Friday Oct. 4th

Review
## Warm Up

1. Solve $\log(x) = 2.61$

2. Solve $\ln(x) = 3$

3. Expand $\log(ab^x)$

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Review
## Warm Up

exponent

1. Solve $\log(x) = 2.61$ $\quad X = 10^{2.61}$

base is 10

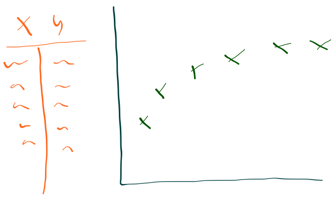
2. Solve $\ln(x) = 3$ $\quad X = e^3$

$\log_e(x) = 3$

3. Expand $\log(ab^x)$ $= \log(a) + \log(b^x)$

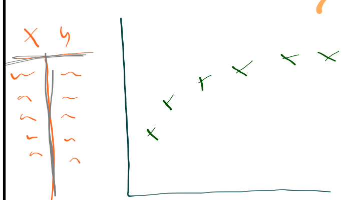
$= \log(a) + x \cdot \log(b)$

Overall Aim for Section 12.2

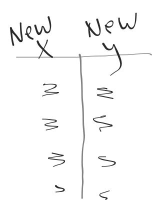



Take data that
• is non-linear

Overall Aim for Section 12.2



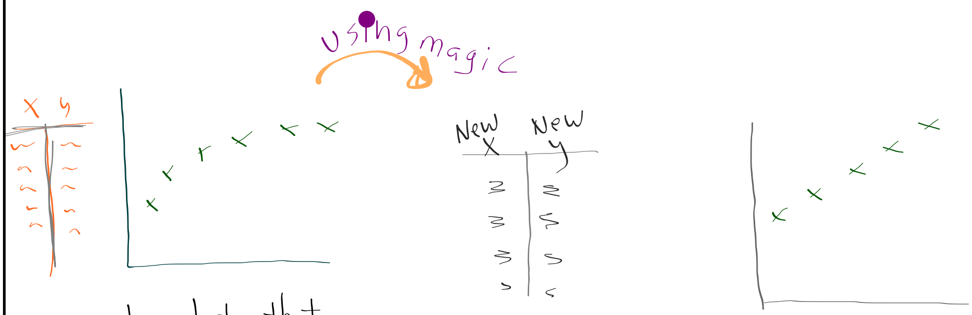

using magic




Take data that
• is non-linear

and transform it

# Overall Aim for Section 12.2




Take data that is non-linear

and transform it

to create linear data

So...,


# Overall Aim for Section 12.2


So we can use the linear tools we already know


Take data that is non-linear

and transform it

to create linear data

So...,

Revenge of the

Iphone Sales → do #1, 2, and 3

need stapplet

2-variable • quantitative

12.2 Day 1

# Revenge of the iPhone Sales


Here is the data of all iPhone sales during their opening weekends:

| iPhone | Year (after 2000) | Units Sold (millions) |
|---|---|---|
| Original | 7 | 0.5 |
| 3G | 8 | 1 |
| 3Gs | 9 | 1 |
| 4 | 10 | 1.7 |
| 4S | 11 | 4 |
| 5 | 12 | 5 |
| 5C, 5S | 13 | 9 |
| 6, 6 Plus | 14 | 10 |
| 6S, 6S Plus | 15 | 13 |

1. Use stapplet.com to create a scatterplot of the data with year as the explanatory variable and units sold as the response. Sketch the scatterplot in the space above.

2. Would you use a linear regression to model the data? Sketch the residual plot below to support your explanation.

**3.** Since we expect that the data is nonlinear, we cannot make a linear regression. However, we can **transform** the data to make it more linear. First we need to decide what type of function we think the data would best fit so that we can transform it.

a. What type of model do you think best fits the data?

exponential

b. What is the general form of this type of model *(think back to Alg 2)*?

$y = ab^x$

$x^2$

$r$

c. Algebraically, what is the inverse of that function?

logarithm

d. How can we transform our data using this inverse?

$y = ab^x$

$y = ab^x$

$\log(y) = \log(ab^x)$

$\log(y) = \log(a) + x \cdot \log(b)$

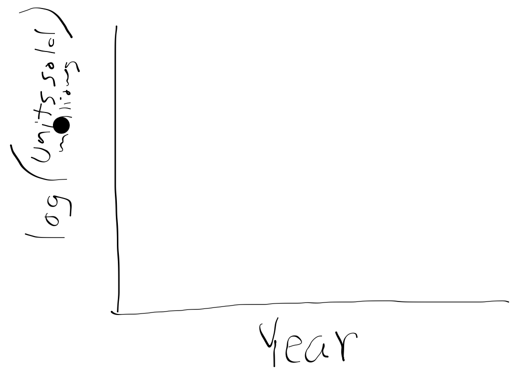
$\log(y) = \log(a) + \log(b) \cdot x$

y-int

slope

**4.** Complete the table below.

| Year | Actual Units Sold (millions) | log(Units Sold (millions) |
|---|---|---|
| x | y | log(y) |
| 7 | 0.5 | -.30 |
| 8 | 1 | |
| 9 | 1 | |
| 10 | 1.7 | |
| 11 | 4 | |
| 12 | 5 | |
| 13 | 9 | |
| 14 | 10 | |
| 15 | 13 | |

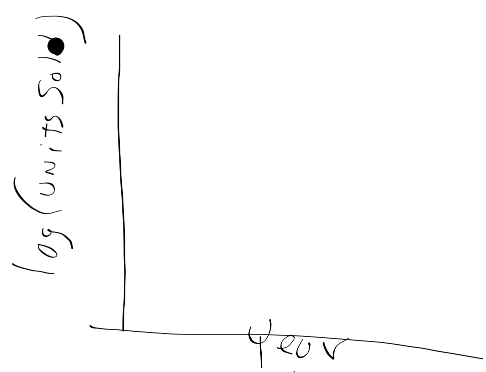



**5.** Use stapplet.com to create a scatterplot of the data with year as the explanatory variable and log(units sold) as the response. Sketch the scatterplot in the space above.

**6.** Calculate the LRSL for the transformed data and write it below.

**4.** Complete the table below.

| Year | Actual Units Sold (millions) | log(Units Sold (millions) |
|---|---|---|
| 7 | 0.5 | -0.301 |
| 8 | 1 | 0 |
| 9 | 1 | 0 |
| 10 | 1.7 | .23 |
| 11 | 4 | .60 |
| 12 | 5 | .70 |
| 13 | 9 | .95 |
| 14 | 10 | 1 |
| 15 | 13 | 1.11 |




$\hat{y} = a + bx$

**5.** Use stapplet.com to create a scatterplot of the data with year as the explanatory variable and log(units sold) as the response. Sketch the scatterplot in the space above.

→ **6.** Calculate the LRSL for the transformed data and write it below.

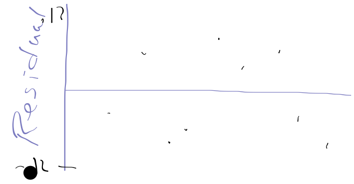
regression

$a = -1.546$

$b = .184$

$\log(\text{UNITS sold}) = -1.546 + .184x$

**7.** Do you think the regression line is a good fit for the transformed data? Why or why not? Explain using the residual plot and sketch it below.




**8.** According to this model, how many iPhones should be sold in 2015?

$\log(\text{UNITS sold}) = -.546 + .184(15)$

$\log(\text{UNITS sold}) = 1.214 \longrightarrow \text{UNITS SOLD} = 10^{1.214} \approx 16.37$ million units sold

**9.** Calculate and interpret the residual for the actual number of iPhones sold in 2015.

$R = A - P$

$= 13 - 16.37$

$= -3.37$

The actual number of iphones sold was 3,370,000 less than what was predicted in 2015

We could have also used natural log

$\ln(y)$

## Transforming Nonlinear Data

Big Ideas:

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Big Ideas:

| Function | Plot |
|---|---|
| linear | |
| Power | |
| Exponential | |

## Transforming Nonlinear Data

Big Ideas:

| Function | Plot |
| --- | --- |
| linear | y vs x |
| Power | log y vs log x |
| Exponential | log y vs x |

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Big Ideas:

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Predictions

Plug in x and solve for y

## Transforming Nonlinear Data

Big Ideas:

| FUNCTION | PLOT |
| --- | --- |
| linear | y vs x |
| Power | log y vs log x |
| Exponential | log y vs x |

**Predictions**

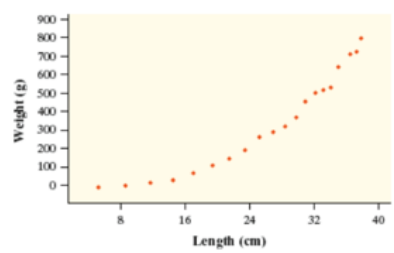
Plug in $x$ and solve for $y$

[may need to undo a root or log]

$y^3 \longleftrightarrow \sqrt[3]{\ }$

### Atlantic Ocean Rockfish

Here is a scatterplot showing the length and weight of Atlantic Ocean rockfish. Is a linear model appropriate?




There are several ways we can attempt to linearize a curved association:

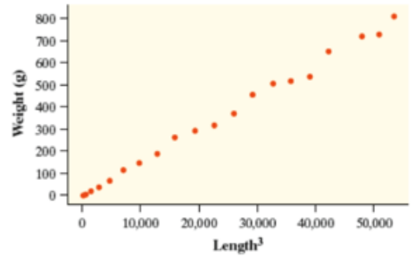
**powers, roots, and logarithms.**

**A. Powers:**

Here is what happens when we *cube* the length values.

State the equation of the least-squares regression line and predict the weight when length = 36 cm.

$\hat{y} = a + bx$




**Regression Analysis: Weight versus Length^3**

| Predictor | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 4.066 | 6.902 | 0.59 | 0.563 |
| Length^3 | 0.0146774 | 0.0002404 | 61.07 | 0.000 |

S = 18.8412 R-Sq = 99.5% R-Sq(adj) = 99.5%

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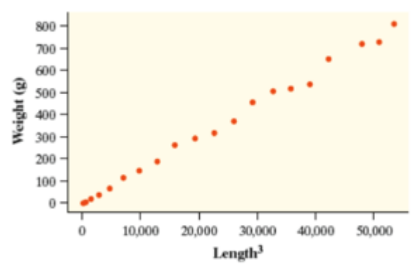
find in computer output

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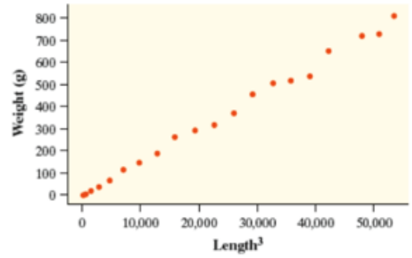


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$\hat{y} = 4.066 + 0.0146774x$

but...

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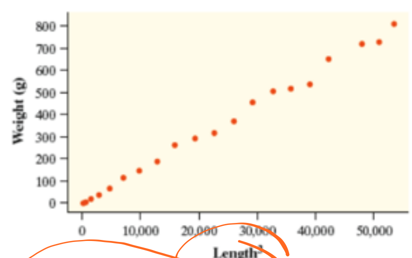


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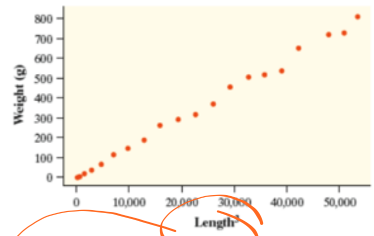


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$\hat{y} = a + bx$

find in computer output

$\hat{y} = 4.066 + 0.0146774x$

but...

$\hat{y} = 4.066 + 0.0146774(\text{Length}^3)$

at 36 cm

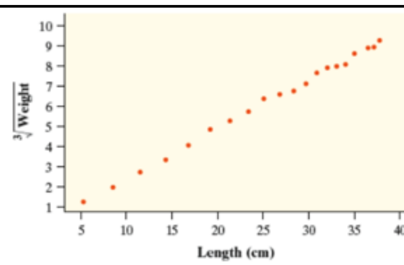
$\widehat{\text{predicted weight}} = 4.066 + 0.0146774(36^3)$

$\approx 688.9$ g

## B. Roots:

Here is what happens when we take the *cube root* of the weight values.

State the equation of the least-squares regression line and predict the weight when length = 36 cm.




**Regression Analysis: $\sqrt[3]{\text{Weight}}$ versus Length**

| Predictor | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | −0.02204 | 0.07762 | −0.28 | 0.780 |
| Length | 0.246616 | 0.002868 | 86.00 | 0.000 |

S = 0.124161   R-Sq = 99.8%   R-Sq(adj) = 99.7%

$\hat{y} = a + bx$

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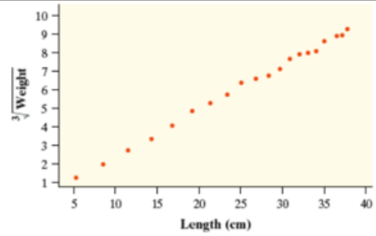


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S = 0.124161  R-Sq = 99.8%  R-Sq(adj) = 99.7%

$\hat{y} = a + bx$

$\sqrt[3]{\text{weight}} = -0.02204 + .24616\,x$

$\sqrt[3]{\text{weight}} = -.02204 + .24616(\text{length})$

36

$\sqrt[3]{\text{weight}} = 8.83972$

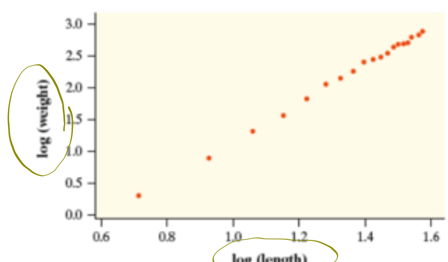
cube both sides

predicted weight $= 690.74$ g

## C. Logarithms of both variables:

*Natural or base-10*

Here is what happens when we take the base-10 logarithm *(log)* of both variables.




State the equation of the least-squares regression line and predict the weight when length = 36 cm.

**Regression Analysis: log(weight) versus log(Length)**

| Predictor | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | −1.89940 | 0.03799 | −49.99 | 0.000 |
| log(Length) | 3.04942 | 0.02764 | 110.31 | 0.000 |

S = 0.0281823  R-Sq = 99.9%  R-Sq(adj) = 99.8%

## C. Logarithms of both variables:

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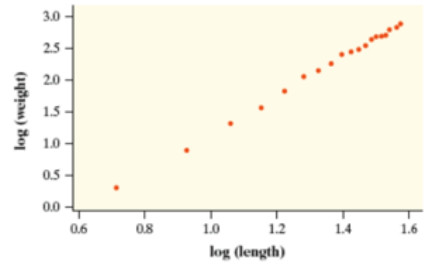


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S = 0.0281823 R-Sq = 99.9% R-Sq(adj) = 99.8%

$\hat{y} = a + bx$

$\log(\text{weight}) = -1.89940 + 3.04942[\log(\text{length})]$

$x$

36

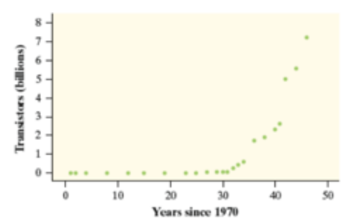
$\log(\text{weight}) = 2.846\ldots$

$\text{weight} = 10^{2.846}$

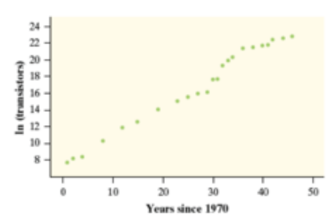
predicted weight = 702.13 g

## D. Single Logarithms

The number of transistors on Intel microprocessors has been growing exponentially since 1970, as seen in the scatterplot.




The second scatterplot shows the results of using the natural logarithm *(ln)* to transform the number of transistors.




State the equation of the least-squares regression line and predict the number of transistors in 2020.

| Predictor | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 7.2272 | 0.3058 | 23.64 | 0.000 |
| Years since 1970 | 0.3542 | 0.0102 | 34.59 | 0.000 |

S = 0.6653 R-Sq = 98.2% R-Sq(adj) = 98.2%

D. **Single Logarithms**

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The second scatterplot shows the results of using the natural logarithm *(ln)* to transform the number of transistors.

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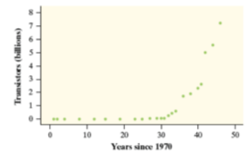


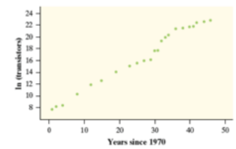


$\hat{y} = a + bx$

$\ln(\text{transistors}) = 7.2272 + .3542\,x$

years since 1970

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| S = 0.6653 | R-Sq = 98.2% | | R-Sq(adj) = 98.2% | |

$\ln(\text{transistors}) = 7.2272 + .3542(50)$

$\ln(\text{transis}) = 24.9$

$\text{transistors (million)} = e^{24.9}$

$6.5 \times 10^{16}$

65,000,000,000 billion transistors!

# 12.2.....33, 35, 37, 39, 41 and p.144…91

study pp.795-802

Don't forget to finish by Monday the "My AP" Personal Progress Check for – Unit 1 [MCQ – Part A]