Stat 13, Intro. to Statistical Methods for the Life and Health Sciences.

1. Multiple testing and publication bias.
2. Two variables and correlation.
3. Linear regression.
4. Calculating correlation.
5. Slope of the regression line.
6. Goodness of fit.
7. Common problems with regression.
8. Inference for regression, theory-based approach.

Read ch7 and 10.
Hw4 is due Fri July 25, 10pm, again by email to statgrader or statgrader2, and is Problems 10.1.8, 10.3.14, 10.3.21, and 10.4.11.
http://www.stat.ucla.edu/~frederic/13/sum25 .

1. Multiple testing and publication bias.

A p-value is the probability, assuming the null hypothesis of no relationship is true, that you will see a difference as extreme as, or more extreme than, you observed.

So, when you are looking at unrelated things, 5% of the time you will find a statistically significant relationship.

This underscores the need for followup confirmation studies. If testing many explanatory variables simultaneously, it can become very likely to find something significant even if nothing is actually related to the response variable.

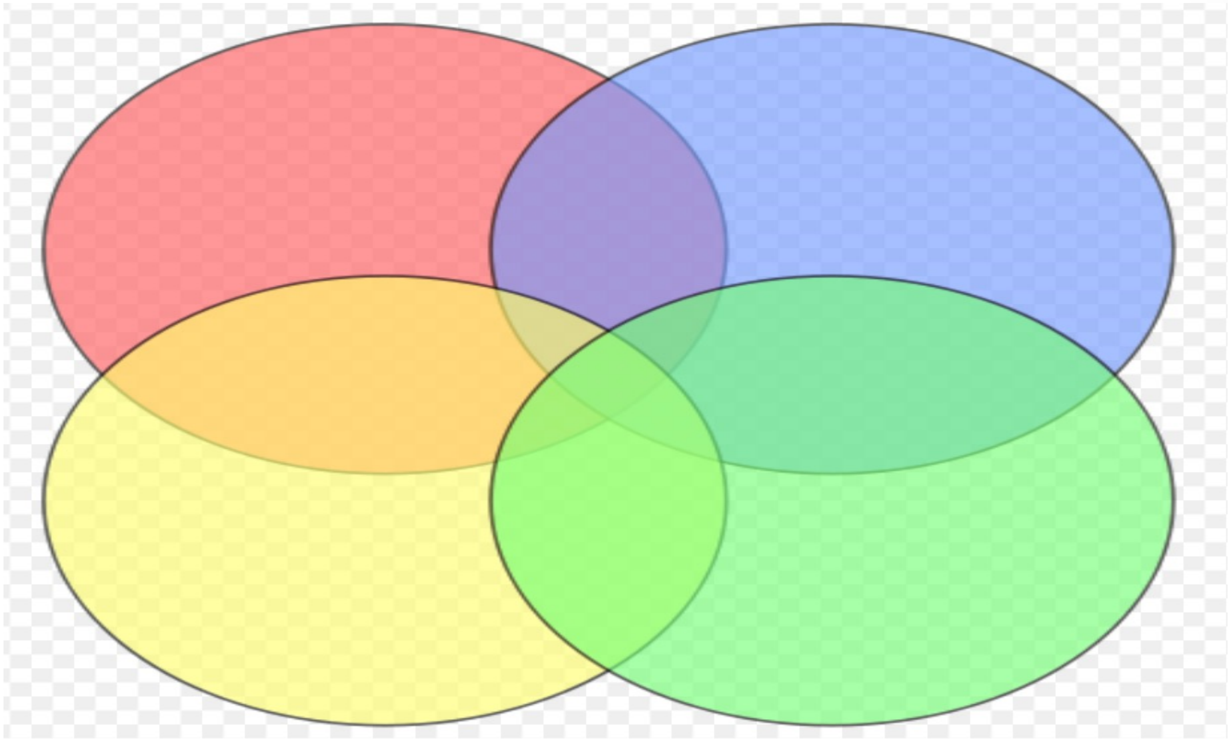
Multiple testing and publication bias.

* For example, if the significance level is 5%, then for 100 tests where all null hypotheses are true, the expected number of incorrect rejections (Type I errors) is 5. If the tests are independent, the probability of at least one Type I error would be 99.4%. P(no Type I errors) = $.95^{100}$ = 0.6%.

* To address this problem, scientists sometimes change the significance level so that, under the null hypothesis that none of the explanatory variables is related to the response variable, the probability of rejecting at least one of them is 5%.

* One way is to use Bonferroni's correction: with *m* explanatory variables, use significance level 5%/m.

P(at least 1 Type I error) will be ≤ m (5%/m) = 5%.



P(Type I error on explanatory 1) = 5%/m.

P(Type I error on explanatory 2) = 5%/m.

P(Type 1 error on at least one explanatory) ≤

P(error on 1) + P(error on 2) + ... + P(error on m) = m x 5%/m.

Multiple testing and publication bias.

Imagine a scenario where a drug is tested many times to see if it reduces the incidence of some response variable. If the drug is tested 100 times by 100 different researchers, the results will be stat. sig. about 5 times.

If only the stat. sig. results are published, then the published record will be very misleading.

Multiple testing and publication bias.

A drug called Reboxetine made by Pfizer was approved as a treatment for depression in Europe and the UK in 2001, based on positive trials.

A meta-analysis in 2010 found that it was not only ineffective but also potentially harmful. The report found that 74% of the data on patients who took part in the trials of Reboxetine were not published because the findings were negative. Published data about reboxetine overestimated its benefits and underestimated its harm.

A subsequent 2011 analysis indicated Reboxetine might be effective for severe depression though.

2. Two quantitative variables.

Chapter 10

Two Quantitative Variables: Scatterplots and Correlation

Section 10.1

Scatterplots and Correlation

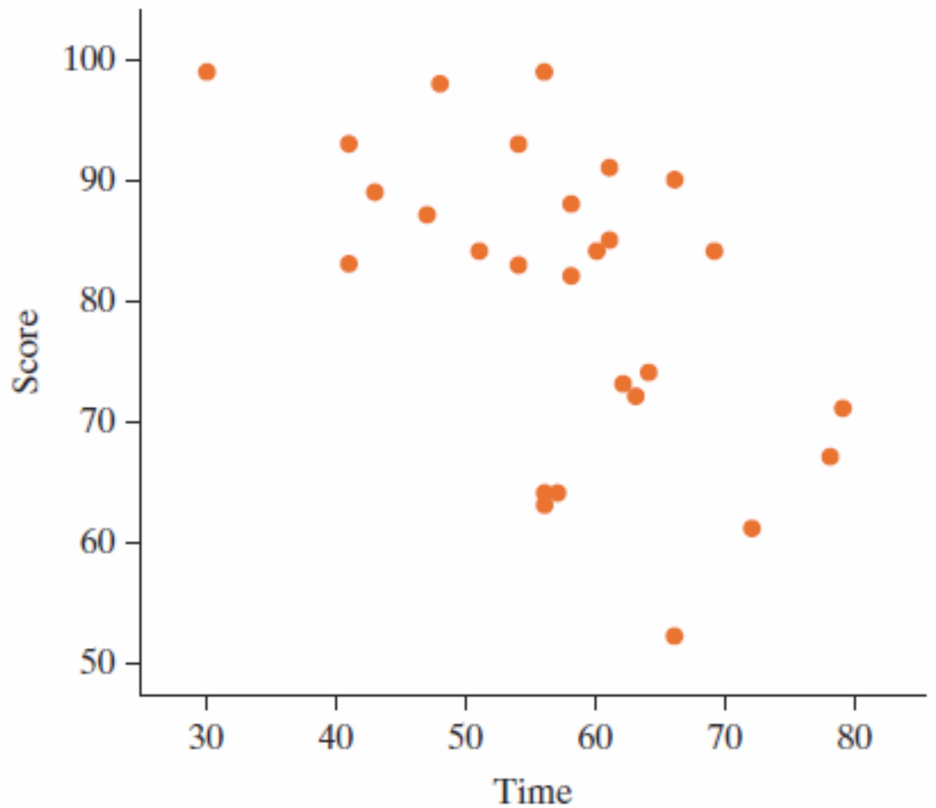
Suppose we collected data on the relationship between the time it takes a student to take a test and the resulting score.

Time	30	41	41	43	47	48	51	54	54	56	56	56	57	58
Score	100	84	94	90	88	99	85	84	94	100	65	64	65	89
Time	58	60	61	61	62	63	64	66	66	69	72	78	79	
Score	83	85	86	92	74	73	75	53	91	85	62	68	72	

Scatterplot

Put explanatory variable on the horizontal axis.

Put response variable on the vertical axis.



Describing Scatterplots

- When we describe data in a scatterplot, we describe the
  - Direction (positive or negative)
  - Form (linear or not)
  - Strength (strong-moderate-weak, we will let correlation help us decide)
  - Unusual Observations
- How would you describe the time and test scatterplot?

Correlation

- **Correlation** measures the strength and direction of a linear association between two quantitative variables.
- Correlation is a number between -1 and 1.
- With positive correlation one variable increases, on average, as the other increases.
- With negative correlation one variable decreases, on average, as the other increases.
- The closer it is to either -1 or 1 the closer the points fit to a line.
- The correlation for the test data is -0.56.

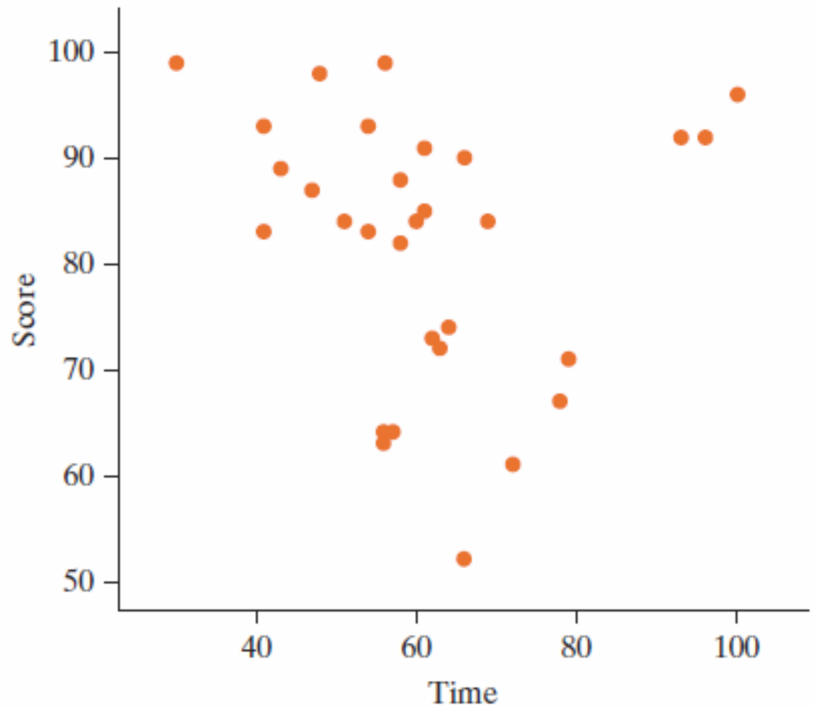
Correlation Guidelines

Correlation Value	Strength of Association	What this means
0.7 to 1.0	Strong	The points will appear to be nearly a straight line
0.3 to 0.7	Moderate	When looking at the graph the increasing/decreasing pattern will be clear, but there is considerable scatter.
0.1 to 0.3	Weak	With some effort you will be able to see a slightly increasing/decreasing pattern
0 to 0.1	None	No discernible increasing/decreasing pattern
Same Strength Results with Negative Correlations		

Back to the test data

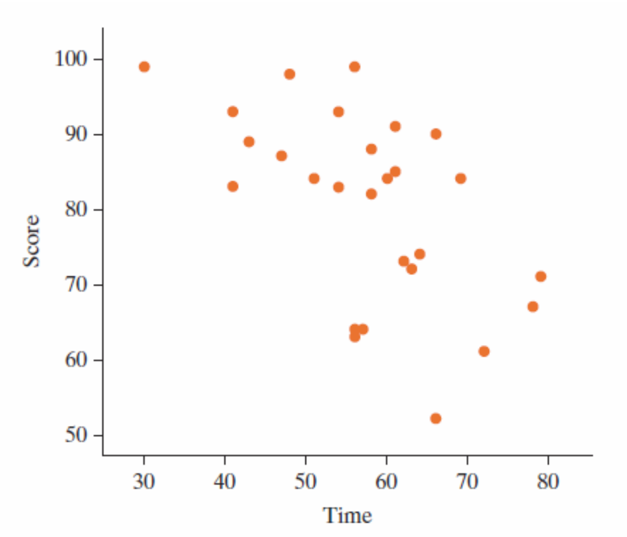
Actually the last three people to finish the test had scores of 93, 93, and 97.

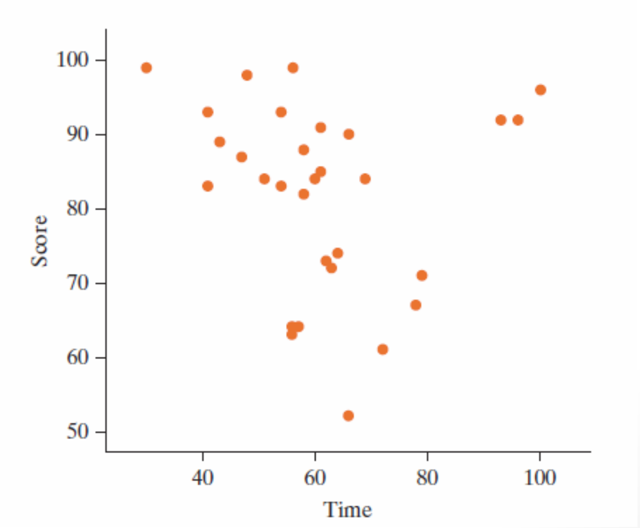
What does this do to the correlation?



Influential Observations

- The correlation changed from -0.56 (a fairly moderate negative correlation) to -0.12 (a weak negative correlation).
- Points that are far to the left or right and not in the overall direction of the scatterplot can greatly change the correlation. (influential observations)





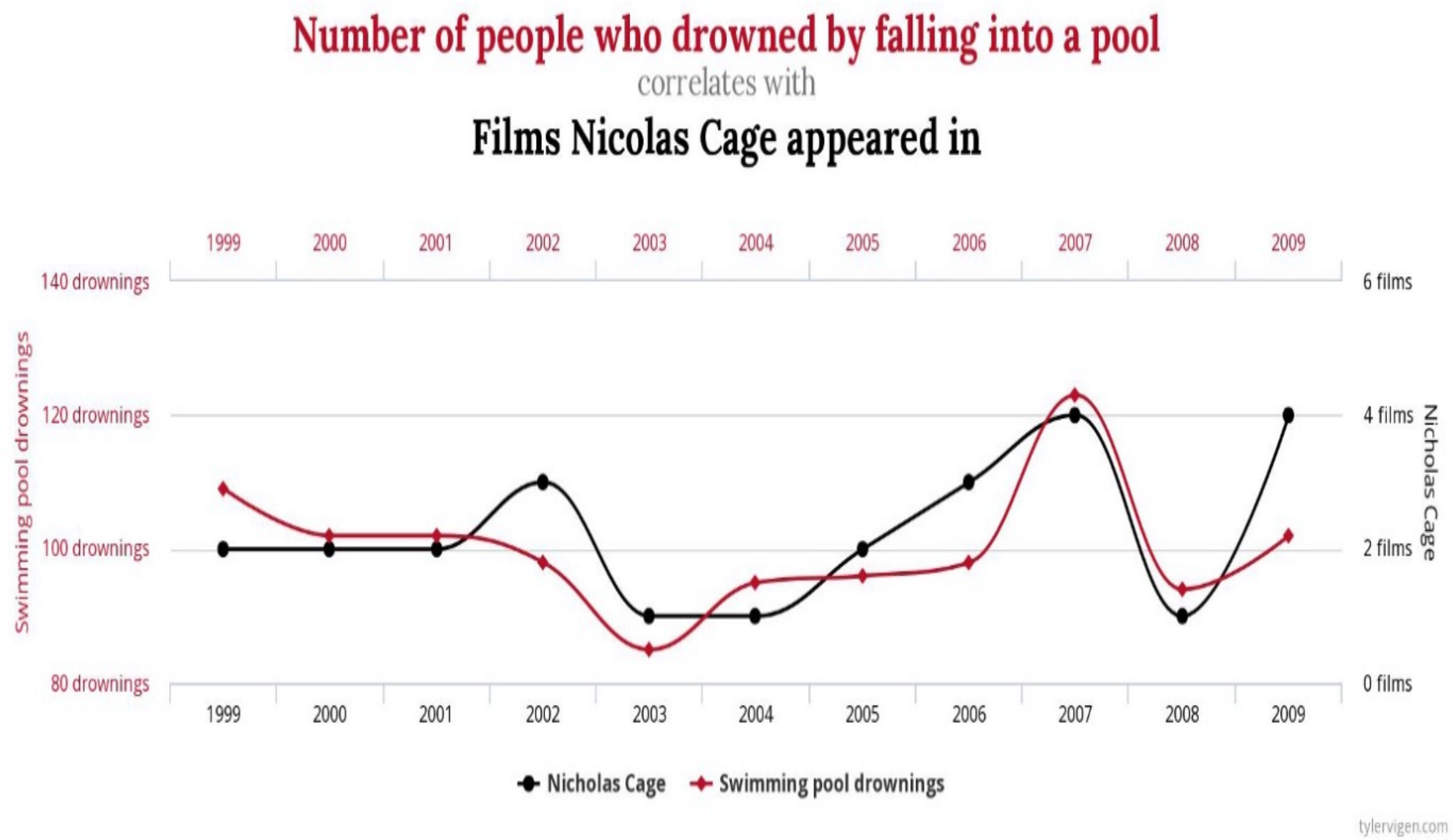
Correlation

- **Correlation** measures the strength and direction of a linear association between two quantitative variables.
  - $-1 \leq r \leq 1$
  - Correlation makes no distinction between explanatory and response variables.
  - Correlation has no units.
  - Correlation is not resistant to outliers. It is sensitive.

Learning Objectives for Section 10.1

- Summarize the characteristics of a scatterplot by describing its direction, form, strength and whether there are any unusual observations.
- Recognize that the correlation coefficient is appropriate only for summarizing the strength and direction of a scatterplot that has linear form.
- Recognize that a scatterplot is the appropriate graph for displaying the relationship between two quantitative variables and create a scatterplot from raw data.
- Recognize that a correlation coefficient of 0 means there is no linear association between the two variables and that a correlation coefficient of -1 or 1 means that the scatterplot is exactly a straight line.
- Understand that the correlation coefficient is influenced by extreme observations.

Note that correlation ≠ causation.



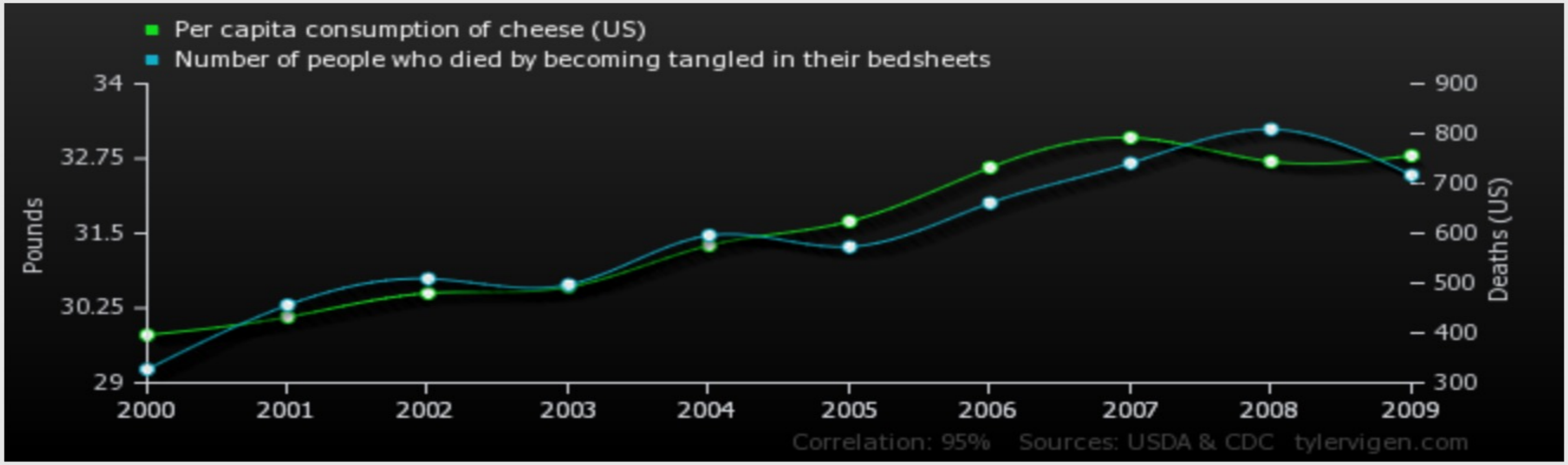
from: http://tylervigen.com

Note that correlation ≠ causation.

Per capita consumption of cheese (US)

correlates with

Number of people who died by becoming tangled in their bedsheets

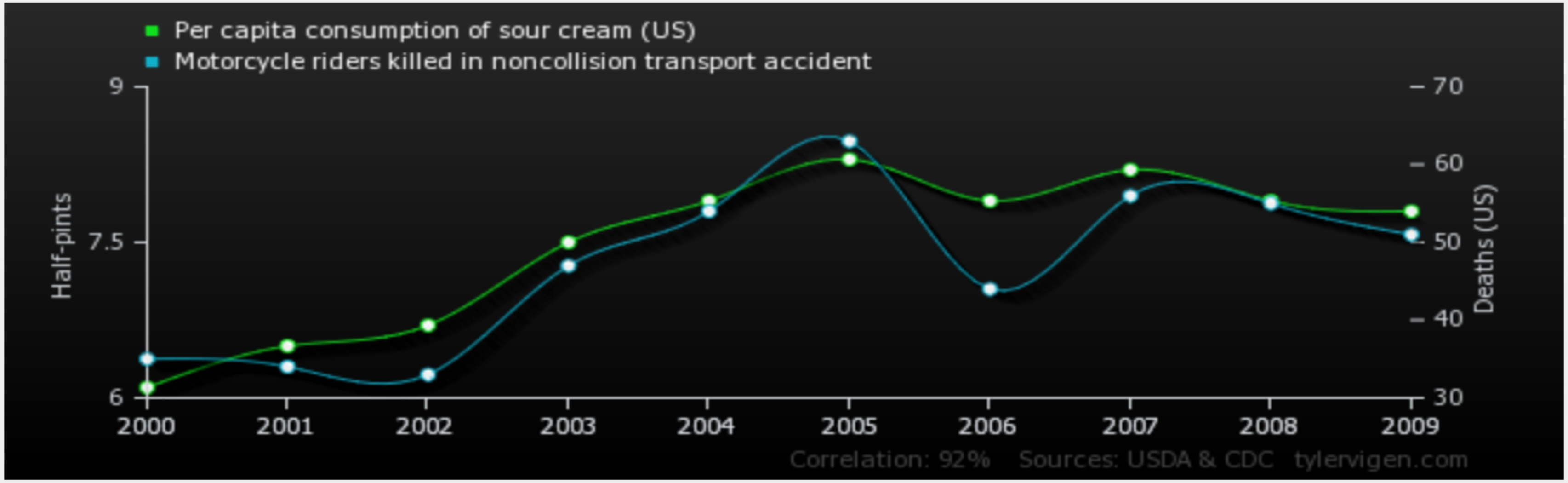


	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Per capita consumption of cheese (US) *Pounds (USDA)*	29.8	30.1	30.5	30.6	31.3	31.7	32.6	33.1	32.7	32.8
Number of people who died by becoming tangled in their bedsheets *Deaths (US) (CDC)*	327	456	509	497	596	573	661	741	809	717

Correlation: 0.947091

Note that correlation ≠ causation.

Per capita consumption of sour cream (US)
correlates with
Motorcycle riders killed in noncollision transport accident



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Per capita consumption of sour cream (US) *Half-pints (USDA)*	6.1	6.5	6.7	7.5	7.9	8.3	7.9	8.2	7.9	7.8
Motorcycle riders killed in noncollision transport accident *Deaths (US) (CDC)*	35	34	33	47	54	63	44	56	55	51

Correlation: 0.916391

Inference for the Correlation Coefficient: Simulation-Based Approach

Section 10.2

We will look at a small sample example to see if body temperature is associated with heart rate.

Temperature and Heart Rate

Hypotheses

- Null: There is no association between heart rate and body temperature. ($\rho = 0$)
- Alternative: There is a positive linear association between heart rate and body temperature. ($\rho > 0$)

ρ = rho

Inference for Correlation with Simulation
(Section 10.2)

1. Compute the observed statistic. (Correlation)
2. Scramble the response variable, compute the simulated statistic, and repeat this process many times.
3. Reject the null hypothesis if the observed statistic is in the tail of the null distribution.

Temperature and Heart Rate

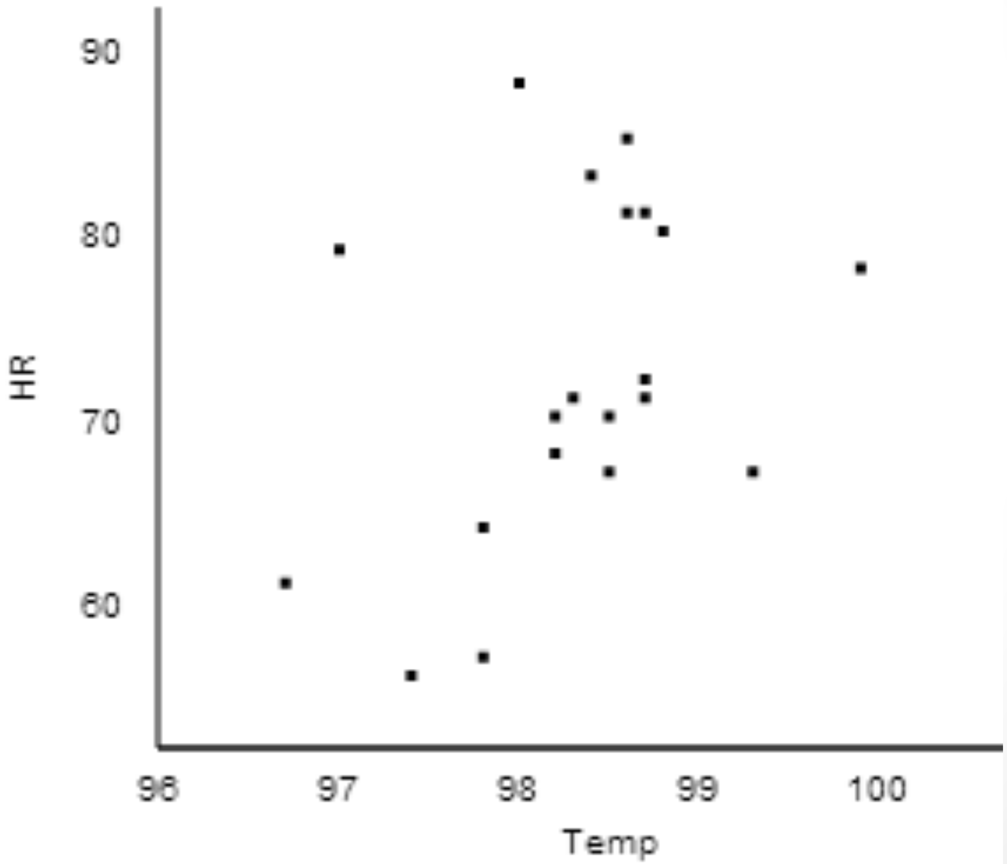
Collect the Data

Tmp	98.3	98.2	98.7	98.5	97.0	98.8	98.5	98.7	99.3	97.8
HR	72	69	72	71	80	81	68	82	68	65
Tmp	98.2	99.9	98.6	98.6	97.8	98.4	98.7	97.4	96.7	98.0
HR	71	79	86	82	58	84	73	57	62	89

Temperature and Heart Rate

Explore the Data

r = 0.378



Temperature and Heart Rate

- If there was no association between heart rate and body temperature, what is the probability we would get a correlation as high as 0.378 just by chance?

- If there is no association, we can break apart the temperatures and their corresponding heart rates. We will do this by shuffling one of the variables.

Shuffling Cards

- Let's remind ourselves what we did with cards to find our simulated statistics.
- With two proportions, we wrote the response on the cards, shuffled the cards and placed them into two piles corresponding to the two categories of the explanatory variable.
- With two means we did the same thing except this time the responses were numbers instead of words.

Dolphin Therapy

Non-improver	Improver	Improver
Non-improver	Improver	Improver
Non-improver	Improver	Improver
Non-improver	Improver	Improver
Non-improver	Improver	Improver

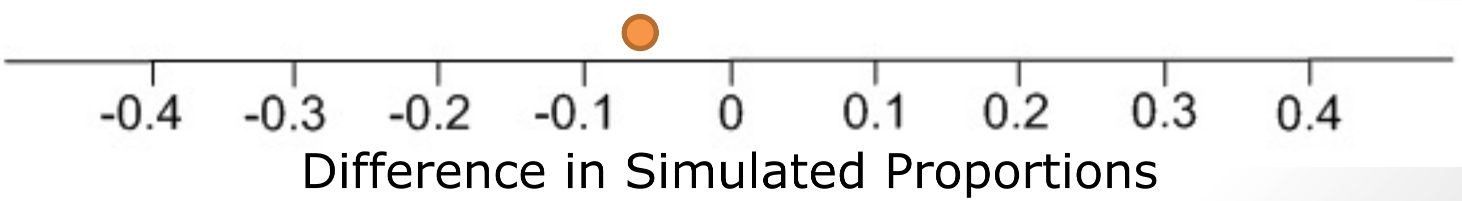
Control

Non-improver	Non-improver	Non-improver
Non-improver	Non-improver	Non-improver
Non-improver	Non-improver	Improver
Non-improver	Non-improver	Improver
Non-improver	Non-improver	Improver

40.0% / 66.7%
Improvers

0.400 – 0.467 = -0.067

46.7% / 26.7%
Improvers



Music No music

Music

25.2	45.6
14.5	11.6
-7.0	18.6
12.6	12.1
34.5	30.5

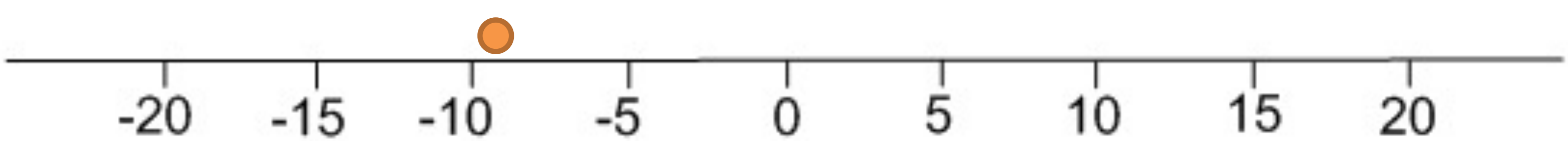
mean = 6.38

No music

-10.7	-10.7	10.0
4.5	9.6	
2.2	2.4	
21.3	21.8	
-14.7	7.2	

mean = 16.12

6.38 – 16.12 = -9.74



Difference in Simulated Means

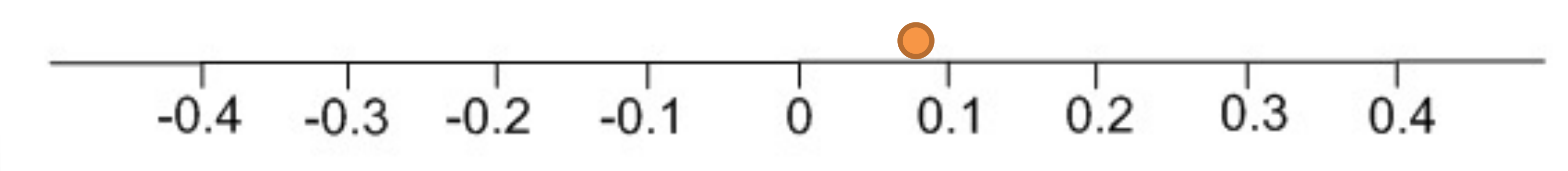
Shuffling Cards

- Now how will this shuffling be different when both the response and the explanatory variable are quantitative?
- We can't put things in two piles anymore.
- We still shuffle values of the response variable, but this time place them next to two values of the explanatory variable.

Body Temperature and Heart Rate

98.3°	98.2°	97.7°	98.5°	97.0°	98.8°	98.5°	98.7°	99.3°	97.8°
72	69	72	71	80	81	68	82	68	65
98.2°	99.9°	98.6°	98.6°	97.8°	98.4°	98.7°	97.4°	96.7°	98.0°
71	79	86	82	58	84	73	57	62	89

r = 0.078



Simulated Correlations

More Simulations

0.097 0.054 0.062 0.259 0.034

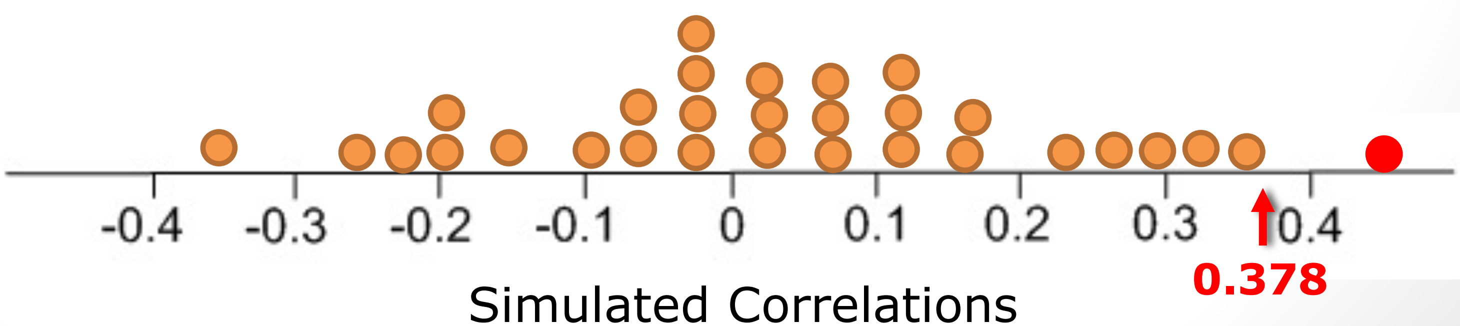
-0.253 -0.345 0.314 0.339

-0.034 0.200 0.212 -0.008

0.059 0.006 0.447 -0.042 0.167

0.067 0.020 0.232 -0.327 0.100 0.329

Only one simulated statistic out of 30 was as large or larger than our observed correlation of 0.378, hence our p-value for this null distribution is 1/30 ≈ 0.03.

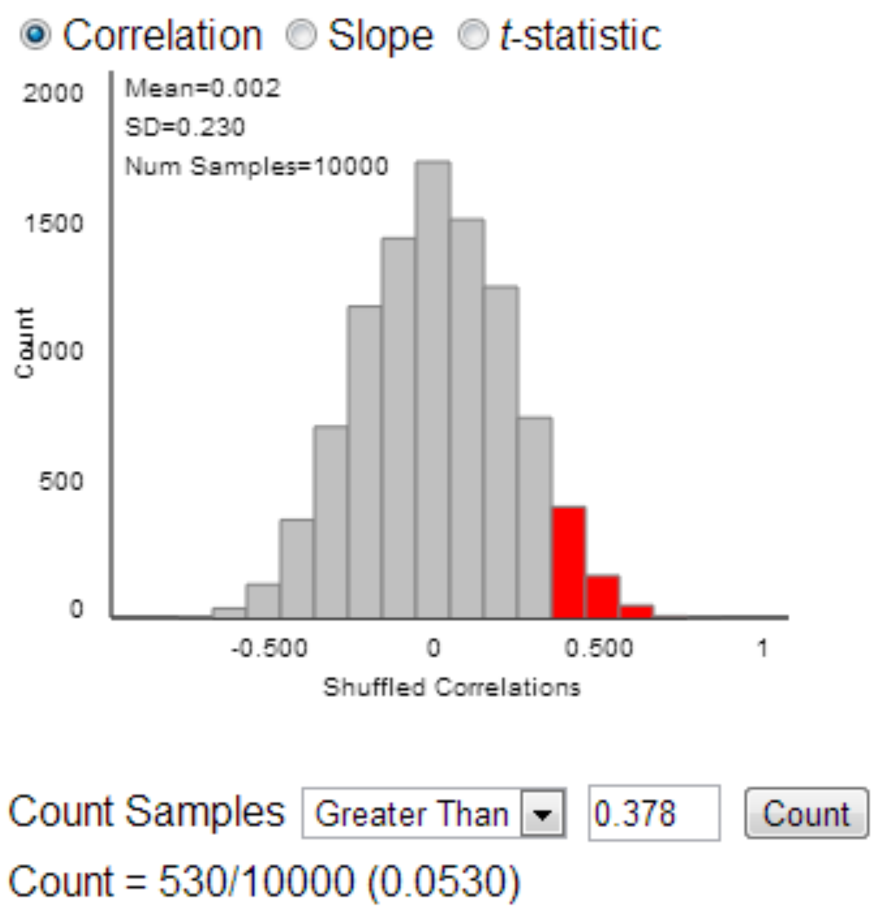


Temperature and Heart Rate

- We can look at the output of 1000 shuffles with a distribution of 1000 simulated correlations.

Temperature and Heart Rate

- Notice our null distribution is centered at 0 and somewhat symmetric.
- We found that 530/10000 times we had a simulated correlation greater than or equal to 0.378.



Temperature and Heart Rate

- With a p-value of 0.053 = 5.3%, we almost but do not quite have statistical significance. We observe a positive linear association between body temperature and heart rate but this association is not statistically significant. Perhaps a larger sample should be investigated to get a better idea if the two variables are related or not.

3. Linear Regression

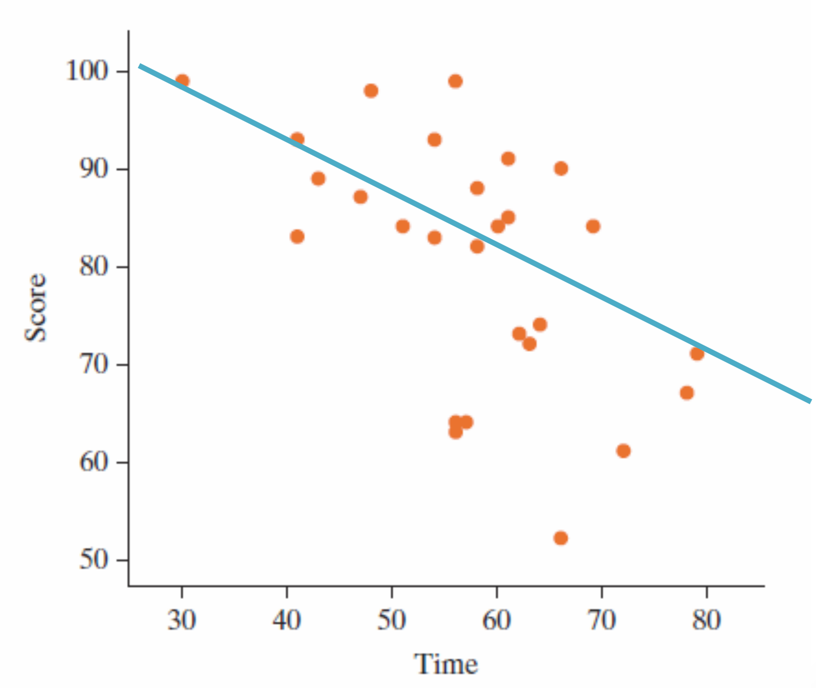
Section 10.3

Introduction

- If we decide an association is linear, it is helpful to develop a mathematical model of that association.
- Helps make predictions about the response variable.
- The ***least-squares regression line*** is the most common way of doing this.

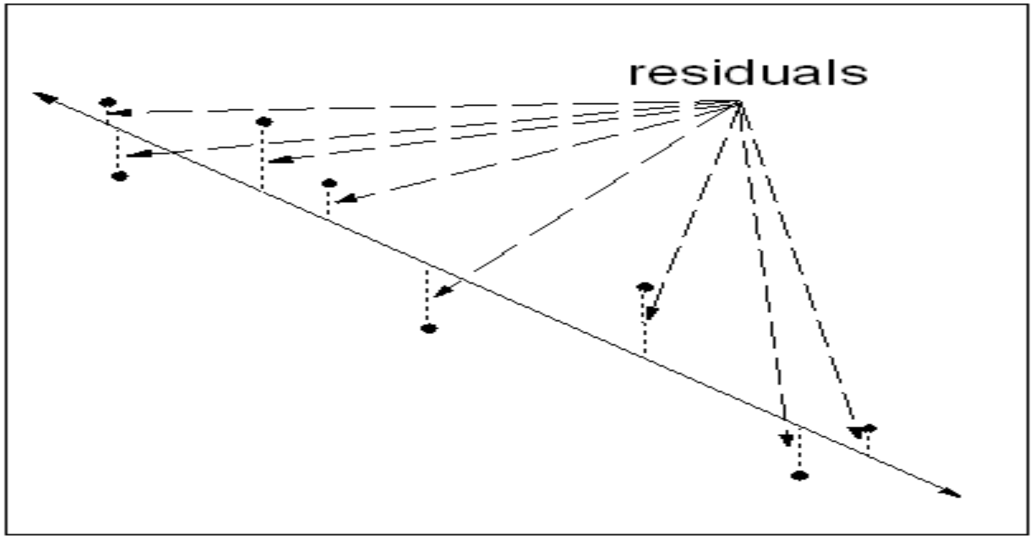
Introduction

- Unless the points are perfectly linearly alligned, there will not be a single line that goes through every point.



Introduction

- We want a line that minimizes the vertical distances between the line and the points
  - These distances are called **residuals.**
  - The line we will find actually minimizes the sum of the squares of the residuals.
  - This is called a **least-squares regression line**.

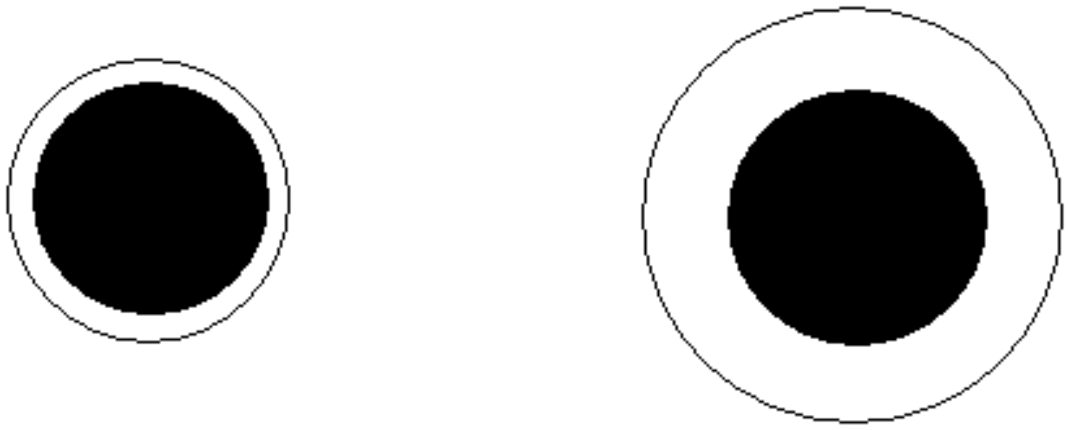


Are Dinner Plates Getting Larger?

Example 10.3

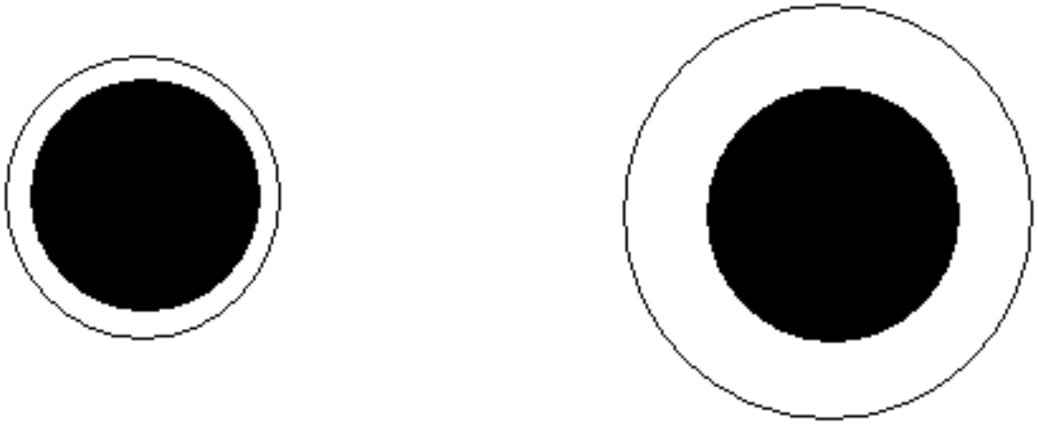
Growing Plates?

- There are many recent articles and TV reports about the obesity problem.
- One reason some have given is that the size of dinner plates are increasing.
- Are these black circles the same size, or is one larger than the other?



Growing Plates?

- They appear to be the same size for many, but the one on the right is about 20% larger than the left.



- This suggests that people will put more food on larger dinner plates without knowing it.
- There is name for this phenomenon: *Delboeuf illusion.*

Growing Plates?

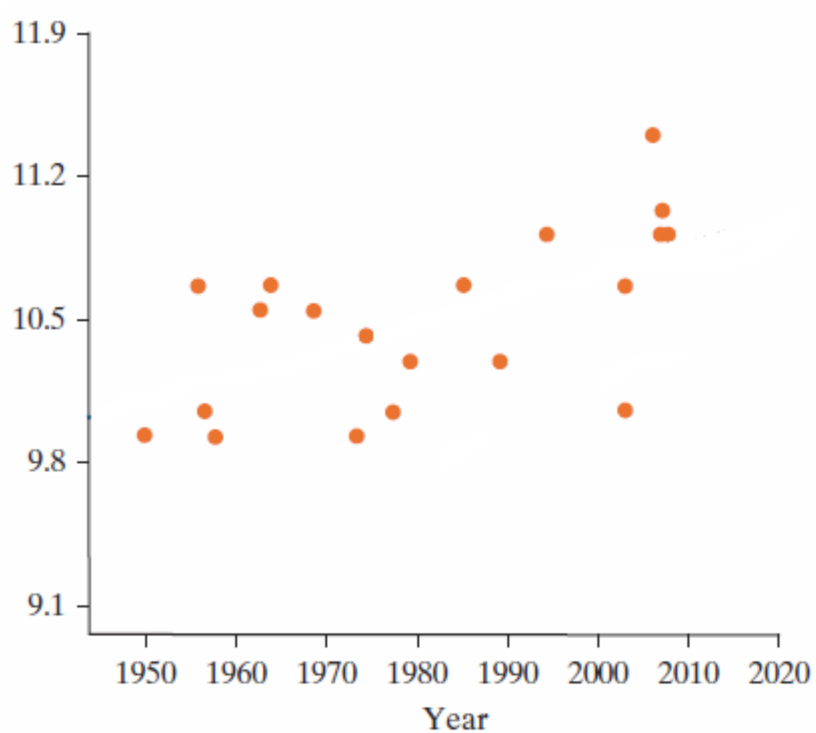
- Researchers gathered data to investigate the claim that dinner plates are growing
- American dinner plates sold on ebay on March 30, 2010 (Van Ittersum and Wansink, 2011)
- Year manufactured and diameter are given.

TABLE 10.1 Data for size (diameter, in inches) and year of manufacture for 20 American-made dinner plates

Year	1950	1956	1957	1958	1963	1964	1969	1974	1975	1978
Size	10	10.75	10.125	10	10.625	10.75	10.625	10	10.5	10.125
Year	1980	1986	1990	1995	2004	2004	2007	2008	2008	2009
Size	10.375	10.75	10.375	11	10.75	10.125	11.5	11	11.125	11

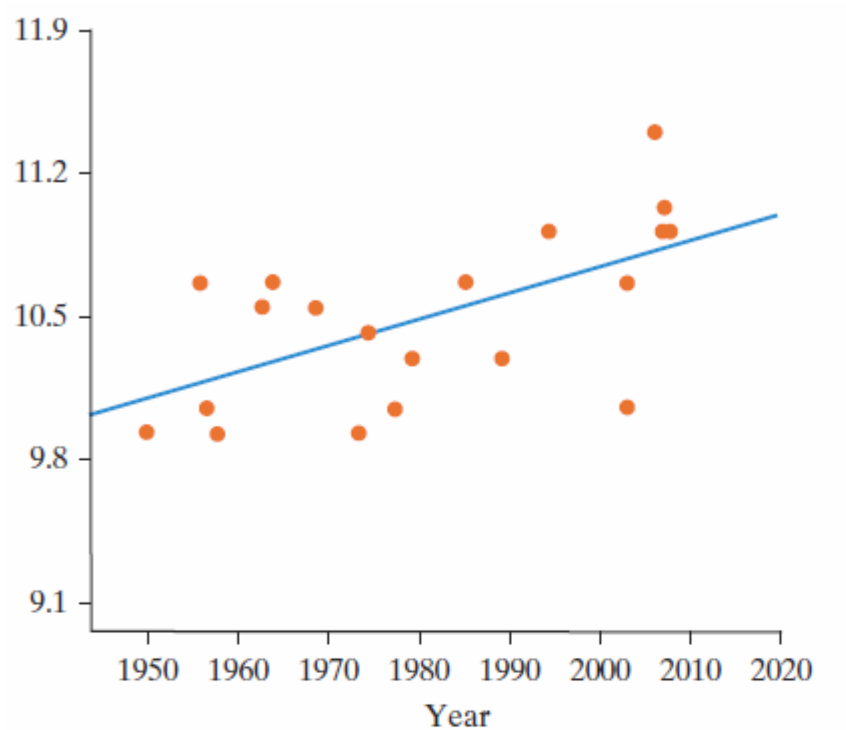
Growing Plates?

- Both year (explanatory variable) and diameter in inches (response variable) are quantitative.
- Each dot in this scatterplot represents one plate.



Growing Plates?

- The association appears to be roughly linear.
- The least squares regression line is added.
- The line slopes upward, but is the slope significant?



Regression Line

The regression equation is $\hat{y} = a + bx$:

- *a* is the *y*-intercept
- *b* is the slope
- *x* is a value of the explanatory variable
- $\hat{y}$ is the predicted value for the response variable

- For a specific value of *x*, the corresponding distance $y - \hat{y}$ (or actual – predicted) is a residual

Regression Line

- The least squares line for the dinner plate data is $\hat{y} = -14.8 + 0.0128x$
- Or $\widehat{\text{diameter}} = -14.8 + 0.0128(\text{year})$
- This allows us to predict plate diameter for a particular year.

Slope

$$\hat{y} = -14.8 + 0.0128x$$

- What is the predicted diameter for a plate manufactured in 2000?
  - -14.8 + 0.0128(2000) = 10.8 in.
- What is the predicted diameter for a plate manufactured in 2001?
  - -14.8 + 0.0128(2001) = 10.8128 in.
- How does this compare to our prediction for the year 2000?
  - 0.0128 larger
- Slope b = 0.0128 means that diameters are predicted to increase by 0.0128 inches per year on average

Slope

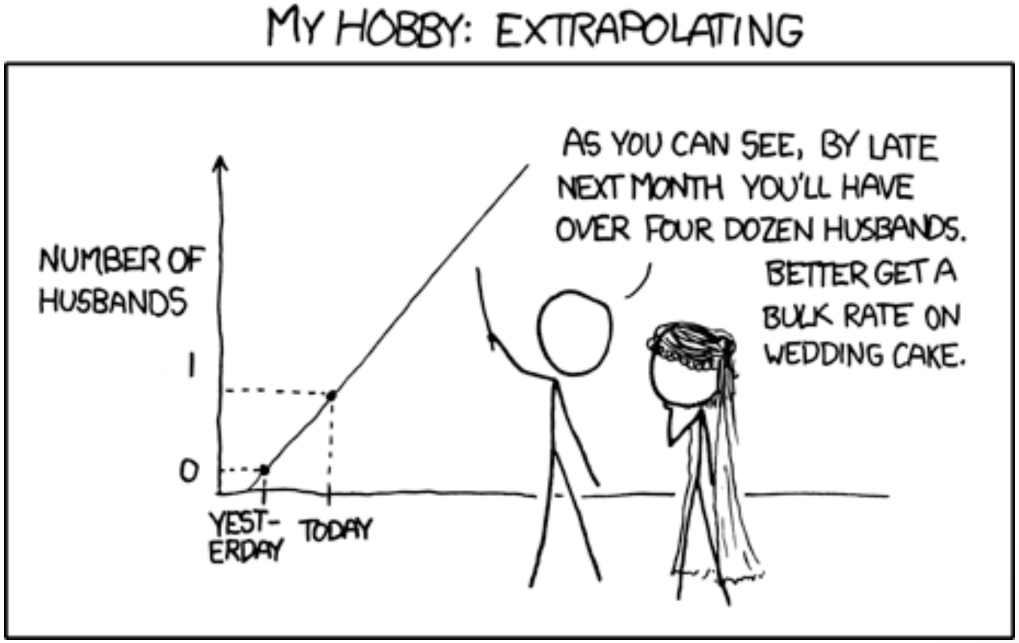
- Slope is the predicted change in the response variable for one-unit change in the explanatory variable.
- Both the slope and the correlation coefficient for this study were positive.
  - The slope is 0.0128
  - The correlation is 0.604
- The slope and correlation coefficient will always have the same sign.

y-intercept

- The *y*-intercept is where the regression line crosses the *y*-axis. It is the predicted response when the explanatory variable equals 0.
- We had a *y*-intercept of -14.8 in the dinner plate equation. What does this tell us about our dinner plate example?
  - Dinner plates in year 0 would be predicted to be -14.8 inches???
- How can it be negative?
  - The equation works well within the range of values given for the explanatory variable, but fails outside that range.
- Our equation should only be used to predict the size of dinner plates from about 1950 to 2010.

Extrapolation

- Predicting values for the response variable for values of the explanatory variable that are outside of the range of the original data is called ***extrapolation***.



Coefficient of Determination

- While the intercept and slope have meaning in the context of year and diameter, remember that the correlation does not. It is just 0.604.
- However, the square of the correlation (coefficient of determination or r^2) does have meaning.
- $r^2 = 0.604^2 = 0.365$ or 36.5%
- 36.5% of the variation in plate size (the response variable) can be explained by its linear association with the year (the explanatory variable).

Learning Objectives for Section 10.3

- Understand that one way a scatterplot can be summarized is by fitting the best-fit (least squares regression) line.
- Be able to interpret both the slope and intercept of a best-fit line in the context of the two variables on the scatterplot.
- Find the predicted value of the response variable for a given value of the explanatory variable.
- Understand the concept of residual and find and interpret the residual for an observational unit given the raw data and the equation of the best fit (regression) line.
- Understand the relationship between residuals and strength of association and that the best-fit (regression) line this minimizes the sum of the squared residuals.

Learning Objectives for Section 10.3

- Find and interpret the coefficient of determination (r^2) as the squared correlation and as the percent of total variation in the response variable that is accounted for by the linear association with the explanatory variable.
- Understand that extrapolation is when a regression line is used to predict values outside of the range of observed values for the explanatory variable.
- Understand that when slope = 0 means no association, slope < 0 means negative association, slope > 0 means positive association, and that the sign of the slope will be the same as the sign of the correlation coefficient.
- Understand that influential points can substantially change the equation of the best-fit line.

4. Calculating correlation, r.

ρ = rho = correlation of the population.
Suppose there are N people in the population,
X = temperature, Y = heart rate,
the mean and sd of temp in the pop. are μ_x and σ_x,
and the pop. mean and sd of heart rate are μ_y and σ_y.

$$\rho = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu_x}{\sigma_x}\right)\left(\frac{y_i - \mu_y}{\sigma_y}\right).$$

Given a sample of size n, we estimate ρ using

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{x_i - \overline{x}}{s_x}\right)\left(\frac{y_i - \overline{y}}{s_y}\right).$$

This is in Appendix A.

5. Slope of regression line.

- Suppose $\hat{y}$ = a + bx is the regression line.
- The slope b of the regression line is b = r $\frac{s_y}{s_x}$.

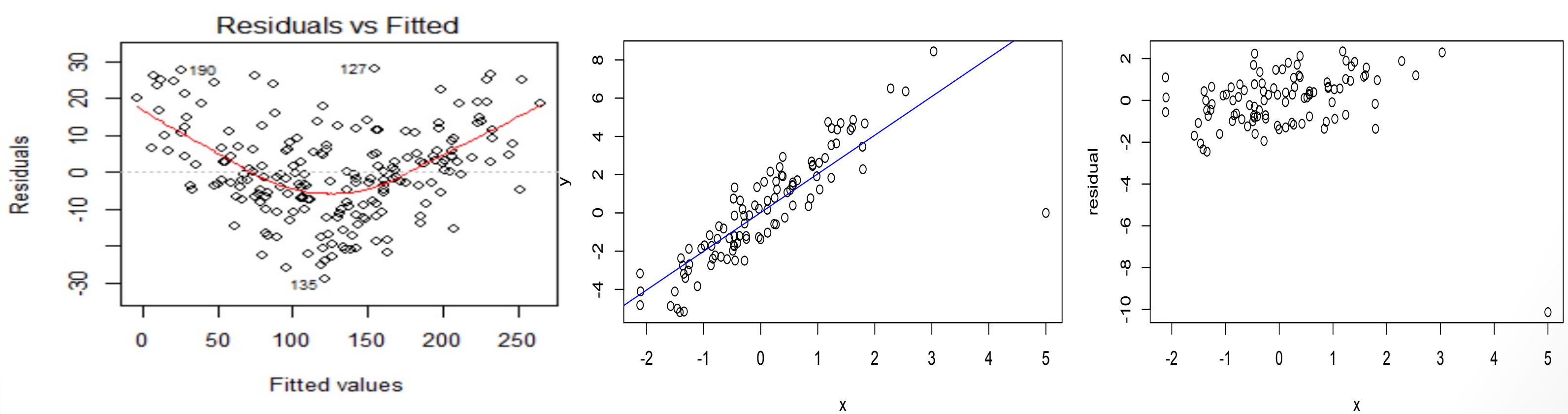
This is usually the thing of primary interest to interpret, as the predicted increase in y for every unit increase in x.

- Beware of assuming causation though, esp. with observational studies. Be wary of extrapolation too.
- The intercept a = $\bar{y}$ - b $\bar{x}$.
- The SD of the residuals is $\sqrt{1-r^2}\, s_y$.

This is a good estimate of how much the regression predictions will typically be off by.

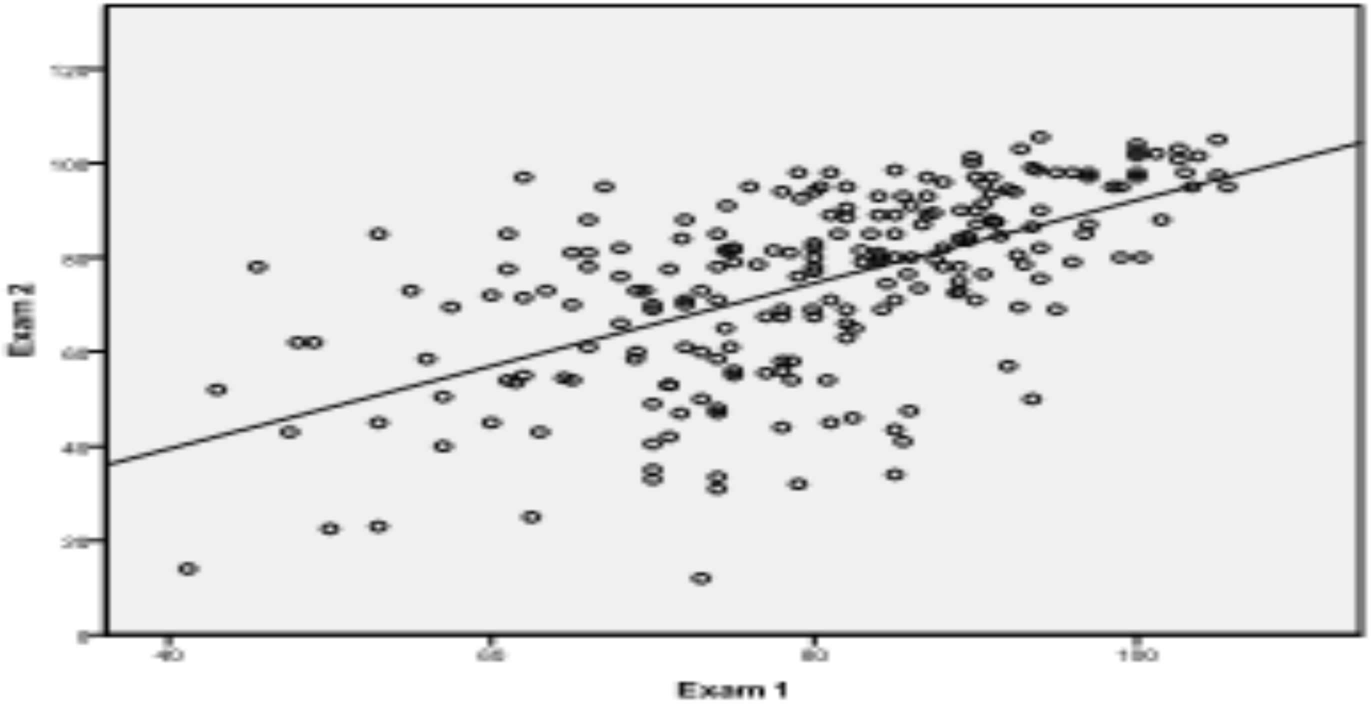
6. How well does the line fit?

- r^2 is a measure of fit. It indicates the amount of scatter around the best fitting line.
- $\sqrt{1 - r^2}\, s_y$ is useful as a measure of how far off predictions would have been on average.
- Residual plots can indicate curvature, outliers, or heteroskedasticity.



- Note that regression residuals have mean zero, whether the line fits well or poorly.

- Heteroskedasticity: when the variability in y is not constant as x varies.

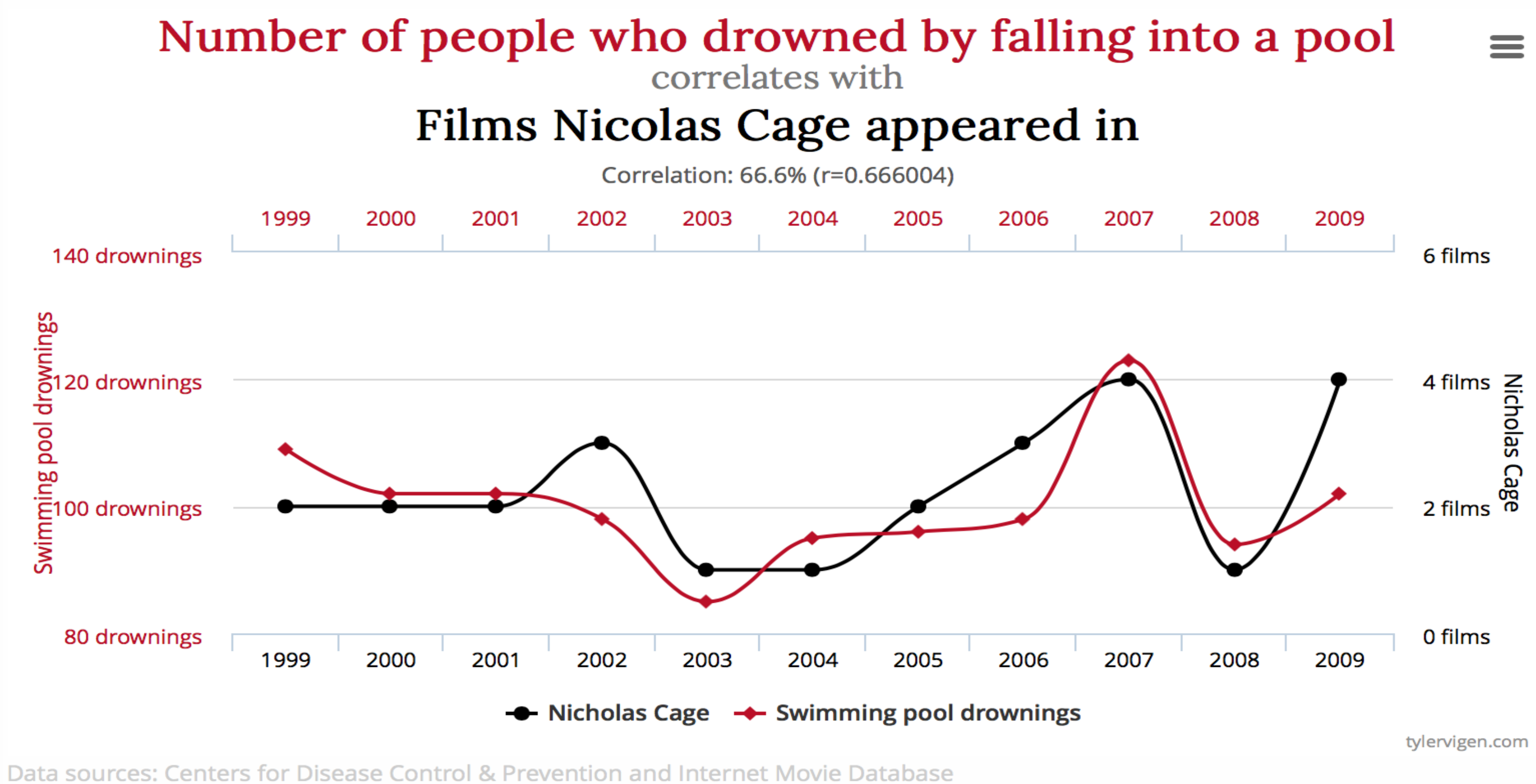


(b)

7. Common problems with regression.

- a. Correlation is not causation.

ESPECIALLY WITH OBSERVATIONAL DATA!



Common problems with regression.

Common problems with regression.

Holmes and Willett (2004) reviewed all prospective studies on fat consumption and breast cancer with at least 200 cases of breast cancer. "Not one study reported a significant positive association with total fat intake.... Overall, no association was observed between intake of total, saturated, monounsaturated, or polyunsaturated fat and risk for breast cancer."

They also state "The dietary fat hypothesis is largely based on the observation that national per capita fat consumption is highly correlated with breast cancer mortality rates. However, per capita fat consumption is highly correlated with economic development. Also, low parity and late age at first birth, greater body fat, and lower levels of physical activity are more prevalent in Western countries, and would be expected to confound the association with dietary fat."

Common problems with regression.

- b. Extrapolation.

Common problems with regression.

- b. Extrapolation.
- Often researchers extrapolate from high doses to low.

D.M. Odom et al.

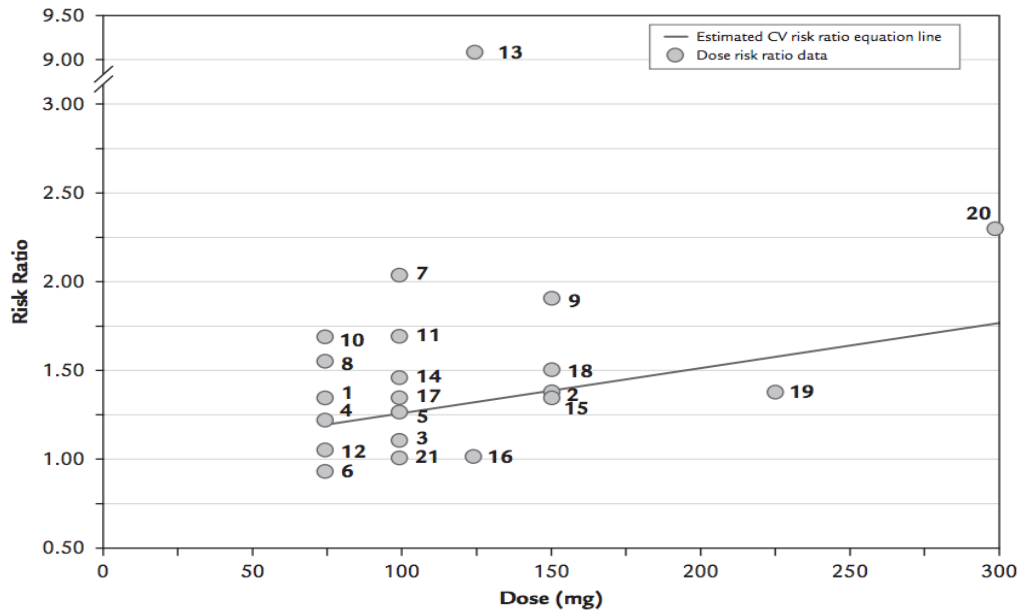


Figure 4. Relationship between diclofenac daily dose and the estimated risk ratio of a cardiovascular event. Numbers correspond to the observations in Table III.

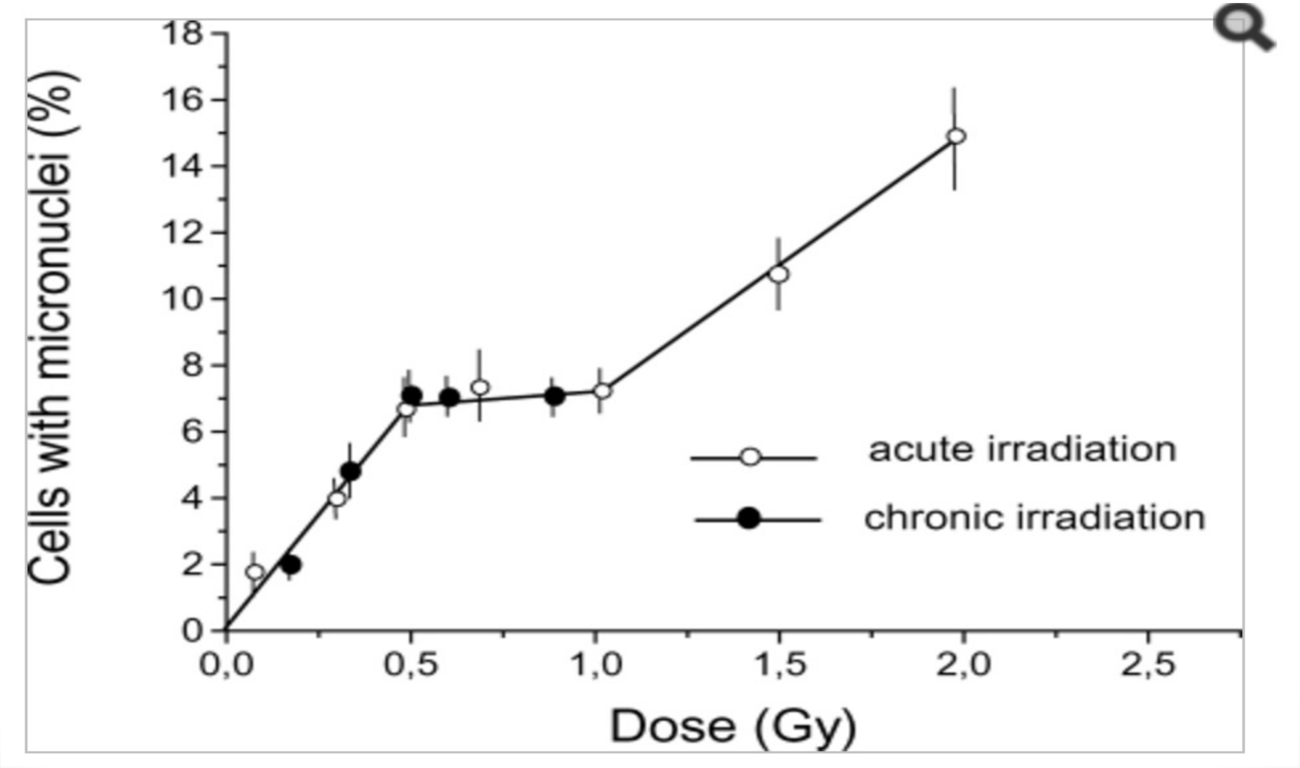
Common problems with regression.

- b. Extrapolation.

The relationship can be nonlinear though.

Researchers also often extrapolate from animals to humans.

Zaichkina et al. (2004) on hamsters



Common problems with regression.

- c. Curvature.

The best fitting line might fit poorly. Port et al. (2005).

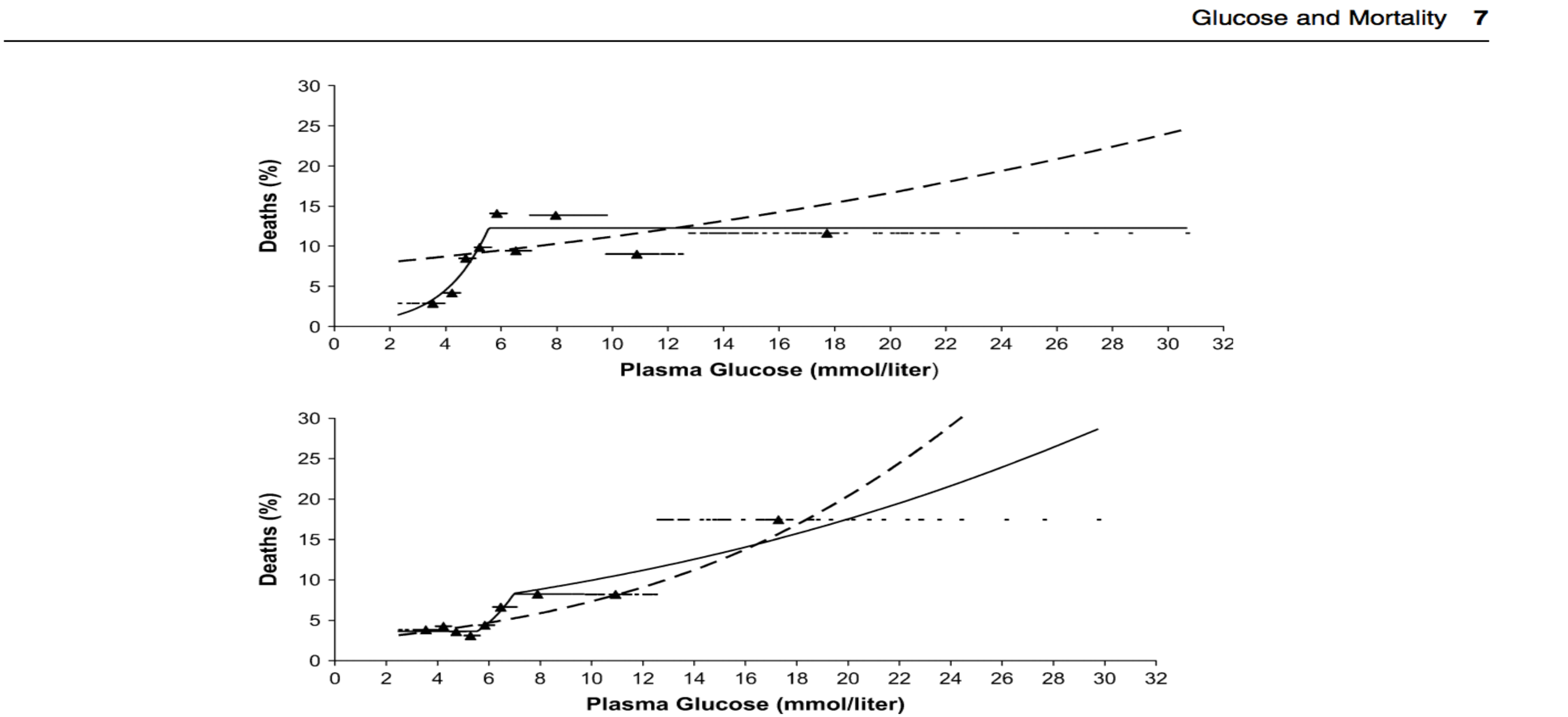
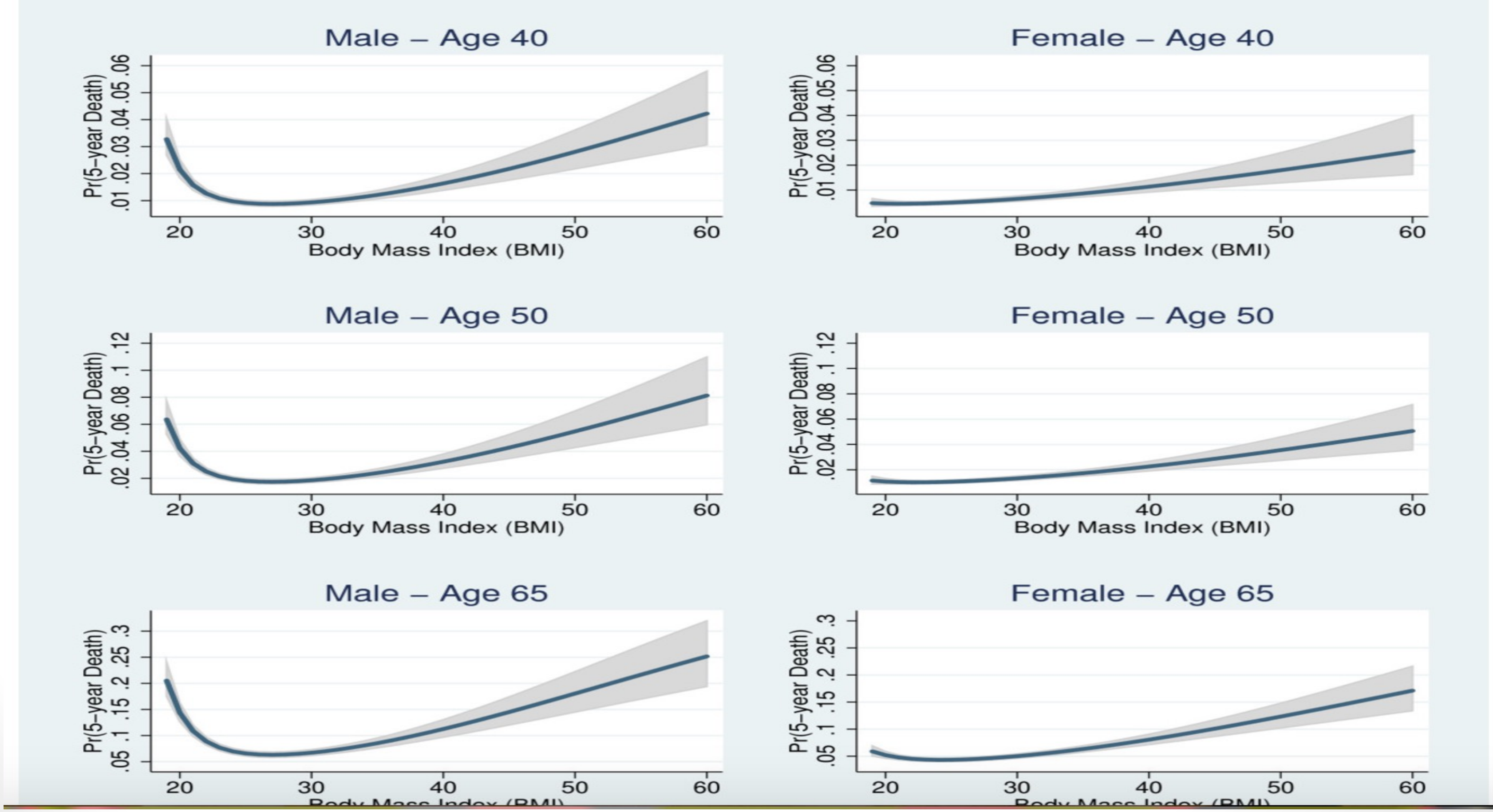


FIGURE 4. Adjusted 2-year rates of death from all causes for men (upper panel) and women (lower panel) separately, by glucose level, predicted by three models, Framingham Heart Study, 1948–1978. Linear model (dashed curve); optimal spline models (solid curve). The horizontal dashed

Common problems with regression.

- c. Curvature.

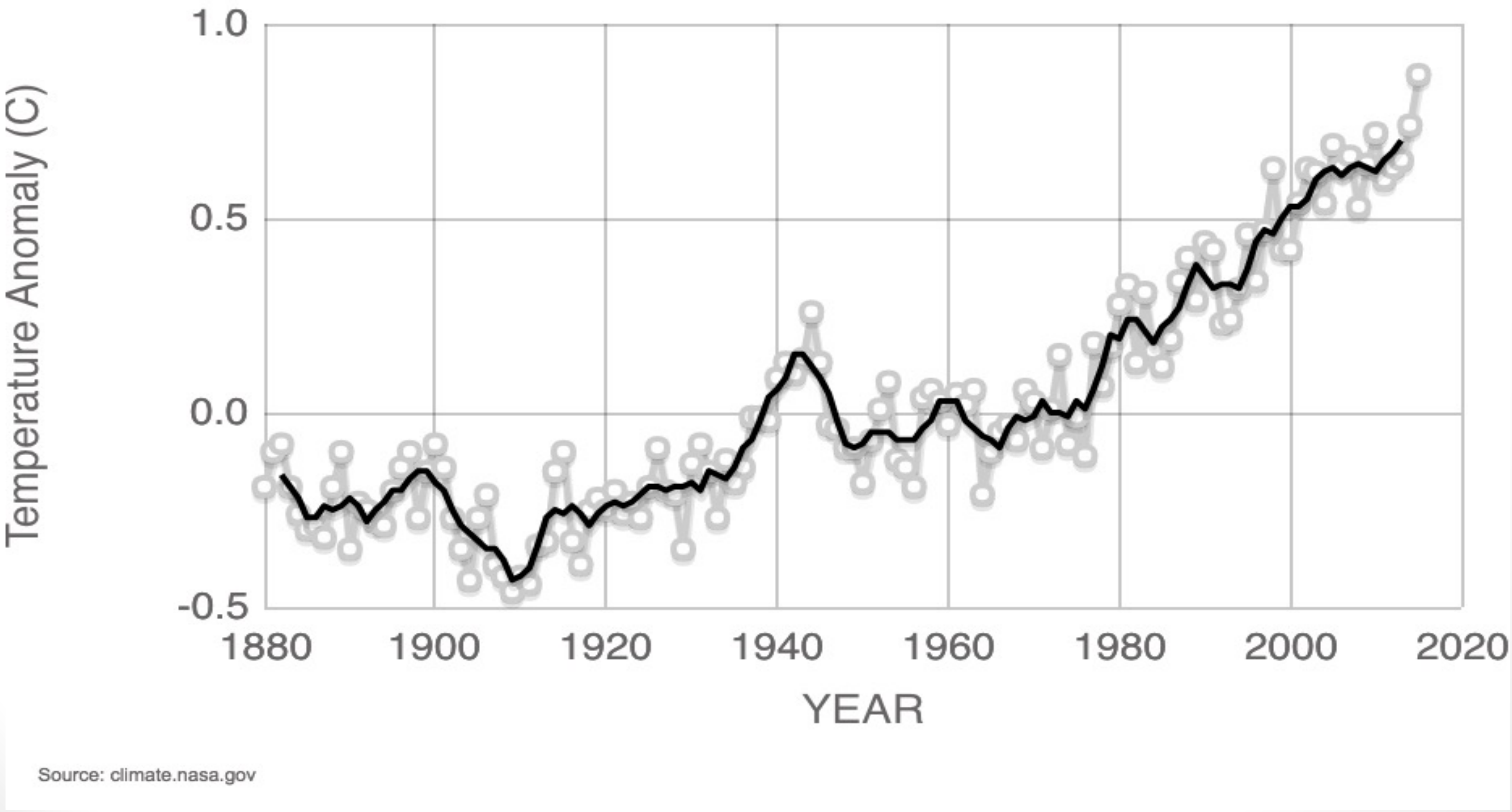
The best fitting line might fit poorly. Wong et al. (2011).



Common problems with regression.

- d. Statistical significance.

Could the observed correlation just be due to chance alone?



8. Inference for the Regression Slope: Theory-Based Approach

Section 10.5

Do students who spend more time in non-academic activities tend to have lower GPAs?

Example 10.4

Do students who spend more time in non-academic activities tend to have lower GPAs?

- The subjects were 34 undergraduate students from the University of Minnesota.
- They were asked questions about how much time they spent in activities like work, watching TV, exercising, non-academic computer use, etc. as well as what their current GPA was.
- We are going to test to see if there is a significant negative association between the number of hours per week spent on nonacademic activities and GPA.

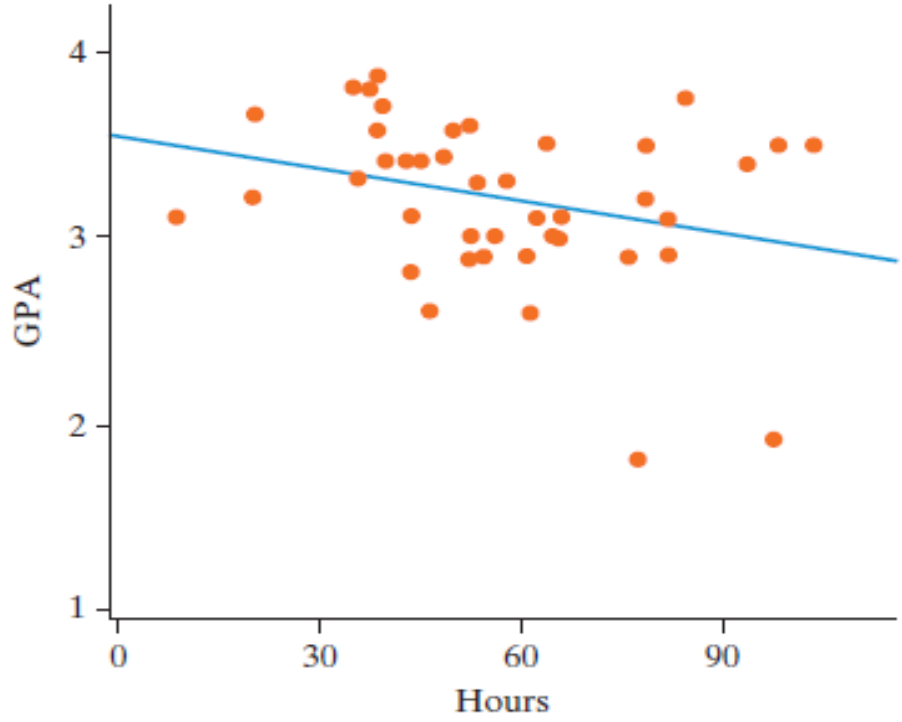
Hypotheses

- Null Hypothesis: There is no association between the number of hours students spend on nonacademic activities and student GPA in the population.

- Alternative Hypothesis: There is a negative association between the number of hours students spend on nonacademic activities and student GPA in the population.

Descriptive Statistics

- $\widehat{\text{GPA}} = 3.60 - 0.0059(\text{nonacademic hours}).$
- Is the slope significantly different from 0?



Shuffle to Develop Null Distribution

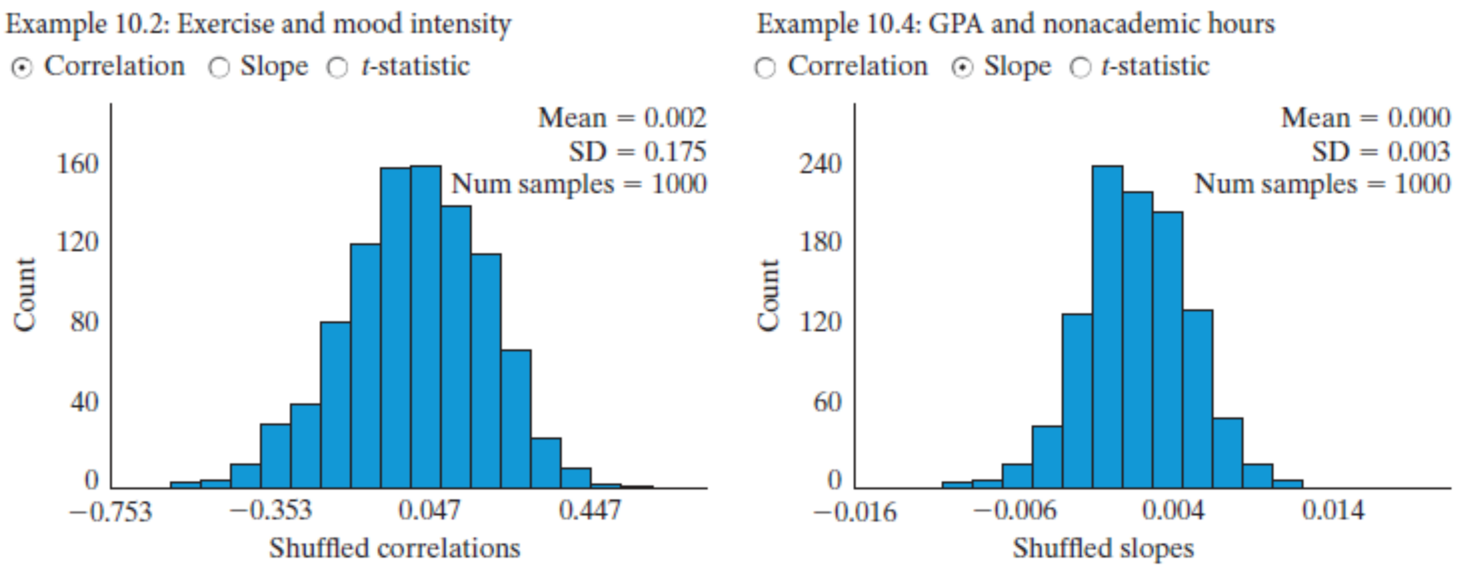
- We are going to shuffle just as we did with correlation to develop a null distribution.
- The only difference is that we will be calculating the slope each time and using that as our statistic.
- **a test of association based on slope is equivalent to a test of association based on a correlation coefficient.**

Beta vs Rho

- Testing the slope of the regression line is equivalent to testing the correlation (same p-value, but obviously different confidence intervals since the statistics are different)
- Hence these hypotheses are equivalent.
  - H_o: β = 0 H_a: β < 0 (Slope)
  - H_o: ρ = 0 H_a: ρ < 0 (Correlation)
- Sample slope (b) Population (β: beta)
- Sample correlation (r) Population (ρ: rho)
- When we do the theory based test, we will be using the *t*-statistic which can be calculated from either the slope or correlation. The formula is t = $\frac{r}{\sqrt{\frac{1-r^2}{n-2}}}$.

Introduction

- Our null distributions are again bell-shaped and centered at 0 (for either correlation or slope as our statistic).



The book on p549 finds a p value of 3.3% by simulation.

Validity Conditions

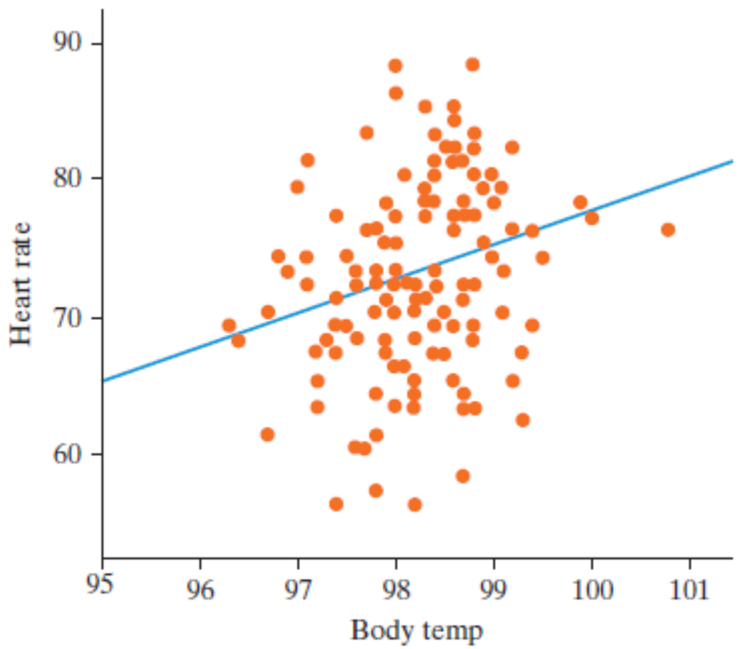
- Under the usual conditions: relationship is linear, observations are iid, both variables are normally distributed, and data are homoscedastic, theory-based inference for correlation or slope of the regression line uses the *t*-distribution.
- We could use simulations or the theory-based methods for the slope of the regression line.
- We would get exactly the same p-value if we used correlation as our statistic.

Predicting Heart Rate from Body Temperature

Example 10.5A

Heart Rate and Body Temp

- Earlier we looked at the relationship between heart rate and body temperature with 130 healthy adults
- Predicted Heart Rate $= -166.3 + 2.44(\text{Temp})$
- r = 0.257

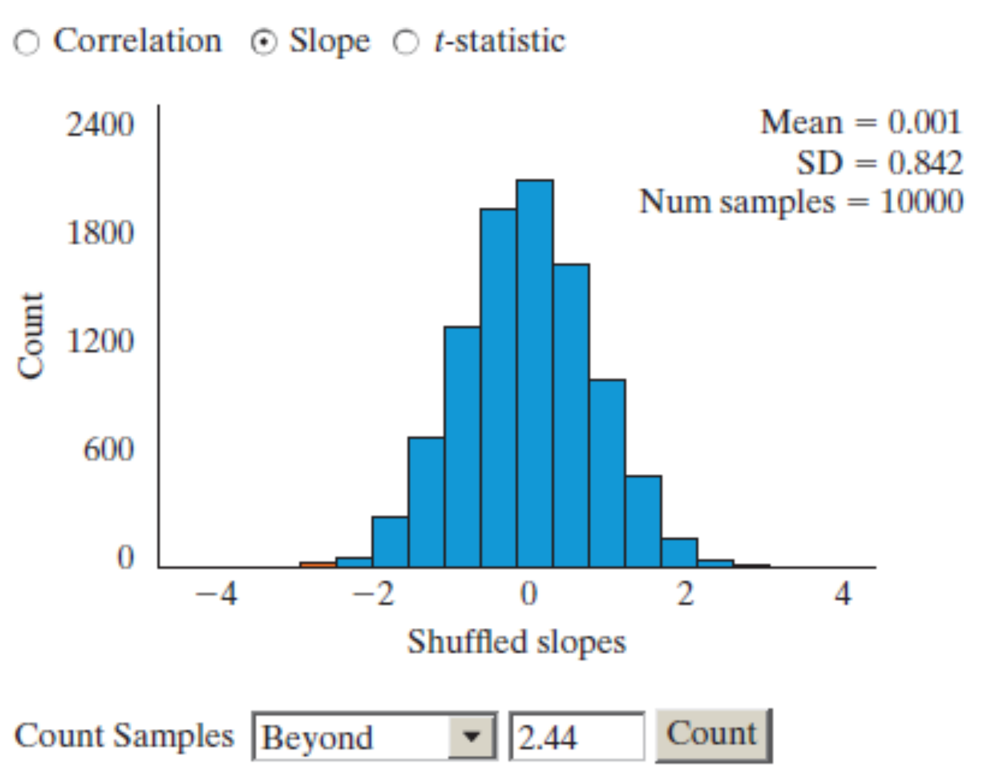


Heart Rate and Body Temp

- We tested to see if we had convincing evidence that there is a positive association between heart rate and body temperature in the population using a simulation-based approach. (We will make it 2-sided this time.)
- **Null Hypothesis**: There is no association between heart rate and body temperature in the population. $\beta = 0$
- **Alternative Hypothesis**: There is an association between heart rate and body temperature in the population. $\beta \neq 0$

Heart Rate and Body Temp

We get a very small p-value (0.0036). Anything as extreme as our observed slope of 2.44 happening by chance is very rare.



Heart Rate and Body Temp

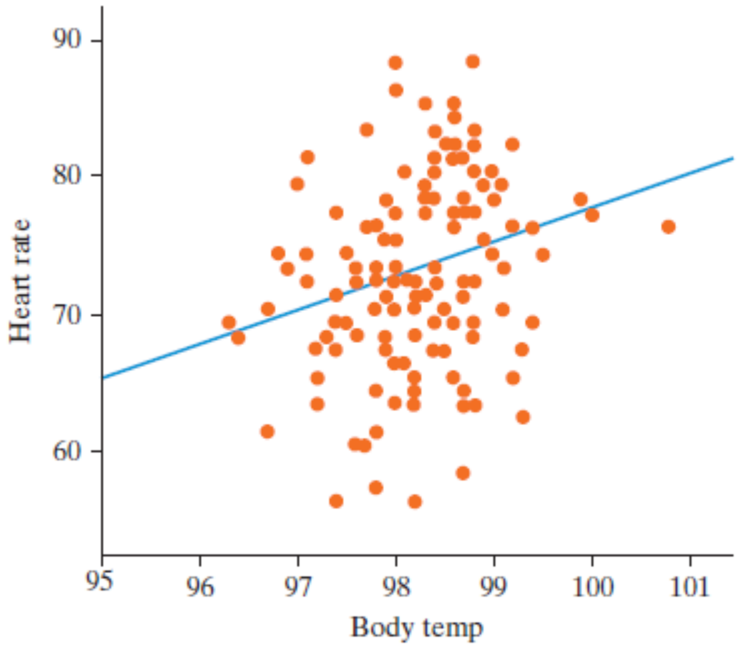
- We can also approximate a 95% confidence interval

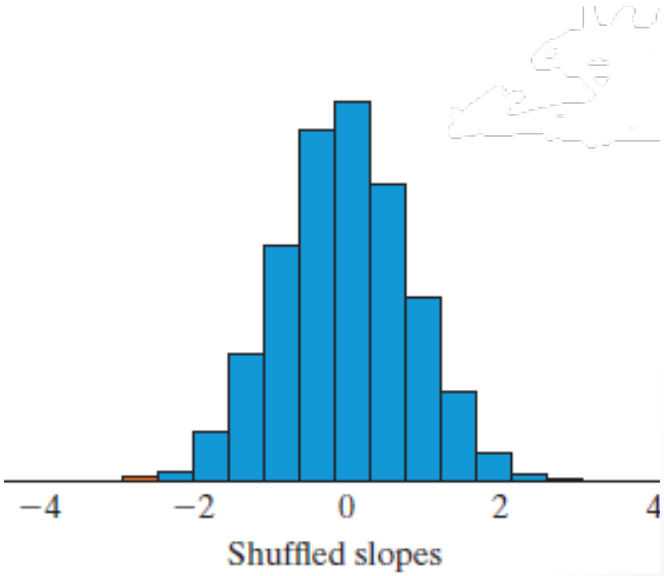
  observed statistic $\pm$ multiplier $\times$ SE

  $2.44 \pm 1.96 \times 0.842 = 0.790$ to 4.09
- When both variables are normally distributed (scatterplot is elliptical), use the t-multiplier instead of 1.96, but when n is large it makes very little difference.
- This means we are 95% confident that, in the population of healthy adults, each 1° increase in body temp is associated with an increase in heart rate of between 0.790 to 4.09 beats per minute.

Heart Rate and Body Temp

- The theory-based approach should work well since the distribution of the slopes has a nice bell shape
- Also check the scatterplot





Heart Rate and Body Temp

- We will use the t-statistic to get our theory-based p-value.
- We will find a theory-based confidence interval for the slope.
- On p554, the book notes the formula t = $\frac{r}{\sqrt{\frac{1-r^2}{n-2}}}$.
- Here the t statistic is 2.97.
- The p-value is 0.36%. So the correlation is statistically significantly greater than zero.

Smoking and Drinking

Example 10.5B

Validity Conditions

Remember our validity conditions for theory-based inference for slope of the regression equation.

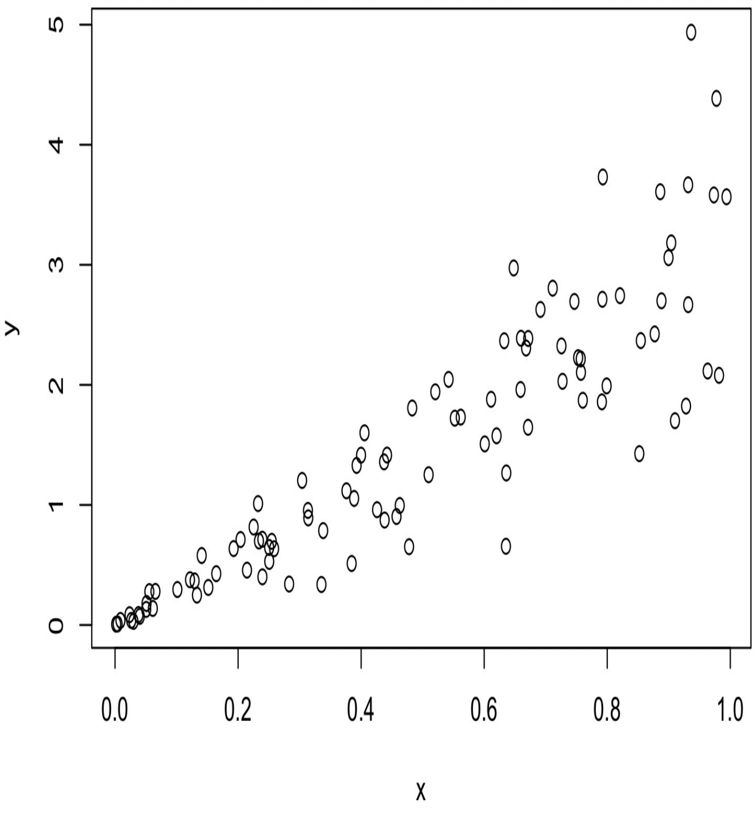
1. The scatterplot should not have obvious curvature.
2. The observations should be iid.
3. For the t-test, both variables should be normal.

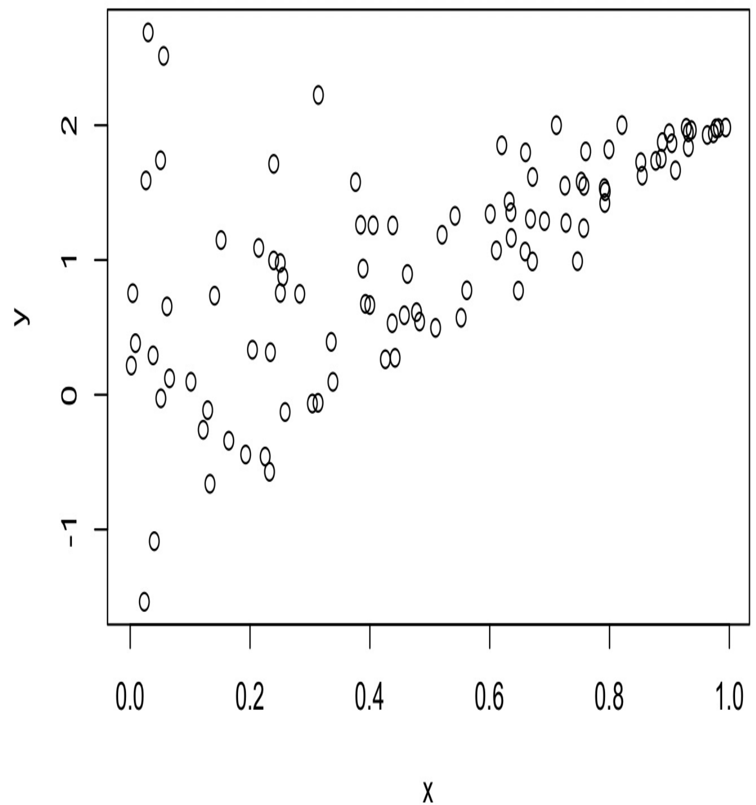
In particular, there should be approximately the same number of points above and below the regression line (symmetry).

4. The variability of vertical slices of the points should be similar. This is called homoskedasticity.

Validity Conditions

- Let's look at some scatterplots that do not meet the requirements.



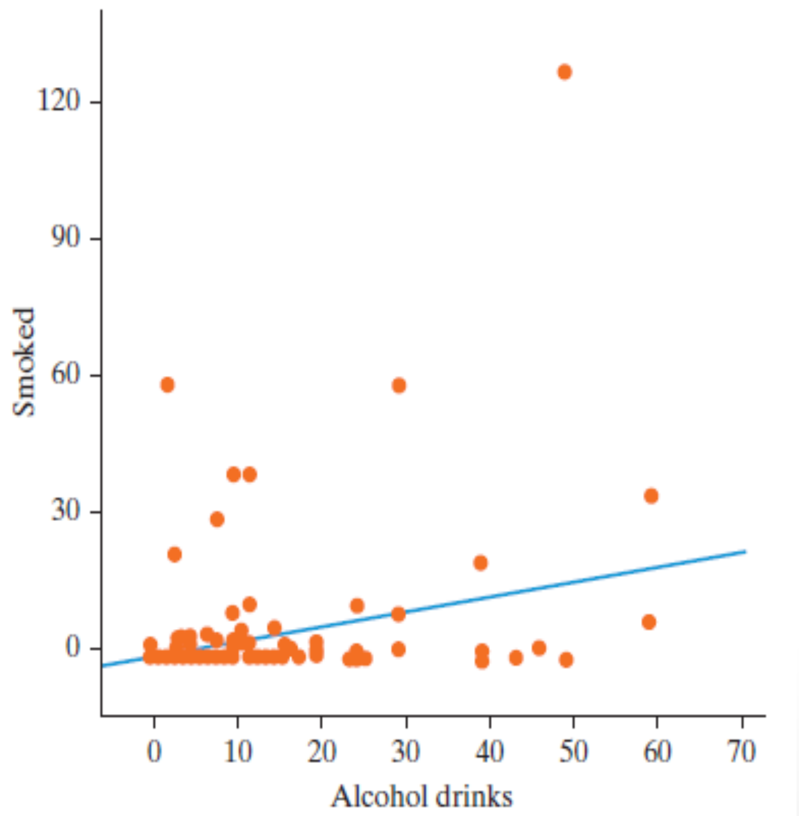


Smoking and Drinking

The relationship between number of drinks and cigarettes per week for a random sample of students at Hope College.

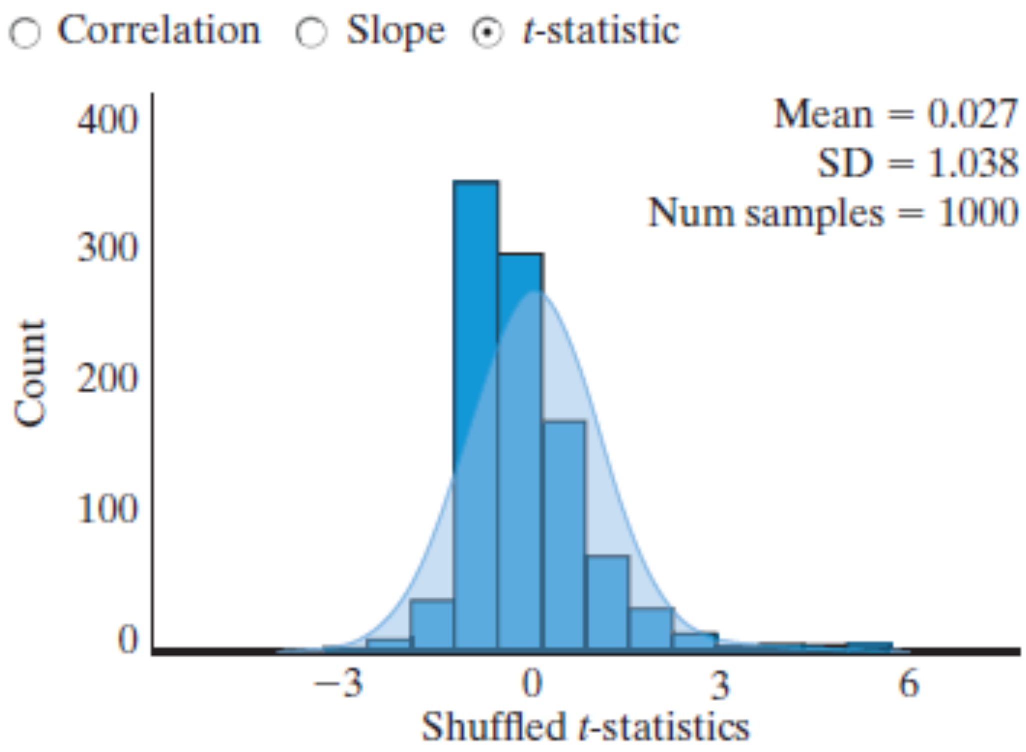
The dot at (0,0) represents 524 students

Are the conditions met? Hard to say. The book says no.



Smoking and Drinking

- When the conditions are not met, applying simulation-based inference is preferable to theory-based t-tests and CIs.



Validity Conditions

- What do you do when validity conditions aren't met for theory-based inference?
  - Use the simulated-based approach.
- Another strategy is to "transform" the data on a different scale so conditions are met.
  - The logarithmic scale is common.
- One can also fit a different curve, not necessarily a line.