chapter 7

Linear Regression



Homework

p195 1-9, 11, 13, 15, 17, 19, 21, 26, 28, 29, 32, 35, 37





Objectives

Determine Least Squares Regression Line (LSRL) describing the association of two variables.



GPA Example

The following case study "SAT and College GPA" contains high school and university grades for 105 computer science majors at a state school.

Describe the relationship.

Objective: Students will determine the line of best fit (Least Squares Regression Line) and describe







The Linear Model

The correlation in the GPA example is 0.7795.

- The strength of the correlation coefficient suggests a linear association between these two variables, but the correlation coefficient tells us nothing about the association itself.
- What we need to describe the linear relationship between two quantitative variables is a model of that association.
- I that model is a linear equation that quantifies the relationship or pattern in the co-variability of those variables.









The Linear Model

- The linear model is nothing more complicated than a linear equation of a straight line through the data.
- is That model (equation) will have a slope and intercept to help us understand and describe the relationship between the two variables.
- It is unlikely in the extreme that the points in a scatterplot of the variables data will actually form a nice, straight line. But a nice straight line might suffice in describing the overall pattern of the scatter plot with the slope and intercept.





Regression

If the relationship between variables is strong, we know that the variables tend to cluster to a line.

- I fhat means we can get some idea about the behavior of one (response) variable by observing the behavior of another (predictor) variable.
- We can then make predictions about the response variable by knowing a value of the predictor variable.
- What we need to do is find the equation of the line that best fits the data. That, of course, begs the question what do we mean by "best fit"?
- That "line of best fit" is called the **regression line** or....









Residuals

First know this, the model will be wrong.

- probably be of great interpolative value.
- the line and some points will be below the prediction model (line).
- The estimate made from a model is the predicted value....





What that means is the data points will rarely actually fall on the line. The model will predict a different value than the observed data, but it may be close and the model will

Similar to the way data values fall above and below the mean, some points will be above

"y-hat" (denoted as y)



Residuals

The difference between the observed value (Y) and its associated predicted value (Y) is called the residual.

To find the residuals, we subtract the predicted value from the observed value:

residual = observed - predicted





Residuals

- A positive residual means the predicted value is less than the actual value (an underestimate).
 - In the figure, the predicted college gpa is 2.5, while the true value of college gpa is 342, and the residual is 0.92.
- A negative residual means the predicted value is greater than the actual value (an overestimate).
 - In the figure, the estimated college gpa is 2.30, while the true value of college gpa is 2.52, thus the residual is -0.28.



"Best Fit" Means Least Squares

Some residuals are positive, others are negative, and, on average, they balance each other out. This is very similar to the calculation for standard deviation.

Ilke we did with deviations, we square the residuals and add the squares, resulting in the "sum of squared residuals" (This is also called "sum of squared errors" or SSE).

The smaller the sum (least squares), the better the fit.

the least squares line.



- The line of best fit is the line for which the sum of the squared residuals is smallest,



Least Squares

This shows a least squares residual line and visually demonstrates the methodology of "least squares".

The line that minimizes the residuals also minimizes the area of the squares.

https://www.desmos.com/calculator/zvrc4lg3cr

Objective: Students will determine the line of best fit (Least Squares Regression Line) and describe





Correlation and the LSRL

- \sim This figure shows the scatterplot of z-scores for the variables ColGPA and HSGPA along with the scatterplot of raw scores.
 - What do you notice about the distributions.



Remember: changing scales does not change r.



Scatter Plot **Collection 1** 1.5 1.0 0.5 0.0 0.0 -0.5 -1.0 Ο 0 -1.5 0 -2.0 0 -2.5--2 2 **zHSGPA**



Correlation and the LSRL

- If an individual have an average HSGPA, we would expect about an average ColGPA as well.
- That suggests the point consisting of the mean for each variable in on the LSRL.
- That would tell us that moving one standard deviation away from the mean in x moves us r standard deviations away from the mean in y.





Let Me Repeat That

The correlation coefficient, r, is the slope of the line of best fit for Z-scores.

That means that if the data have been changed to z-scores, the line best fitting that data will have a slope of r.



However, if the data is NOT re-expressed as z-scores, the slope of the Isri IS NOT r.



So Whai?

- A slope of r for the line of best fit for z-scores means that a change of 1 unit in z_x predicts a change of r units in $\hat{z_y}$.
 - In terms of raw values x and y, a change in 1 standard deviation in x predicts a change of **r** standard deviations in $\hat{\mathbf{y}}$
 - Now we can express the slope of the Isrl in terms of r.







Correlation and the LSRL

So now you know that a line that models our scatterplot of **z-scores** goes through the mean z-score values, the origin (0, 0),

Since the standard deviation of z-scores is 1, The slope of that line from z scores is **r**.





Correlation and the LSRL

So now you know that a line that models our scatterplot of **raw scores** goes through the mean raw scores, (\bar{x}, \bar{y}) ,

 \sim The standard deviation of raw scores are s_{χ} . sy and the slope of that line is ...





Correlation and the LSRL

- Thus, moving any number of standard deviations away from the mean in x moves us r times that number of standard deviations away from the mean in y.
- In cannot be bigger than 1, so each predicted y tends to be closer to its mean than its corresponding x.

regression line.



This property of the linear model is called regression to the mean; the line is called the



Definition

Solution A regression line is a line that models how changes in an explanatory variable (x) predict changes in a response variable (\hat{y}).

\mathbf{W} Thus, the regression line is used to **predict** the value of $\hat{\mathbf{y}}$ for a given value of \mathbf{x} .



- The Regression Line in Real Units.
 - \sim Remember from Algebra that a straight line can be written as: $\gamma = m \times + b$
 - In Statistics we use a slightly different notation:

$$\hat{y} = b_1 x + b_0$$

- not the actual data values (y).
- The model that is a straight line are our predictions.
- The more closely the model fits the data, the closer the data values will fit around the line of best fit (Isrl).

or
$$\hat{y} = b_0 + b_1 x$$

We write Y to indicate that the points that satisfy this equation are our predicted values,



The Regression Line in Real Units.

We write b_1 and b_0 for the slope and y-intercept of the line.

1 is the slope of the regression line, which tells us how much the response variable, $\hat{\mathbf{y}}$, changes with a <u>one unit</u> change in the predictor variable, \mathbf{x} .

 $\sim b_0$ is the y-intercept, which tells where the line crosses (intercepts) the vertical (y) axis. That tells us the predicted value of the response variable when the value of the predictor variable is 0.

You want to remember these definitions. You will be asked to repeat them, repeatedly.



The Real World

Vour TI-84, and many texts, use



and which value is the y-intercept.

for the regression equation.

It is only important that you keep in mind which value is the slope of the regression line



Reporting Slope and Intercept

When interpreting the slope of the regression model the sentence frame you will use is:



Do not be creative or clever. Do not attempt to impress me as a vocabulist.



Just use some variation of the given sentence frame or risk not getting credit.



Reporting Slope and Intercept



- Sometimes this is a meaningless statistic, and sometimes it is meaningful.
- What is the cost of renting a car when the number of miles driven is 0? This may make sense since you may rent the car but never use it.
- What is the weight of a person that is 0" tall? This definitely is nonsense.



LSRL in real units

\sim In our model, we have a slope (b_1)

The slope is built from the correlation and the standard deviations:



of y (response variable) per unit of x (predictor variable).

The size of the slope is determined by the units of the variables. The size of the slope is **NOT** a measure of strength or significance.



LSRL in real units

 \sim In our model, we also have an intercept (b_0)

The intercept is built from the data means and the slope:



Obviously, our intercept is always in units of y.

of the standard deviations given with r.

- Remember this, you will be asked to find the regression model from computer output



High School vs College GPA

The regression line for the HSGPA and College GPA seems to fit pretty well.

The model is: $\widehat{ColGPA} = 1.1 + 0.67 HSGPA$

The predicted college GPA for student with a high school GPA of 3.0 is 1.1 + 0.67(3.0) = 3.11.

For every increase of <u>1 point</u> in <u>high school GPA</u>, there is a predicted <u>increase</u> of <u>0.67 points in the college GPA.</u>

We predict a college GPA of 1.1 when the high school GPA is 0.





High School vs College GPA

- Since regression and correlation are from the same math, we must check the same conditions for regressions as we did for correlations:
 - Quantitative Variables
 - Sufficiently Linear
 - No significant Outliers
- Our data is quantitative, the pattern in the scatter plot is sufficiently linear and there are some data points that could be outliers such as (2.1, 3.4) or (2.5, 2.1), but I do not think they significantly affect our model.

But there is a problem with the data!





Another Example

- Suppose we collected the weight of a male white lab rat for the first 25 weeks after its birth.
 - A scatterplot of the weight (grams) and time since birth (weeks) shows a fairly strong, positive linear relationship. The linear regression equation models the data fairly well.

- increase in weight of 40 grams.

weight = 100 + 40(time)

1. What is the slope of the regression line? Explain what it means in context.

The slope of 40 indicates that as the rat ages one week the model predicts an



Growth of a rat

- 2. What's the y intercept Explain what it means in context.
 - weight = 100 + 40(time)

0 weeks (birth weight).

- **3.** Predict the rat's weight after 16 weeks.
 - weight = 100 + 40(16) = 740 grams

The y-intercept is 100 grams which is the predicted weight of the rat at



Growth of a rat

4. Should you use this line to predict the rat's weight at age 2 years?

weight = 100 + 40(time)

Use the equation to make the prediction and think about the reasonableness of the result. There are 52 weeks in a year and 454 grams in a pound.

$weight = 100 + 40(104) = 4260 \, grams \approx 9.4 \, pounds$

The result is not reasonable and highlights the danger in extrapolating a regression line beyond the data.

W e I I, maybe not







regression line, then describe your results.

						-			
	Body weight	120	187	109	103	131	165	158	116
	Backpack weight	26	30	26	24	29	35	31	28
STAT >> CALC	4:LinReg(ax+b) 8:LinReg(a+bx) F S	(List: 'List: [:] reqLi Store f Calcula	st: RegE ate	Q:	<pre></pre>	= .79 = .6; = 16	4692 3153 .2649	2667 6436 9273	;1 3 + .(

backpack = 16.2649 + .0908(body weight)

There is a moderately strong, positive, linear relationship between body weight and weight of the backpack. As Body weight increases, backpack weight tends to increase. About 63% of the variability in backpack weight is accounted for by body weight. For every 1 pound increase in body weight the pack increases by .09 pounds and a 0 pound person is predicted to carry a 16.3 pound backpack.



 \mathbf{w} Enter the following data into the calculator and find r, r², and the formula for the least squares

- 0907994319x





Now find the linear regression equation by hand.



w r = .794692667, s_x = 30.29586252, s_y = 3.461523199

$$b_1 = r \frac{s_y}{s_x} = .794692667 \frac{3.4615}{30.295}$$

 $b_0 = \overline{Y} - b_1 \overline{X} = 28.625 - .0907994318(136.125) = 16.26492735$

					Ser.			
Body weight	120	187	109	103	131	165	158	
ackpack weight	26	30	26	24	29	35	31	

- $\frac{523199}{586252} = .0907994318$
- backpack = 16.2649 + .0908(body weight)





Draw a picture

Plot the points and draw the least squares regression line.

Objective: Students will determine the line of best fit (Least Squares Regression Line) and describe

Body weight	120	187	109	103	131	165	158	
Backpack weight	26	30	26	24	29	35	31	

backpack = 16.2649 + .0908(body weight)

Not the reciprocal

- Remember that the regression model gives a prediction for the value of the response variable.
- We cannot use the same regression model to predict a value of the explanatory variable from the response variable. That requires a new model.
 - The new model requires that we switch the roles of the variables.

It is unlikely you will be asked to do this reversal, but it is important that you understand that the Isrl is not a two way model. The model is based on minimizing the residuals in the y variable, not in the x variable.

Not the reciprocal

Reversing the roles of explanatory and response variables

$$b_1 = r \frac{s_x}{s_y} = .794692667 \frac{30.29}{3.46}$$

$$b_0 = \overline{X} - b_1 \overline{Y} = 136.125 - 6.9552$$

bodywt = -62.97019357 + 6.955290605(pack weight)

So if we find a pack weighing 27 lbs, we would predict a body weight of 124.8 lbs.

$\frac{9586252}{1523199} = 6.955290605$

290605(28.625) = -62.97019357

$bodywt = -62.97019357 + 6.955290605(27) \approx 124.823$

What do the residuals have to say?

The linear model assumes that the relationship between the two variables is a perfectly straight line.

Data = Model + Residual

or (equivalently)

Residual = Data - Model

Or, in symbols,

Objective: Students will determine the line of best fit (Least Squares Regression Line) and describe

In the residuals are the part of the data that has not been accounted for by the model.

Residuals Speak

- Residuals are a good indication of how well the model will predict response variable values. Does the model have value? Does the model make sense?
 - When a regression model is of value, there should be nothing of interest in the residuals.
 - In our GPA model, we note that the points above (positive residual) and points below (negative residual) are about even. That suggests the sum of the residuals should be 0.
 - Moditionally, we hope that most points are near our LSRL so the residuals are small. Large residuals should be more infrequent, suggesting a unimodal and symmetric distribution of the residuals.
 - After we fit a regression model, we usually plot the residuals in the hope of finding...

Residual Plot

- A residual plot is a scatterplot of the residuals. The residual plot is the final test of how well our model represents the data.
- There should no pattern to the residual scatterplot. If you do find a pattern in the residuals, there may be a problem with your model.
- Mattern in the residuals suggests a systematic relationship between the variables that has not been accounted for by our model.

Residuals

A histogram of the residuals should appear unimodal and symmetric.

The histogram of our gpa residuals appears sufficiently unimodal and symmetric. The model appears to meet all our requirements.

- \mathbf{W} Define L₃ as the predicted values from the regression equation. $(L_1 \text{ and } L_2 \text{ should still be the body weights and pack weights})$
 - \sim Define L₄ as the observed y-value (L₂) minus the predicted y-value (L₃).
 - Make sure all other plots are turned off. Choose Plot2 dot plot (first choice) with L_1 as x and L_4 as y. ZoomStat to see the residual plot.
 - \sim Just for snicks and giggles, lets look at the statistics of the residuals (L4). In the mean should be 0, any difference is due to rounding (remember what I said about
- rounding too soon?).
 - What do you think s_x tells us? ($s_x = 2.101$)

- Finally, we can find the residual plot by using a list created by the calculator called (not surprisingly) resid.
- Each time you ask for a regression analysis the calculator calculates the residuals automatically and stores them in a reserved calculator list 'resid'.
- We cannot manipulate or find the statistics for the 'resid' list but we can use it to create a residual plot.
- $w x list = L_1$ or wherever you put the explanatory variable.

The Residual Standard Deviation

- \sim The standard deviation of the residuals, s_e , measures the variability of the residuals or how the points vary above and below the regression line.
- \sim For the GPA data, s_e , is .2801. Our data has a typical deviation of .28 from the predicted value.
- Check to make sure the residual plot has a consistent amount of scatter throughout the distribution. Check the Equal Variance Assumption with what your book calls the "Poes the Plot Thicken? Condition".
- Our data does display changes in the variability of the residuals. It appears the model is not as accurate at lower HSGPA levels. So we note that in our conclusion.

Another example

Calculate and plot the residuals for our example of Body and Backpack weights.

Body weight	Pack weight
120	26
187	30
109	26
103	24
131	29
165	35
158	31
116	28

backpack = 16.3 + .09(body weight)

The Residual Standard Deviation

We can estimate the SD of the residuals, s_e , using:

$$s_e = \sqrt{\frac{\Sigma e^2}{n-2}}$$

Iook familiar? This is a modification resulting from two variables being involved.

we will let the calculator do that for us if we ever need to do the calculations.

$$s_e = \sqrt{\frac{\Sigma(\gamma - \hat{\gamma})^2}{n - 2}}$$

The Residual Standard Deviation

We do not need to subtract the mean because the mean of the residuals is 0. e = 0

- Make a histogram (or normal probability plot) of the residuals of the backpack data. It should look unimodal and roughly symmetric. (Does it?)
- Then we can apply the 68-95-99.7 Rule to see how well the regression model describes the data. Do 95% of our residuals fall within 2 standard deviations of 0?
- 100% of our residuals fall within 2 standard deviations of 0.

The coefficient of determinations; r²

- is accounted for by the least-squares regression model.
- We can calculate r^2 using the formula:
 - SSE = Sum of Squares Error and SST = Sum of Squares Total

Where
$$SSE = \sum_{i=1}^{n} (Y - \widehat{Y})^2$$
 $SST = \sum_{i=1}^{n} (Y - \overline{Y})^2$

If the coefficient of determination r^2 is the portion of the variation in the values of y that

$$R^2 = 1 - rac{SSE}{SST}$$

 $\sim \mathbb{R}^2$ is 1 - the proportion of variation not accounted for by the model out of the total variation in the response variable. Thus the variation that is accounted for.

The coefficient of determinations: r²

- The variation in the residuals is one big factor in assessing how well the model fits.
 - In our GPA data the variation in the residuals was .2801.
 - The variation in the response variable was 4472.
 - That is comforting, suggesting the model has less variability than the original data.

Objective: Students will determine the line of best fit (Least Squares Regression Line) and describe

Collection 1	
	resid
	0.0116819
	105
	0.280099
	0.0273349
	0
S1 = mean()	
S2 = count()	
S3 = stdDev()	
S4 = stdError()
S5 = count (missi)	na ())

Collection 1				
	3.17286			
	105			
univ_GPA	0.447194			
	0.0436416			
	0			
S1 = mean()				
S2 = count()				
S3 = stdDev()				
S4 = stdError()				
S5 = count(missing())				

The coefficient of determinations: r²

- If the correlation were 1.0 and the model predicted the college GPAs perfectly, the residuals would all be zero and have no variation.
 - What we found for the correlation was 0.7795 not quite perfection.
 - We did see that the model residuals had less variation than total college GPA.

We can determine how much of the variation is accounted for by the model and how much is left in the residuals.

The coefficient of determinations: r²

- The squared correlation, r², gives the fraction of the data's variance accounted for by the model.
 - Thus, $1 r^2$ is the fraction of the original variance left in the residuals.
 - $1 r^2$ is the coefficient of non-determination.
 - For the GPA data, r² = .7915² = .6076, Thus 61% of the variability in college GPA is accounted for by variability in high school GPA, and 39% of the variability in college GPA has been left in the residuals.

The coefficient of determinations: r^2

- All regression analyses include this statistic, although by tradition, it is written \mathbb{R}^2 .
 - We have the second seco it is still in the residuals.
 - \sim When interpreting a regression model you must always correctly interpret \mathbb{R}^2 .
 - let me say that again.
 - every single time, correctly interpret R².

Anytime you are working with a correlation and regression model you must always,

Let Me Repeat That

w When discussing \mathbb{R}^2 in the model this is the sentence frame you will use:

As I have indicated previously, do not be creative or clever. Just use the sentence structure or risk not getting credit.

Explanatory Variable (or model)

How Big Should R² Be?

- 🐷 🌠 is always between 0% and 100%. What makes a "good" 🧖 value depends on the kind of data you are analyzing and on what you intend to do with it.
 - model by telling us how much our actual data deviates from the predicted values.

The standard deviation of the residuals is a good indicator of the validity of the regression

When reporting a regression model you must report Pearson's r, the slope and intercept of the model, and \mathbb{R}^2 . This will give the audience a complete picture of the value of the model.

Reporting R²

- Along with the slope and intercept for the least squares regression line, you should always report \mathbb{R}^2 so that readers can judge for themselves how successful the regression is at fitting the data.
- in interpreting and analyzing a regression model you now have several items that must of residuals, histogram of residuals (and/or normal probability plot).

be included. Scatter plot of data, description of distribution, r, \mathbb{R}^2 , interpretation of \mathbb{R}^2 , the model itself, description of model (interpretation of slope and intercept), scatterplot

Real Example

- Here is some recent data. Note scale along both axes.
 - Describe the relationship.
 - Negative, moderately weak, linear, no outliers. As undocumented share of population increases, violent crime tends to decrease.
 - **Estimate r.**
 - Since these are z-scores, the slope = r. \leq 5 (-1,.2) and (1, -.2) ₩r = -.2

one state observed in one year.

Objective: Students will determine the line of best fit (Least Squares Regression Line) and describe the meaning. How well does the first test predict final grade?

This is actual data, taken from an actual statistics class in a previous year. Find a linear model. Describe the distribution.

Grade First	Final Grade	Grade First Test	Final Grad
	02	52	69
94	93	90	94
90	87	35	58
42	67	61	83
39	46	58	65
97	75	45	70
65	91	61	76
65	78	61	73
84	84	67	78
77	44	58	75
45	46	61	03
55	75	77	93 01
65	72		
		29	/5
51	/0	81	82
87	93	94	94
84	90	77	93

How well does the first test predict final grade?

 $\hat{y} = 4632x + 45.8596$

- $r = .6161, r^2 = .3796$
- $\hat{\mathbf{y}}$ = predicted final grade x = score on first test

Predicted Final Grade = 4632(score on first test) + 45.8596

FinalGrade = .4632(*firsttest*) + 45.8956

Intervention of the second grade. As scores on first test increase, scores on final grade tend to increase. About 37.96% of the variability in final grade is accounted for by score on first test. There are distinct outliers at (77, 44), (29, 76), and (96, 75). For every 1 percentage point increase in first test score the final grade is predicted to increase by .4632 points and a 0 on first test predicts a 45.90% final grade.

Interpreting regression output cohot

How well does the number of beers a person drinks predict his or her blood alcohol content (BAC)? Sixteen volunteers with an initial BAC of 0 drank a randomly assigned number of cans of beer. Thirty minutes later, a police officer measured their BAC. Leastsquares regression was performed on the data. A scatterplot with the regression line added, a residual plot, and some computer output from the regression are shown below.

No Selector R squared = 80% s = 0.0204 with

Variable Constant Beers

Interpreting regression output

```
Dependent variable is: BAC
R squared (adjusted) = 78.6%
16 - 2 = 14 degrees of freedom
```

Coefficient	s.e. of Coeff	t-ratio	prob
-0.012701	0.0126	-1.00	0.3320
0.017964	0.0024	7.48	≤0.0001

Strong, positive, linear model, with one possible outlier at about (9, .19) as the number of beers increases blood alcohol trends to increase.

Mo pattern in residuals. We are good to go.

the meaning. Interpreting regression output

The equation is $\overrightarrow{BAC} = -0.0127 + .017964(beers)$

- 0.018 BAC, 80% of the variability in BAC is accounted for by the model.
- A linear model does seem appropriate for this data.

Objective: Students will determine the line of best fit (Least Squares Regression Line) and describe

For every additional beer consumed, the model predicts a BAC increase of about

Interpreting regression output

The residuals are between -.03 and .03 except for the subject drinking 9 beers. On average, predictions of BAC using the regression line would be off by about s = 0.02 for the 16 people in the study.

Siven the legal limit for BAC of 0.08 that error may be too much.

Assumptions and Conditions

- Quantitative Variables Condition:
 - Regression can only be done on two quantitative variables (and not two categorical variables), so you must check and report on the quantitative condition.

Sufficiently Linear Condition:

- More a linear model describes a relationship between the variables that is linear. If the data is not linear, a linear model is not appropriate.
- A scatterplot will indicate that the assumption is reasonable.
- If the data is not linear, you are done.
- Some nonlinear relationships can be saved by re-expressing the data to make the scatterplot more linear. We will revisit this at year end.

Assumptions and Conditions

- It is a necessary to check linearity again after computing the regression model when we can examine the residuals for any pattern that may have been missed in the scatterplot.
 - is worth running.

Equal Variance Assumption Condition:

Check the residual plot and the standard deviation of the residuals to summarize the scatter. The residuals should have the same spread throughout the domain of the predictor variable. Check for changes in the spread of the residual scatterplot.

Outlier Condition:

- Watch out for outliers.
- Outlying points can dramatically change the correlation and the regression model. In extreme cases outliers can even change the direction of the slope, completely misinforming the reader about the relationship between the variables.

Outliers and Influential Observations

- An outlier is an observation that lies outside the overall pattern of the other observations.
 - and, thus, not have large residuals.
 - squares regression line.

Points that are outliers in the y direction but not in the x direction of a scatterplot have large residuals. Outliers in the x direction may have undue influence on the model

Monopoly is influential if removing it would significantly change the results. Points that are outliers in the x direction of a scatterplot are often influential for the least-

Reality Check: Is the Regression Reasonable?

- 🐷 Statistics do not come from out of the blue. Statistics are based on data.
 - The results of a statistical analysis should make sense, be logical.
 - If the results are surprising, then either you have made a new discovery and added to the human lexicon about the world or your analysis is wrong.
 - When you perform a regression, think about the slope and intercept and consider if the relationship makes sense.

- Don't fit a straight line to a nonlinear relationship.
 - Examine extraordinary points ly-values that appear far away from the linear pattern or extreme x-values).
 - Do not extrapolate beyond the data—the linear model may no longer hold outside of the range of the data.
 - w PO NOT infer causality; that the predictor variable causes the response variable to change simply because there is a good linear model for the relationship.
 - **Association** is not causation.

the data and model. Do not judge a model based on \mathbb{R}^2 alone.

🐨 💦 is a valuable indicator, and must be included in any regression, but look at the entirety of

Summary

- A regression line is a straight line that describes how a response variable y changes as an explanatory variable x changes.
 - \mathbf{W} You can use a regression line to predict the value of $\hat{\mathbf{y}}$ for any value of x by substituting the x into the equation of the line.
 - \sim The slope b₁ of a regression line $\hat{y} = b_0 + b_1 x$ is the rate at which the predicted response y changes along the line as the explanatory variable x changes.
 - If the y-intercept bo of a regression line $\hat{y} = b_0 + b_1 x$ is the predicted response y when the explanatory variable x = 0. This prediction is of no statistical use unless x can actually take values near 0.

Summary

Avoid extrapolation.

- w Do not use the model for values of the predictor variable outside the range of the data from which the line was calculated.
 - The most common method of fitting a line to a scatterplot is least squares. The leastsquares regression line is the straight line $y = b_0 + b_1x$ that minimizes the sum of the squares of the vertical distances of the observed points from the line.
 - \sim The least-squares regression line of y on x is the line with slope $b_1 = r(s_y/s_x)$ and intercept $b_0 = \overline{y} - b_1 \overline{x}$. This line always passes through the point $(\overline{x}, \overline{y})$.
 - Most of all, be careful not to conclude that there is a cause-and-effect relationship between two variables just because they are strongly associated.

