Building a Robot Judge: Data Science for Decision-Making

2. Causal Inference Essentials

Instructions before we begin:

(1) Turn on video and set audio to mute
(2) In Participants panel, set zoom name to “Full Name, School / Degree”
(ex: “Leon Smith, ETH Data Science Msc”)
(3) If you are new, say “hi” in the chat.

Online Lecture Norms

Let's make the most of online learning!

- Live attendance at lectures is required.
- Keep video on if connection allows.
- Stay muted when not talking.
- To make questions or comments, type in the chat (private or public) or use the "raise hand" function.

Weekly Q&A

https://bitly.com/BRJ_Padlet10

Learning Objectives

1. Implement and evaluate machine learning pipelines.
2. **Implement and evaluate causal inference designs.**
    - Evaluate (find problems in) causal claims.
    - Apply the standard research designs to produce causal evidence for a given empirical setting – or articulate why it is not possible.
    - Implement these research designs using Stata regressions.
3. Understand how (not) to use data science tools (ML and CI) to support expert decision-making.

Outline

What is causality?

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Non-causal questions are also important:

- can I predict ticket sales next quarter based on all available variables this quarter?

Machine Learning vs Causal Inference

Machine Learning (Weeks 3, 5, 7, 9):

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- Causal inference is about what *we don't know yet*.
- how do we know if a new policy will work?
  - for example, wearing masks and coronavirus spread.

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Causal Inference (Weeks 2, 4, 6, 8):

- Causal inference is about what *we don't know yet*.
- how do we know if a new policy will work?
  - for example, wearing masks and coronavirus spread.
- There isn't a machine learning dataset to train a model on.
  - we can't experimentally force people to wear a mask or not.
- How do we solve that?

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  - e.g., variation in number of coronavirus cases before/after openings, using differences in the timing of openings (differences-in-differences).

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  - e.g., variation in number of coronavirus cases before/after openings, using differences in the timing of openings (differences-in-differences).
- Tech companies understand importance of causality with A/B testing
  - and also with hiring lots of economists, who specialize in causal analysis.
- Social scientists want to use causal inference to understand society and assist public policy.

Causal Statements

- A light switch being flipped turns on the lights.
- Getting a college degree increases career earnings.
- Higher cigarette taxes decrease smoking.
- Higher minimum wages decrease employment.
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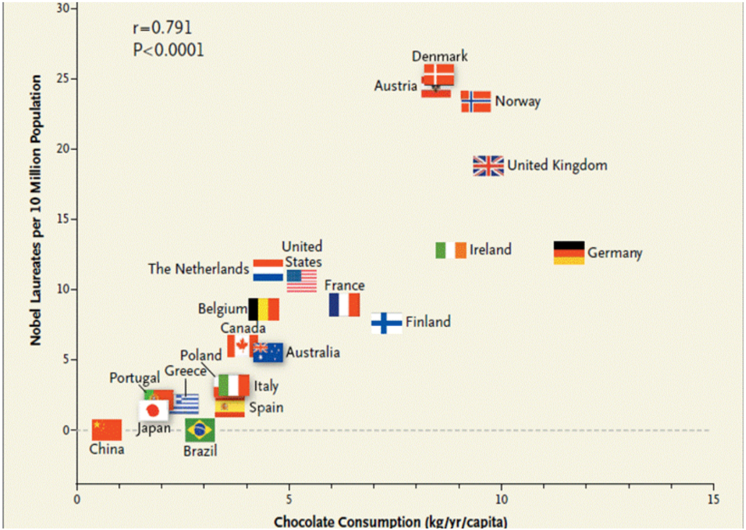
Compare to:

- When people carry umbrellas, there is increased probability of rain
- When ice cream trucks are out, people wear shorts more often.
- Colds tend to clear up after taking cold medicine.

Correlation does not imply causation



More here: `http://www.tylervigen.com/spurious-correlations`

Important Notes

- "X causes Y":
  - does not mean that X is the only thing that causes Y
  - does not mean that all Y must be X
- For example, using a light switch causes the light to go on:
  - But not if the bulb is burned out (no Y, despite X), or if the light was already on (Y without X)
  - We would still say that using the switch causes the light.
  - The important thing is that X changes the probability that Y happens, not that it necessarily makes it happen for certain.

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- Example:
  - $X = 0$ or 1 for getting a vaccine or not
  - Y $=$ 0 or 1, for catching flu or not
  - Take one person – Angela – set her X to zero and check Y, then set her X to one and check Y.
  - If Y's are different, then X causes Y.

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  - Take one person – Angela – set her X to zero and check Y, then set her X to one and check Y.
  - If Y's are different, then X causes Y.
- Problem:
  - Angela can't be in two places at once. either she got the vaccine or not.

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  - Problem (time-varying confounders):
    - other things are changing in Angela's life that affect her chances of catching the flu.

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- The goal of causal inference is making as good a guess as possible as to what Y would have been if X had been different.
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- Put differently: We would like to get close to having two people that are exactly the same except that one has X=0 and one has X=1

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- Put differently: We would like to get close to having two people that are exactly the same except that one has X=0 and one has X=1
- In many scientific fields, you get causal variation with **experiments**.
  - If X is a randomly assigned **treatment** in a large sample, we know that the people in each **treatment group** are identical on average.
  - but in many contexts – especially in social science – experiments are not possible to do.

Activity: Limitations of Experiments (2 minutes)

- Last Names A-L:
  - think of a social science setting where an experiment would be impossible or unethical.
- Last Names M-Z:
  - think of a natural science setting where an experiment would be impossible or unethical.
- Type them down privately. At the end of the 2 minutes, we will post them in the zoom chat.

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- The **research design**, **identification strategy**, or **empirical strategy** is the approach used with observational data (i.e. data not generated by a randomized trial) to approximate a randomized experiment.

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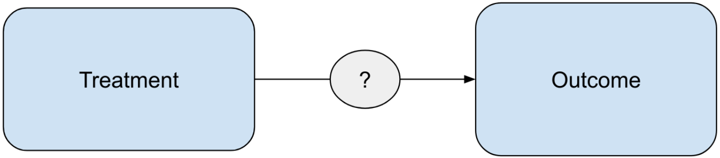
- Today:
  - Adjusting (controlling) for observed confounders
- Week 4:
  - Regression discontinuity design
  - Differences-in-differences
- Week 6:
  - Adjusting $\times$ machine learning: Double ML
- Week 8:
  - Instrumental variables

Outline

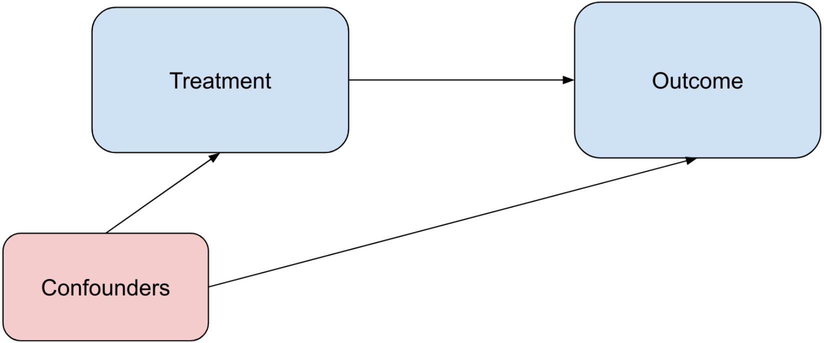
Causal Graphs



- We are interested in determining whether a significant correlation between "treatment" and "outcome" indicates a causal link.

Confounders

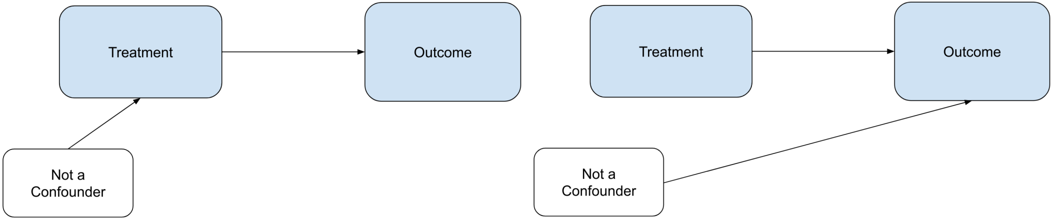
- Confounders affect both the treatment and the outcome:



- **In the presence of confounders, a correlation between the treatment and the outcome does not indicate a causal link.**
  - Example: eating ice cream causes heat stroke.

Not Confounders

- Variables that affect just the treatment, or just the outcome, are not confounders.



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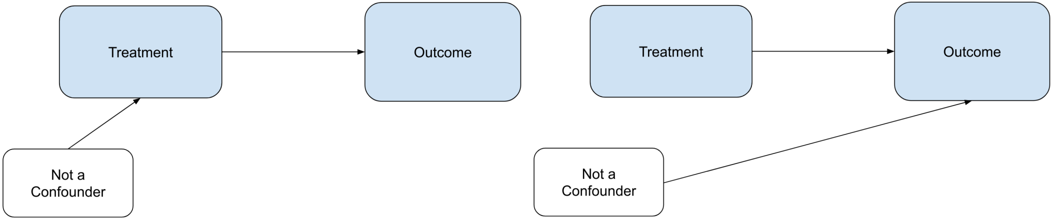

- E.g.:
  - presence of ice cream truck affects probability of eating ice cream, but not probability of heat stroke.
  - old age increases probability of heat stroke, but not probability of eating ice cream
- Note: Randomized experiments knock out the arrow from all potential confounders to the treatment.

Identification with Observed Confounders

- Another example: Effect of a person's income D on committing crimes Y.
  - what is a potential confounder A that might affect income D and crime choices Y?
  - That is, the estimated correlation between D and Y is **biased** by the presence of A.

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- Assume that:
  - A is education, affecting both income and crime.
  - we can measure A.
  - A is the only confounder.
- Under these assumptions, we can **identify** the effect of D on Y by netting out the components of D and Y that are driven by A.
  - this is called "adjusting for" or "controlling for" A

Adjusting (controlling) for observables

1. learn the function $\hat{D}(A)$, compute residual $\tilde{D} = D - \hat{D}$
2. learn the function $\hat{Y}(A)$, compute residual $\tilde{Y} = Y - \hat{Y}$
3. $\rightarrow$ the relationship between $\tilde{D}$ and $\tilde{Y}$ is causal.

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- In standard econometrics, one would assume linearity, e.g.

$$D(A) = \beta A, Y(A) = \gamma A$$

  - learn $\hat{\beta}$ and $\hat{\gamma}$ with linear regression (ordinary least squares)
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- Notes:
  - A can be multivariate, e.g. $D(\boldsymbol{A}) = \boldsymbol{A}'\beta$
  - with newer approaches using machine learning for causal inference, can have arbitrary functional relationships for $D(\boldsymbol{A})$ and $Y(\boldsymbol{A})$.

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2. unobserved variables that do not affect the outcome, or do not affect the treatment:
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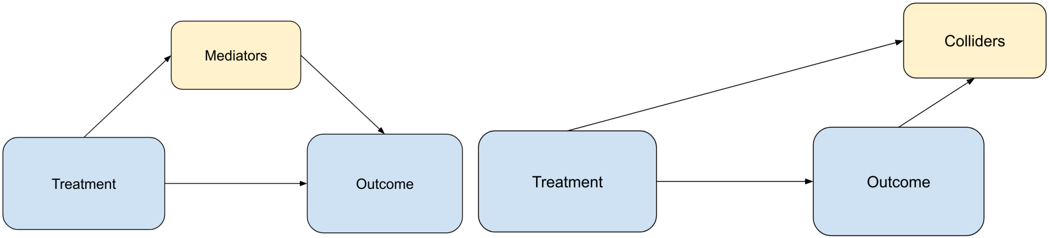
3. unobserved variables that affect both the treatment and outcome.
   - **this is the problem – unobserved confounders or "omitted variable bias".**
   - in general, there is no way to know for sure whether all confounders are observed.

Why not control for everything? Colliders and Mediators

- **Mediators** are intermediate outcomes / mechanisms.
  Colliders are affected by both the treatment and the outcome.



- The presence of mediators and colliders does not produce omitted variable bias.
  - instead, **adjusting for them will induce bias**.
  - $\rightarrow$ have to be careful about what variables to adjust for.

Reverse Causation or Joint Causation

- **Reverse causation**: "Outcome" affects "Treatment".
  Joint causation: there is bidirectional causation.

- e.g., effect of policing on crime rates.
- In this case, cannot recover a causal relationship, even if adjusting for observables.
  - have to use natural experiments (weeks 4, 6, 8)

Activity on Confounders: Via Zoom Chat (2 minutes)

Consider the **effect of education on income**:

- If last name starts with A-H:
  - what are likely **confounders** for the effect of education on income?
- If last name starts with I-P:
  - what are likely **mediators** for the effect of education on income?
- If last name starts with Q-Z:
  - what are likely **colliders** for the effect of education on income?
- Type it privately — will post in zoom chat in 2 minutes.

Outline

Linear Regression Models

- How does schooling affect income?
- Assume a linear model

$$Y_i = \alpha + \beta s_i + \epsilon_i$$

  - Y_i = the income of person i (“outcome variable”)
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- β = the slope parameter summarizing how wages vary with schooling.

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- Assume that Y_i and s_i are de-meaned. Then the OLS estimator is given by

$$\hat{\beta} = \frac{\sum_{i=1}^{n} s_i Y_i}{\sum_{i=1}^{n} s_i^2} = \frac{\mathrm{Cov}[Y_i, s_i]}{\mathrm{Var}[s_i]}$$

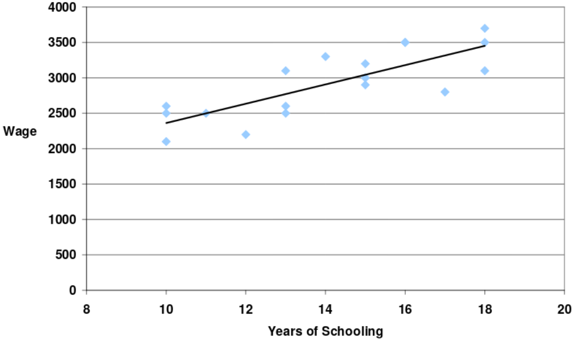
```
import statsmodels.formula.api as smf
ols = smf.ols(formula='price ~ CRIM', data=df).fit()
ols.summary()
```

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.203
Model:	OLS	**Adj. R-squared:**	0.201
Method:	Least Squares	**F-statistic:**	124.0
Date:	Sat, 02 Oct 2021	**Prob (F-statistic):**	8.11e-26
Time:	17:17:08	**Log-Likelihood:**	-1649.9
No. Observations:	490	**AIC:**	3304.
Df Residuals:	488	**BIC:**	3312.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	23.1147	0.344	67.143	0.000	22.438	23.791
CRIM	-0.4059	0.036	-11.135	0.000	-0.478	-0.334

Interpreting OLS Coefficients



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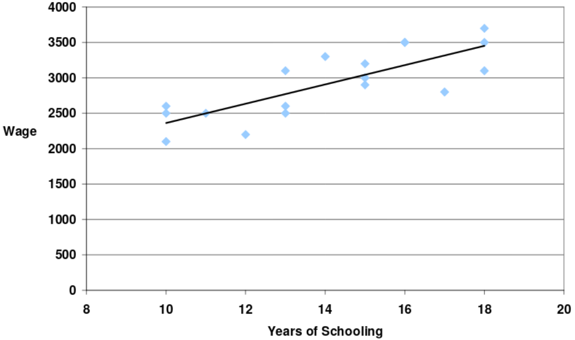

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  - In this example, the average increase in income for taking one more year of school.
- Using the estimated constant $\hat{\alpha}$ and estimated slope coefficient $\hat{\beta}$, we obtain a predicted income $\hat{Y}$ for any level of schooling s as

$$\hat{Y}(s) = \hat{\alpha} + \hat{\beta}s$$

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&= (\frac{\sum_{i=1}^n s_i^2}{\sum_{i=1}^n s_i^2})\beta + \frac{\sum_{i=1}^n s_i(\epsilon_i)}{\sum_{i=1}^n s_i^2} \\
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$$= \beta + \frac{\sum_{i=1}^n s_i \epsilon_i}{\sum_{i=1}^n s_i^2}$$

- Taking expectations:

$$\mathbb{E}[\hat{\beta}] = \beta + \mathbb{E}[\frac{\sum_{i=1}^n s_i \epsilon_i}{\sum_{i=1}^n s_i^2}]$$
$$= \beta + \frac{\text{Cov}[s_i, \epsilon_i]}{\text{Var}[s_i]}$$
$$= \beta$$

Endogeneity

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  - That is, an explanatory variable s_i is said to be **endogenous** if it is correlated with unobserved factors (confounders) that are also correlated with the outcome variable.

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  - That is, an explanatory variable s_i is said to be **endogenous** if it is correlated with unobserved factors (confounders) that are also correlated with the outcome variable.
- Since the error term ϵ_i includes all unobserved factors affecting the outcome, we can define **endogeneity** as correlation between an explanatory variable and the error term:

$$\text{Cov}[s_i, \epsilon_i] \neq 0$$

Formalizing omitted variable bias

- Assume that the "true" model is

$$Y_i = \beta s_i + \gamma a_i + \eta_i \tag{1}$$

where η_i is exogenous by assumption ($\text{Cov}[s_i, \eta_i] = 0$), but we cannot measure ability a_i.

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where η_i is exogenous by assumption ($\text{Cov}[s_i, \eta_i] = 0$), but we cannot measure ability a_i.

- Now we have

$$\hat{\beta} = \frac{\sum_{i=1}^{n} s_i Y_i}{\sum_{i=1}^{n} s_i^2} = \frac{\sum_{i=1}^{n} s_i(\beta s_i + \gamma a_i + \eta_i)}{\sum_{i=1}^{n} s_i^2}$$
$$= \beta + \frac{\sum_{i=1}^{n} s_i(\gamma a_i)}{\sum_{i=1}^{n} s_i^2} + \frac{\sum_{i=1}^{n} s_i \eta_i}{\sum_{i=1}^{n} s_i^2}$$

- Taking expectations gives

$$\mathbb{E}[\hat{\beta}] = \beta + \underbrace{\gamma \frac{\text{Cov}[s_i, a_i]}{\text{Var}[s_i]}}_{\text{Omitted variable bias}} + \underbrace{\frac{\text{Cov}[s_i, \eta_i]}{\text{Var}[s_i]}}_{=0 \text{ by assumption}}$$

$\rightarrow$ if ability is correlated with schooling ($\text{Cov}[s_i, a_i] \neq 0$), $\hat{\beta}$ is a biased estimate for β.

Understanding omitted variable bias

$$\mathbb{E}[\hat{\beta}] = \beta + \underbrace{\gamma \frac{\text{Cov}[s, a]}{\text{Var}[s]}}_{\text{Omitted variable bias}}$$

		Correlation of omitted variable with explanatory variable	
		$\text{Cov}[s, a] > 0$	$\text{Cov}[s, a] < 0$
Correlation of omitted variable with outcome	$\gamma > 0$	$\hat{\beta} > \beta$	$\hat{\beta} < \beta$
	$\gamma < 0$	$\hat{\beta} < \beta$	$\hat{\beta} > \beta$

Outline

Intro to Causal Inference

Causal Graphs and Confounders

Causal Inference with Linear Regression

- Exogeneity and Omitted Variable Bias
- Standard Errors and Statistical Inference

Discrimination: Evidence

Appendix on Course Projects

Statistical Significance

- The value for β provides a prediction for the effect of the explanatory variable on the outcome.
  - But if this prediction is very noisy, then it might not be useful for policy analysis.

Statistical Significance

- The value for β provides a prediction for the effect of the explanatory variable on the outcome.
  - But if this prediction is very noisy, then it might not be useful for policy analysis.
- To do causal *inference*, we have to determine whether the effect is statistically significant.
  - This is generally achieved by computing a **standard error** for each coefficient, and then using the standard error to compute **confidence intervals** and a ***p*-value** for the hypothesis that $\beta \neq 0$.

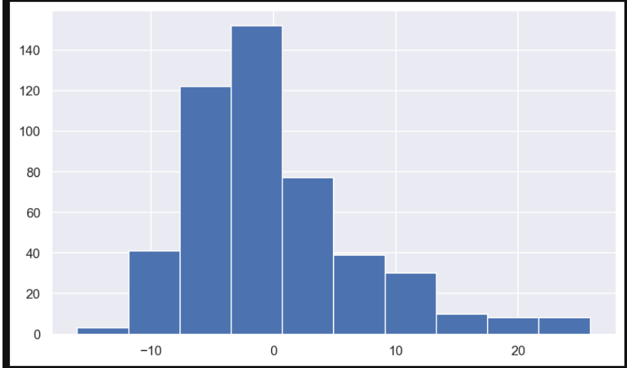
Residuals

- The **residuals** or **errors** from an OLS regression are defined as

$$\begin{aligned}\tilde{\epsilon}_i &= Y_i - \hat{Y}_i \\ &= Y_i - \hat{\alpha} - \hat{\beta} s_i\end{aligned}$$

```
ols.resid.hist()
```

```
<AxesSubplot:>
```



Standard Errors

- The **standard error** (SE) for the OLS estimate $\hat{\beta}$ is

$$\hat{\sigma}_\beta = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\tilde{\epsilon}_i^2},$$

  the square root of the average of the squared residuals.

- SE provides information about the precision of the estimate: a lower standard error is a more precise estimate.
  - On regression tables, usually reported in parentheses right beneath the point estimate.

```
ols.summary()
```

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.203
Model:	OLS	**Adj. R-squared:**	0.201
Method:	Least Squares	**F-statistic:**	124.0
Date:	Sat, 02 Oct 2021	**Prob (F-statistic):**	8.11e-26
Time:	17:17:08	**Log-Likelihood:**	-1649.9
No. Observations:	490	**AIC:**	3304.
Df Residuals:	488	**BIC:**	3312.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	23.1147	0.344	67.143	0.000	22.438	23.791
CRIM	-0.4059	0.036	-11.135	0.000	-0.478	-0.334

t-statistics, p-values, and confidence intervals

- A rule of thumb for statistical significance is to compute the ***t*-statistic**:

$$t = \frac{\hat{\beta}}{\hat{\sigma}_\beta}$$

  - $t > 2 \rightarrow$ statistically significant positive effect, $t < 2 \rightarrow$ statistically significant negative effect
- A high t (in absolute value) is associated with a small ***p*-value** (e.g., $t = \pm 1.96 \rightarrow p = .05$).
  - Small p-values are often indicated on regression tables with stars to indicate statistical significance.
- **95% confidence intervals** indicate (roughly) that the coefficient is 95% likely to reside within that interval.

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Multivariate Regression

- Setup: n_D observations with n_x explanatory variables.
  - Let Y be the $n_D \times 1$ vector for the outcome variable (also called dependent variable).
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  - Let X be the $n_D \times n_x$ matrix of explanatory variables (also called independent variables or predictors)
- The $n_x \times 1$ vector of OLS coefficients (one for reach explanatory variable) is

$$\hat{\beta} = (X'X)^{-1}X'Y$$

with standard errors given by the diagonal entries of the $n_x \times n_x$ matrix

$$\hat{\sigma}\sqrt{(X'X)^{-1}}$$

```
ols = smf.ols(formula='price ~ CRIM + TAX', data=df).fit()
```

Outline

Empirical Analysis of Discrimination

$$Y_i = \alpha G_i + \boldsymbol{X}'_i \beta + \epsilon_i$$

- Y_i= wage, G_i= group , $\boldsymbol{X}_i$= other factors
- $\alpha < 0$ often estimated for women/minorities

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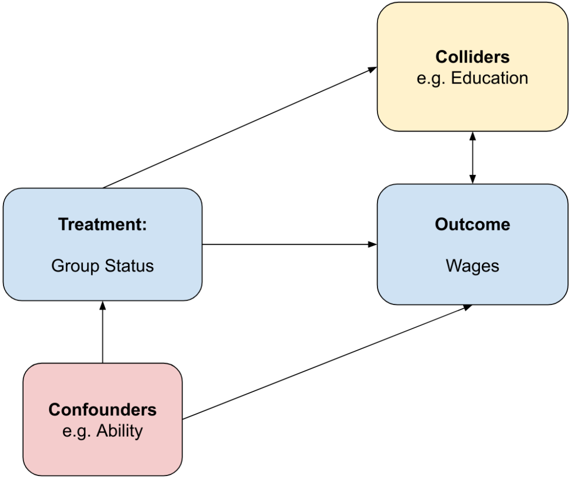

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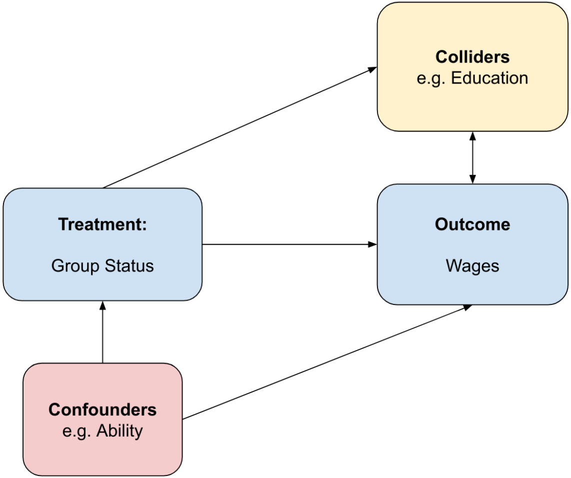

- The usual concern: (unobserved) confounders
- e.g. in one study, adding an ability test score (AFQT) explained 3/4 of racial wage gap in income (Neal and Johnson 1996).

Blind Orchestra Auditions

Goldin and Rouse (2000)

- natural experiment: orchestras moved to blind auditions.
  - compare rate that women were hired before and after.

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- positive effect: blind auditions helped women get positions in the orchestra.

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Bertrand and Mullainathan (2004)

- 5,000 resumes sent to help-wanted ads in Boston and Chicago
- Randomized otherwise equivalent resumes to have African-American or White sounding names:
  - Emily Walsh or Greg Baker relative to Lakisha Washington or Jamal Jones

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- Results:
  - 50% gap in callback rate for black-sounding names
- Caveats:
  - "Lakisha" or "Jamal" might signal non-racial factors, e.g. socioeconomic status.
  - Fryer and Levitt (2004) find no long-term life outcome differences for people with more black-sounding names, adjusting for other background factors.

Outline

Course Project Logistics

`https://bit.ly/BRJ_proj`

- If you are signed up for the credits, the focus of your work in this course should be on the project.
  - Can be done individually or in small groups (up to 4 students).
  - Do an original analysis using methods learned in the course, and write a paper about it.

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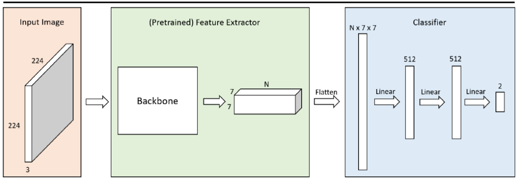
- Deliverables:
  - description of topic (October 26th 10% of grade)
  - proposal/outline (November 23rd, 10% of grade)
  - Poster session (early December, 10% of grade).
  - Rough draft with data/methods/results (January 4th 2021, 20% of grade)
  - Final draft (February 1st 2021, 50% of grade)

Previous Projects (1)

Dominik Borer: Predicting Candidate Party from Political Television Ads

Figure 3: Overview of Model Architecture



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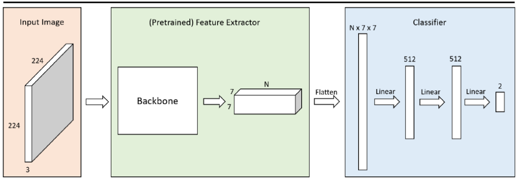

Panel C. Confusion matrix for test set

	Predicted Democratic	**Predicted Republican**
Actual Democratic	44.88% (793)	7.98% (141)
Actual Republican	15.73% (278)	31.41% (555)

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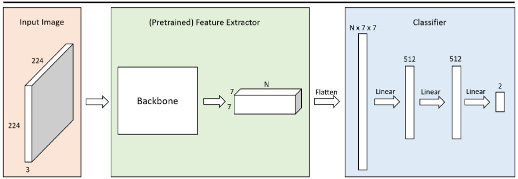

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Panel A: News Show Images with Highest Democrat Slant

Panel B: News Show Images with Highest Republican Slant

Previous Projects (2)

Philip Nikolaus: Deep Instrumental Variables for Causal Effects of Judicial Text

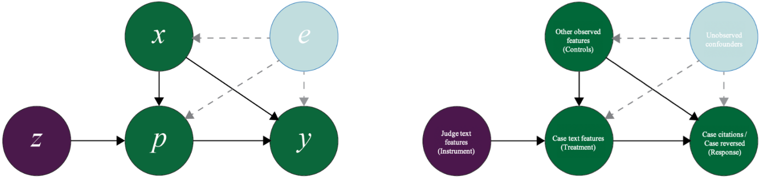

Figure 1: (Left) Directed graph with arrows representing causal effects (Hartford et al. 2017). (Right) Directed graph showing the causal relationship structure for this work.

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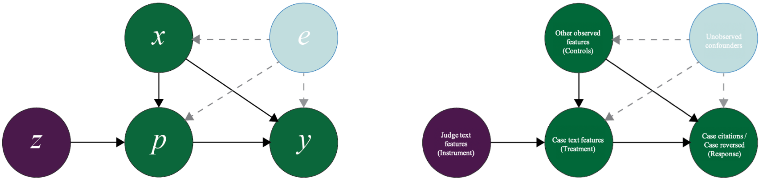

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Top 20 Words in Cluster	Feature Importance (Deep-IV – OLS)
cognitive, concentrating, moderate, cognition, functioning, concentration, cope, psychomotor, ability, impulsivity, socialization, difficulty, auditory, interact, mood, pace, irritability, learning, impaired, distractibility	0.245
misappropriation, breach, tortious, tort, misappropriate, fiduciary, enrich, enrichment, interference, secret, wrongful, misappropriated, meruit, trade, conversion, dealing, contractual, contract, defamation, negligent	0.0416
consonant, embody, embrace, rigid, traditional, hew, engraft, dictate, eschew, adherence, incompatible, recognize, animate, jurisprudential, universal, concurring, modern, antithetical, comport, override	0.0314
complicate, depend, crucial, illustrate, elusive, focus, important, straightforward, elide, critical, underscore, differ, complicated, nuance, conceptual, precise, central, grapple, particular, murky	0.0309
coverage, insured, insurer, insure, indemnity, indemnification, insurance, indemnify, reinsurer, uninsured, subrogation, endorsement, cover, umbrella, policyholder, policy, covered, indemnitee, reinsure, insuring	0.0234
conclusory, Twombly550, plausible, Iqbal556, bare, true, allegation, twombly127, formulaic, plausibility, speculative, averment, survive, enough, mere, threadbare, bald, twombly550, recital, suffice	0.0229

Previous Projects (3)

- One of the groups began building a legal research application for Swiss lawyers:
  - feature-rich legal search engine.
  - MSWord plugin that would suggest cite references as you type.
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- *Note: These projects were above expectation.*

New Project Ideas

- We have a list of potential project ideas, will share with interested students.