

# Linear Regression II

Nate Wells

Math 141, 2/25/21

# Outline

In this lecture, we will . . .

# Outline

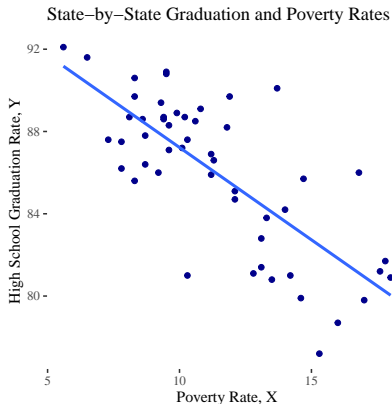
In this lecture, we will . . .

- Introduce statistical modeling
- Investigate the linear model
- Discuss predictions and residuals

## Section 1

# Introduction to Linear Regression

# Scatterplots and Linear Relationships



- Explanatory Variable:
  - Poverty Rate ( $X$ )
- Response Variable:
  - High School Graduation Rate ( $Y$ )
- Relationship:
  - Linear, negative, moderately strong
- Model (hand-fitted):

$$\hat{Y} = \beta_0 + \beta_1 X = 96.2 - 0.9X$$

# Residuals

- **Residuals** are the leftover variation in the data after accounting for model fit.

## Residuals

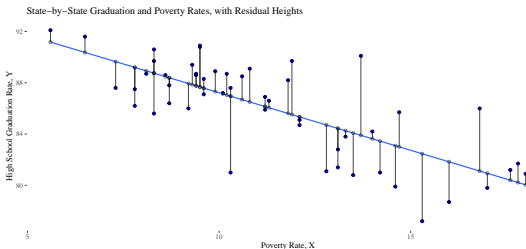
- **Residuals** are the leftover variation in the data after accounting for model fit.
- Each observation  $(X_i, Y_i)$  has its own residual  $e_i$ , which is the difference between the observed  $(Y_i)$  and predicted  $(\hat{Y}_i)$  value:

$$e_i = Y_i - \hat{Y}_i$$

# Residuals

- **Residuals** are the leftover variation in the data after accounting for model fit.
- Each observation  $(X_i, Y_i)$  has its own residual  $e_i$ , which is the difference between the observed  $(Y_i)$  and predicted  $(\hat{Y}_i)$  value:

$$e_i = Y_i - \hat{Y}_i$$

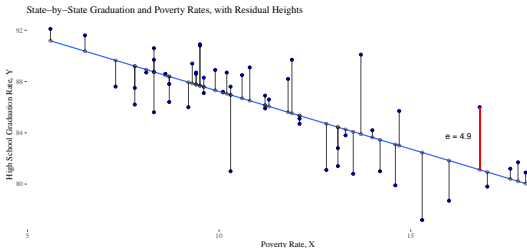




# Residuals

- **Residuals** are the leftover variation in the data after accounting for model fit.
- Each observation  $(X_i, Y_i)$  has its own residual  $e_i$ , which is the difference between the observed ( $Y_i$ ) and predicted ( $\hat{Y}_i$ ) value:

$$e_i = Y_i - \hat{Y}_i$$



- D.C.'s residual is

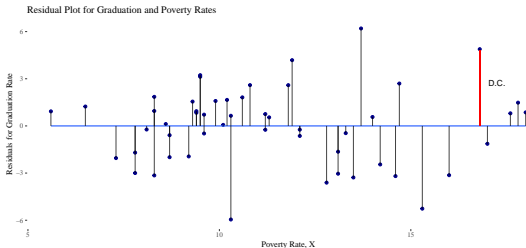
$$e = Y - \hat{Y} = 86 - 81.1 = 4.9$$

## Residual Plot

- To visualize the degree of accuracy of a linear model, we use residual plots:

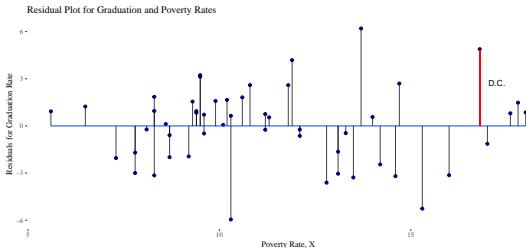
# Residual Plot

- To visualize the degree of accuracy of a linear model, we use residual plots:



# Residual Plot

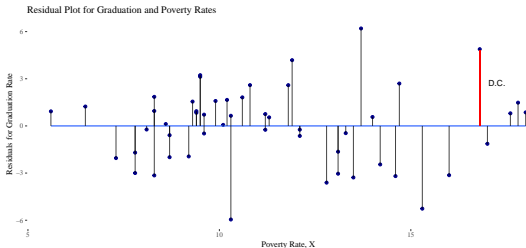
- To visualize the degree of accuracy of a linear model, we use residual plots:



- Points preserve original  $x$ -position, but with  $y$ -position equal to residual.

# Residual Plot

- To visualize the degree of accuracy of a linear model, we use residual plots:



- Points preserve original  $x$ -position, but with  $y$ -position equal to residual.
- Tighter clustering around the horizontal axis indicates stronger fit.

## Quantifying Goodness-of-Fit

- **Correlation**  $R$  describes the strength of a linear relationship between two variables, and is always a number between  $-1$  and  $1$ .

## Quantifying Goodness-of-Fit

- **Correlation**  $R$  describes the strength of a linear relationship between two variables, and is always a number between  $-1$  and  $1$ .

If $R$ is close to ...	Then linear relationship is...
1	strong, positive
$-1$	strong, negative
0	weak

## Quantifying Goodness-of-Fit

- **Correlation**  $R$  describes the strength of a linear relationship between two variables, and is always a number between  $-1$  and  $1$ .

If $R$ is close to ...	Then linear relationship is...
1	strong, positive
$-1$	strong, negative
0	weak

- Correlation can be computed via formula using the mean and standard deviation of each variable.



## Quantifying Goodness-of-Fit

- **Correlation**  $R$  describes the strength of a linear relationship between two variables, and is always a number between  $-1$  and  $1$ .

If $R$ is close to ...	Then linear relationship is...
1	strong, positive
$-1$	strong, negative
0	weak

- Correlation can be computed via formula using the mean and standard deviation of each variable.

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

## Quantifying Goodness-of-Fit

- **Correlation**  $R$  describes the strength of a linear relationship between two variables, and is always a number between  $-1$  and  $1$ .

If $R$ is close to ...	Then linear relationship is...
1	strong, positive
$-1$	strong, negative
0	weak

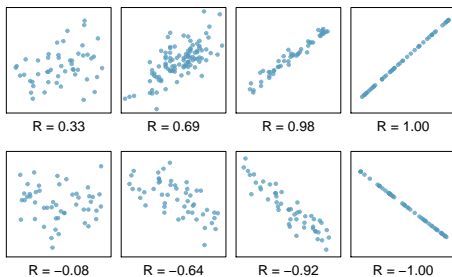
- Correlation can be computed via formula using the mean and standard deviation of each variable.

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

- But in practice, we will always use technology to compute  $R$ .

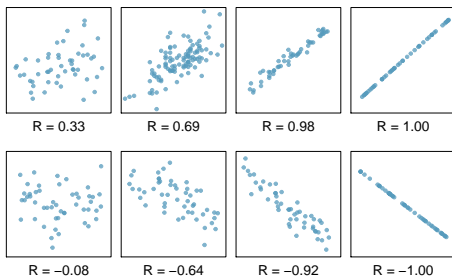
# Correlation

- Correlation gives a **relative** sense of the strength of a linear relationship



# Correlation

- Correlation gives a **relative** sense of the strength of a linear relationship



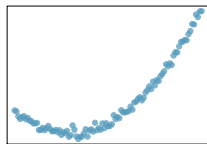
- In practice, correlation is...
  - strong, if  $|R| > 0.7$
  - moderate, if  $0.3 < |R| < 0.7$
  - weak, if  $|R| < 0.3$

## Correlation is not Association

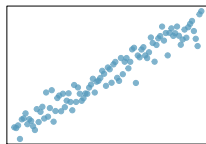
- Correlation measures strength of **LINEAR** relationship:

## Correlation is not Association

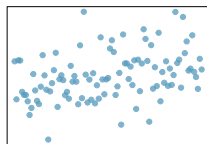
- Correlation measures strength of **LINEAR** relationship:
- Which of the following has the strongest correlation (largest value of  $|R|$ )?



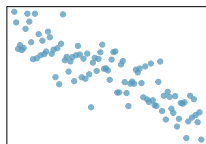
(a)



(b)



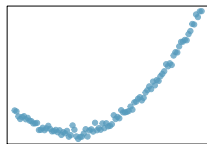
(c)



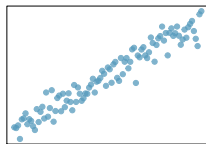
(d)

## Correlation is not Association

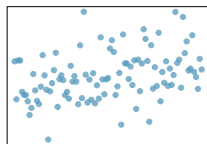
- Correlation measures strength of **LINEAR** relationship:
- Which of the following has the strongest correlation (largest value of  $|R|$ )?



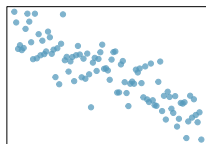
(a)



(b)



(c)



(d)

- Answer: (b), not (a)

## Correlation isn't the Whole Story

- Computing a correlation coefficient is no substitute for data visualization.

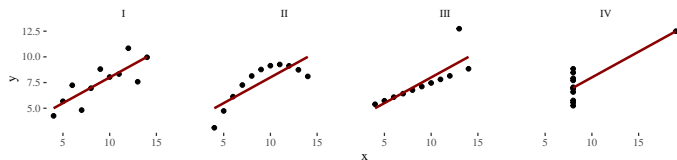


## Correlation isn't the Whole Story

- Computing a correlation coefficient is no substitute for data visualization.
- All of the following have identical, strong positive correlation ( $R = 0.8$ ):

## Correlation isn't the Whole Story

- Computing a correlation coefficient is no substitute for data visualization.
- All of the following have identical, strong positive correlation ( $R = 0.8$ ):



## Section 2

# Fitting a Line by Least-Squares Regression

## Measure for **BEST** Line

- The line of best fit to a scatterplot should minimize residuals, meaning:

## Measure for **BEST** Line

- The line of best fit to a scatterplot should minimize residuals, meaning:
  - Option 1: Minimizing the sum of absolute values

$$|e_1| + |e_2| + \cdots + |e_n|$$

## Measure for **BEST** Line

- The line of best fit to a scatterplot should minimize residuals, meaning:
  - Option 1: Minimizing the sum of absolute values

$$|e_1| + |e_2| + \cdots + |e_n|$$

- Option 2: Minimize the sum of squares

$$e_1^2 + e_2^2 + \cdots + e_n^2$$

## Measure for **BEST** Line

- The line of best fit to a scatterplot should minimize residuals, meaning:
  - Option 1: Minimizing the sum of absolute values

$$|e_1| + |e_2| + \cdots + |e_n|$$

- Option 2: Minimize the sum of squares

$$e_1^2 + e_2^2 + \cdots + e_n^2$$

- Option 2 is usually preferred.

## Measure for **BEST** Line

- The line of best fit to a scatterplot should minimize residuals, meaning:
  - Option 1: Minimizing the sum of absolute values

$$|e_1| + |e_2| + \cdots + |e_n|$$

- Option 2: Minimize the sum of squares

$$e_1^2 + e_2^2 + \cdots + e_n^2$$

- Option 2 is usually preferred.
  - ① Most commonly used.



## Measure for **BEST** Line

- The line of best fit to a scatterplot should minimize residuals, meaning:
  - Option 1: Minimizing the sum of absolute values

$$|e_1| + |e_2| + \cdots + |e_n|$$

- Option 2: Minimize the sum of squares

$$e_1^2 + e_2^2 + \cdots + e_n^2$$

- Option 2 is usually preferred.
  - ① Most commonly used.
  - ② More computationally efficient.

## Measure for **BEST** Line

- The line of best fit to a scatterplot should minimize residuals, meaning:
  - Option 1: Minimizing the sum of absolute values

$$|e_1| + |e_2| + \cdots + |e_n|$$

- Option 2: Minimize the sum of squares

$$e_1^2 + e_2^2 + \cdots + e_n^2$$

- Option 2 is usually preferred.
  - ① Most commonly used.
  - ② More computationally efficient.
  - ③ Has theoretical advantages (by analogy with distance and pythagorean thm.)

## Measure for **BEST** Line

- The line of best fit to a scatterplot should minimize residuals, meaning:
  - Option 1: Minimizing the sum of absolute values

$$|e_1| + |e_2| + \cdots + |e_n|$$

- Option 2: Minimize the sum of squares

$$e_1^2 + e_2^2 + \cdots + e_n^2$$

- Option 2 is usually preferred.
  - ① Most commonly used.
  - ② More computationally efficient.
  - ③ Has theoretical advantages (by analogy with distance and pythagorean thm.)
  - ④ Appropriately weights one large residuals as “worse” than many small ones.

## An Aside on Some Important Formulas

- You **do not** need to memorize these formulas

## An Aside on Some Important Formulas

- You **do not** need to memorize these formulas
  - But you should understand where they come from and what they mean

## An Aside on Some Important Formulas

- You **do not** need to memorize these formulas
  - But you should understand where they come from and what they mean
- Suppose  $x_1, x_2, \dots, x_n$  are a list of numerical observations...
- The **mean** of this data set is

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n}$$

## An Aside on Some Important Formulas

- You **do not** need to memorize these formulas
  - But you should understand where they come from and what they mean
- Suppose  $x_1, x_2, \dots, x_n$  are a list of numerical observations...
- The **mean** of this data set is

$$\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{n}$$

- The mean is a measure of center.
- The standard deviation of this data is

$$s = \sqrt{\frac{(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \dots + (x_n - \bar{x})^2}{n - 1}}$$

## An Aside on Some Important Formulas

- You **do not** need to memorize these formulas
  - But you should understand where they come from and what they mean
- Suppose  $x_1, x_2, \dots, x_n$  are a list of numerical observations...
- The **mean** of this data set is

$$\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{n}$$

- The mean is a measure of center.
- The standard deviation of this data is

$$s = \sqrt{\frac{(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \dots + (x_n - \bar{x})^2}{n - 1}}$$

- The standard deviation is a measure of spread.



## A Formula for the Least Squares Regression Line

- Suppose  $n$  observations for variables  $X$  and  $Y$  are collected:

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$$

with means  $\bar{x}, \bar{y}$  and standard deviations  $s_x, s_y$  and correlation  $R$ .

## A Formula for the Least Squares Regression Line

- Suppose  $n$  observations for variables  $X$  and  $Y$  are collected:

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$$

with means  $\bar{x}, \bar{y}$  and standard deviations  $s_x, s_y$  and correlation  $R$ .

- The **Least Squares Regression Line** modeling  $Y$  as a function of  $X$  is

$$\hat{Y} = \beta_0 + \beta_1 X$$

## A Formula for the Least Squares Regression Line

- Suppose  $n$  observations for variables  $X$  and  $Y$  are collected:

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$$

with means  $\bar{x}, \bar{y}$  and standard deviations  $s_x, s_y$  and correlation  $R$ .

- The **Least Squares Regression Line** modeling  $Y$  as a function of  $X$  is

$$\hat{Y} = \beta_0 + \beta_1 X$$

where the slope  $\beta_1$  is given by

$$\beta_1 = \frac{s_y}{s_x} R$$

## A Formula for the Least Squares Regression Line

- Suppose  $n$  observations for variables  $X$  and  $Y$  are collected:

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$$

with means  $\bar{x}$ ,  $\bar{y}$  and standard deviations  $s_x$ ,  $s_y$  and correlation  $R$ .

- The **Least Squares Regression Line** modeling  $Y$  as a function of  $X$  is

$$\hat{Y} = \beta_0 + \beta_1 X$$

where the slope  $\beta_1$  is given by

$$\beta_1 = \frac{s_y}{s_x} R$$

and where the intercept is given by

$$\beta_0 = \bar{y} - \beta_1 \bar{x}$$

## Conditions for Using Linear Regression

In order to responsibly use linear regression. . .

## Conditions for Using Linear Regression

In order to responsibly use linear regression. . .

- ① Relationship between explanatory and response variables must be approximately linear.  
(**Linear**)
  - Check using scatterplot and/or residual plot

## Conditions for Using Linear Regression

In order to responsibly use linear regression. . .

- ① Relationship between explanatory and response variables must be approximately linear. **(Linear)**
  - Check using scatterplot and/or residual plot
- ② The distribution of residuals should be bell-shaped, unimodal, symmetric, and centered at 0. **(Normal)**
  - Check using histogram of residuals

## Conditions for Using Linear Regression

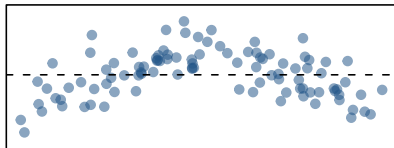
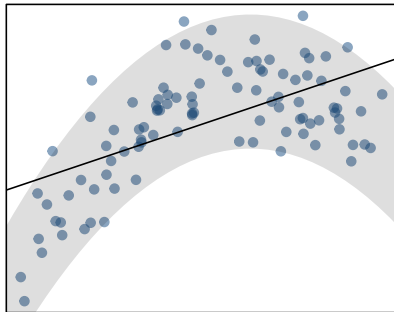
In order to responsibly use linear regression. . .

- ① Relationship between explanatory and response variables must be approximately linear.  
**(Linear)**
  - Check using scatterplot and/or residual plot
- ② The distribution of residuals should be bell-shaped, unimodal, symmetric, and centered at 0. **(Normal)**
  - Check using histogram of residuals
- ③ The variability of residuals should be roughly constant across entire data set.  
**(Homoscedastic)**
  - Check using residual plot.



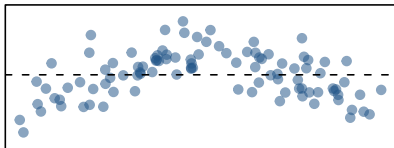
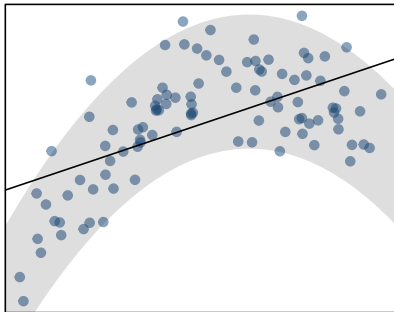
# Checking Conditions I

- What condition is this linear model most obviously violating?
  - a. Linearity
  - b. Normalacy
  - c. Homoscedasticity
  - d. Extreme Outliers



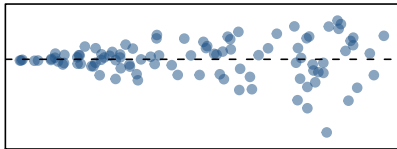
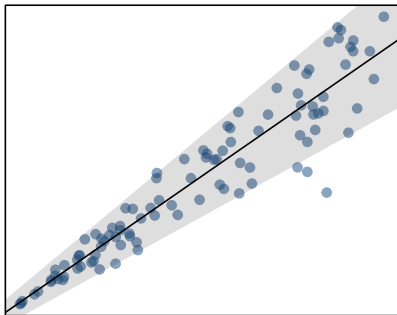
# Checking Conditions I

- What condition is this linear model most obviously violating?
  - a.** Linearity
  - b. Normalacy
  - c. Homoscedasticity
  - d. Extreme Outliers



## Checking Conditions II

- What condition is this linear model most obviously violating?
  - a. Linearity
  - b. Normalacy
  - c. Homoscedasticity
  - d. Extreme Outliers



## Checking Conditions II

- What condition is this linear model most obviously violating?
  - a. Linearity
  - b. Normalacy
  - c. Homoscedasticity
  - d. Extreme Outliers

