

# **Inference & Causality Week 1**

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Lecturer: Narges Chinichian

IU University of Applied Science, Berlin

# About Me

- Dr. Narges Chinichian
- PhD in Physics (Computational Neuroscience), with 8+ years experience in data science & machine learning.
- Hobby teacher, I also teach rope climbing at the neighboring gym Der Kegel!
- Fun fact about me: I'm a grand-grand-...-grand student of Gauss.

# About You?

Please share briefly:

- 1. Your name & if you'd like: where you're from.
  - 2. What languages you speak/read.
  - 3. What is your educational background.
  - 4. How would you rate your Python and Git skills?
  - 5. What are your expectations for this course? What do you hope to learn?
- 
- Bonus: If causality were a person, how would they look and what would they be like?



# Course Overview

- 6 weeks | 2 day per week (12 sessions) | 4 × 45min units
- Hands-on, project-based learning
- Check the course hub on Notion for up-to-date information:  
<https://tinyurl.com/mrcjp79s>

The course will be covering:

- Statistical inference
- Introduction to causality
- Interventions
- Do-calculus
- Fallacies





# Outline of Week 1

- Set up the infrastructure (GitHub).
- Explain the difference between frequentist and Bayesian inference
- Apply Bayes' theorem to simple problems
- Update beliefs with new evidence

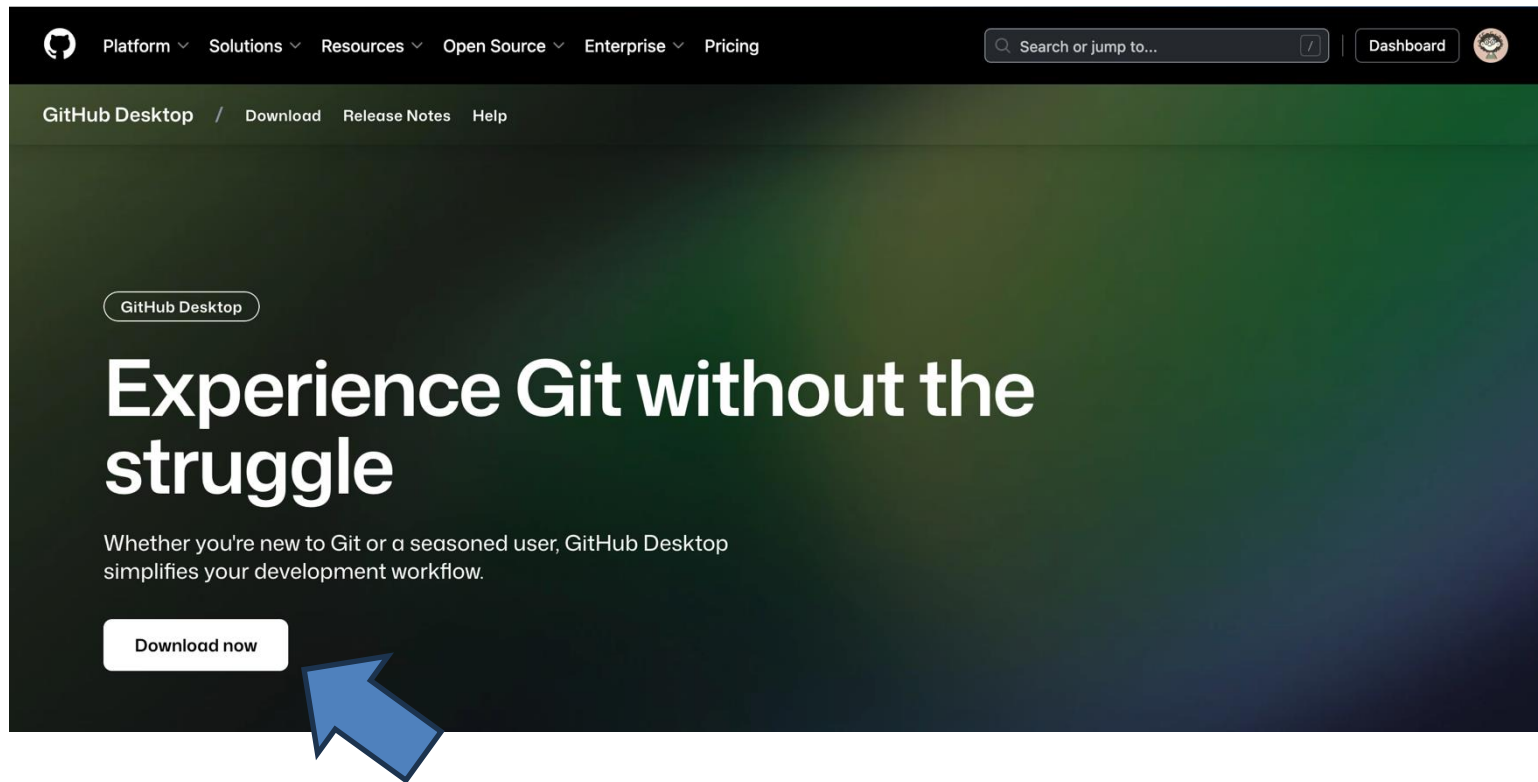
# Setting Up Your GitHub

- Please all add your GitHub handle and name here: <https://tinyurl.com/4xxzhphf>
- You handle is what you get in your url when you are on your profile page:
- So if you see:
- <https://github.com/NoCh-Git>
- Your handle is NoCh-Git.



# Install GitHub Desktop (Optional)

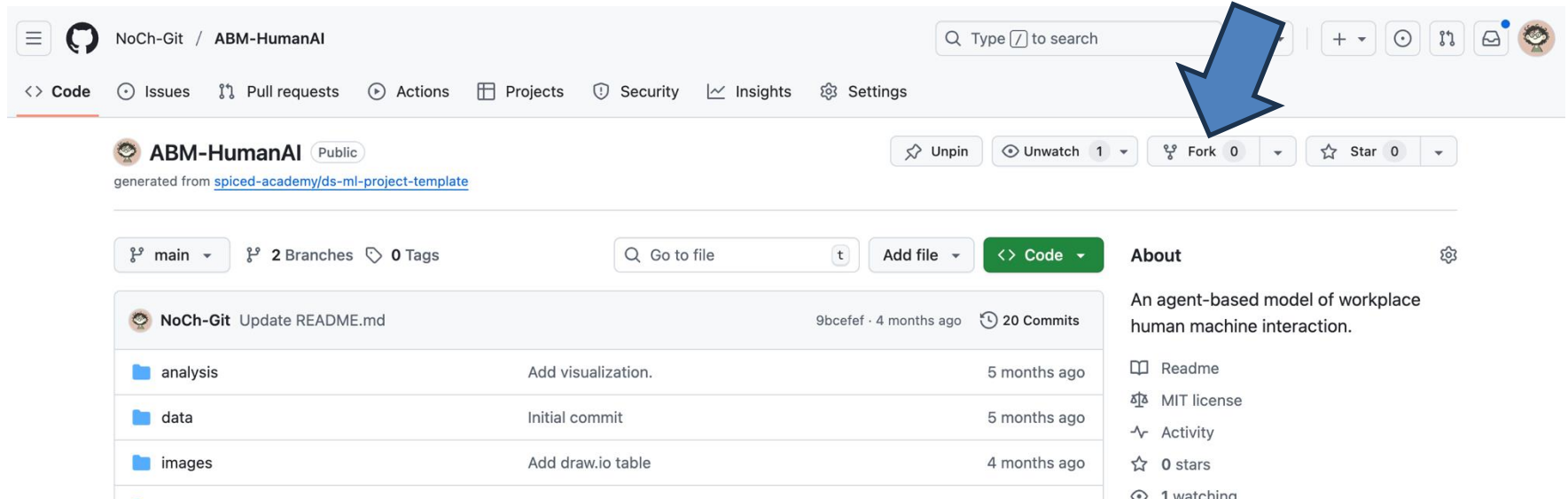
<https://github.com/apps/desktop>





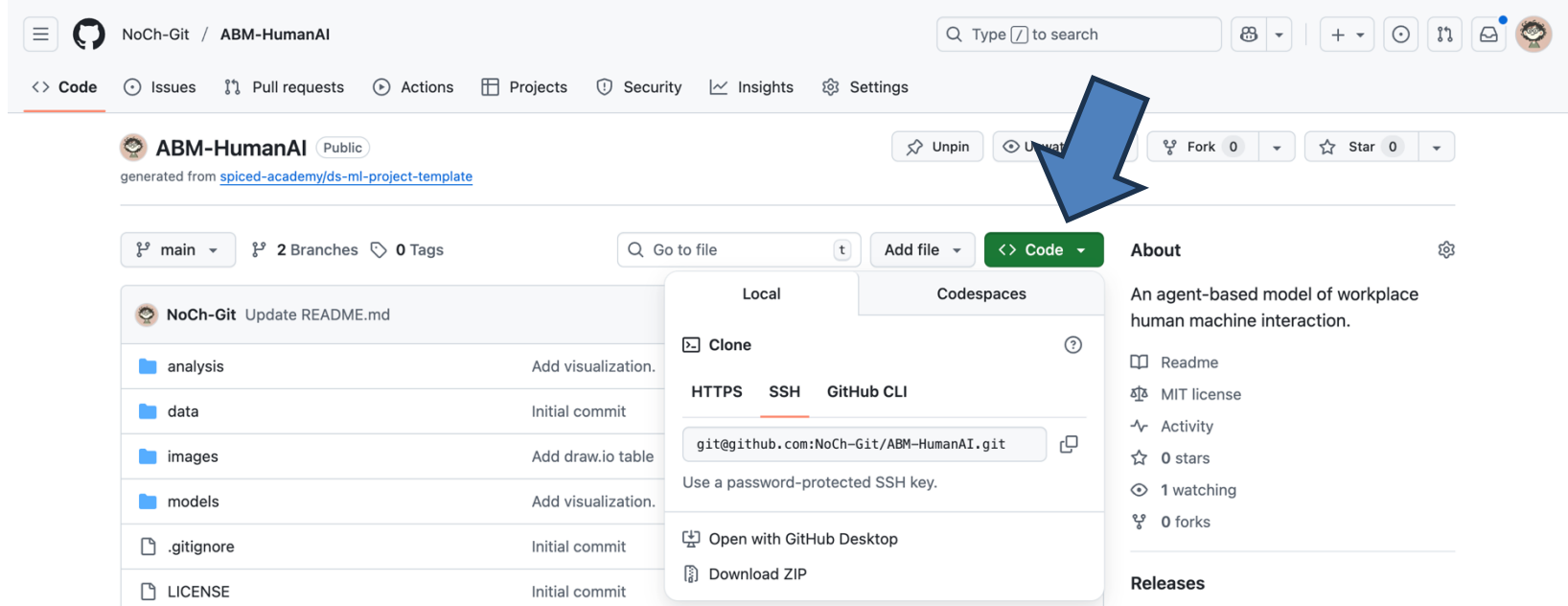
# Fork Repo of Today

- Forking a repo would create a copy of that repo for you that you can play with.
- Choose yourself as the owner and untick the “Copy the main branch only” box.



# Clone the Forked Repo to Your Machine Using GitHub Desktop or CLT

- You need to have a local copy of the Python notebooks.





**Ready?**

# **Notebook 1**

Notebook 1 of week 1 in your  
“notebooks” folder.



# What is Statistical Inference?

- Drawing conclusions about unknowns from data
- Two paradigms:
  - Frequentist: parameters fixed, data random
  - Bayesian: parameters uncertain, updated via evidence
- Both appear throughout this module; today we compare and practice



**Want to play a  
quick game?**

# Two Paradigms:

## Frequentist

- Probability = long-run frequency
- Parameters are fixed (unknown), data is random
- Confidence intervals, hypothesis tests

## Bayesian

- Probability = degree of belief
- Parameters have distributions (prior  $\rightarrow$  posterior)
- Bayes' theorem combines prior and likelihood

# Bayes' Theorem

$$P(H|D) = \frac{P(D|H)}{P(D)} P(H)$$

- Where:
- $H$  = Hypothesis for example some “disease”
- $D$  = Data for example a “positive test”
- $P(H)$  is the probability of the hypothesis before we see the data, called the **prior** probability, or just prior.
- $P(H|D)$  is the probability of the hypothesis after we see the data, called the **posterior**.
- $P(D|H)$  is the probability of the data under the hypothesis, called the **likelihood**.
- $P(D)$  is the **total probability** of the data, under any hypothesis.



# Cookie Problem

From Allen Downey's version of Urn problem

- Suppose there are two bowls of cookies.
- Bowl 1 contains 30 vanilla cookies and 10 chocolate cookies.
- Bowl 2 contains 20 vanilla cookies and 20 chocolate cookies.
- Now suppose you choose **one of the bowls at random** and, without looking, choose **a cookie at random**. If the cookie is **vanilla**, what is the probability that it came from **Bowl 1**?

$$P(B_1|V) = \frac{P(B_1)P(V|B_1)}{P(V)}$$

$$P(V|B_1) = \frac{3}{4} \text{ and } P(B_1) = \frac{1}{2}$$

$$P(V) = P(B_1)P(V|B_1) + P(B_2)P(V|B_2)$$

$$P(V) = \frac{1}{2} \times \frac{3}{4} + \frac{1}{2} \times \frac{1}{2} = \frac{5}{8}$$

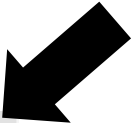
$$P(B_1|V) = \frac{\frac{1}{2} \times \frac{3}{4}}{\frac{5}{8}} = \frac{3}{5}$$

# Bayes Tables


Useful tools to calculate Bayesian probabilities.

	prior	likelihood	unnorm	posterior
Bowl 1	0.5	0.75	0.375	0.6
Bowl 2	0.5	0.50	0.250	0.4

Normalized  
multiplication of  
prior and likelihood  
= Posterior



Unnormalized  
multiplication of prior  
and likelihood



# Dice Problem (more than two distributions)

From Allen Downey's book, Think Bayes

- Suppose there are three dice:
- A 6 sided, an 8 sided and a 12 sided.
- We choose one of the dice at random, roll it, and report that the outcome is a 1.
- What is the probability that I chose the 6-sided die?

	prior	likelihood	unnorm	posterior
6	$1/3$	$1/6$	$1/18$	$4/9$
8	$1/3$	$1/8$	$1/24$	$1/3$
12	$1/3$	$1/12$	$1/36$	$2/9$

I GRAB 2 OF THE 10 ARROWS WITHOUT  
LOOKING AND FIRE THEM, HOPING I DIDN'T  
GRAB ONE OF THE 5 CURSED ONES. DID I?

SIGH. UMM. OKAY.

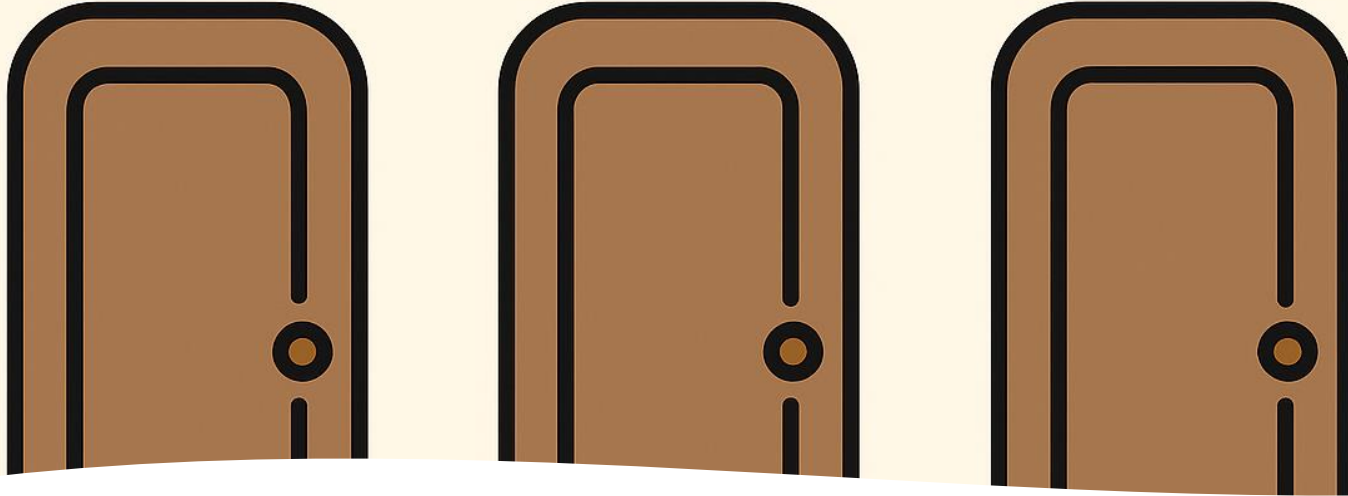
ROLL...UH...HANG ON...

ROLL 3D6 AND A D4. YOU  
NEED...16 OR BETTER TO  
AVOID THE CURSED ARROWS.



I GOT WAY MORE ANNOYING TO  
PLAY D&D WITH ONCE I LEARNED  
THAT OUR DM HAS A COMBINATORICS  
DEGREE AND CAN'T RESIST PUZZLES.

# MONTY HALL PROBLEM



## Monty Hall Problem

Selvin, S. (1975)

- Based on a show called “Let’s Make a Deal”.
- You are on a game show and have to choose one of three doors:
- Behind one door is a car, and behind the other two are goats.
- You pick a door (say, Door 1).
- The host, who knows what’s behind each door, opens another door (say, Door 3) revealing a goat.
- You are then asked:  
“Do you want to stick with your choice, or switch to the other unopened door?”

**What should you do to maximize your chance of winning the car?**

- If the car is behind Door 1, Monty chooses Door 2 or 3 at random, so the probability he opens Door 3 is  $\frac{1}{2}$ .
- If the car is behind Door 2, Monty has to open Door 3, so the probability of the data under this hypothesis is 1.
- If the car is behind Door 3, Monty does not open it, so the probability of the data under this hypothesis is 0.

	prior	likelihood	unnorm	posterior
<b>Door 1</b>	$\frac{1}{3}$	$\frac{1}{2}$	$\frac{1}{6}$	$\frac{1}{3}$
<b>Door 2</b>	$\frac{1}{3}$	1	$\frac{1}{3}$	$\frac{2}{3}$
<b>Door 3</b>	$\frac{1}{3}$	0	0	0

# **Notebook 2**

Let's get some hands-on  
experience with Python.

# Recap

- Two views: frequentist vs Bayesian (both useful)
- Bayes' theorem links prior, evidence, posterior
- Next: Bayesian networks & probabilistic modelling





# Homework

- Exercise: Fill out the exercises on Jupyter notebooks 1 and 2 for this week, commit your answers and submit .
- Optional: Come up with a new example of where Frequentist/Bayesian approaches are the best.