# What You Can Do

Nick Eubank

## Modeling

Developing Model to Faithfully Represent Data

**Modeling**

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$\Downarrow$

**Inference**

Interpreting Model Parameters
for Application

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for Application

1. Are my estimates causal?
2. Will they generalize?
3. Do they reflect biases in an unethical way?

# Day 1

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  Developing, along the way, great portfolio pieces!

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4. Differences-in-Differences

   Adjust for pre-existing baseline differences $\rightarrow$ same potential outcomes in trends

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There are no statistical tests that can tell you if a model is behaving in an ethical manner.

- The same model may be ethical when used for one purpose, but not in another.

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- Used diff-in-diffs to understand impact of drug legalization on crime

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- militant activity on women's education,
- changes in labor laws on wages,
- election results on hate crimes,
- changes in policing practices on police violence and arrests,
- sex education on teenage pregnancy,
- school policy on covid rates,
- tournament tennis game duration on future success,
- renewable targets on CO2 emissions,
- pandemics on stress and dreaming, and
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And while doing Kyle's class.

**erika**
@brownbearika

Maybe...just maybe.... the real treasure...was the friends we made along the way... (end scene)

I hope you feel really proud of everything you've accomplished.