Chapter 8 (More on Assumptions for the Simple Linear Regression)

Chapter 8 covers the assumptions behind the SLR, and some alternative models that can be used. One of those alternatives involves the use of transformations to fit data that does not form a straight line when plotted.

Examples of curves: The exponential model (exponential growth and decay or mortality model)



Increasing line: $b_0 = 2$, $b_1 = +0$. 953, $e^{b_1} = 1.1$

For this model the raw data should actually appear non-homogeneous

- The equation is $Y_i = b_0 exp^{b_1X_i}e_i$, taking logs we get $ln(Y_i) = ln(b_0) + b_1X_i + ln(e_i)$. This is a simple linear regression where the dependent variable is $ln(Y_i)$ and the independent variable is X_i . Once fitted the estimated slope is equal to b_1 . The estimated intercept is $ln(b_0)$ and the antilog must be taken to get back to the original equation ($Y_i = b_0 exp^{b_1X_i}e_i$).
- When fitted in SAS the model would be "MODEL LY = X;" where LY is the log of the Y variable and X is the unaltered X variable. These transformations must be done in the data step; they cannot be done in the proc step.
- When the model is fitted on the log transformed data all of the usual assumptions apply. However, they apply to the log transformed version of the data, not to the raw data. Also, all tests of hypothesis and confidence intervals must be done on the log transformed data. Once all estimates of parameters, predicted values and confidence intervals are done they can be detransformed. Standard errors cannot be detransformed, so any estimates and confidence intervals must be done on the log transformed data.

In general, when the dependent variable, Y, is transformed the homogeneity is altered. If only the independent variable, X, is altered then the homogeneity is unchanged.

Another examples of curves: The power model



Values of b₀ and b₁: (29, -1), (19, 0), (4, 0.5), (1, 1), (0.03, 2)

For this model the raw data should appear non-homogeneous

- The equation is $Y_i = b_0 X_i^{b_1} e_i$, taking logs we get $ln(Y_i) = ln(b_0) + b_1 ln(X_i) + ln(e_i)$. This is a simple linear regression where the dependent variable is $ln(Y_i)$ and the independent variable is $ln(X_i)$. Once fitted the estimated slope is equal to b_1 . The estimated intercept is $ln(b_0)$ and the antilog must be taken to get back to the original equation ($Y_i = b_0 exp^{b_1 X_i} e_i$).
- When fitted in SAS the model would be "MODEL LY = LX;" where LY is the log of the Y variable and LX is the log of the X variable. These transformations must be done in the data step; they cannot be done in the proc step.



The example offered in your books is of the power model type above. In this example biologists have noted a possible relationship between the size of an island and the number of species of animals and plants on that island. The data in this example are for reptile and amphibian species on seven islands in the West Indies. Results for this analysis are given below.

Obs	AREA	SPECIES	Name
1	44218	100	Cuba
2	29371	108	Hispaniola
3	4244	45	Jamaica
4	3435	53	Puerto Rico
5	32	16	Monserrat
6	5	11	Saba
7	1	7	Redonda

According to the biologists the "relation" between species and islands is given by the formula $Median\{S|A\} = CA^{\gamma}$. If this model is fitted using logs we have $Log(Median\{S|A\}) = log(C) + \gamma*log(A)$. When estimated with SAS we get estimates of log(C) = 1.93651 and $\gamma = 0.24968$. Lower and upper limits of the confidence interval on the parameter γ are 0.21856 and 0.28080, respectively.

- This model is used for many other purposes. In instrument standardization, where two instruments are compared for readings on a range of standards this model is often used. If the two instruments match perfectly the model, $Y=b_0X^{b_1}$ becomes Y=X where $b_0=1$ and $b_1=1$. Note that this model always goes through the intercept, so when X = 0 then Y = 0.
- This model is also used for fitting morphometric relationships in the biological sciences. These are relationships between the body parts of organism. For example, in various studies biologists will use total length or thoracic length to measure shrimp, or total length or fork length to measure fish. Subsequently, conversion formulas are needed to compare across studies. Paleontologists predict the size of dinosaurs from a few bones because the relationship between total size and selected bones, say the femur, is known for similar animals. A related use is the prediction of body mass from linear measurements. When comparing linear measurements with the equation $Y=b_0X^{b1}$, the power term (b₁) is expected to be 1, relating cm to cm. However, for body mass, relating gm to cm we expect the power term to be approximately 3, since gm must be related to cm³.

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1 Biologists have noted a possible relationship between the size of an island 2 and the number of species of animals and plants on that island. The data in 3 this example are for reptile and amphibian species on seven islands in the 4 5 West Indies. 6 */ 7 8 dm'log;clear;output;clear'; 9 options nodate nocenter nonumber ps=512 ls=99 nolabel; 10 ODS HTML style=minimal rs=none 10 ! body='C:\Geaghan\Current\EXST3201\Fall2005\SAS\IsleSpecies01.html' ; NOTE: Writing HTML Body file: C:\Geaghan\Current\EXST3201\Fall2005\SAS\IsleSpecies01.html 11 12 Titlel 'Chapter 8: Correlation between the size of an island and the number of species' 12 !; filename input1 'C:\Geaghan\Current\EXST3201\Datasets\ASCII\case0801.csv'; 13 14 data Islands; infile input1 missover DSD dlm="," firstobs=2; 15 input AREA SPECIES; 16 17 label SPECIES = 'Number of reptile and amphibian species' 18 AREA = 'AREA (square miles)'; 19 LArea = log(area); *** the LOG(X) function gives the natural log (base e) ***; 20 LSPECIES = log(SPECIES); *** the LOG10(X) function gives log base 10 ***; 21 datalines; NOTE: The infile INPUT1 is: File Name=C:\Geaghan\Current\EXST3201\Datasets\ASCII\case0801.csv, RECFM=V, LRECL=256 NOTE: 7 records were read from the infile INPUT1. The minimum record length was 3. The maximum record length was 9. NOTE: The data set WORK.ISLANDS has 7 observations and 4 variables. NOTE: DATA statement used (Total process time): real time 0.03 seconds cpu time 0.03 seconds 22 run; 23 24 Title2 'Raw data listing'; 25 proc print data=Islands; run; NOTE: There were 7 observations read from the data set WORK.ISLANDS. NOTE: The PROCEDURE PRINT printed page 1. NOTE: PROCEDURE PRINT used (Total process time): real time 0.01 seconds cpu time 0.01 seconds

Chapter 8 : Correlation between the size of an island and the number of species Raw data listing

AREA	SPECIES	LArea	LSPECIES
44010	100	10 6060	
44218	100	10.6969	4.60517
29371	108	10.2878	4.68213
4244	45	8.3533	3.80666
3435	53	8.1418	3.97029
32	16	3.4657	2.77259
5	11	1.6094	2.39790
1	7	0.0000	1.94591
	AREA 44218 29371 4244 3435 32 5 1	AREA SPECIES 44218 100 29371 108 4244 45 3435 53 32 16 5 11 1 7	AREASPECIESLArea4421810010.69692937110810.28784244458.35333435538.141832163.46575111.6094170.0000

27 options ps=52 ls=111; Title2 'Scatter plot of the taw data'; 28 proc plot data=Islands; plot SPECIES * AREA; run; 29 Title2 'Scatter plot of the log transformed data'; 30 NOTE: There were 7 observations read from the data set WORK.ISLANDS. NOTE: The PROCEDURE PLOT printed page 2. NOTE: PROCEDURE PLOT used (Total process time): real time 0.00 seconds cpu time 0.00 seconds proc plot data=Islands; plot LSPECIES * LAREA; run; 31 32 options ps=512 ls=99; NOTE: There were 7 observations read from the data set WORK.ISLANDS. NOTE: The PROCEDURE PLOT printed page 3. NOTE: PROCEDURE PLOT used (Total process time): real time 0.00 seconds 0.00 seconds cpu time

Chapter 8 : Correlation between the size of an island and the number of species Scatter plot of the taw data $\$





Chapter 8 : Correlation between the size of an island and the number of species Regression without transformed values

The REG Procedure Model: MODEL1 Dependent Variable: LSPECIES

Number	of	Observations	Read	7
Number	of	Observations	Used	7

	An	alysis of Var	iance		
		Sum of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
Model	1	6.99619	6.99619	425.30	<.0001
Error	5	0.08225	0.01645		
Corrected Total	6	7.07844			
Root MSE	0.12826	R-Square	0.9884		
Dependent Mean Coeff Var	3.45438 3.71289	Adj R-Sq	0.9861		

			Paramete:	r Estimates			
		Parameter	Standard				
Variable	DF	Estimate	Error	t Value	Pr > t	95% Confidence	ce Limits
Intercept	1	1.93651	0.08813	21.97	<.0001	1.70996	2.16306
LArea	1	0.24968	0.01211	20.62	<.0001	0.21856	0.28080

Chapter 8 : Correlation between the size of an island and the number of species Regression without transformed values Listing of results from the regression output statement

Obs	AREA	SPECIES	LArea	LSPECIES	yhat	resid
1	44218	100	10.6969	4.60517	4.60731	-0.00214
2	29371	108	10.2878	4.68213	4.50516	0.17698
3	4244	45	8.3533	3.80666	4.02215	-0.21549
4	3435	53	8.1418	3.97029	3.96935	0.00095
5	32	16	3.4657	2.77259	2.80183	-0.02924
б	5	11	1.6094	2.39790	2.33835	0.05954
7	1	7	0.0000	1.94591	1.93651	0.00940

The original equation is then Median $\{S|A\} = CA^{\gamma} = \exp(1.93651)A^{0.24968} = 6.935*A^{0.250}$. When plotted this should form a curve



A]	prochure for the Intel Corporation, a major producer of computer processor chips, contains
	information about the history of it's chips. The table below was derived from that
	information.

Processor	Year of	Number of	Logarithm of No.	Approx. MIPS
	introduction	Transistors (x1000)	of Transistors	(million instructions
				per second)
4004	1971	2.3	0.83	0.04
8080	1974	9	2.2	0.16
8086	1978	20	3	0.36
8088	1979	29	3.37	0.53
80286	1982	134	4.9	2.44
80386	1985	275	5.62	5
80486	1989	1200	7.09	21.82
Pentium (5)	1993	3000	8.01	54.55
Pentium Pro (6)	1995	5500	8.61	100

The first plot below is a plot of the data with an "exponential growth curve" graphed through the data. This appears to be a pretty good fit.



Below is a plot of the relationship between the independent variable "year of introduction" and the dependent variable plotted on a logarithmic scale (log 10 in this case) This fit also looks pretty good.



This same effect can be achieved by taking logarithms of the variable instead of plotting on a log scale. That graph, with natural logs, is given below.



This is the linear version of the exponential curve, and as you can see it is a simple linear regression. This data was regressed in SAS using PROC REG and the data is given in in separate pages. Answer

the questions below from that computer output. Note that the intercept is meaningless in this particular example because there were no computers in the year "0000".

In 1965 Gordon Moore (a co-founder of Intel)) wrote an article that claimed that the rate of increase in computer capacity double every 18 months. On our logarithmic scale this translates into a rate of 0.462 logTRANS per year. This value was tested and rejected (P>F < 0.0001)

This doubling rate can be easily calculated. The curve is of the "exponential growth" type, $Y_i = b_0 \exp^{b_1 X_i} e_i$. For this model the value of b_0 is the "initial value" and the value of b_1 is the instantaneous rate of increase. The doubling time is calculated as

$$\begin{split} Y_i &= b_0 e^{b_1 X_i} = (1.5254*10^{-275}) e^{0.32150*year} \\ 2b_0 &= b_0 e^{b_1 (doubling time)} = 3.0508E-275 = (1.5254*10^{-275}) e^{0.32150(doubling time)} \\ 2 &= e^{0.32150(doubling time)} \text{ and } \ln(2) = 0.32150*(doubling time) \text{ then} \\ doubling time &= \ln(2) / 0.32150 = 2.155978789 \end{split}$$

The annual rate is $e^{0.32150} = 1.379195006$, or about 38% per year, but this rate is "compounded" continously.

This model is used to describe the growth (positive b_1) of biological organisms and populations, growth in technology, and anything that grows proportionally, such as interest in the bank.

It is also used extensively in biology to describe various types of mortality (negative b_1) and types of decay for both biological material and radioactive material. Half lives are calculated in a fashion similar to the doubling time above.

1 *** A brochure from the Intel Corporation, a major producer ***; 2 3 *** of computer processor chips, contains information about ***; 4 *** the history of it's chips. The information in this ***; 5 *** example is from that brochure. ***: б 7 8 dm'log;clear;output;clear'; 9 options nodate nocenter nonumber ps=512 ls=99 nolabel; 10 ODS HTML style=minimal rs=none ! body='C:\Geaghan\Current\EXST3201\Fall2005\SAS\Intel01.html' ; 10 NOTE: Writing HTML Body file: C:\Geaghan\Current\EXST3201\Fall2005\SAS\Intel01.html 11 OPTIONS LS=111 PS=256 NODATE NOCENTER NONUMBER; 12 13 DATA Intel; INFILE CARDS MISSOVER; LENGTH CHIP \$ 16; 14 TITLE1 'Data from Intel Corporation'; TITLE2 'Increasing power of Intel computer processor chips over years'; 15 16 INPUT CHIP \$ 1-16 YEAR TRANS; 17 logTRANS = log(TRANS); LABEL YEAR = 'Year of microchip introduction'; 18 LABEL TRANS = 'Equivalent power of chip in 1000 transistors'; 19 20 MIPS = trans * 0.01818181818; 21 CARDS; NOTE: The data set WORK.INTEL has 12 observations and 5 variables. NOTE: DATA statement used (Total process time): 0.03 seconds real time 0.03 seconds cpu time 34 ; 35 PROC PRINT DATA=Intel; TITLE3 'Raw data Listing'; RUN; NOTE: There were 12 observations read from the data set WORK.INTEL. NOTE: The PROCEDURE PRINT printed page 1. NOTE: PROCEDURE PRINT used (Total process time): 0.01 seconds real time cpu time 0.01 seconds Data from Intel Corporation Increasing power of Intel computer processor chips over years Raw data Listing loq Obs TRANS CHIP YEAR TRANS MIPS 1 4004 1971 2.3 0.8329 0.042 2 2.5 8008 1972 0.9163 0.045 3 1974 8080 4.5 1.5041 0.082 4 29.0 8086 1978 3.3673 0.527 5 134.0 80286 1982 4.8978 2.436 6 80386 275.0 5.000 1985 5.6168 7 80486 1989 1200.0 7.0901 21.818 8 Pentium (5) 1993 3100.0 8.0392 56.364 Pentium Pro (6) 9 1995 5500.0 8.6125 100.000 10 Pentium II 1997 7500.0 8.9227 136.364 11 Pentium III 1999 9500.0 9.1590 172.727 12 Pentium 4 2000 42000.0 10.6454 763.636

37 options ps=52 ls=111; proc plot data=intel; plot trans * year; TITLE3 'Plot of the raw data'; run; 38 NOTE: There were 12 observations read from the data set WORK.INTEL. NOTE: The PROCEDURE PLOT printed page 2. NOTE: PROCEDURE PLOT used (Total process time): real time 0.00 seconds cpu time 0.00 seconds 39 proc plot data=intel; plot logtrans * year; TITLE3 'Plot of the log transformed data'; run; 40 options ps=512 ls=111; 41 NOTE: There were 12 observations read from the data set WORK.INTEL. NOTE: The PROCEDURE PLOT printed page 3. NOTE: PROCEDURE PLOT used (Total process time): real time 0.00 seconds 0.00 seconds cpu time Data from Intel Corporation Increasing power of Intel computer processor chips over years Plot of the raw data Plot of TRANS*YEAR. Legend: A = 1 obs, B = 2 obs, etc. TRANS 50000 + Α 40000 + 30000 + 20000 + 10000 + Α А Α Α А 0 + A A А А А А ----+------1970 1975 1980 1985 1990 1995 2000 YEAR

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Data from Intel Corporation Increasing power of Intel computer processor chips over years Plot of the log transformed data

Plot of logTRANS*YEAR. Legend: A = 1 obs, B = 2 obs, etc.



EXST3201 – Chapter 8a

Data from Intel Corporation Increasing power of Intel computer processor chips over years Computer Chip example using REG with CLM

The REG Procedure Model: MODEL1 Dependent Variable: logTRANS

Number	of	Observations	Read	12
Number	of	Observations	Used	12

		Anal	ysis of Varia	ance		
			Sum of	Mean		
Source		DF	Squares	Square	F Value	Pr > F
Model		1	131.29985	131.29985	850.47	<.0001
Error		10	1.54386	0.15439		
Corrected I	Total	11	132.84371			
Root MSE Dependent M Coeff Var	lean	0.39292 5.80034 6.77408	R-Square Adj R-Sq	0.9884 0.9872		

Parameter Estimates										
		Parameter	Standard							
Variable	DF	Estimate	Error	t Value	Pr > t	95% Confide	ence Limits			
Intercept	1	-632.78864	21.89772	-28.90	<.0001	-681.57980	-583.99749			
YEAR	1	0.32150	0.01102	29.16	<.0001	0.29694	0.34607			

					Output Sta	tistics				
			Dependent	Predicted	Std Error					
0bs	YEAR	2	Variable	Value	Mean Predict	95% CL	Mean	95% CL P	redict	Residual
1		1971	0.8329	0.8974	0.2028	0.4455	1.3493	-0.0878	1.8826	-0.0645
2		1972	0.9163	1.2189	0.1938	0.7872	1.6506	0.2427	2.1950	-0.3026
3		1974	1.5041	1.8619	0.1764	1.4689	2.2549	0.9023	2.8215	-0.3578
4		1978	3.3673	3.1479	0.1454	2.8240	3.4719	2.2144	4.0814	0.2194
5		1982	4.8978	4.4339	0.1227	4.1605	4.7074	3.5168	5.3511	0.4639
6		1985	5.6168	5.3985	0.1143	5.1439	5.6530	4.4867	6.3102	0.2183
7		1989	7.0901	6.6845	0.1174	6.4229	6.9461	5.7707	7.5982	0.4056
8		1993	8.0392	7.9705	0.1357	7.6682	8.2728	7.0443	8.8967	0.0687
9		1995	8.6125	8.6135	0.1489	8.2817	8.9453	7.6773	9.5497	-0.001002
10		1997	8.9227	9.2565	0.1640	8.8910	9.6220	8.3078	10.2052	-0.3339
11		1999	9.1590	9.8995	0.1806	9.4971	10.3020	8.9360	10.8631	-0.7405
12		2000	10.6454	10.2210	0.1893	9.7992	10.6429	9.2492	11.1928	0.4244
Sum	of	Resid	duals		-5.6503E	-13				
Sum	of	Squared Residuals		1.54	386					

Predicted Residual SS (PRESS) 2.30901

Test 1	Results for	r Dependent V	ariable logT	RANS		
	Mean					
Source	DF	Squar	e F Value	Pr > F		
Numerator	1	25.0733	3 162.41	<.0001		
Denominator	c 10	0.1543	9			

48 TITLE3 'Plot of residuals'; 49 Proc plot; PLOT resid*YEAR / vref=0; 50 RUN; NOTE: There were 12 observations read from the data set WORK.NEXT. NOTE: The PROCEDURE PLOT printed page 7. NOTE: PROCEDURE PLOT used (Total process time): real time 0.01 seconds cpu time 0.00 seconds 51 PROC UNIVARIATE DATA=NEXT NORMAL PLOT; VAR resid; 52 RUN; NOTE: The PROCEDURE UNIVARIATE printed pages 8-10. NOTE: PROCEDURE UNIVARIATE used (Total process time): real time 0.01 seconds 0.01 seconds cpu time Data from Intel Corporation Increasing power of Intel computer processor chips over years Plots of raw data & residuals Plot of resid*YEAR. Legend: A = 1 obs, B = 2 obs, etc. resid | 0.6 + А 0.4 + А Α 0.2 + А А А 0.0 +----Α -0.2 + А А А -0.4 + -0.6 + Α -0.8 + 1975 1980
 1985
 1990
 1995
 2000
 1970 YEAR

* *+++*

Data from Intel Corporation Increasing power of Intel computer processor chips over years Plots of raw data & residuals The UNIVARIATE Procedure Variable: resid Moments Ν 12 Sum Weights 12 Mean 0 Sum Observations 0 0.37463418 Variance -0.5243539 Kurtosis 0.14035077 Std Deviation Skewness -0.4472994 Corrected SS Uncorrected SS 1.54385842 1.54385842 Coeff Variation Std Error Mean 0.10814757 . Basic Statistical Measures Variability Location Std Deviation Mean 0.000000 0.37463 Median 0.033830 Variance 0.14035 Mode Range 1.20437 . Interquartile Range 0.63072 Tests for Location: Mu0=0 -Statistic- ----p Value-----Test Student's t t 0 Pr > |t| 1.0000М 0 Pr >= |M| 1.0000 Sign Pr >= |S| 0.8501 Signed Rank S 3 Tests for Normality Test --Statistic--- ----p Value-----
 Shapiro-Wilk
 W
 0.939064
 Pr < W</th>
 0.4860

 Kolmogorov-Smirnov
 D
 0.136633
 Pr > D
 >0.1500

 Cramer-von Mises
 W-Sq
 0.040599
 Pr > W-Sq
 >0.2500

 Anderson-Darling
 A-Sq
 0.292949
 Pr > A-Sq
 >0.2500
 Extreme Observations -----Highest-----Value Obs Value Obs 0.218314 -0.7404772 11 6 3 -0.3578260 0.219373 4
 -0.3338563
 10

 -0.3026030
 2

 -0.0644798
 1
 0.405601 0.424396 7 2 12 1 0.463898 5 Stem Leaf # Boxplot Normal Probability Plot 4 126 0.5+ 3 | 2 22 2 +---+ * *++++ | 07 1 *--+--* + * + + + + ++*+* 2 | | -0 60 -0.1+ *++*++* 3 +----+ -2 630 -4 i i -64 1 -0.7++++++* ____+ -2 -1 0 +1 +2 Multiply Stem.Leaf by 10**-1