Social Data Science: Machine Learning & Econometrics

Exercise class 3

March 5, 2020

Todays quick warmup

Q: Today a bit different from the last times. We will have a quiz on tracebacks and simple mistakes!

Q: What is wrong?

```
TypeError
                  Traceback (most recent call last)
<ipython-input-2-28f4dd90f3ff> in <module>
      2
           return x + y
----> 4 add('a', 3)
<ipython-input-2-28f4dd90f3ff> in add(x, y)
      1 def add(x,y):
----> 2 return x + y
     4 add('a', 3)
TypeError: can only concatenate str (not "int") to str
```

Q: What is wrong?

```
TypeError
                  Traceback (most recent call last)
<ipython-input-2-28f4dd90f3ff> in <module>
      2
           return x + y
----> 4 add('a', 3)
<ipython-input-2-28f4dd90f3ff> in add(x, y)
      1 def add(x,y):
----> 2 return x + y
     4 add('a', 3)
TypeError: can only concatenate str (not "int") to str
```

- ▶ Integers and strings dont add: add('a', 3)
- ► This fails exactly when the function tries to add. *There is no type checking!*

Q: What is wrong? How do you do this in a way that doesn't fail?

```
KeyError Traceback (most recent call last)
<ipython-input-14-758aff63242d> in <module>
----> 1 {'a':1, 'b':2,'c':3}['d']

KeyError: 'd'
```

Q: What is wrong? How do you do this in a way that doesn't fail?

```
KeyError
                       Traceback (most recent call last)
<ipython-input-14-758aff63242d> in <module>
----> 1 {'a':1, 'b':2,'c':3}['d']
KeyError: 'd'
 ► {'a':1, 'b':2,'c':3} doesn't have a d key.
 ► Either {'a':1, 'b':2,'c':3}.get('d') (returns None), or
        try:
             {'a':1, 'b':2,'c':3}['d']
        except KeyError:
             # do something
```

 \mathbf{Q}_1 : How do you read a traceback? Top-to-bottom, or bottom-to-top?

 $\boldsymbol{\mathsf{Q}}_2 \boldsymbol{:}$ What do you do if you don't understand the traceback after reading

it?

 \mathbf{Q}_3 : Could you do (2) before attempting (1)?

Q₄: Why is the middle part of a traceback often useless to read?

 \mathbf{Q}_1 : How do you read a traceback? Top-to-bottom, or bottom-to-top?

 \mathbf{Q}_2 : What do you do if you don't understand the traceback after reading it?

 \mathbf{Q}_3 : Could you do (2) before attempting (1)?

Q₄: Why is the middle part of a traceback often useless to read?

- ▶ Bottom-to-top!
- Paste it into google.
- ► Yes!
- This is often library-code that is doing error handling.

- **Q:** Finally produce code that raises the following errors
 - SyntaxError
 - ▶ NameError
 - ▶ ValueError
 - ► ZeroDivisionError
 - ► FileNotFoundError

Last lecture in a nutshell

Potential outcomes framework (for causal inference):

- ▶ Each unit has associated with every value $D_i \in \{0,1\}$ an outcome $Y_i(D_i)$.
- ▶ We only observe one version of the world so $D_i = 0$ xor $D_i = 1 \ \forall i$.
- ▶ We want to estimate $E[Y_i|D_i=1] E[Y_i|D_i=0]$, but subtracting means gives

$$E[Y_i(1) - Y_i(0)|D_i = 1] + E[Y_i(0)|D_i = 1] - E[Y_i(0)|D_i = 0]$$

Standard solution: (quasi)-randomization (NOT controlling for observables! (why?))

Note: we will use (quasi)-randomization throughout, so standard assumptions apply and must be fulfilled.

Last lecture in a nutshell

What we will be dealing with:

- (PS)Matching is one approach to this; basic idea is to compare apples to apples only (or maybe pears, but surely not bananas)
 - Intuitively this improves precision of the ATE
 - But importantly also a way to get local treatment effects.
- Methods to estimate the treatment effect locally (i.e. dropping the A in ATE).
 - who and how should we "match" to get consistent estimates of Y(1) Y(0) on the individual level?

Last lecture in a nutshell

Honest trees: step 1 is to understand honesty; no standard errors \Rightarrow no causal inference.

- Imagine using a decision tree to "group similar observations"; then compute local $\hat{\tau}(\ell(x)) = \hat{\mu}_{D_i=1}^{\ell(x)} \hat{\mu}_{D_i=0}^{\ell(x)}$ where $\ell(x)$ is the chosen leaf given x.
- Issue now is that grouping on standard CART criterion (1) groups "spuriously similar observations" → downwards bias on in-leaf variance.

$$Q^{CART}(\pi) = -\mathbb{E}_{\mathcal{S}^{te}, \mathcal{S}^{tr}}[MSE_{\mu}(\mathcal{S}^{te}, \mathcal{S}^{tr}, \pi(\mathcal{S}^{tr}))]$$
(1)

▶ Solution? Estimate in-leaf variance using a separate estimation dataset \mathcal{S}^{est} . Take this step into account in the tree-building phase by modifying $Q(\pi)$ to

$$Q^{H}(\pi) = -\mathbb{E}_{\mathcal{S}^{te}, \mathcal{S}^{est}, \mathcal{S}^{tr}}[MSE_{\mu}(\mathcal{S}^{te}, \mathcal{S}^{est}, \pi(\mathcal{S}^{tr}))]$$
(2)

To get treatment effects, produce an unbiased estimator of MSE_{τ}

