Simple Linear Regression: Estimation

EC 320: Introduction to Econometrics

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Prologue

Last Time

We considered a simple linear regression of Y_i on X_i :

$$Y_i = \beta_1 + \beta_2 X_i + u_i.$$

- β_1 and β_2 are **population parameters** that describe the "*true*" relationship between X_i and Y_i .

- **Problem:** We don't know the population parameters. The best we can do is to estimate them.

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Last Time

We derived the OLS estimator by picking estimates that minimize $\sum_{i=1}^{n} \hat{u}_i^2$.

- **Intercept:**

$$\hat{\beta}_1 = \bar{Y} - \hat{\beta}_2 \bar{X}.$$

- **Slope:**

$$\hat{\beta}_2 = \frac{\sum_{i=1}^{n}(Y_i - \bar{Y})(X_i - \bar{X})}{\sum_{i=1}^{n}(X_i - \bar{X})^2}.$$

We used these formulas to obtain estimates of the parameters β_1 and β_2 in a regression of Y_i on X_i .

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Last Time

With the OLS estimates of the population parameters, we constructed a regression line:

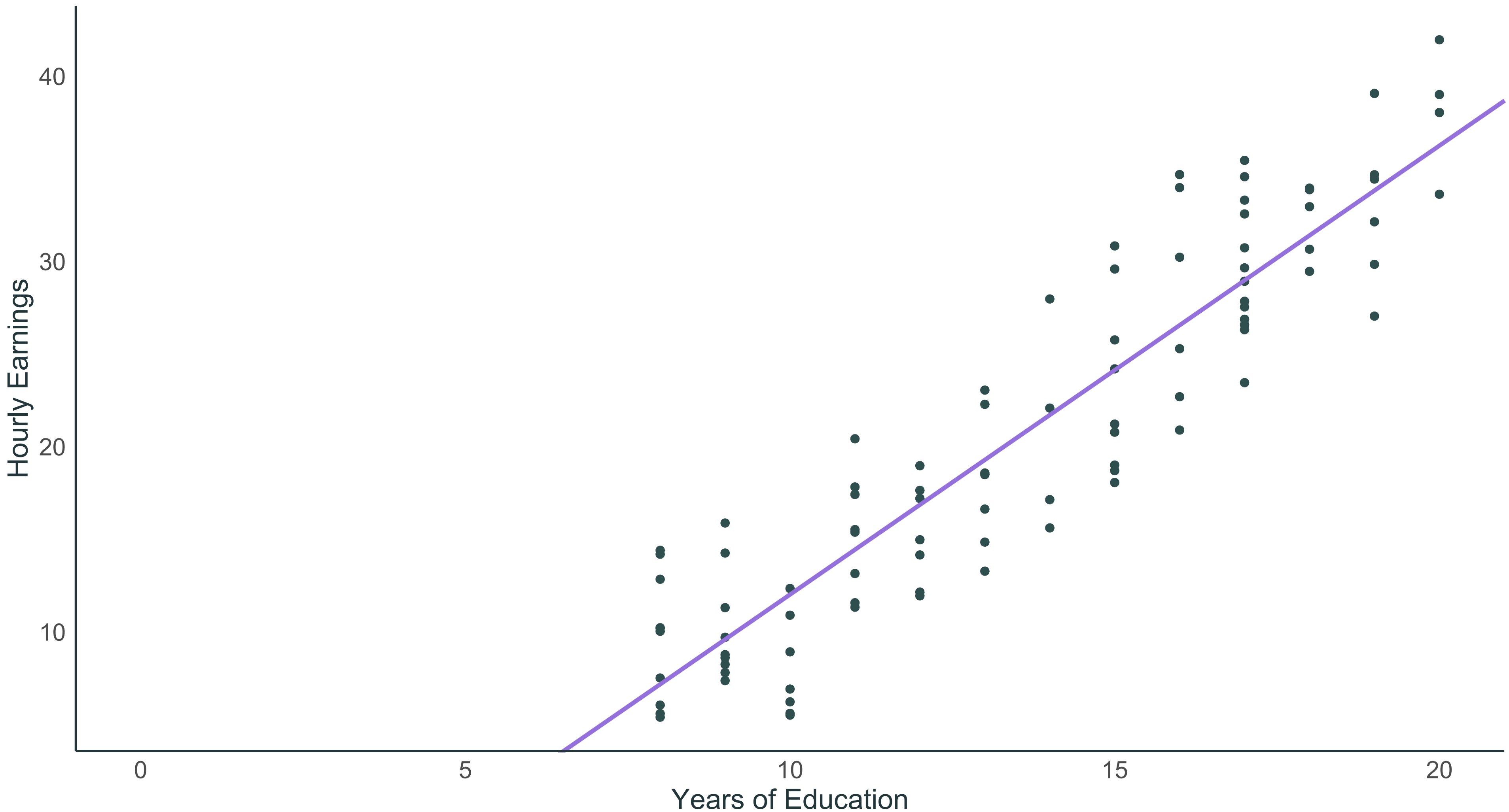
$$\hat{Y}_i = \hat{\beta}_1 + \hat{\beta}_2 X_i.$$

- $\hat{Y}_i$ are predicted or **fitted** values of Y_i .
- You can think of $\hat{Y}_i$ as an estimate of the average value of Y_i given a particular of X_i .

OLS still produces prediction errors: $\hat{u}_i = Y_i - \hat{Y}_i$.

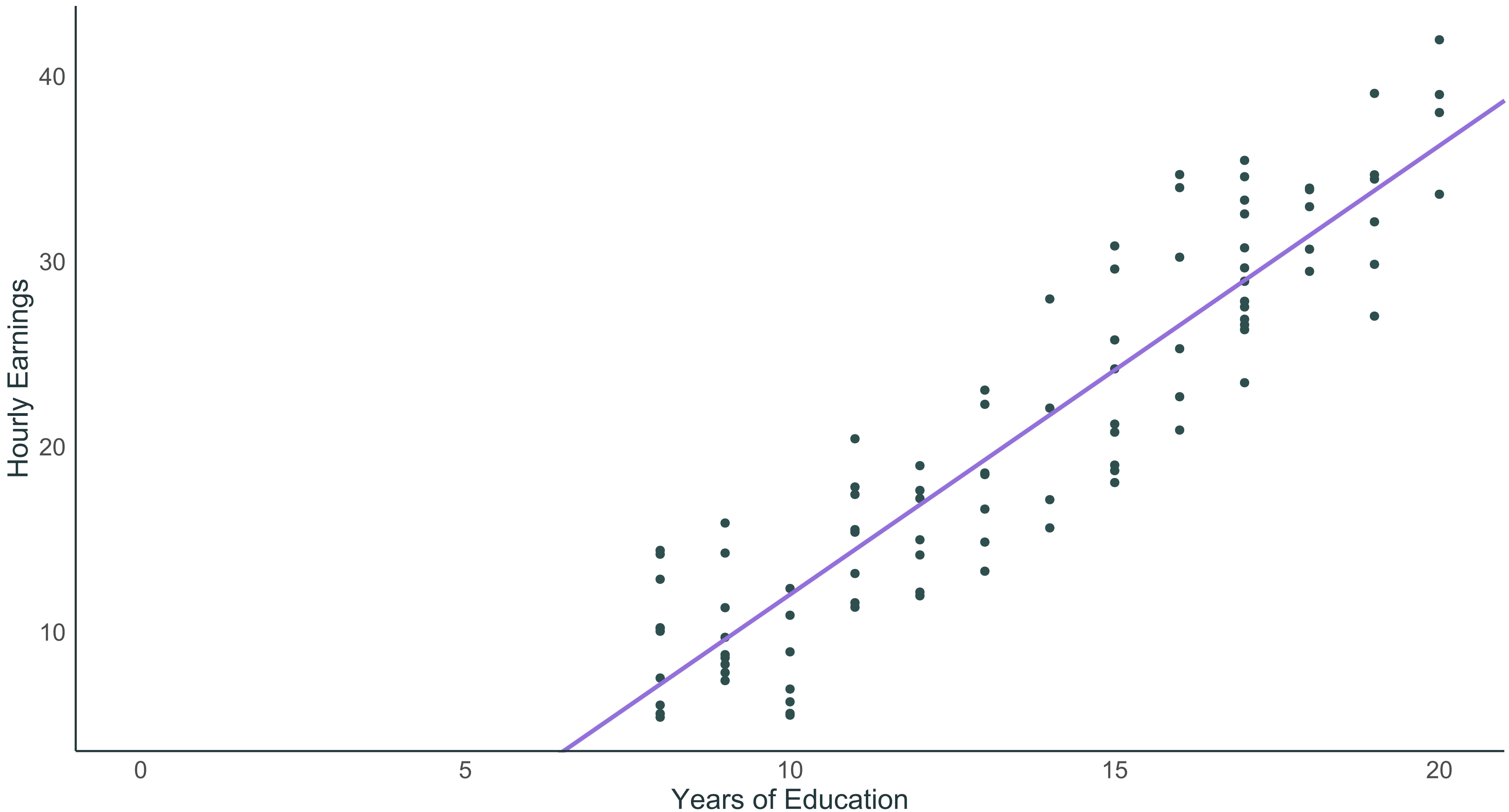
- Put differently, there is a part of Y_i we can explain and a part we cannot: $Y_i = \hat{Y}_i + \hat{u}_i$.

What is the equation for the regression model estimated below?



Review

The estimated **intercept** is -12.26. What does this tell us?



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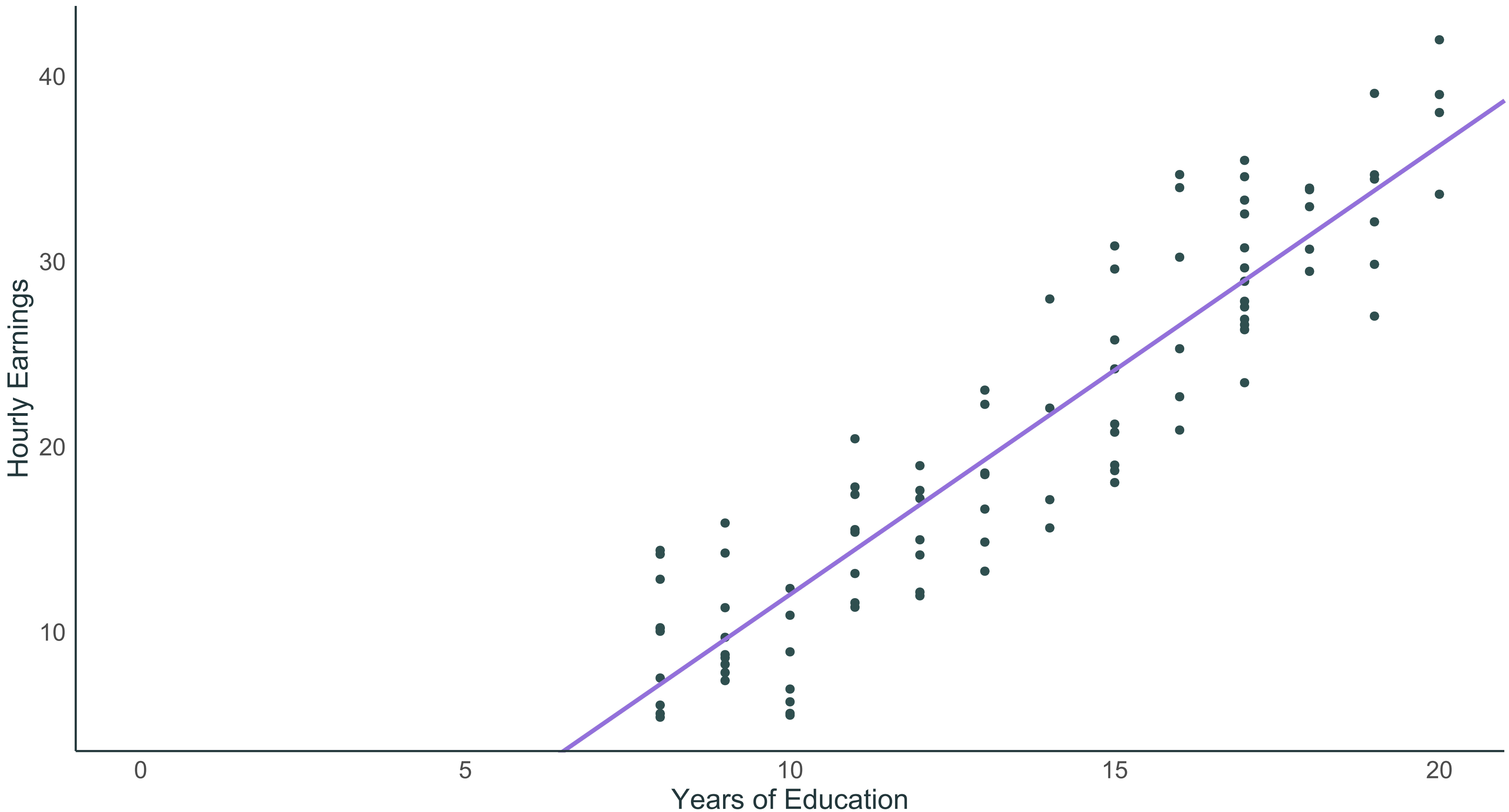
Review

The estimated **slope** is 2.43. How do we interpret it?



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Agenda

1. Highlight important properties of OLS.
2. Discuss goodness of fit: how well does one variable explain another?
3. Units of measurement.

OLS Properties

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OLS Properties

The way we selected OLS estimates $\hat{\beta}_1$ and $\hat{\beta}_2$ gives us three important properties:

1. Residuals sum to zero: $\sum_{i=1}^{n} \hat{u}_i = 0$.

2. The sample covariance between the independent variable and the residuals is zero: $\sum_{i=1}^{n} X_i \hat{u}_i = 0$.

3. The point $(\bar{X}, \bar{Y})$ is always on the regression line.

OLS Residuals

Residuals sum to zero: $\sum_{i=1}^{n} \hat{u}_i = 0$.

- By extension, the sample mean of the residuals are zero.

- You will prove this in Problem Set 3.

OLS Residuals

The sample covariance between the independent variable and the residuals is zero:

$\sum_{i=1}^{n} X_i \hat{u}_i = 0$.

- You will prove a version of this in Problem Set 3.

OLS Regression Line

The point $(\bar{X}, \bar{Y})$ is always on the regression line.

- Start with the regression line: $\hat{Y}_i = \hat{\beta}_1 + \hat{\beta}_2 X_i$.
- $\hat{Y}_i = \bar{Y} - \hat{\beta}_2 \bar{X} + \hat{\beta}_2 X_i$.
- Plug $\bar{X}$ into X_i :

$$\begin{aligned}\hat{Y}_i &= \bar{Y} - \hat{\beta}_2 \bar{X} + \hat{\beta}_2 \bar{X} \\ &= \bar{Y}.\end{aligned}$$

Goodness of Fit

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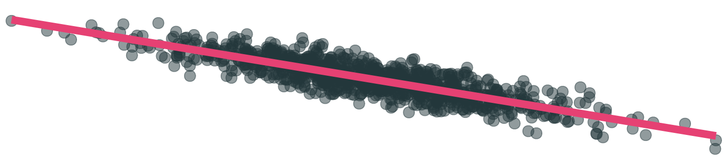
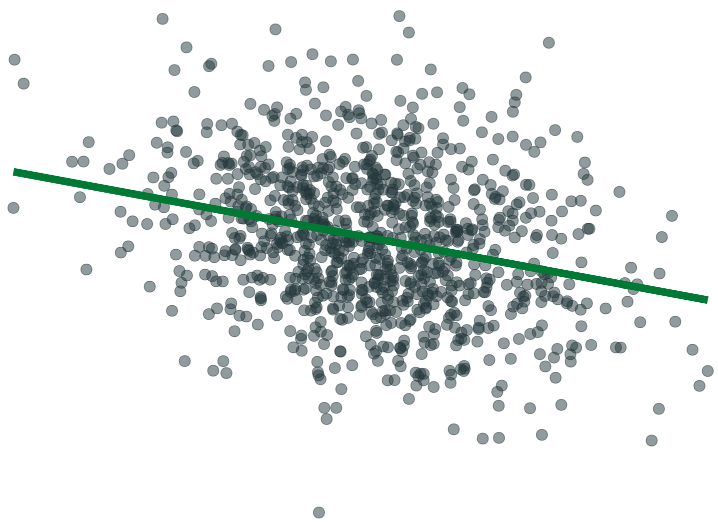
Regression 1 *vs.* **Regression 2**

- Same slope.
- Same intercept.

Q: Which fitted regression line *"explains"*[*] the data better?





[*] *Explains* = *fits*.

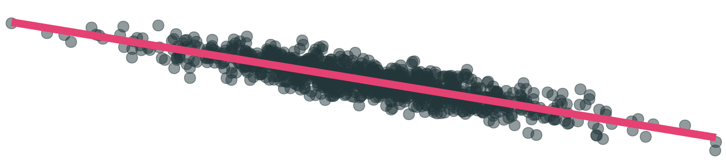
Goodness of Fit

Regression 1 *vs.* Regression 2

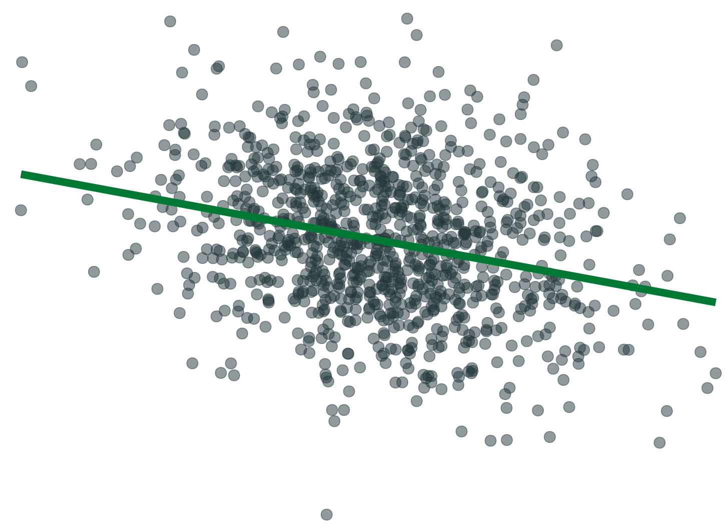
The **coefficient of determination** R^2 is the fraction of the variation in Y_i *"explained"* by X_i in a linear regression.

- $R^2 = 1 \implies X_i$ explains *all* of the variation in Y_i .
- $R^2 = 0 \implies X_i$ explains *none* of the variation in Y_i .

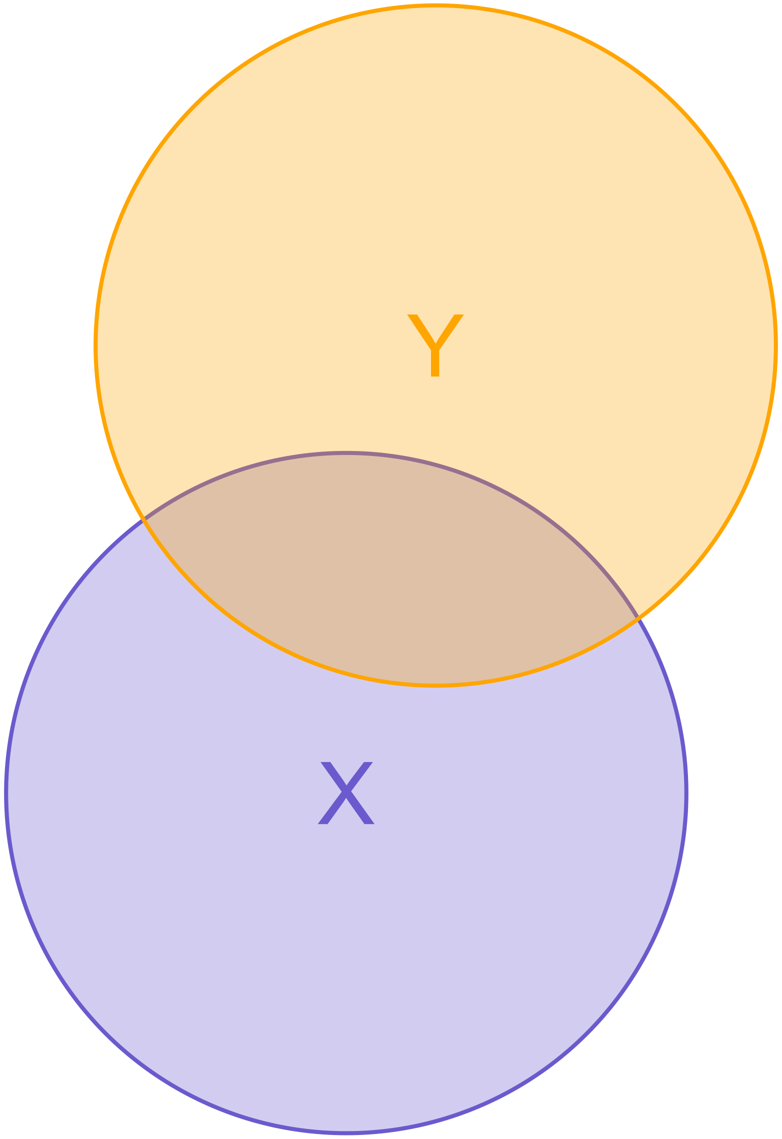
R^2 = 0.73



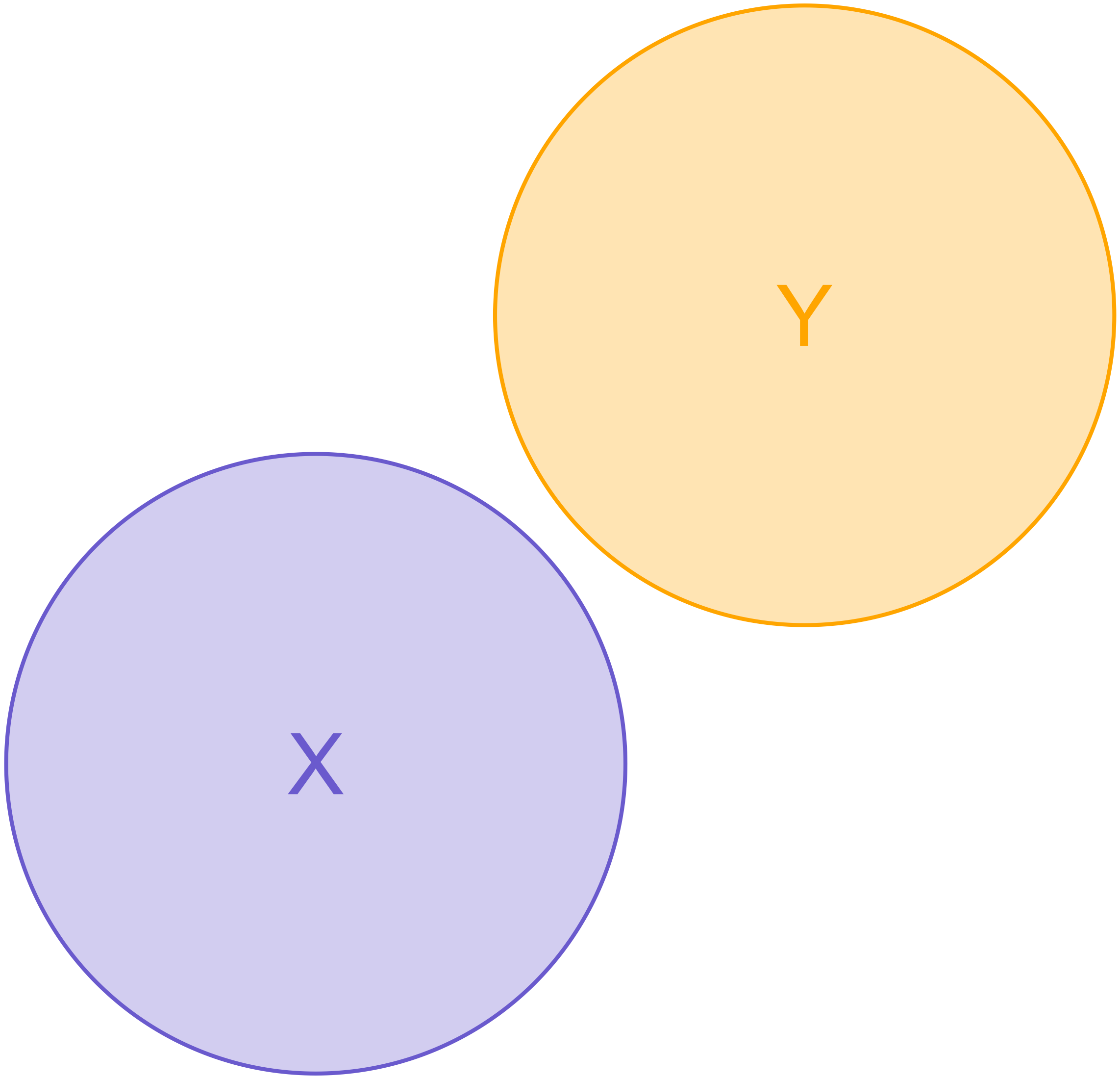
R^2 = 0.08



Goodness of Fit



Goodness of Fit



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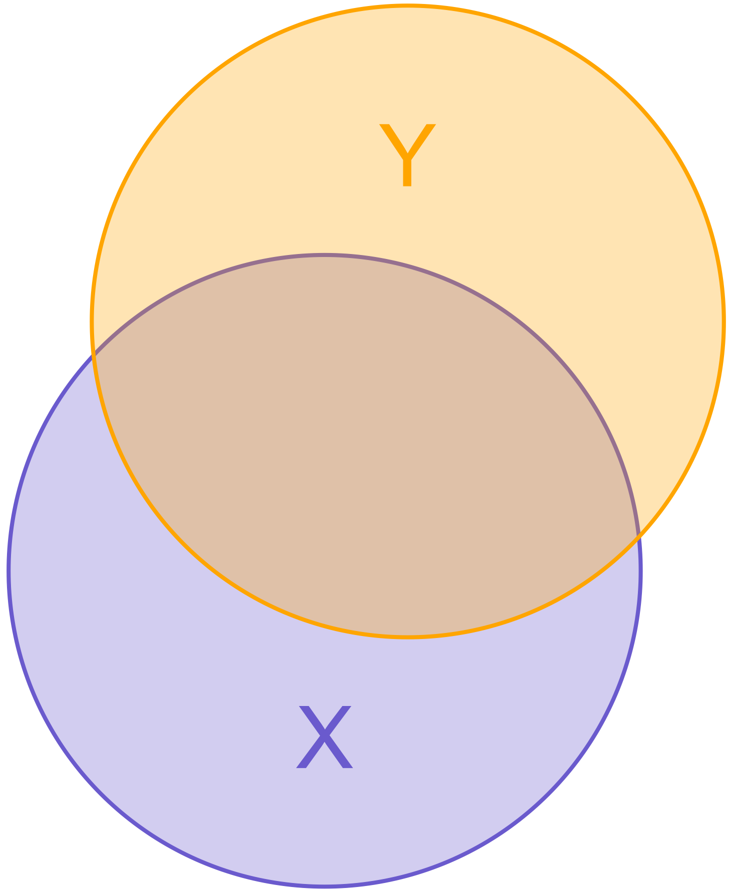
Goodness of Fit



Explained and Unexplained Variation

Residuals remind us that there are parts of Y_i we can't explain.

$$Y_i = \hat{Y}_i + \hat{u}_i$$

- Sum the above, divide by n , and use the fact that OLS residuals sum to zero to get $\bar{\hat{u}} = 0 \implies \bar{Y} = \bar{\hat{Y}}$.

Total Sum of Squares (TSS) measures variation in Y_i :

$$\text{TSS} \equiv \sum_{i=1}^{n} (Y_i - \bar{Y})^2.$$

- We will decompose this variation into explained and unexplained parts.

Explained and Unexplained Variation

Explained Sum of Squares (ESS) measures the variation in $\hat{Y}_i$:

$$\text{ESS} \equiv \sum_{i=1}^{n} (\hat{Y}_i - \bar{Y})^2.$$

Residual Sum of Squares (RSS) measures the variation in $\hat{u}_i$:

$$\text{RSS} \equiv \sum_{i=1}^{n} \hat{u}_i^2.$$

Goal: Show that $\text{TSS} = \text{ESS} + \text{RSS}$.

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Step 1: Plug $Y_i = \hat{Y}_i + \hat{u}_i$ into TSS.

$$
\begin{aligned}
\text{TSS} \\
&= \sum_{i=1}^{n} (Y_i - \bar{Y})^2 \\
&= \sum_{i=1}^{n} ([\hat{Y}_i + \hat{u}_i] - [\bar{\hat{Y}} + \bar{\hat{u}}])^2
\end{aligned}
$$

Step 2: Recall that $\bar{\hat{u}} = 0$ and $\bar{Y} = \bar{\hat{Y}}$.

$$
\begin{aligned}
\text{TSS} \\
&= \sum_{i=1}^{n} \left([\hat{Y}_i - \bar{Y}] + \hat{u}_i \right)^2 \\
&= \sum_{i=1}^{n} \left([\hat{Y}_i - \bar{Y}] + \hat{u}_i \right) \left([\hat{Y}_i - \bar{Y}] + \hat{u}_i \right) \\
&= \sum_{i=1}^{n} (\hat{Y}_i - \bar{Y})^2 + \sum_{i=1}^{n} \hat{u}_i^2 + 2 \sum_{i=1}^{n} \left((\hat{Y}_i - \bar{Y}) \hat{u}_i \right)
\end{aligned}
$$

Step 3: Notice **ESS** and **RSS**.

TSS

$$= \sum_{i=1}^{n} (\hat{Y}_i - \bar{Y})^2 + \sum_{i=1}^{n} \hat{u}_i^2 + 2\sum_{i=1}^{n} \left((\hat{Y}_i - \bar{Y})\hat{u}_i \right)$$

$$= \text{ESS} + \text{RSS} + 2\sum_{i=1}^{n} \left((\hat{Y}_i - \bar{Y})\hat{u}_i \right)$$

Step 4: Simplify.

$$
\begin{aligned}
\text{TSS} \\
&= \text{ESS} + \text{RSS} + 2\sum_{i=1}^{n}\left((\hat{Y}_i - \bar{Y})\hat{u}_i\right) \\
&= \text{ESS} + \text{RSS} + 2\sum_{i=1}^{n}\hat{Y}_i\hat{u}_i - 2\bar{Y}\sum_{i=1}^{n}\hat{u}_i
\end{aligned}
$$

Step 5: Shut down the last two terms. Notice that

$$
\begin{aligned}
\sum_{i=1}^{n}\hat{Y}_i\hat{u}_i \\
&= \sum_{i=1}^{n}(\hat{\beta}_1 + \hat{\beta}_2 X_i)\hat{u}_i \\
&= \hat{\beta}_1\sum_{i=1}^{n}\hat{u}_i + \hat{\beta}_2\sum_{i=1}^{n}X_i\hat{u}_i \\
&= 0
\end{aligned}
$$

Calculating R^2

- $R^2 = \dfrac{\text{ESS}}{\text{TSS}}$.
- $R^2 = 1 - \dfrac{\text{RSS}}{\text{TSS}}$.

R^2 is related to the correlation between the actual values of Y and the fitted values of Y .

- Can show that $R^2 = (r_{Y,\hat{Y}})^2$.

So what?

In the social sciences, low R^2 values are common.

Low R^2 doesn't mean that an estimated regression is useless.

- In a randomized control trial, R^2 is usually less than 0.1.

High R^2 doesn't necessarily mean you have a *"good"* regression.

- Worries about selection bias and omitted variables still apply.

Units of Measurement

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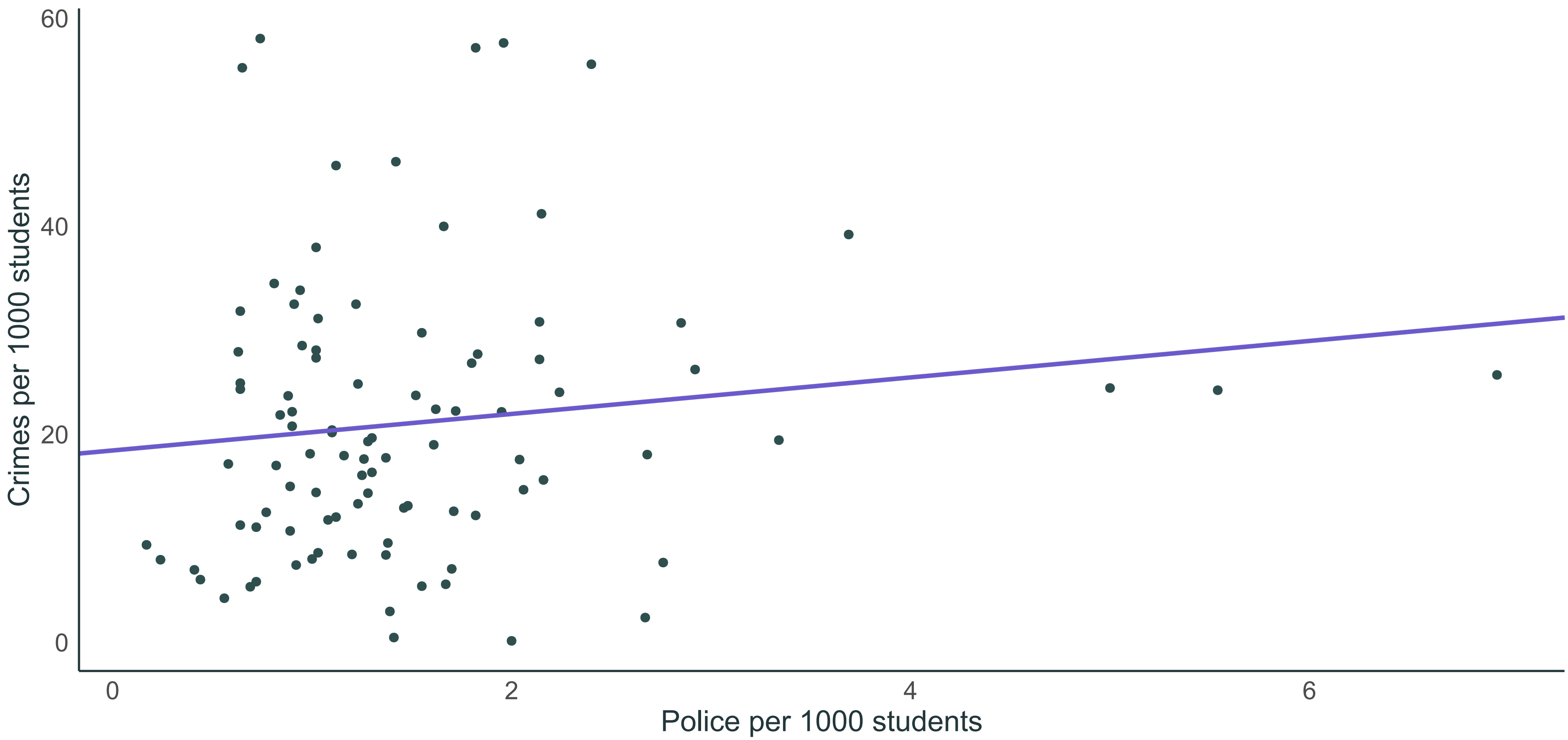
Last Time

We ran a regression of crimes per 1000 students on police per 1000 students. We found that $\hat{\beta}_1$ = 18.41 and $\hat{\beta}_2$ = 1.76.



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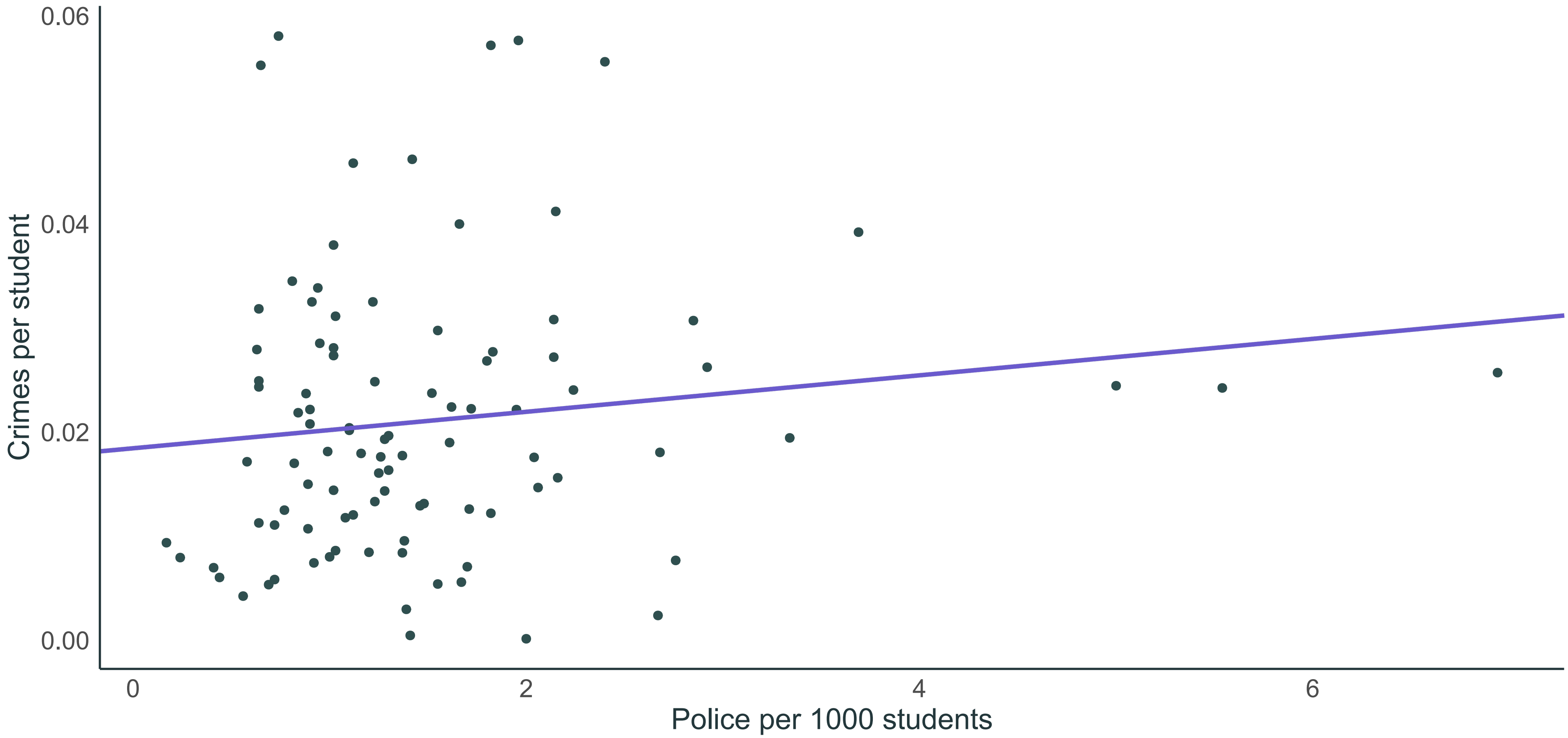
Last Time

What if we had run a regression of crimes per student on police per 1000 students? What would happen to the slope?



$\hat{\beta}_2 = 0.001756.$

Practice problem

Suppose that, before running a regression of Y_i on X_i, you decided to *demean* each variable by subtracting off the mean from each observation. This gave you $\tilde{Y}_i = Y_i - \bar{Y}$ and $\tilde{X}_i = X_i - \bar{X}$.

Then you decide to estimate

$$\tilde{Y}_i = \beta_1 + \beta_2 \tilde{X}_i + u_i.$$

What will you get for your intercept estimate $\hat{\beta}_1$?