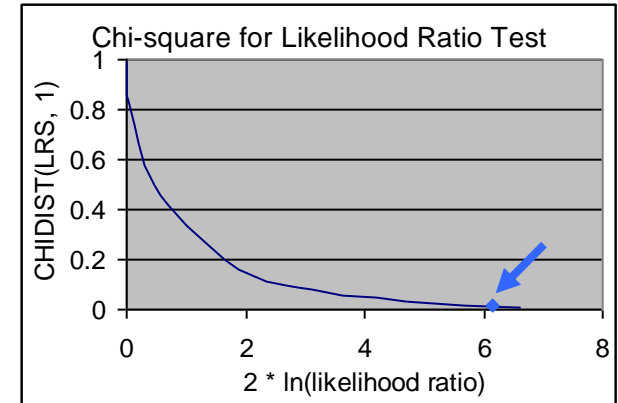
Chi-square distributed:

$$CHIDIST(LR, \Delta DoF)$$

$$= CHIDIST(6.17, 1) = 0.013 \text{ (not likely)}$$

p-value

Acceleration is **not** valid



## Case 1: One Distribution

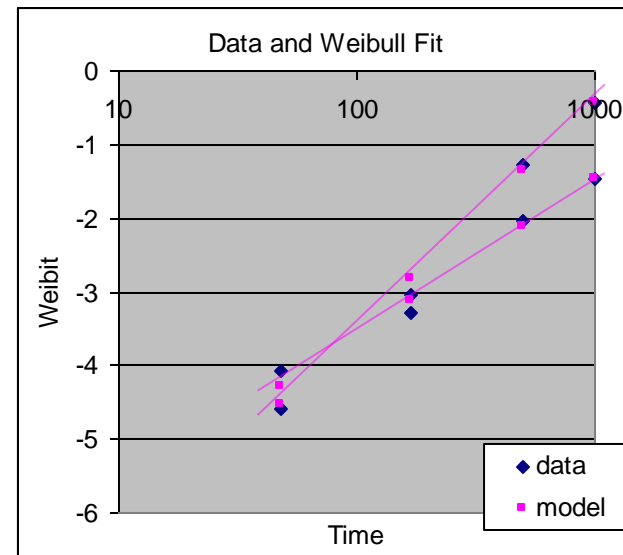
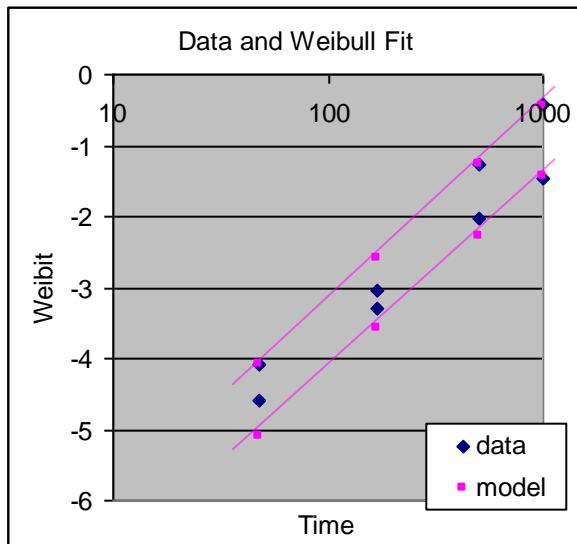
shape	1.198326
lifetime	3344.311
Ea	0.475108

$$\log \Gamma_1 = -580.91$$

## Case 2: Separate Distributions

leg1	shape	0.933166
	lifetime	4782.319
leg2	shape	1.350774
	lifetime	5607.301

-226.744	Leg1
-351.081	Leg2

$$\log \Gamma_2 = -577.826$$


# Exercise b

- Do a likelihood ratio test to see if the acceleration concept is valid for the Ex17 data set. You will have to use 2 separate likelihood sums and two sets of mu and sigma parameters with no  $E_a$ , and compare that to what you have for part (a).







