Precept 10: Causal identification and estimation

Soc 500: Applied Social Statistics

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Learning Objectives

1. More data manipulation with dplyr
2. Practice evaluating causal identification strategies in published papers
R.A. Fisher’s Irises

R.A. Fisher published a paper in 1936 using data on the length and width of the **petals** and **sepals** of a sample of irises. The data is now a common R example dataset.

(Flower above is not an iris)
Three species of irises
Photos from Wikipedia

Setosa

Virginica

Versicolor
Explore and load the iris data

See where this comes from:

> head(iris)

    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
  1         5.1       3.5         1.4       0.2  setosa
  2         4.9       3.0         1.4       0.2  setosa
  3         4.7       3.2         1.3       0.2  setosa
  4         4.6       3.1         1.5       0.2  setosa
  5         5.0       3.6         1.4       0.2  setosa
  6         5.4       3.9         1.7       0.4  setosa
Iris goal 1

**Goal:** Plot the distribution of sepal lengths and petal lengths in the data, by species

**Steps:**

1. select the variables of interests
Iris goal 1

**Goal:** Plot the distribution of sepal lengths and petal lengths in the data, by species

**Steps:**

1. **select** the variables of interests
2. **melt** the data so that the lengths are stored in a single column
Iris goal 1

**Goal:** Plot the distribution of sepal lengths and petal lengths in the data, by species

**Steps:**

1. **select** the variables of interests
2. **melt** the data so that the lengths are stored in a single column
3. **ggplot** the density plot, using **fill** to distinguish the petal vs. sepal
Iris goal 1

**Goal:** Plot the distribution of sepal lengths and petal lengths in the data, by species

**Steps:**

1. **select** the variables of interests
2. **melt** the data so that the lengths are stored in a single column
3. **ggplot** the density plot, using **fill** to distinguish the petal vs. sepal
4. **facet_wrap** to separate by species
Start with the data frame

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sepal.Length</td>
</tr>
<tr>
<td>1</td>
<td>5.1</td>
</tr>
<tr>
<td>2</td>
<td>4.9</td>
</tr>
<tr>
<td>3</td>
<td>4.7</td>
</tr>
<tr>
<td>4</td>
<td>4.6</td>
</tr>
<tr>
<td>5</td>
<td>5.0</td>
</tr>
<tr>
<td>6</td>
<td>5.4</td>
</tr>
</tbody>
</table>
Select the variables of interest

Reference:
https://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>iris %&gt;% select(Sepal.Length, Sepal.Width, Species)</td>
<td>Sepal.Length</td>
</tr>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>6</td>
</tr>
</tbody>
</table>
Melt so that the variable to be plotted is in one column
Reference: http://seananderson.ca/2013/10/19/reshape.html

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
</table>
| iris %>%
  select(Sepal.Length,
        Sepal.Width,
        Species) %>%
melt(id.vars = "Species") | Species    | variable  | value |
|      | setosa  | Sepal.Length | 5.1   |
|      | setosa  | Sepal.Length | 4.9   |
|      | setosa  | Sepal.Length | 4.7   |
|      | setosa  | Sepal.Length | 4.6   |
|      | setosa  | Sepal.Length | 5.0   |
|      | setosa  | Sepal.Length | 5.4   |
Plot the density
Reference: http://docs.ggplot2.org/current/

Code

```r
iris %>%
  select(Sepal.Length, Sepal.Width, Species) %>%
melt(id.vars = "Species") %>%
ggplot(aes(x = value, fill = variable)) +
geom_density(alpha = .2)
```

Output
## Facet by species

Reference: [http://docs.ggplot2.org/current/](http://docs.ggplot2.org/current/)

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
</table>
| iris %>%
  select(Sepal.Length, Sepal.Width, Species) %>%
melt(id.vars = "Species") %>%
ggplot(aes(x = value, fill = variable)) +
geom_density(alpha = .2) +
facet_wrap(~Species, ncol = 1) | ![Output Diagram] |
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by

- species AND
- petal/sepal

<table>
<thead>
<tr>
<th>Species</th>
<th>Petal</th>
<th>Sepal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Setosa</td>
<td>Mean(L - W)</td>
<td>Mean(L - W)</td>
</tr>
<tr>
<td>Versicolor</td>
<td>Mean(L - W)</td>
<td>Mean(L - W)</td>
</tr>
<tr>
<td>Virginica</td>
<td>Mean(L - W)</td>
<td>Mean(L - W)</td>
</tr>
</tbody>
</table>

Table: Structure of the goal data table
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal

**Steps:**
1. **mutate** the iris data to add an id number to the rows
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal

**Steps:**
1. **mutate** the iris data to add an id number to the rows
2. **melt** the data so that the lengths are stored in a single column
Goal: Compare length vs. width, within strata defined by:
- species AND
- petal/sepal
Steps:
1. **mutate** the iris data to add an id number to the rows
2. **melt** the data so that the lengths are stored in a single column
3. **separate** the petal/sepal and length/width into two variables
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal

**Steps:**
1. **mutate** the iris data to add an id number to the rows
2. **melt** the data so that the lengths are stored in a single column
3. **separate** the petal/sepal and length/width into two variables
4. **spread** the data wider so that length and width are each variables
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal

**Steps:**
1. **mutate** the iris data to add an id number to the rows
2. **melt** the data so that the lengths are stored in a single column
3. **separate** the petal/sepal and length/width into two variables
4. **spread** the data wider so that length and width are each variables
5. **mutate** the data to calculate the difference in length and width
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal

**Steps:**
1. **mutate** the iris data to add an id number to the rows
2. **melt** the data so that the lengths are stored in a single column
3. **separate** the petal/sepal and length/width into two variables
4. **spread** the data wider so that length and width are each variables
5. **mutate** the data to calculate the difference in length and width
6. **group_by** species and type
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal

**Steps:**
1. **mutate** the iris data to add an id number to the rows
2. **melt** the data so that the lengths are stored in a single column
3. **separate** the petal/sepal and length/width into two variables
4. **spread** the data wider so that length and width are each variables
5. **mutate** the data to calculate the difference in length and width
6. **group_by** species and type
7. **summarize** to calculate the mean difference within each group
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal

**Steps:**
1. **mutate** the iris data to add an id number to the rows
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4. **spread** the data wider so that length and width are each variables
5. **mutate** the data to calculate the difference in length and width
6. **group_by** species and type
7. **summarize** to calculate the mean difference within each group
8. **select** the variables for our table
Iris goal 2

**Goal:** Compare length vs. width, within strata defined by
- species AND
- petal/sepal

**Steps:**
1. **mutate** the iris data to add an id number to the rows
2. **melt** the data so that the lengths are stored in a single column
3. **separate** the petal/sepal and length/width into two variables
4. **spread** the data wider so that length and width are each variables
5. **mutate** the data to calculate the difference in length and width
6. **group_by** species and type
7. **summarize** to calculate the mean difference within each group
8. **select** the variables for our table
9. **spread** them out to make a nice table
# Making a table

Start with a data frame

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sepal.Length</td>
</tr>
<tr>
<td></td>
<td>5.1</td>
</tr>
<tr>
<td>1</td>
<td>4.9</td>
</tr>
<tr>
<td>2</td>
<td>4.7</td>
</tr>
<tr>
<td>3</td>
<td>4.6</td>
</tr>
<tr>
<td>4</td>
<td>5.0</td>
</tr>
<tr>
<td>5</td>
<td>5.4</td>
</tr>
<tr>
<td>6</td>
<td></td>
</tr>
</tbody>
</table>
Making a table
Add id number. Reference:
https://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
</table>
| iris %>%
mutate(idnum = 1:nrow(iris))            | Sepal.Length  Sepal.Width  Petal.Length  Petal.Width  Species  idnum |
| 1                                         | 5.1           | 3.5          | 1.4           | 0.2          | setosa   | 1            |
| 2                                         | 4.9           | 3.0          | 1.4           | 0.2          | setosa   | 2            |
| 3                                         | 4.7           | 3.2          | 1.3           | 0.2          | setosa   | 3            |
| 4                                         | 4.6           | 3.1          | 1.5           | 0.2          | setosa   | 4            |
| 5                                         | 5.0           | 3.6          | 1.4           | 0.2          | setosa   | 5            |
| 6                                         | 5.4           | 3.9          | 1.7           | 0.4          | setosa   | 6            |
Making a table

Melt to make the data long. Reference:
http://seananderson.ca/2013/10/19/reshape.html

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
</table>
| iris %>%
  mutate(idnum = 1:nrow(iris)) %>%
  melt(id = c("idnum","Species")) | idnum | Species | variable      | value |
|      | 1     | 1       | setosa      | Sepal.Length | 5.1   |
|      | 2     | 2       | setosa      | Sepal.Length | 4.9   |
|      | 3     | 3       | setosa      | Sepal.Length | 4.7   |
|      | 4     | 4       | setosa      | Sepal.Length | 4.6   |
|      | 5     | 5       | setosa      | Sepal.Length | 5.0   |
|      | 6     | 6       | setosa      | Sepal.Length | 5.4   |
Making a table
Separate type and measure. Reference:
https://blog.rstudio.org/2014/07/22/introducing-tidyr/

Code

```
iris %>%
mutate(idnum = 1:nrow(iris)) %>%
melt(id = c("idnum","Species")) %>%
separate(col = "variable",
        into = c("Type","Measure"),
        sep = "\.")
```

<table>
<thead>
<tr>
<th>idnum</th>
<th>Species</th>
<th>Type</th>
<th>Measure</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>setosa</td>
<td>Sepal</td>
<td>Length</td>
<td>5.1</td>
</tr>
<tr>
<td>2</td>
<td>setosa</td>
<td>Sepal</td>
<td>Length</td>
<td>4.9</td>
</tr>
<tr>
<td>3</td>
<td>setosa</td>
<td>Sepal</td>
<td>Length</td>
<td>4.7</td>
</tr>
<tr>
<td>4</td>
<td>setosa</td>
<td>Sepal</td>
<td>Length</td>
<td>4.6</td>
</tr>
<tr>
<td>5</td>
<td>setosa</td>
<td>Sepal</td>
<td>Length</td>
<td>5.0</td>
</tr>
<tr>
<td>6</td>
<td>setosa</td>
<td>Sepal</td>
<td>Length</td>
<td>5.4</td>
</tr>
</tbody>
</table>
Making a table
Spread to make wide. Reference: https://blog.rstudio.org/2014/07/22/introducing-tidyr/

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>iris <code>%&gt;%</code> mutate(idnum = 1:nrow(iris)) <code>%&gt;%</code> melt(id = c(&quot;idnum&quot;,&quot;Species&quot;)) <code>%&gt;%</code> separate(col = &quot;variable&quot;, into = c(&quot;Type&quot;,&quot;Measure&quot;), sep = &quot;.&quot;) <code>%&gt;%</code> spread(key = Measure, value = value)</td>
<td>idnum Species Type Length Width</td>
</tr>
<tr>
<td>1 1 setosa Petal 1.4 0.2</td>
<td></td>
</tr>
<tr>
<td>2 1 setosa Sepal 5.1 3.5</td>
<td></td>
</tr>
<tr>
<td>3 2 setosa Petal 1.4 0.2</td>
<td></td>
</tr>
<tr>
<td>4 2 setosa Sepal 4.9 3.0</td>
<td></td>
</tr>
<tr>
<td>5 3 setosa Petal 1.3 0.2</td>
<td></td>
</tr>
<tr>
<td>6 3 setosa Sepal 4.7 3.2</td>
<td></td>
</tr>
</tbody>
</table>
Making a table
Mutate to make a difference variable. Reference:
https://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
</table>
| iris %>%
mutate(idnum = 1:nrow(iris)) %>%
melt(id = c("idnum","Species")) %>%
separate(col = "variable",
  into = c("Type","Measure"),
  sep = ".") %>%
spread(key = Measure, value = value) %>%
mutate(difference = Length - Width) |

<table>
<thead>
<tr>
<th>idnum</th>
<th>Species</th>
<th>Type</th>
<th>Length</th>
<th>Width</th>
<th>difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>setosa</td>
<td>Petal</td>
<td>1.4</td>
<td>0.2</td>
<td>1.2</td>
</tr>
<tr>
<td>2</td>
<td>setosa</td>
<td>Sepal</td>
<td>5.1</td>
<td>3.5</td>
<td>1.6</td>
</tr>
<tr>
<td>3</td>
<td>setosa</td>
<td>Petal</td>
<td>1.4</td>
<td>0.2</td>
<td>1.2</td>
</tr>
<tr>
<td>4</td>
<td>setosa</td>
<td>Sepal</td>
<td>4.9</td>
<td>3.0</td>
<td>1.9</td>
</tr>
<tr>
<td>5</td>
<td>setosa</td>
<td>Petal</td>
<td>1.3</td>
<td>0.2</td>
<td>1.1</td>
</tr>
<tr>
<td>6</td>
<td>setosa</td>
<td>Sepal</td>
<td>4.7</td>
<td>3.2</td>
<td>1.5</td>
</tr>
</tbody>
</table>
Making a table

Group by species and type, summarize to get mean, sd, and n in each group. Reference: https://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
</table>
| iris %>%
mutate(idnum = 1:nrow(iris)) %>%
melt(id = c("idnum","Species")) %>%
separate(col = "variable",
into = c("Type","Measure"),
sep = "\." ) %>%
spread(key = Measure, value = value) %>%
mutate(difference = Length - Width) %>%
group_by(Species,Type) %>%
summarize(mean_difference = mean(difference),
          sd_difference = sd(difference),
          count = n()) |
| Source: local data frame [6 x 5]
Groups: Species [3]

<table>
<thead>
<tr>
<th>Species</th>
<th>Type</th>
<th>mean_difference</th>
<th>sd_difference</th>
<th>count</th>
</tr>
</thead>
<tbody>
<tr>
<td>setosa</td>
<td>Petal</td>
<td>1.216</td>
<td>0.1706650</td>
<td>50</td>
</tr>
<tr>
<td>setosa</td>
<td>Sepal</td>
<td>1.578</td>
<td>0.2636401</td>
<td>50</td>
</tr>
<tr>
<td>versicolor</td>
<td>Petal</td>
<td>2.934</td>
<td>0.3372215</td>
<td>50</td>
</tr>
<tr>
<td>versicolor</td>
<td>Sepal</td>
<td>3.166</td>
<td>0.4410609</td>
<td>50</td>
</tr>
<tr>
<td>virginica</td>
<td>Petal</td>
<td>3.526</td>
<td>0.5313863</td>
<td>50</td>
</tr>
<tr>
<td>virginica</td>
<td>Sepal</td>
<td>3.614</td>
<td>0.5664101</td>
<td>50</td>
</tr>
</tbody>
</table>
Making a table

Select the variables of interest. Reference:
https://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
</table>
| iris %>%
  mutate(idnum = 1:nrow(iris)) %>%
  melt(id = c("idnum","Species")) %>%
  separate(col = "variable",
    into = c("Type","Measure"),
    sep = ".") %>%
  spread(key = Measure, value = value) %>%
  mutate(difference = Length - Width) %>%
  group_by(Species,Type) %>%
  summarize(mean_difference = mean(difference),
            sd_difference = sd(difference),
            count = n()) %>%
  select(mean_difference, Species, Type) | mean_difference Species Type
                                           (dbl) (fctr) (chr)
                                           1 1.216 setosa Petal
                                           2 1.578 setosa Sepal
                                           3 2.934 versicolor Petal
                                           4 3.166 versicolor Sepal
                                           5 3.526 virginica Petal
                                           6 3.614 virginica Sepal |
Making a table
spread to make the data wide for a pretty table. Reference:
https://blog.rstudio.org/2014/07/22/introducing-tidyr/

```
iris %>%
  mutate(idnum = 1:nrow(iris)) %>%
  melt(id = c("idnum","Species")) %>%
  separate(col = "variable",
           into = c("Type","Measure"),
           sep = ".") %>%
  spread(key = Measure, value = value) %>%
  group_by(Species, Type) %>%
  summarize(mean_difference = mean(difference),
           sd_difference = sd(difference),
           count = n()) %>%
  select(mean_difference, Species, Type) %>%
  spread(Type, mean_difference)
```

Source: local data frame [3 x 3]
Groups: Species [3]

<table>
<thead>
<tr>
<th>Species</th>
<th>Petal</th>
<th>Sepal</th>
</tr>
</thead>
<tbody>
<tr>
<td>setosa</td>
<td>1.216</td>
<td>1.578</td>
</tr>
<tr>
<td>versicolor</td>
<td>2.934</td>
<td>3.166</td>
</tr>
<tr>
<td>virginica</td>
<td>3.526</td>
<td>3.614</td>
</tr>
</tbody>
</table>
Making a figure
Going back a few steps

```
iris %>%
  mutate(idnum = 1:nrow(iris)) %>%
  melt(id = c("idnum","Species")) %>%
  separate(col = "variable",
           into = c("Type","Measure"),
           sep = ".") %>%
  spread(key = Measure, value = value) %>%
  mutate(difference = Length - Width) %>%
  group_by(Species,Type) %>%
  summarize(mean_difference = mean(difference),
            sd_difference = sd(difference),
            count = n())
```

Source: local data frame [6 x 5]
Groups: Species [3]

<table>
<thead>
<tr>
<th>Species</th>
<th>Type</th>
<th>mean_difference</th>
<th>sd_difference</th>
<th>count</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>setosa</td>
<td>1.216</td>
<td>0.1706650</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>Sepal</td>
<td>1.578</td>
<td>0.2636401</td>
<td>50</td>
</tr>
<tr>
<td>versicolor</td>
<td>Petal</td>
<td>2.934</td>
<td>0.3372215</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>Sepal</td>
<td>3.166</td>
<td>0.4410609</td>
<td>50</td>
</tr>
<tr>
<td>virginica</td>
<td>Petal</td>
<td>3.526</td>
<td>0.5313863</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>Sepal</td>
<td>3.614</td>
<td>0.5664101</td>
<td>50</td>
</tr>
</tbody>
</table>
Making a figure

Using geom\_bar. Reference: http://docs.ggplot2.org/current/

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
</table>
| iris %>%
  mutate(idnum = 1:nrow(iris)) %>%
  melt(id = c("idnum","Species")) %>%
  separate(col = "variable",
           into = c("Type","Measure"),
           sep = ".") %>%
  spread(key = Measure, value = value) %>%
  mutate(difference = Length - Width) %>%
  group\_by(Species,Type) %>%
  summarize(mean\_difference = mean(difference),
            sd\_difference = sd(difference),
            count = n()) %>%
  ggplot(aes(x = Type,
             fill = Species)) +
  geom\_bar(stat = "identity", position = "dodge") |
Making a figure
Adding error bars. Reference: http://docs.ggplot2.org/current/

Code

```
iris %>%
  mutate(idnum = 1:nrow(iris)) %>%
  melt(id = c("idnum","Species")) %>%
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  group_by(Species,Type) %>%
  summarize(mean_difference = mean(difference),
            sd_difference = sd(difference),
            count = n()) %>%
  ggplot(aes(x = Type,
             y = mean_difference,
             ymin = mean_difference -
                   qnorm(.975) * sd_difference /
                   sqrt(count),
             ymax = mean_difference +
                   qnorm(.975) * sd_difference /
                   sqrt(count),
             fill = Species)) +
  geom_bar(stat = "identity", position = "dodge") +
  geom_errorbar(position = "dodge")
```

Output
Making a figure

Add titles. We’re finished! Reference: http://docs.ggplot2.org/current/

<table>
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    sqrt(count),
    fill = Species)) +
  geom_bar(stat = "identity", position = "dodge") +
  geom_errorbar(position = "dodge") +
  ylab("Mean length - width") +
  ggtitle("Mean difference within strata")|
Slight shift of focus
Slight shift of focus

- We’ve been doing lots of Applied Social Statistics.
Slight shift of focus

- We’ve been doing lots of Applied Social Statistics.
- Let’s do some Applied Social Statistics!
Causal inference examples

We will walk through examples of causal social science papers that assume observed confounding. For each paper, we will:

- Draw the DAG
Causal inference examples

We will walk through examples of causal social science papers that assume observed confounding. For each paper, we will:

- Draw the DAG
- Define the potential outcomes: $Y_i(0), Y_i(1)$
Causal inference examples

We will walk through examples of causal social science papers that assume observed confounding. For each paper, we will:

- Draw the DAG
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- Discuss potential violations of the identifying assumptions.
We will walk through examples of causal social science papers that assume observed confounding. For each paper, we will:

- Draw the DAG
- Define the potential outcomes: $Y_i(0), Y_i(1)$
- Discuss potential violations of the identifying assumptions.
- Conclude: **Do we buy it?**
Example 1: An ethnographic experiment


- Ethnographic study of book vendors in Greenwich Village in NYC.
Example 1: An ethnographic experiment


- Ethnographic study of book vendors in Greenwich Village in NYC.
- Duneier noticed that black vendors were pushed around by police officers.
Example 1: An ethnographic experiment


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- Duneier noticed that black vendors were pushed around by police officers.
- **Question:** Does a vendor's race and legal knowledge affect how the police treat him?
Example 1: An ethnographic experiment


- Ethnographic study of book vendors in Greenwich Village in NYC.
- Duneier noticed that black vendors were pushed around by police officers.
- **Question:** Does a vendor’s race and legal knowledge affect how the police treat him?
- **Approach:** A creative small-scale experiment.
NYC street vendors
When the Law “Means Nothing” to the Police

Two days later, on Christmas afternoon, I saw Ishmael again. When I arrived, Hakim was standing on the corner. Ishmael had set up his table in his usual spot on the corner of Sixth Avenue and Eighth Street. Ten minutes later, Officer X (as I’ll call him) approached and said something to the effect of: Ishmael, you have to break down, guy.¹⁵

I’m not breaking down, man, he responded.

Ishmael clearly was not showing the kind of deference the men on the block normally observe. I took out my tape recorder and turned it on, though neither Ishmael nor the officer saw me do so.

“You have to break down,” the officer insisted.

“But I’m not. Because there’s no such thing as a law telling me that. I’m not gonna break down, man. If I can’t work, what the hell you working for?”

“Step over here for a second. Ishmael...”
If this was a test designed to find out whether an upper-middle-class white person would be treated differently from an unhoused, poor black vendor, I thought to myself, then it was not a good one. To begin with, the officer had just closed Ishmael down. The odds were very small that a black police officer who had to enforce the law against black vendors every day would let himself be seen as one who would allow a white man to stay in the same spot. Furthermore, he might notice the microphone sticking out of my pocket, and this would probably affect what he’d say to me.

I had been standing at the table for about ten minutes when I saw the officer and his beat partner walking toward me.

As I waited, approximately ten black vendors, including Hakim and Ishmael, stood by, offering their support.

“It’s showtime!” yelled Ishmael.
"My man. There's no selling here today. Break it down."
"Excuse me," I said.
"No selling here today. Break it down."
I took a copy of the municipal law out of my pocket. "I'm exercising my right under Local Law 33 of 1982, and Local Law 45 of 1993, to sell written matter."
Potential outcomes

- Units of analysis are interactions with police
Potential outcomes

- Units of analysis are interactions with police
- Sample size is 2, but 2 high-quality observations
Potential outcomes

- Units of analysis are interactions with police
- Sample size is 2, but 2 high-quality observations
- **Treatment:** Vendor is a black male Greenwich Village bookseller.
Potential outcomes

- Units of analysis are interactions with police
- Sample size is 2, but 2 high-quality observations
- **Treatment:** Vendor is a black male Greenwich Village bookseller.
- **Control:** Vendor is Mitch Duneier who explicitly defends his rights
Example 2: Occupational attainment model


- **Research question**: How does family background affect the educational and occupational attainment of the next generation?

- **Method**: Linear structural equation models, which were the precursor to DAGs
Example 2: Blau-Duncan (1967) status attainment model

Figure 5.1. Path coefficients in basic model of the process of stratification.
What to condition on for the effect of..

1. first job on occ. in 1962?
What to condition on for the effect of..

1. first job on occ. in 1962?
2. respondent’s education on first job?
What to condition on for the effect of..

1. first job on occ. in 1962?
2. respondent’s education on first job?
3. respondent’s education on occ. in 1962?
What to condition on for the effect of...

1. first job on occ. in 1962?
2. respondent’s education on first job?
3. respondent’s education on occ. in 1962?
4. father’s occupation/education on son’s occupation in 1962?
What to condition on for the effect of...

1. first job on occ. in 1962?
2. respondent’s education on first job?
3. respondent’s education on occ. in 1962?
4. father’s occupation/education on son’s occupation in 1962?
5. If we condition on respondent’s education and first job, will father’s education be associated with son’s occupation in 1962?
What to condition on for the effect of..

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5. If we condition on respondent’s education and first job, will father’s education be associated with son’s occupation in 1962?

Answers:

1. Respondent’s education, father’s occupation
2. father’s occupation is sufficient
3. father’s occupation is sufficient
4. No conditioning needed! But I doubt the DAG holds.
5. No. But only because the DAG assumes the unobserved influences are uncorrelated!
Blau-Duncan assumptions

PATH COEFFICIENTS

Whether a path diagram, or the causal scheme it represents, is adequate depends on both theoretical and empirical considerations. At a minimum, before constructing the diagram we must know, or be willing to assume, a causal ordering of the observed variables (hence the lengthy discussion of this matter earlier in this chapter). This information is external or a priori with respect to the data, which merely describe associations or correlations. Moreover, the causal scheme must be complete, in the sense that all causes are accounted for. Here, as in most problems involving analysis of observational data, we achieve a formal completeness of the scheme by representing unmeasured causes as a residual factor, presumed to be uncorrelated with the remaining factors lying behind the variable in question. If
By the time the data were actually collected the investigators had developed the first of two major sets of specifications for tabulations. It should be mentioned here that at no time have we had access to the original survey documents or to the computer tapes on which individual records are stored. This information is confidential and not available to private research workers. Consequently it was necessary for us to provide detailed outlines of the statistical tables we desired for analysis without inspecting the “raw” data, and to provide these, moreover, some 9 to 12 months ahead of the time when we might expect their delivery. This lead time was required for programming the computer runs that would produce the tables. Evidently this circumstance precluded our following the common strategy of looking at a few marginal totals before running some two-way tables and deciding on interesting three-way or higher-order tabulations after having studied the two-way tables. We had to state in advance just which tables were wanted, out of the virtually unlimited number that conceivably might have been produced, and to be prepared to make the best of what we got. Cost factors, of course, put strict limits on how many tables we could request. We had to imagine in advance most of the analysis we would want to make, before having any advance indications of what any of the tables would look like.
Example 3: Bringing in aspirations


- Challenged Blau and Duncan
Example 3: Bringing in aspirations


- Challenged Blau and Duncan
- Argued that **aspirations** of children were an important pathway linking parental and child attainment
Example 3: Bringing in aspirations


- Challenged Blau and Duncan
- Argued that *aspirations* of children were an important pathway linking parental and child attainment
- Became known as the Wisconsin model of status attainment
Example 3: Wisconsin model of status attainment
Sewell, Haller, and Portes (1969), *ASR*
Wisconsin model: What to condition on to identify the effect of...

1. $X_2$ on $X_1$?
Wisconsin model: What to condition on to identify the effect of...

1. $X_2$ on $X_1$?
2. $X_5$ on $X_2$?
Wisconsin model: What to condition on to identify the effect of...

1. $X_2$ on $X_1$?
2. $X_5$ on $X_2$?
Wisconsin model: What to condition on to identify the effect of...

1. $X_2$ on $X_1$?
2. $X_5$ on $X_2$?

**Answers:**

1. $X_5$ or $X_3$
2. No conditioning needed!
Example 4: Heterogeneous effects of college

Brand and Xie (2010)

Research question:
Brand and Xie (2010)

- Research question:
  - Does college affect earnings?
Brand and Xie (2010)

- Research question:
  - Does college affect earnings?
  - Is the effect moderated by social origin?
Brand and Xie (2010)

- Research question:
  - Does college affect earnings?
  - Is the effect moderated by social origin?
- Identification strategy: Selection on observables
Brand and Xie (2010)

- Research question:
  - Does college affect earnings?
  - Is the effect moderated by social origin?

- Identification strategy: Selection on observables
Research question:

- Does college affect earnings?
- Is the effect moderated by social origin?

Identification strategy: Selection on observables
Theoretically: Why heterogeneous effects?

Figure 1. Hypothetical Model: Origin, Education, and Destination
Theoretically: Why heterogeneous effects?

**Figure 1. Hypothetical Model: Origin, Education, and Destination**

**Question:** Can we write the potential outcomes here?
Ignorability

What is the assumption of ignorability here?
Ignorability

What is the assumption of ignorability here?
**Ignorability**

What is the assumption of ignorability here?

To infer causality with observational data, it is necessary to introduce unverifiable assumptions. In this research, we first introduce the ignorability assumption:

\[ E(y^0|X, d = 1) = E(y^0|X, d = 0) \quad (6a) \]

and

\[ E(y^1|X, d = 0) = E(y^1|X, d = 1). \quad (6b) \]

Equation 6a assumes that the average earnings of college-educated workers, had they not completed college, would be the same as the average earnings of non-college-educated workers, conditional on observed covariates. Likewise, Equation 6b assumes that the average earnings of non-college-educated workers, had they completed college, would be the same as the average earnings of college-educated workers, conditional on observed covariates.
# Conditioning set: Measuring “social origin”

## Table 1. Descriptive Statistics of Precollege Covariates

<table>
<thead>
<tr>
<th>Variables</th>
<th>NLSY Means</th>
<th>WLS Means</th>
<th></th>
<th></th>
<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>Men (N = 1,265)</td>
<td>Women (N = 1,209)</td>
<td>Men (N = 3,690)</td>
<td>Women (N = 4,215)</td>
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<td>College Graduate</td>
<td>Non-College Graduate</td>
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<td>Parents' income</td>
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<tr>
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<td>.00</td>
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<td>Class rank</td>
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<tr>
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<tr>
<td>Teachers' encouragement</td>
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<tr>
<td>Friends' college plans</td>
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<td>.48</td>
<td>.81</td>
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<tr>
<td>Weighted Sample Proportion</td>
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<td>.24</td>
<td>.77</td>
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Note: Parents’ income is measured as total net family income in 1979 dollars in the NLSY and in 1957 dollars in the WLS. Urban residency/proximity to college indicates whether a respondent lived in an SMSA in the NLSY and whether a respondent's high school was within 15 miles of a college or university in the WLS. Mental ability is measured with a scale of standardized residuals of the ASVAB in the NLSY and with the Henmon-Nelson IQ test in the WLS. College-prep indicates whether a student was enrolled in a college-preparatory curriculum in the NLSY or whether a student completed the requirements for UW-Madison in the WLS.
Conditioning set: Measuring "social origin"

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**Question:** How might the identifying assumptions be violated? Can we write it in terms of DAGs? Potential outcomes?
Example 5: Neighborhoods


- **Research question:** How does long-term exposure to disadvantaged neighborhoods affect one’s probability of high school graduation?
Example 5: Neighborhoods


- **Research question:** How does long-term exposure to disadvantaged neighborhoods affect one’s probability of high school graduation?

- **Problem:** Family income and neighborhood disadvantage affect each other through childhood
We might want to have a bidirectional arrow linking neighborhood disadvantage and family income.
We might want to have a bidirectional arrow linking neighborhood disadvantage and family income.

Neighborhood disadvantage

Family income

High school graduation

Can we write sequentially to avoid the bi-directional edge?
Neighborhood Effects in Temporal Perspective
Wodtke, Harding, and Elwert 2011 ASR

- $L =$ Family income
- $A =$ Neighborhood disadvantage
- $Y =$ High school graduation
- Subscripts $=$ time
What do you condition on to identify:

1. The effect of $A_2$ on $Y$?
What do you condition on to identify:

1. The effect of $A_2$ on $Y$?
2. The effect of $A_1$ on $Y$?
What do you condition on to identify:

1. The effect of $A_2$ on $Y$?
2. The effect of $A_1$ on $Y$?
What do you condition on to identify:

1. The effect of $A_2$ on $Y$?
2. The effect of $A_1$ on $Y$?

**Answers:**

1. $\{L_2, A_1\}$
2. $\{L_1\}$
Key point: We cannot just condition on family income ($L$) since part of it is caused by neighborhood disadvantage ($A$). Nor can we not condition on it. What to do?
A challenging identification problem!

**Figure 1.** Causal Graphs for Exposure to Disadvantaged Neighborhoods with Two Waves of Follow-up

*Note:* $A_k$ = neighborhood context, $L_k$ = observed time-varying confounders, $U$ = unobserved factors, $Y$ = outcome.
Result from Wodtke, Harding, and Elwert 2011

Figure 3. Predicted Probability of High School Graduation by Neighborhood Exposure History

Note: NH = Neighborhood
Example 6. Wealth and college attainment


- **Research question**: Does family wealth affect educational attainment?
**Conditioning set**

Conley 2001, *Sociology of Education*

<table>
<thead>
<tr>
<th>Model</th>
<th>Total Years of Schooling (Ages 19–30)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Respondents' Characteristics</strong></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>.320** (.104)</td>
</tr>
<tr>
<td>Latino</td>
<td>-.113 (.354)</td>
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<tr>
<td>Other</td>
<td>.866 (.548)</td>
</tr>
<tr>
<td>Female</td>
<td>.372*** (.086)</td>
</tr>
<tr>
<td>Age (1992)</td>
<td>.095*** (.015)</td>
</tr>
<tr>
<td>Number of siblings</td>
<td>-.107*** (.027)</td>
</tr>
</tbody>
</table>

| Parental Characteristics      |                                       |
| Age of head of household (1984) | .017* (.008)                        |
| Proportion of years female head (1980-84) | -.001 (.162)                      |
| Education of head of household (1984) | .167*** (.021)                     |
| Proportion of years head of household unemployed (1980-84) | -.587* (.296)                      |
| Occupational prestige of head of household (1980-84) | .017*** (.004)                      |
| Natural logarithm of income (1980-84, constant dollars) | .017 (.114)                        |
| Natural logarithm of net worth (1984) | .172*** (.033)                     |
| Constant                      | 5.311 (.1056)                       |

Can we draw the DAG? What assumptions are made?
Tying causal inference to big theories
Conley 2001, *Sociology of Education*

**DISCUSSION**

Parkin (1979:47–48) argued that “in modern capitalist society the two main exclusionary devices by which the bourgeoisie constructs and maintains itself as a class are, first, those surrounding the institutions of property; and second, academic or professional qualifications and credentials.” This article has shown that these two “exclusionary devices” are not independent of each other, since parents may use wealth—that is, property—to finance their children’s educational and professional credentials, thereby solidifying their class position on the human capital dimension. In other words, nonhuman capital (property) and human capital are linked across generations. The analysis presented here demonstrated the impact of parental wealth on the educational outcomes of young adults, specifically in the transition to postsecondary schooling.
Example 7: Divorce and child development

The Causal Effects of Father Absence

Sara McLanahan, Laura Tach, and Daniel Schneider

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Annual Review of Sociology piece summarizes many causal research designs (it’s a good overview). We will focus on one.
Example 7: Divorce and child development

Cherlin et al. 1991

- **Research question:** Is divorce bad for kids?
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- **Controls:** Social class, race, mother employed outside the home in 1976, outcome measured in 1976
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Can we draw the DAG? Write the potential outcomes? Critique the paper?
A 1991-era way of showing results
A 1991-era way of showing results

How could this figure be improved?
A 1991-era way of showing results

**Fig. 2.** Effects of a parental divorce between 1976 and 1981 on the behavior problems of children in 1981, when the children were ages 11 to 16, based on a behavior problems scale score as reported by parents from the U.S. National Survey of Children (estimates are restricted to children living with two married parents in 1976). The height of the boxes shows the percentage by which the score of children whose parents divorced between 1976 and 1981 was greater (or less) than the score of children whose parents remained married. Three estimates of the effects of divorce are shown: model 1 controls only for social class, race, and whether the mother was employed outside the home in 1976; model 2 controls additionally for the child’s score on the behavior problems scale in 1976, as reported by parents, before anyone’s parents were divorced; and model 3 adds further controls for the parents’ score on a nine-item marital conflict scale in 1976. Error bars represent one standard error.
Example 8: Heterogeneous treatment effects


- This is a paper that **looks very hard**
Example 8: Heterogeneous treatment effects


- This is a paper that *looks very hard*
- There are lots of equations
Example 8: Heterogeneous treatment effects


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- BUT it’s really just a fancy version of the **imputation estimator** Brandon showed on Wednesday!
Example 8: Heterogeneous treatment effects


- This is a paper that **looks very hard**
- There are lots of equations
- BUT it’s really just a fancy version of the **imputation estimator** Brandon showed on Wednesday!
- You already know what you need to understand the key concepts!
Substantive question
Hill (2011)

Do home visits and child care promote child cognitive development?

- **Sample:** Low birth weight, premature infants in 1985
Substantive question
Hill (2011)

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- **Sample:** Low birth weight, premature infants in 1985
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- **Treatment**: Randomly chosen treated infants received home visits and child care
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- **Pretreatment covariates**:
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  - Infant characteristics: birth weight, head circumference, weeks born preterm, birth order, first born, neonatal health index, sex, twin status
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  - Mother variables in pregnancy: smoked cigarettes, drank alcohol, took drugs
  - Mother variables at birth: age, marital status, educational attainment, whether she worked during pregnancy, whether she received prenatal care
  - A few residential location variables
Heterogeneous effects in terms of potential outcomes

Recall potential outcomes:

- Potential outcome under control: $Y_i(0) = f(X_i)$

All are functions of pre-treatment covariates.
Heterogeneous effects in terms of potential outcomes

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Heterogeneous effects in terms of potential outcomes

Recall potential outcomes:

- Potential outcome under control: \( Y_i(0) = f(X_i) \)
- Potential outcome under control: \( Y_i(1) = g(X_i) \)
- The treatment effect is \( \tau_i = g(X_i) - f(X_i) = h(X_i) \)

All are functions of pre-treatment covariates.
Imputation approach from lecture
Imputation approach from lecture
Visualizing heterogeneous effects

Bayesian Nonparametric Modeling

The nature of the algorithm, which conditions on the $X$ values in the sample, a natural set of estimands are the conditional average treatment effect (CATE)

$$\frac{1}{n} \sum_{i=1}^{n} E(Y_i(1) \mid X_i) - E(Y(0) \mid X_i) = \frac{1}{n} \sum_{i=1}^{n} f(1, x_i) - f(0, x_i),$$

and the conditional average treatment effect for the treated (CATT)

$$\frac{1}{n_t} \sum_{i:Z_i=1} E(Y_i(1) \mid X_i) - E(Y(0) \mid X_i) = \frac{1}{n_t} \sum_{i:Z_i=1} f(1, x_i) - f(0, x_i).$$
Defining causal effects with covariate-based heterogeneity

Figure 6. Left panel displays plot of BART-predicted 3-year IQ test scores against CDC participation (in hundreds of days) for children in the treatment group (upper line). The lower line shows predicted scores for the same children if they had not attended any CDC days. Lines were smoothed using lowess. The right panel displays a smoothed function of the treatment effect estimates at each level of CDC participation (conditional on having that level of participation in the treatment group). Dashed lines represent 95% uncertainty bounds. A color version of this figure is available in the electronic version of this article.
Example 9: Contagion in social networks


Also a related book, which is a good read.
Christakis and Fowler 2007

- **Research question:** Does having obese friends cause you to become obese?
Christakis and Fowler 2007

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- **Sample:** Framingham Heart Study, 1971-2003, following 12,067 people
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Treatment: Alter’s obesity at $t + 1$
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- **Sample:** Framingham Heart Study, 1971-2003, following 12,067 people
- **Measured confounders:** Ego’s age, sex, education
- **Lagged dependent variable:** obesity at $t - 1$ (control for $U$)
- **Lagged predictor:** Alter’s weight at $t - 1$ (control for homophily)
- **Treatment:** Alter’s obesity at $t + 1$
- **Outcome:** Ego’s obesity at $t + 1$
Christakis and Fowler 2007: Conclusion

“A person’s chances of becoming obese increased by 57% (95% confidence interval [CI], 6 to 123) if he or she had a friend who became obese in a given interval.” (quoted from abstract)
Regression weighting from lecture
Slide by Brandon Stewart

\[ W_i = \frac{\sigma_d^2(X_i)}{E[\sigma_d^2(X_i)]} \]

- Why does OLS weight like this?
- OLS is a **minimum-variance estimator** \( \rightsquigarrow \) more weight to more precise within-strata estimates.
- Within-strata estimates are most precise when the treatment is evenly spread and thus has the highest variance.
- If \( D_i \) is binary, then we know the conditional variance will be:

\[ \sigma_d^2(x) = P(D_i = 1 \mid X_i = x)[1 - P(D_i = 1 \mid X_i = x)] \]

- Maximum variance with \( P[D_i = 1 \mid X_i = x] = 1/2 \).
OLS weighting example
Slide by Brandon Stewart

- Binary covariate:
  \[ P[X_i = 1] = 0.75 \quad P[X_i = 0] = 0.25 \]
  \[ P[D_i = 1 | X_i = 1] = 0.9 \quad P[D_i = 1 | X_i = 0] = 0.5 \]
  \[ \sigma^2_d(1) = 0.09 \quad \sigma^2_d(0) = 0.25 \]
  \[ \tau(1) = 1 \quad \tau(0) = -1 \]

- Implies the ATE is \( \tau = 0.5 \)
- Average conditional variance: \( \mathbb{E}[\sigma^2_d(X_i)] = 0.13 \)
- \( \rightsquigarrow \) weights for \( X_i = 1 \) are: \( 0.09/0.13 = 0.692 \), for \( X_i = 0 \): \( 0.25/0.13 = 1.92 \).

\[
\tau_R = \mathbb{E}[\tau(X_i)W_i] \\
= \tau(1)W(1)P[X_i = 1] + \tau(0)W(0)P[X_i = 0] \\
= 1 \times 0.692 \times 0.75 + (-1) \times 1.92 \times 0.25 \\
= 0.039
\]