# **Gov 2002: Introduction**

Fall 2023

Matthew Blackwell

Gov 2002 (Harvard)

• Methods popular since I started grad school:

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  - Machine learning

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  - · Machine learning, deep learning

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  - · Understanding your tools will make you better at your craft.
- You should never have to abandon a project because "you don't know how to do it."



Being asked a question about a method you don't understand in a job talk.

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Overall goal: be empowered to learn any new method with relative ease.

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- Understand the goals and logistics of the course
- · Understand the basic definition of probability

# 1/ Course Details

### **Staff**

• Instructor: Matthew Blackwell

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· Course Assistant: Noah Dasanaike

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- · Computing:
  - We'll assume knowledge of R Math Prefresher.

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- Success in academia is a mix of: luck, creativity, knowledge, and consistent hard work
  - · Becoming "fluent" in methods will pay off in the long (and short) run

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- · Office hours: ask even more questions.

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- Other good book referenced on syllabus.

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- Make sure R, RStudio, and rmarkdown are all updated and work.

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- $\bullet \ \, \text{Probability} \rightarrow \text{Inference} \rightarrow \text{Regression}$

# 2/ Overview of Probability and Statistics

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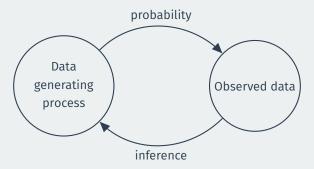
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- · Probability to the rescue!