

# FLS 6441 - Methods III: Explanation and Causation

Week 1 - Review

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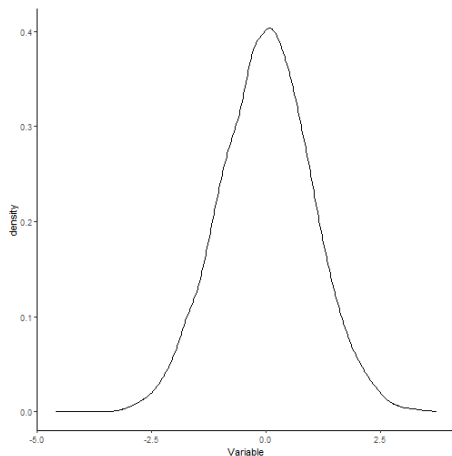
# Course Objectives

## 1. temp

## Data

### 1. We work with variables, which VARY!

	Variable
1	-1.21
2	0.73
3	-0.51
4	-1.41
5	0.62
6	0.33
7	-0.66
8	0.31
9	-0.12
10	0.16



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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

- ▶ Regression is a **Conditional Expectation Function**



```
## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Depend
##   in Christine Choirat, Christopher Gandrud, James H
##   "Zelig: Everyone's Statistical Software," http://z
##
## % Table created by stargazer v.5.2.2 by Marek Hlavac
## % Date and time: Thu, Feb 28, 2019 - 8:57:42 AM
## \begin{table}[!htbp] \centering
##   \caption{}
##   \label{}
## \begin{tabular}{@{\extracolsep{5pt}}lc}
## \\\[-1.8ex]\hline
## \hline \\\[-1.8ex]
## & \multicolumn{1}{c}{\textit{Dependent variable:}}
## \cline{2-2}
## \\\[-1.8ex] & y \\\
```

```
## \hline \[-1.8ex]
## x & 0.758 $\hat{***}$ $ \\\
## & (0.066) \\\
## & \\\
## Constant & $-$0.000 \\\
## & (0.066) \\\
## & \\\
## \hline \[-1.8ex]
## Observations & 100 \\\
## R $\hat{^2}$ $ & 0.575 \\\
## Adjusted R $\hat{^2}$ $ & 0.571 \\\
## Residual Std. Error & 0.655 (df = 98) \\\
## F Statistic & 132.700 $\hat{***}$ $ (df = 1; 98) \\\
## \hline
## \hline \[-1.8ex]
## \textit{Note:} & \multicolumn{1}{r}{ $\hat{^*}$ $p$<$0.1;
## \end{tabular}
```

```
## \end{table}
```

## Regression

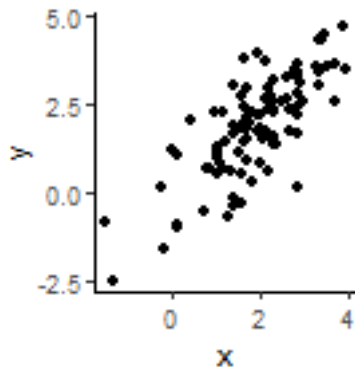
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## Regression

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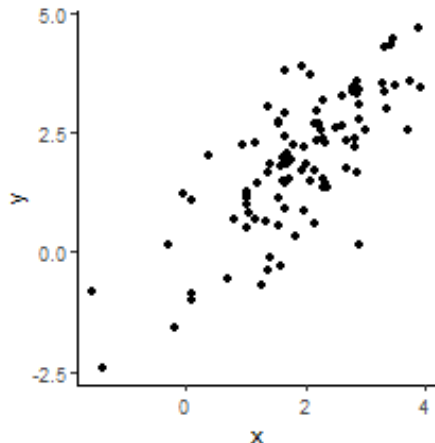
## Regression

- ▶ Regression with two variables is very similar to calculating correlation
- ▶  $\hat{\beta} = \text{cor}(x, y) * \frac{\sigma_Y}{\sigma_X}$
- ▶ It's *identical* if we standardize both variables first ( $\frac{(x-\bar{x})}{\sigma_x}$ )



## Regression

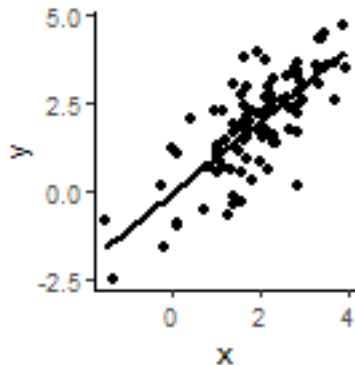
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Correlation is 0.758

## Regression

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The regression result is:

---



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*Dependent Variable*

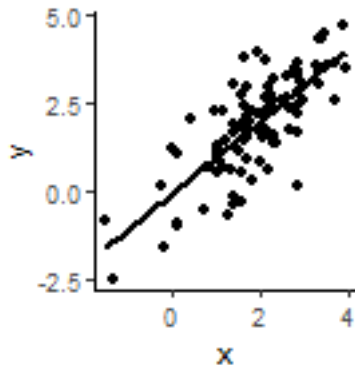
*Independent Variable*

Constant



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The regression result is:

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*Depe*

---

x

Constant

## 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")
```

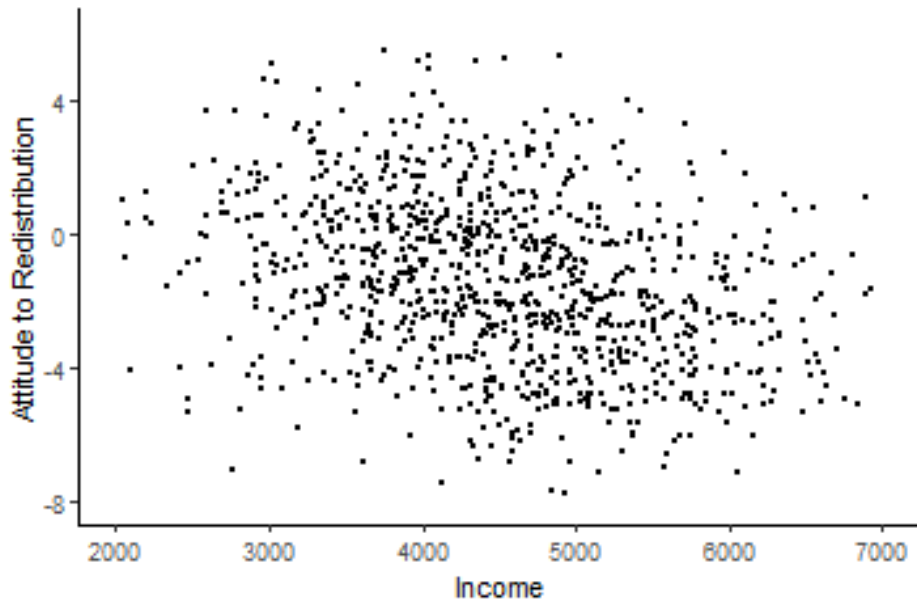
## Interpreting Regression Results

- ▶ 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  $\beta$  [unit of outcome variable] change in the outcome

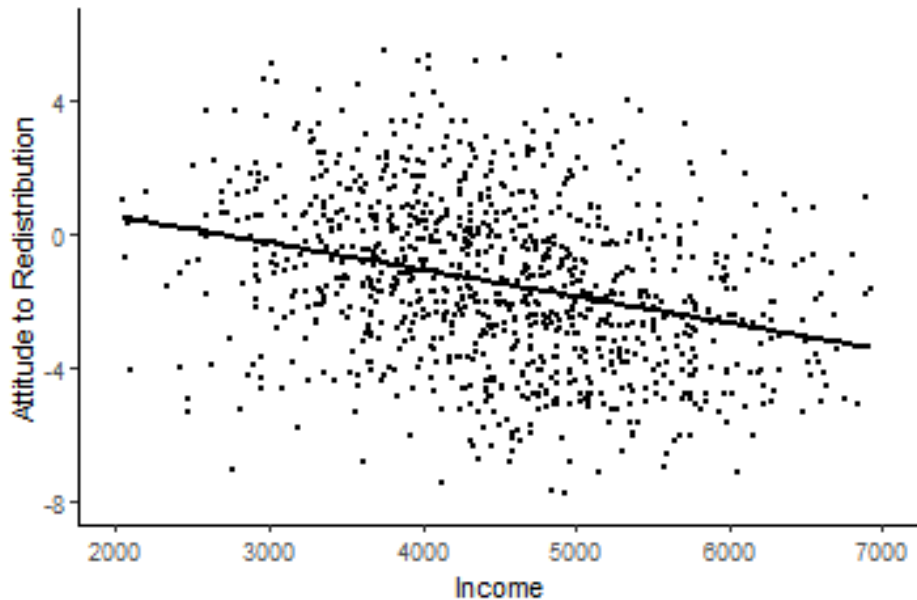
# Predictions from Regressions

- temp

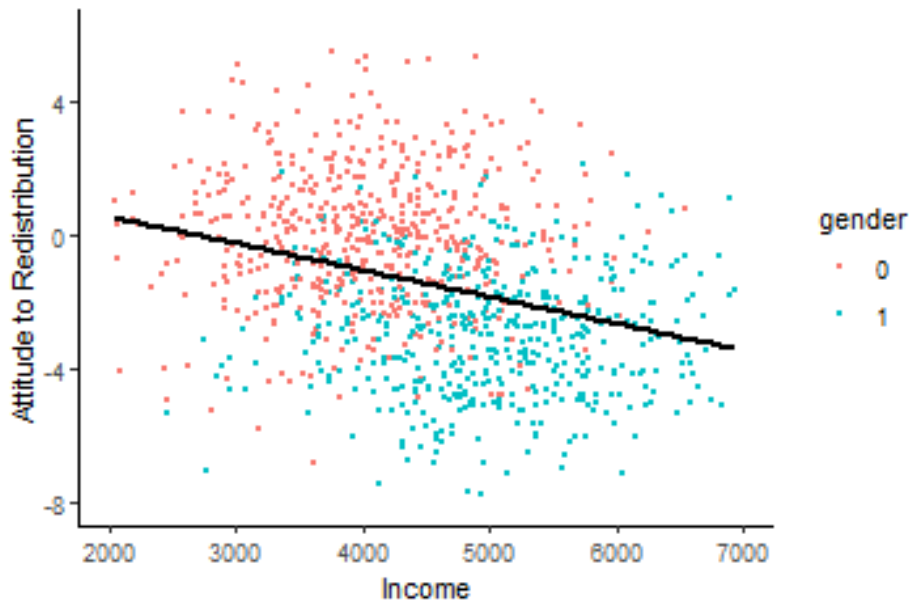
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