Introduction to Linear Models

Prof. Wells

STA 209, 2/15/23

Outline

In this lecture, we will...

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- Investigate the linear model
- Discuss predictions and residuals
- Explore a formula for finding the line of best fit

Section 1

Introduction to Linear Regression

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What is the Relationship between Income and Life Expectancy?

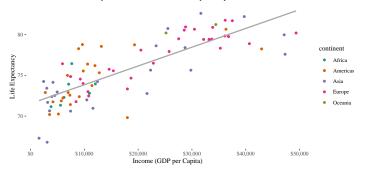


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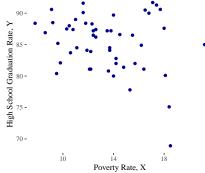
$$Y = \beta_0 + \beta_1 X$$
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 Of course, in the wild, the observed values of Y will not be perfectly predicted by the values of X.

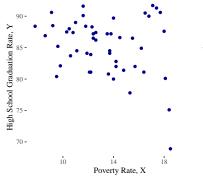
$$Y = \beta_0 + \beta_1 X + \epsilon$$
 where ϵ is the error

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State-by-State Graduation and Poverty Rates

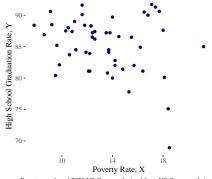


State-by-State Graduation and Poverty Rates



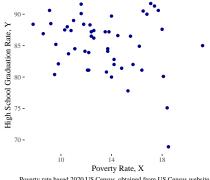
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State-by-State Graduation and Poverty Rates



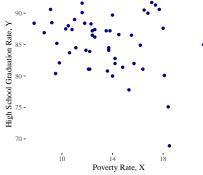
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State-by-State Graduation and Poverty Rates



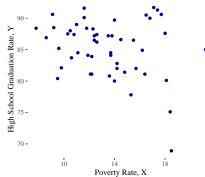
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State-by-State Graduation and Poverty Rates



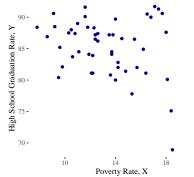
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State-by-State Graduation and Poverty Rates



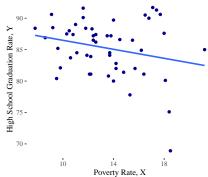
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State-by-State Graduation and Poverty Rates



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- Relationship:
 - Linear, negative, moderate

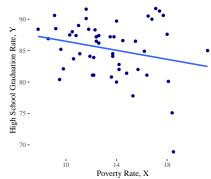
State-by-State Graduation and Poverty Rates



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$$\hat{Y} = \beta_0 + \beta_1 X = 90 - 0.4X$$

State-by-State Graduation and Poverty Rates

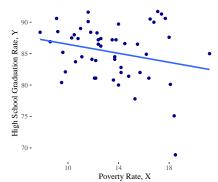


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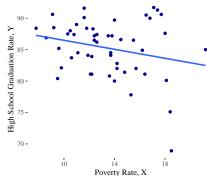


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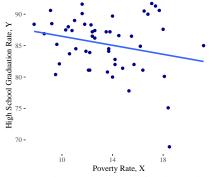


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- Intercept of $\beta_0 = 90$ means model predicts graduation rate of 90% when poverty rate is 0%.

State-by-State Graduation and Poverty Rates

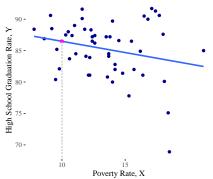


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State-by-State Graduation and Poverty Rates

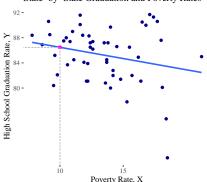


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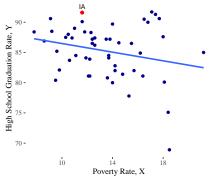
$$\hat{Y} = 90 - 0.4 \cdot X$$

 What does the model predict to be the graduation rate for a state with theoretical poverty rate 7%?

$$\hat{Y} = 90 - 0.4 \cdot 10 = 86$$

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State-by-State Graduation and Poverty Rates



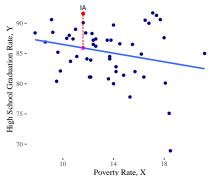
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But Iowa's actual graduation rate is 91.6

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:

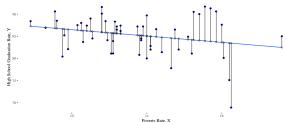
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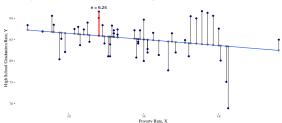


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State-by-State Graduation and Poverty Rates, with Residual Heights



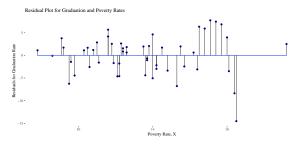
lowa's residual is

$$e = Y - \hat{Y} = 91.6 - 85.36 = 6.24$$

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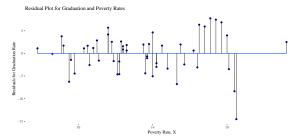
Residual Plot

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



Residual Plot

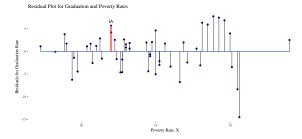
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Section 2

Quantifying Goodness-of-Fit

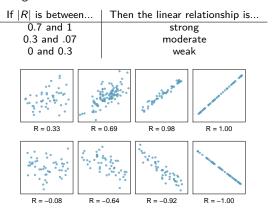
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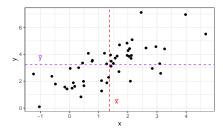
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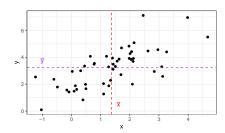
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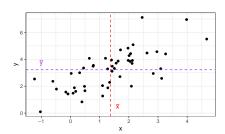


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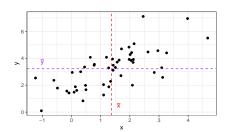
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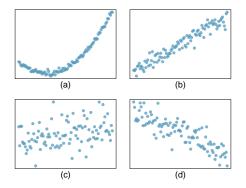
$$R = 0.6995848$$

Correlation is not Association

• Correlation measures strength of *LINEAR* relationship:

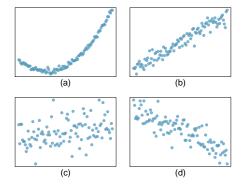
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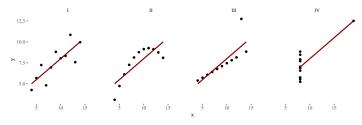


• Answer: (b), not (a)

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

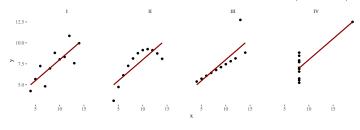
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```
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- ## I II III IV ## Correlation 0.82 0.82 0.82 0.82
 - However, each graphic tells a radically different story about the relationship between the variables.

Section 3

Fitting a Line by Least-Squares Regression

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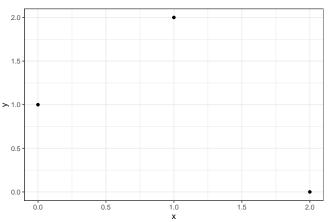
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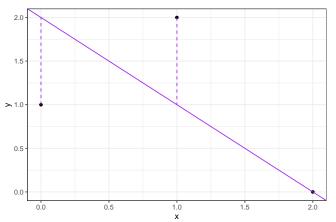
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 - 6 Has well-understood properties for inference

For the three data points below, consider candidates for the line of best fit:



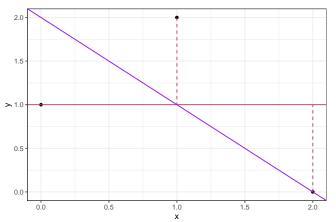
Goal: minimize
$$e_1^2 + e_2^2 + e_3^2$$

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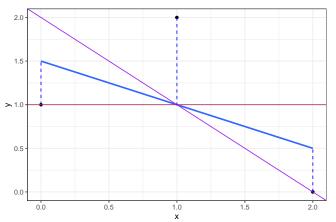
Purple line:
$$e_1^2 + e_2^2 + e_3^2 = 1^2 + 0^2 + 1^2 = 2$$

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Maroon line:
$$e_1^2 + e_2^2 + e_3^2 = 0^2 + 1^2 + 1^2 = 2$$

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Blue line:
$$e_1^2 + e_2^2 + e_3^2 = 0.5^2 + 1^2 + 0.5^2 = 1.5$$

• Suppose *n* observations for variables *X* and *Y* are collected:

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

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

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where the slope β_1 is given by

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

• Suppose *n* observations for variables *X* and *Y* are collected:

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

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

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

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where the slope β_1 is given by

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and where the intercept is given by

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

• The least squares line is

$$\hat{Y} = \beta_0 + \beta_1 X$$
 $\beta_1 = \frac{s_y}{s_x} R$ $\beta_0 = \bar{y} - \beta_1 \bar{x}$

• The least squares line is

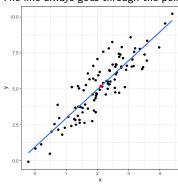
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mean_x mean_y ## 1 2.108887 5.179967

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 $\beta_1 = \frac{s_y}{s_x} \mathbf{R}$ $\beta_0 = \bar{\mathbf{y}} - \beta_1 \bar{\mathbf{x}}$

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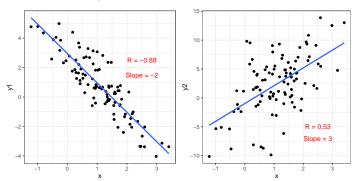
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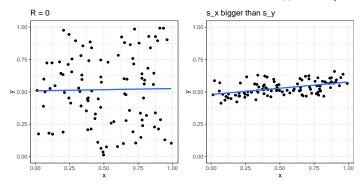
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Prof. Wells