FLS 6441 - Methods III: Explanation and Causation

Week 1 - Review

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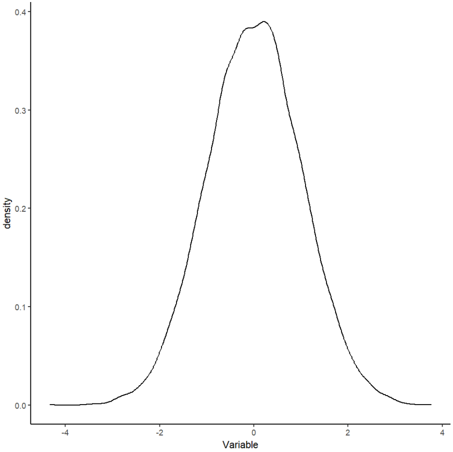
Course Objectives

1. temp

Data

1. We work with variables, which VARY!

	Variable
1	1.10
2	1.57
3	-0.08
4	-0.92
5	1.77
6	1.17
7	0.61
8	1.58
9	-2.29
10	-0.81



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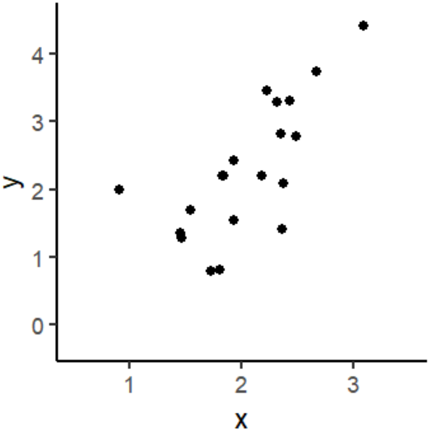

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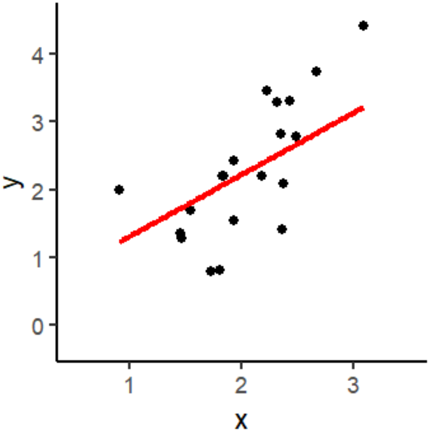

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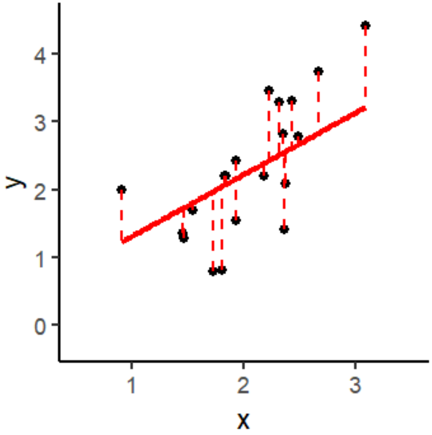

- Sum of Squared distances = 10.39

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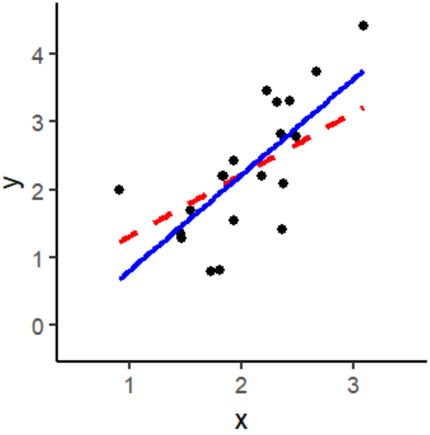

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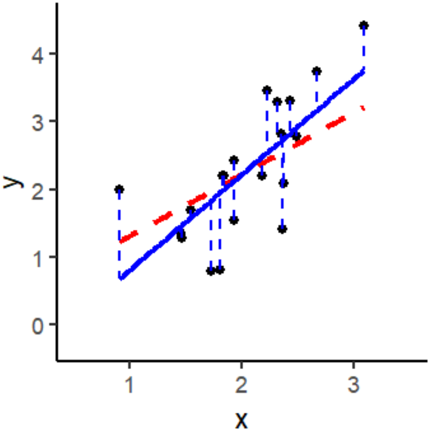

- Sum of Squared distances = 9.19

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- $E(y|x)$
- When age is 20 ($x = 40$), the average salary is R1.000 ($y = 1.000$)
- When age is 40 ($x = 40$), the average salary is R2.000 ($y = 2.000$)

Regression

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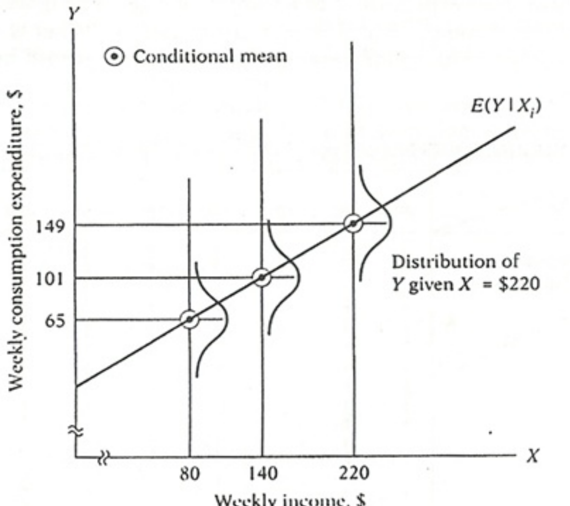
- It predicts the **mean**, not the median, not the minimum, not the maximum



Regression

$$\hat{\beta}_1 = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

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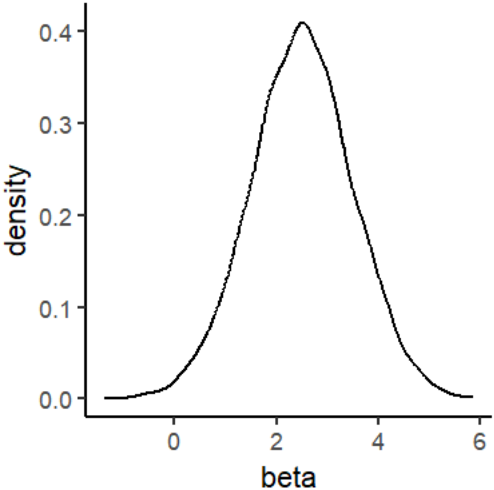

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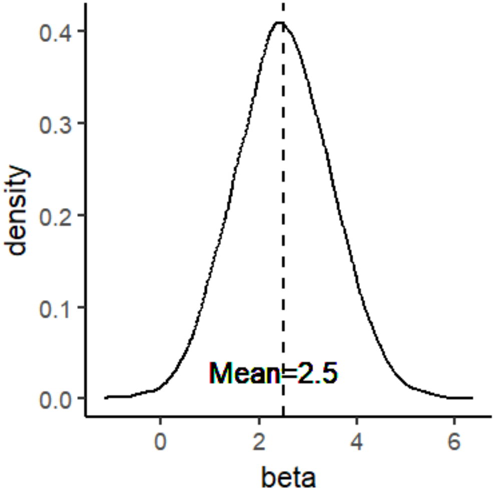

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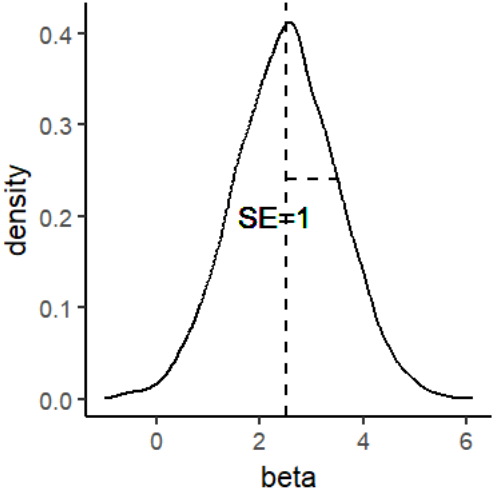

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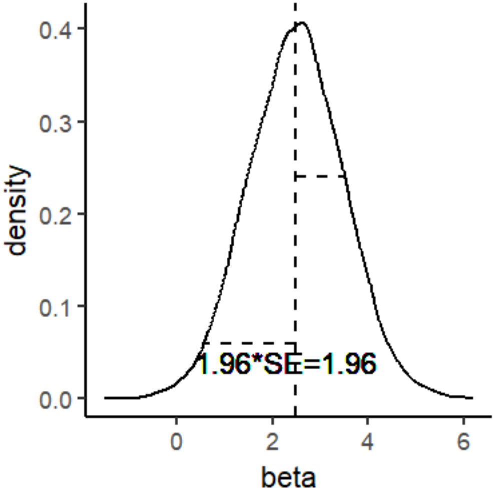

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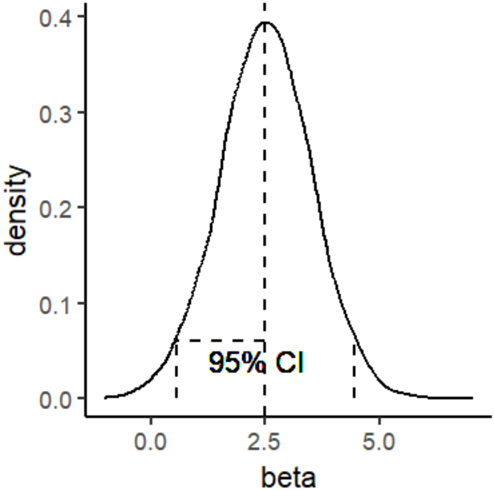

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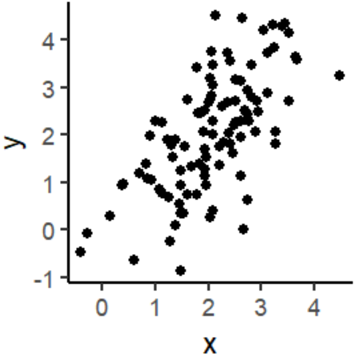

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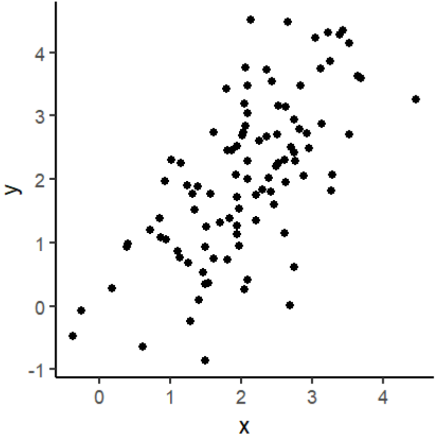

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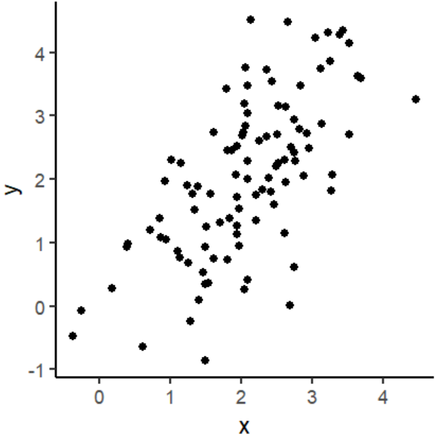

- Correlation is 0.658
- Regression Results:

	term	estimate
1	(Intercept)	0.101
2	x	0.933

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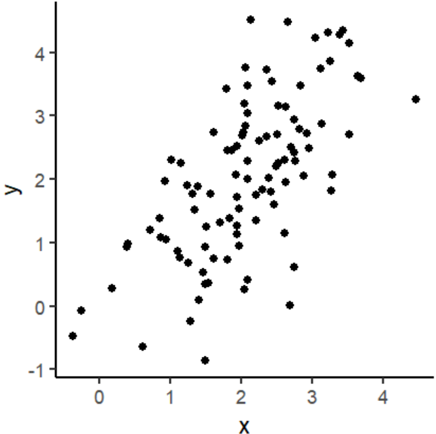

- Correlation is 0.658
- Standardized Regression Results:

	term	estimate
1	(Intercept)	0.000
2	x	0.658

Regression

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- Just a small difference in the denominator (how we standardize the measure)

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$$\beta_{x_1} = \frac{r_{yx_1} - r_{yx_2} r_{x_1x_2}}{1 - r^2_{x_1x_2}}$$

$$r_{yx_1|x_2} = \frac{r_{yx_1} - r_{yx_2} r_{x_1x_2}}{\sqrt{(1 - r^2_{yx_2})(1 - r^2_{x_1x_2})}}$$

- **There is no magic in regression, it's just correlation**

Regression Guide

1. **Choose variables and measures:** To test a specific hypothesis
2. **Choose a Model/Link Function:** Should match the data type of your outcome variable
3. **Choose Covariates:** To match your strategy of inference
4. **Choose Fixed Effects:** To focus on a specific level of variation
5. **Choose Standard Error Structure:** To match known dependencies/clustering in the data
6. **Interpret the coefficients:** Depending on the type/scale of the explanatory variable

Regression Models

The Regression Model reflects the data type of the outcome variable:

- Continuous -> Ordinary Least Squares

```
zelig(Y   X,data=d,model="ls")
```

- Binary -> Logit

```
zelig(Y   X,data=d,model="logit")
```

- Unordered categories -> Multinomial logit

```
zelig(Y   X,data=d,model="mlogit")
```

- Ordered categories -> Ordered logit

```
zelig(Y   X,data=d,model="ologit")
```

- Count -> Poisson

```
zelig(Y   X,data=d,model="poisson")
```

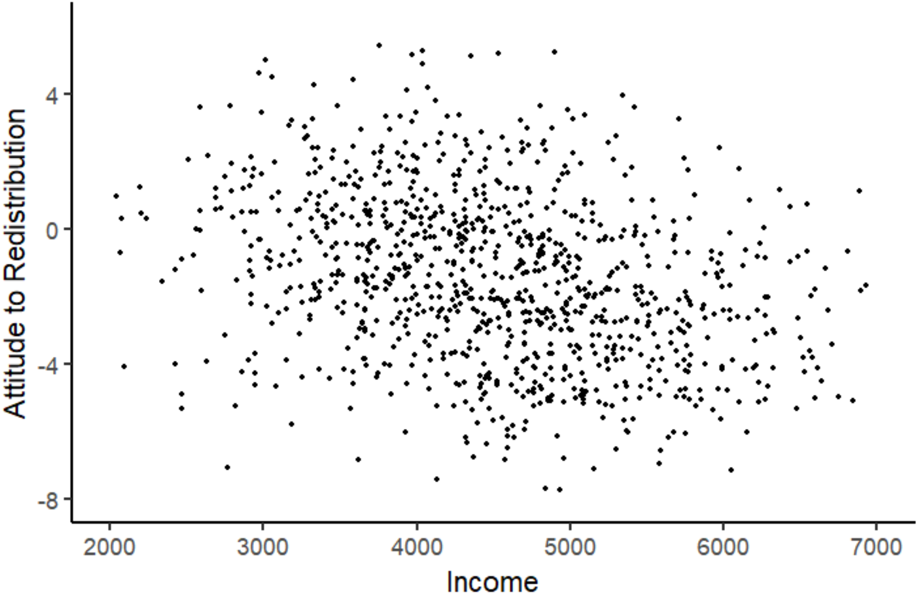
Interpreting Regression Results

- Difficult! It depends on the scale of the explanatory variable, scale of the outcome, the regression model we used, and the presence of any interaction
- Basic OLS:
  - 1 [unit of explanatory variable] change in the explanatory variable is associated with a β [unit of outcome variable] change in the outcome

Predictions from Regressions

- temp

Omitted Variable Bias



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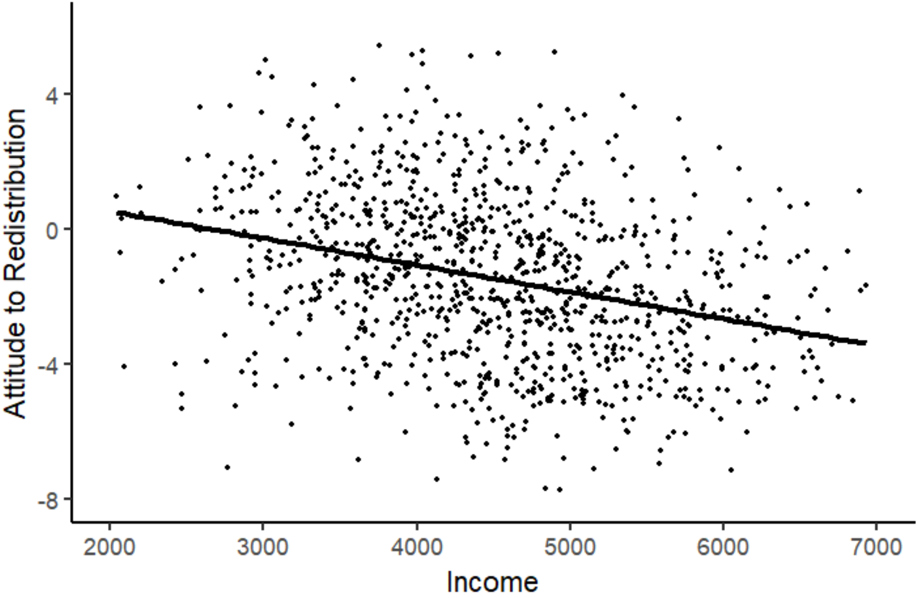

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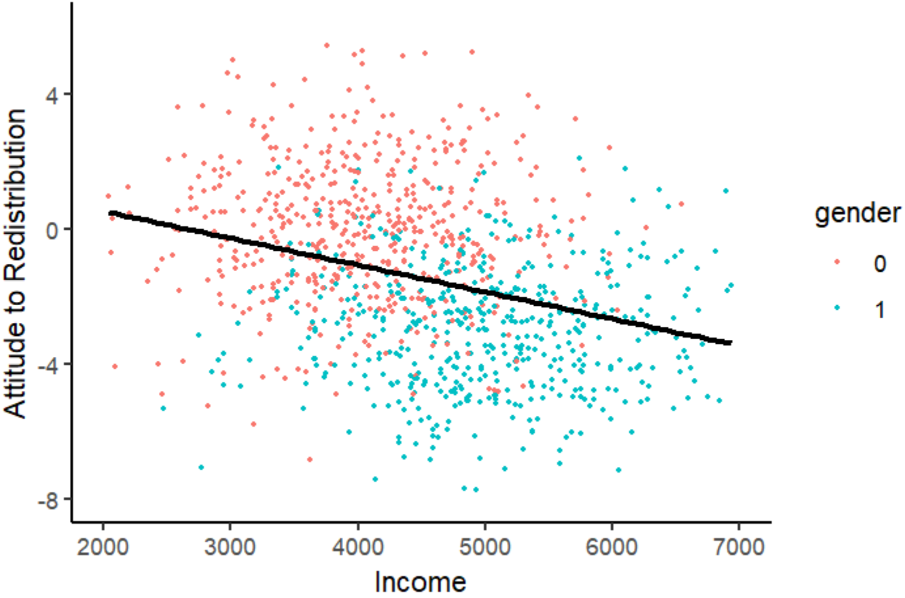

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