COMS BC1016: Introduction to Computational Thinking and Data Science

Lecture 1: Introduction

Spring 2025

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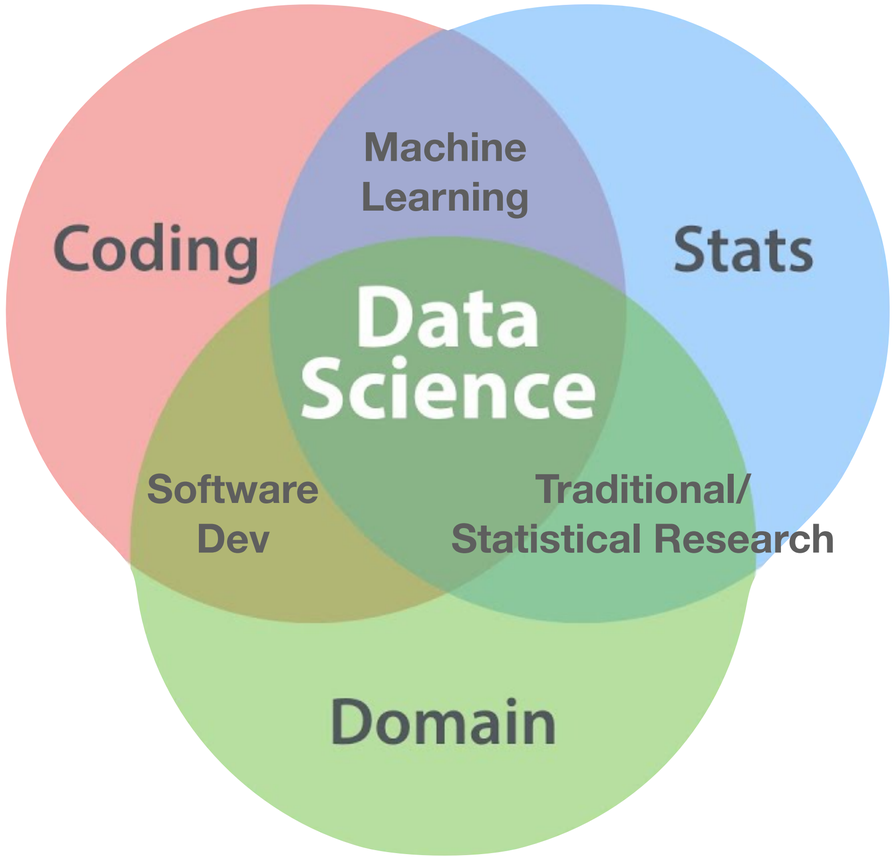
Reformulating a seemingly difficult problem into one we know how to solve

COMS BC1016: Introduction to Computational Thinking and Data Science

Reformulating a seemingly difficult problem into one we know how to solve

“Data science is the study of **extracting value** from data”

Math + Computer Science + Domain Knowledge

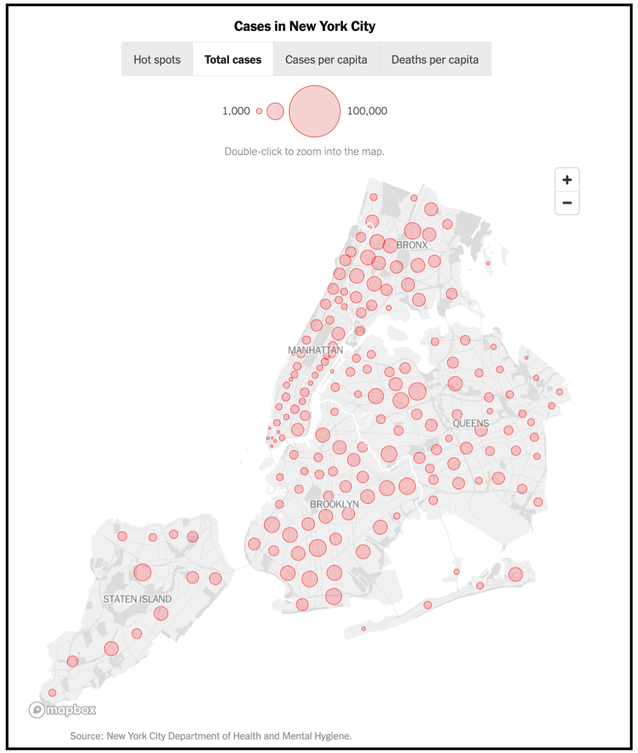


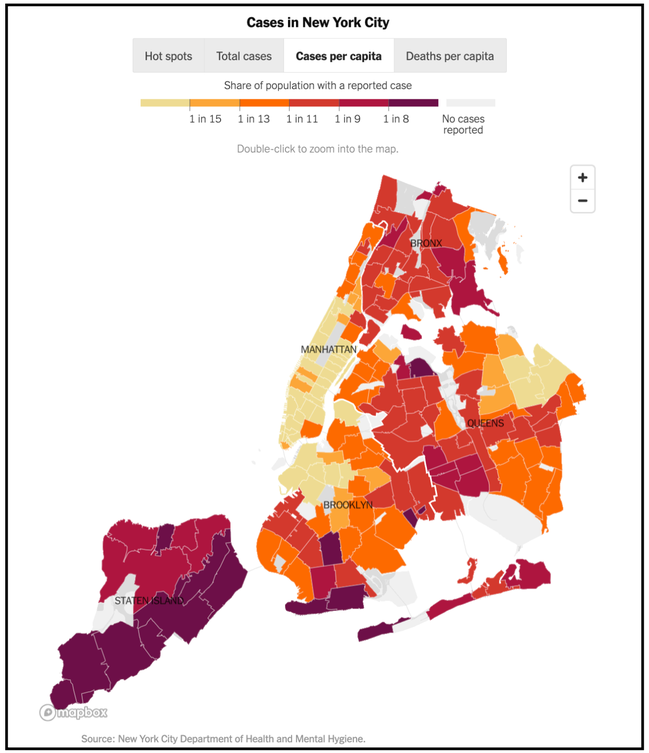
Data Science in this class

Data science is about drawing useful conclusions from large and diverse data sets through…

Data Science in this class

- **Exploration**: Identifying patterns and trends using data (e.g., through visualization)



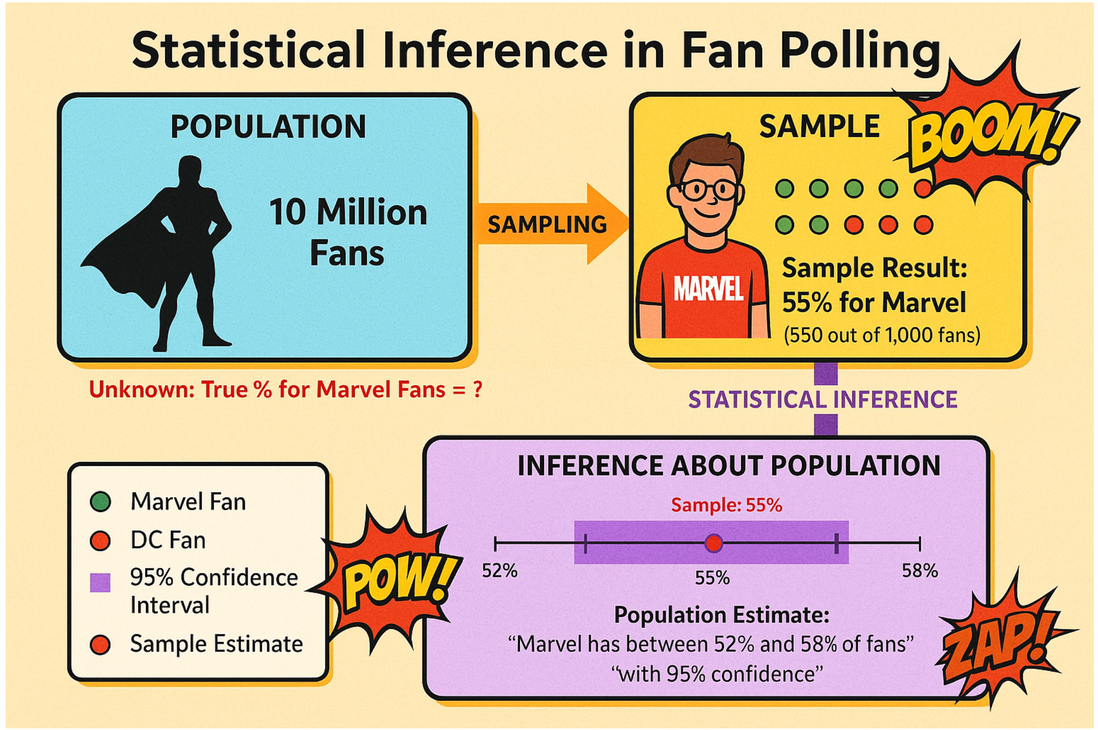


Source: https://www.nytimes.com/interactive/2020/nyregion/new-york-city-coronavirus-cases.html
Data as of May 25, 2021

Data Science in this class

- **Exploration**: Identifying patterns and trends using data (e.g., through visualization)

- **Inference**: Drawing reliable conclusions using statistics



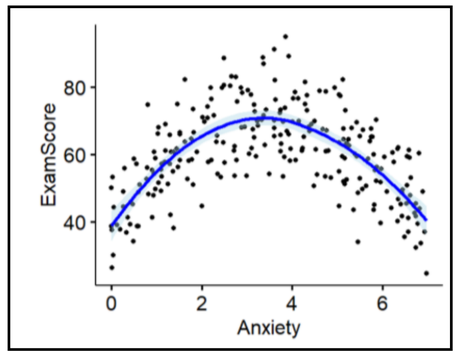
Source: Murad Megjhani and his AI image generator of choice

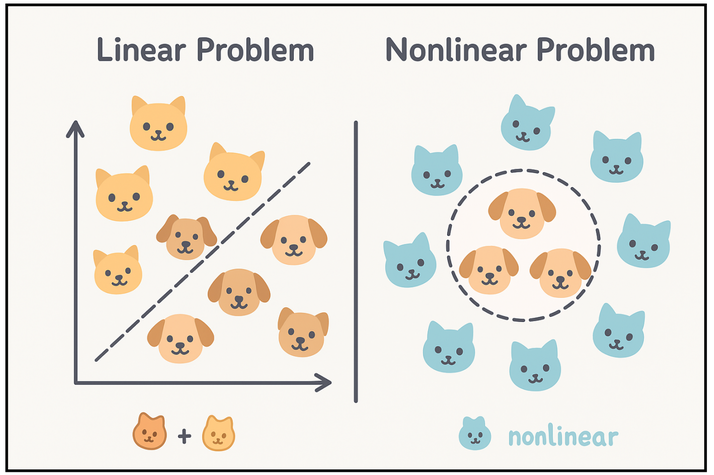
Data Science in this class

- **Exploration**: Identifying patterns and trends using data (e.g., through visualization)

- **Inference**: Drawing reliable conclusions using statistics

- **Prediction**: Making informed guesses about patterns using models





Source: Murad Megjhani and his AI image generator of choice

Course Outline

- **Exploration**: Identifying patterns and trends using data (e.g., through visualization)
- **Inference**: Drawing reliable conclusions using statistics
- **Prediction**: Making informed guesses about patterns using models

Introduction to Python, working with data — **Week 1 - 5**

Probability, statistics — **Week 6 - 11**

Machine Learning, Regression & Classification — **Week 13 - 15**

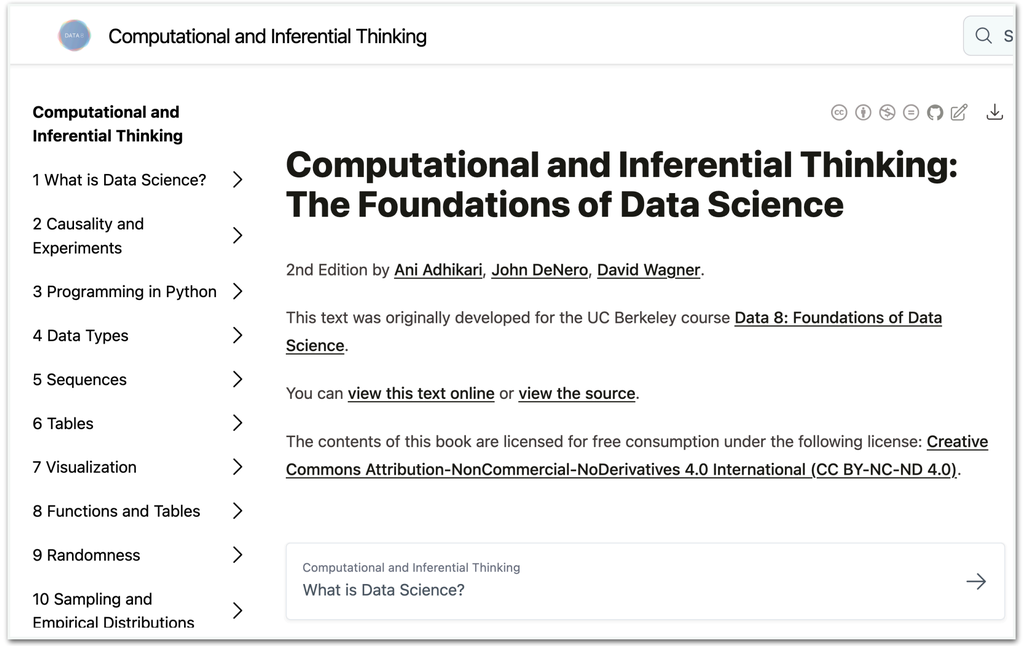
Course Acknowledgments

- Builds on top of Data 8 (Berkeley Data Science course)
  - Lots of universities build on top of it (UW, NYU, UCSD, McGill, Cornell, etc.), including us!
  - You may see many references to California in the assignments



- Some aspects of our version are different
  - Specifically, exam(s) and project(s)

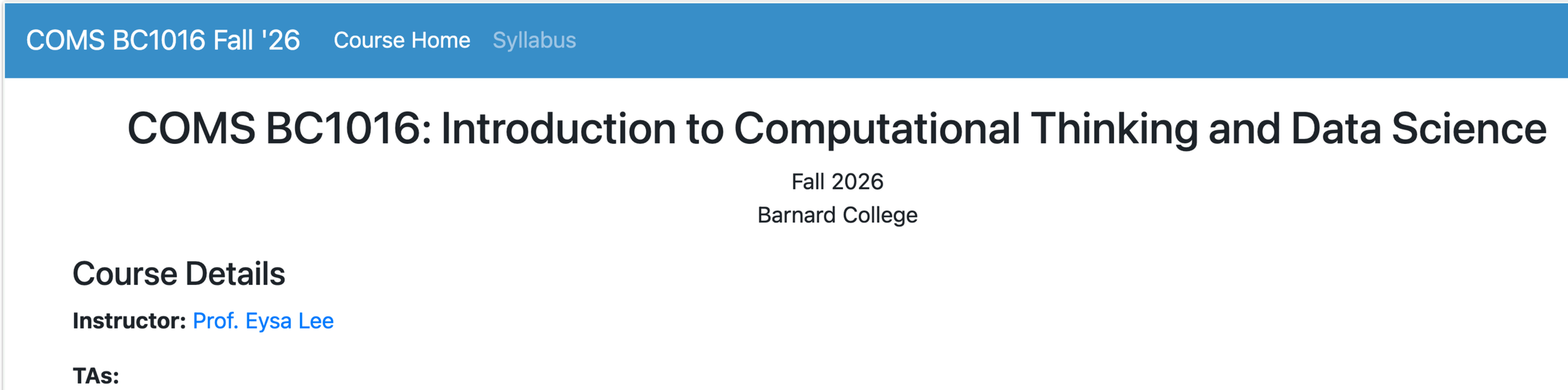
- Their textbook is great!
  - It's free and a great supplement for lectures
  - https://inferentialthinking.com/



Course Logistics

Communication

- Course website: https://www.eysalee.com/courses/f26/bc1016.html
  - Contains all of the following links and contacts of the teaching staff
- EdStem: https://edstem.org/us/courses/100846/discussion
- Courseworks: https://courseworks2.columbia.edu/courses/245263



EdStem

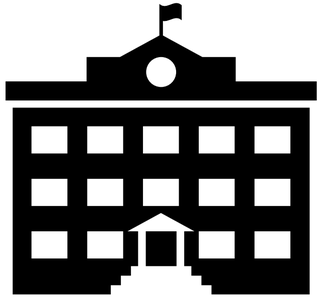
- Where we post updates to office hours, due dates, or classes
- This is the place to ask/answer questions about assignments!
  - Do not post solutions to assignments!
  - When in doubt, you can post privately to teaching staff
- Unless it is something that only the professor is able to help with, please post on EdStem
  - We have many great TAs who will be monitoring the class forum
  - Plus this helps ensure we don’t miss your question



Assignments

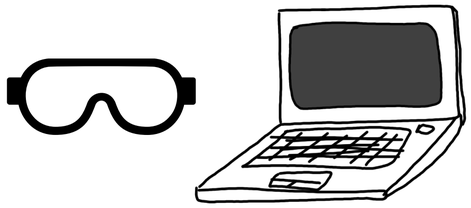
COMS BC1016 (Lecture):

- 30% - Homeworks
- 25% - Midterm
- 35% - Final Project
- 10% - Participation



COMS BC1017 (Lab):

- 50% - Labs
- 50% - Attendance



Lecture Grading: Homeworks

- 9 (mostly) weekly programming assignments
  - To be completed individually
  - May take more time… Start early!
- Can be submitted up to 5 days late with a 10% penalty per day
  - Example: 2 days late receives a 20% deduction
- Submit on Gradescope
- Lowest homework grade will be dropped at the end of the semester



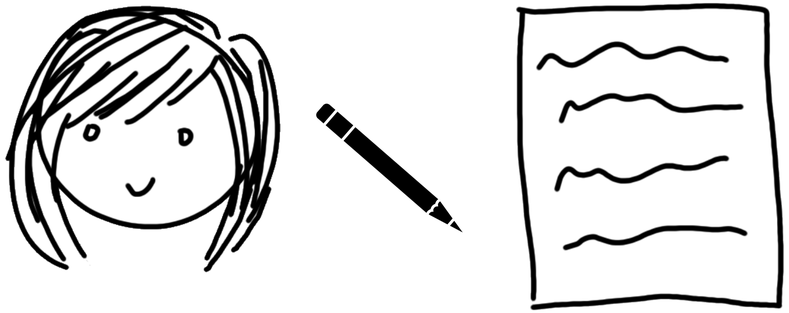
gradescope® by Turnitin

Lecture Grading: Midterm

- **Written midterm** testing conceptual understanding
  - Scheduled for in-class **October 26, 2026**
- You will be allowed a small note sheet to use as reference during the exam
- Please contact CARDS if you need particular accommodations



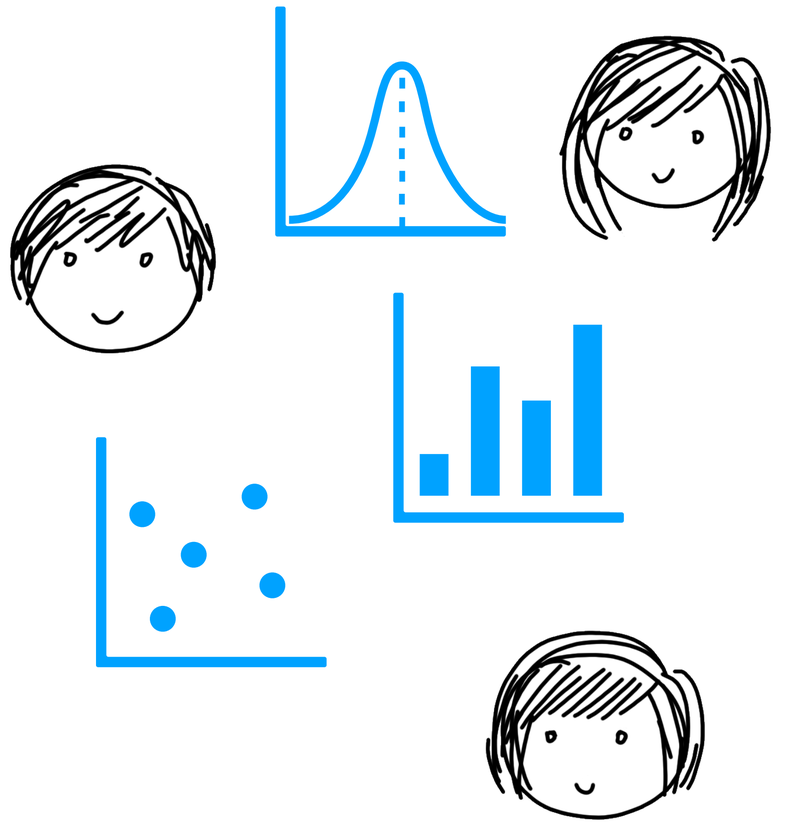
Alice is sad she can't use ChatGPT on her midterm



… but it's okay because she's been working hard all semester and knows material!

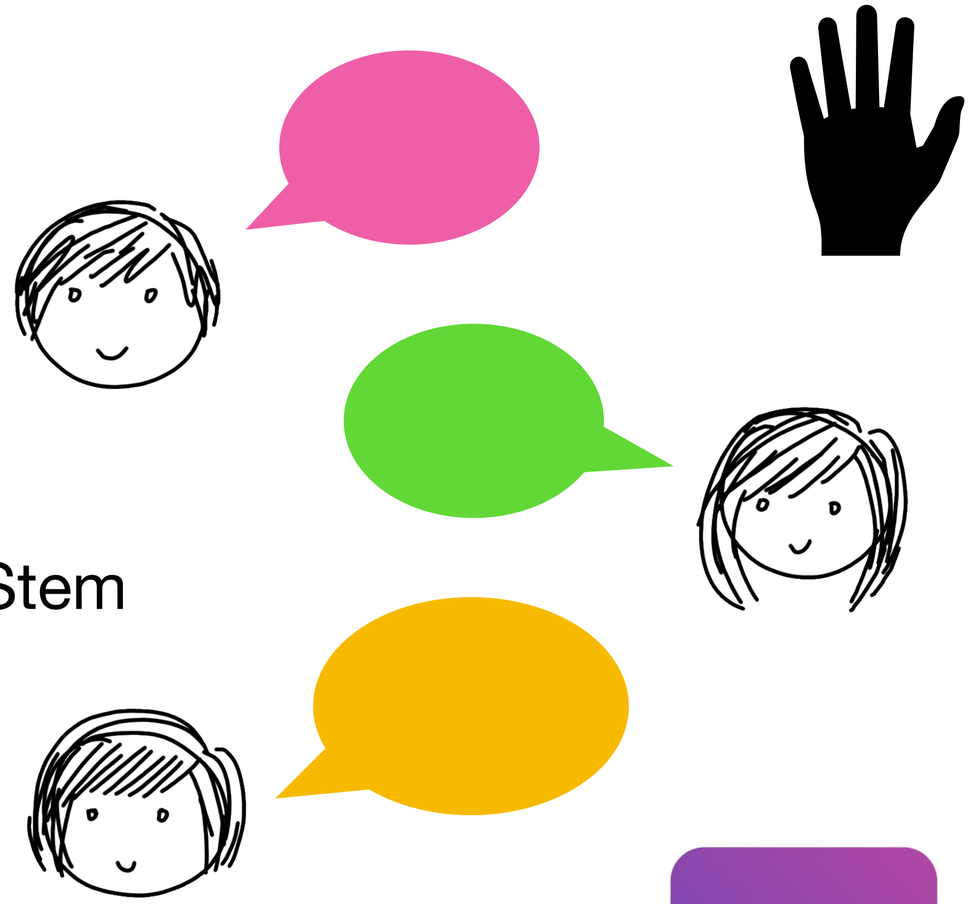
Lecture Grading: Final Project

- Groups of 2-3 from the same lecture section
- Open-ended assignment
  - Choose from a few real world datasets (or propose your own!)
  - Develop a question to ask about the dataset
  - Apply what you've learned from the course!
- Final project report and code will be due at the beginning of Finals Week
- More info after the midterm

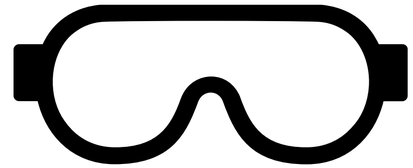


Lecture Grading: Participation

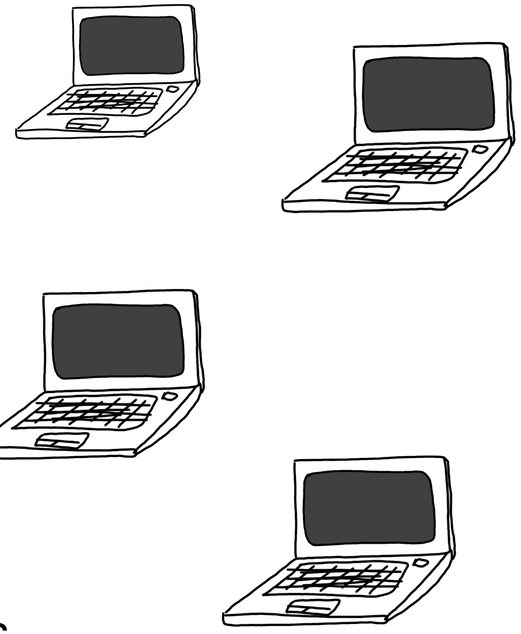
- Participation includes:
  - Asking questions during class
  - In-class activities and discussions
  - Asking and/or answering questions on EdStem



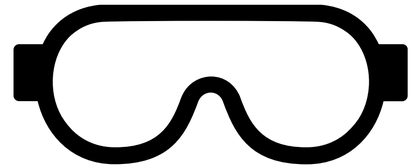
Labs



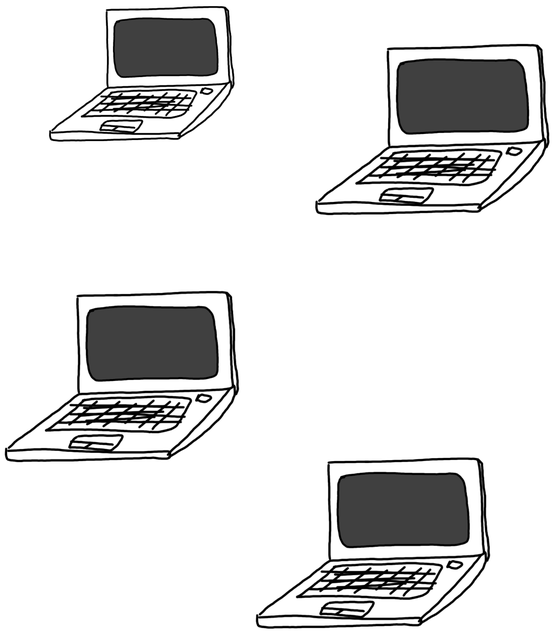
- You can register for any lab section, but **you must be registered for one**!
  - **Labs start next week** (no labs this week!!)
- Each lab is headed by a TA (Data Science Masters student) and a Computing Fellow (Barnard undergraduate)
- Labs have mandatory attendance
  - You are allowed 1 unexcused absence from lab during the semester
  - Email your lab TA and the professor as early as possible for excused absences



Lab Grading



- Each lab is graded 50% attendance and 50% assignment
  - Excessive tardiness may result in a lower attendance grade
- Lab assignments are intended to be doable to complete during the lab itself
  - If you finish early, you may show your TA your completed assignment to leave early
- The lowest lab grade will be dropped



Course Staff

Who am I?

Eysa Lee (eylee@barnard.edu)

- 2nd year Assistant Professor in the Computer Science Department at Barnard

- 3rd semester teaching this course
  - I teach this class because I enjoy teaching non-majors skills/tools that are useful for whatever area you pursue :)

- My area of research is cryptography
  - I'm always happy to chat about computer security and privacy!



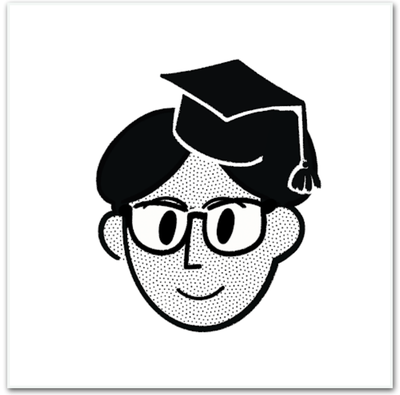
Who are your TAs?

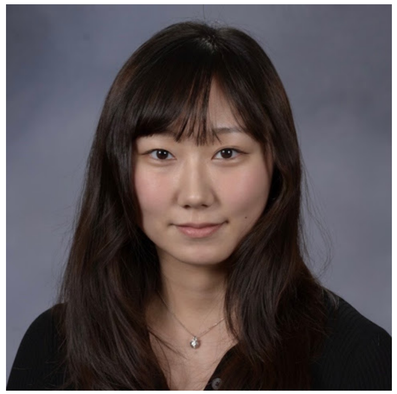
Teaching Assistants:

- Aarya Dharm (add2180@columbia.edu)
- Aditya Pendyala (ap4839@columbia.edu)
- Minh Le (ml5536@columbia.edu)
- Yeonji Baek (yb2662@columbia.edu)









Data Science Master’s Students from Columbia

Who will be leading the labs?

Teaching Assistants:

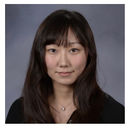
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- Minh Le (ml5536@columbia.edu)
- Yeonji Baek (yb2662@columbia.edu)

Labs:


Wednesday 2:40-3:55


Wednesday 4:10-5:25


Thursday 9:40-11


~~Thursday 11:20-12:50~~

Wednesday 4:10-5:25

Who are the Computing Fellows?

- Computing Fellows:
  - Aarani Narenthiran (Wednesday 2:40-3:55)
  - Aayusha Pokharel (Wednesday 4:10-5:25)
  - Winnie Wang (Thursday 9:40-11)
  - Sonali Sinha ~~(Thursday 11:20-12:50)~~ Wednesday 4:10-5:25
- Computing Fellows are Barnard undergraduates! Peer mentors!
  - They assist the TAs during the lab sections
  - They do *not* handle grades, so please do not go to them about grading!

Office Hours

Monday: 4-5pm (Eysa in Milstein 512)

Tuesday: 9-10am (Minh in Milstein 503)

Wednesday: 4-5pm (Aarya in Milstein 503 and Eysa in Milstein 512)

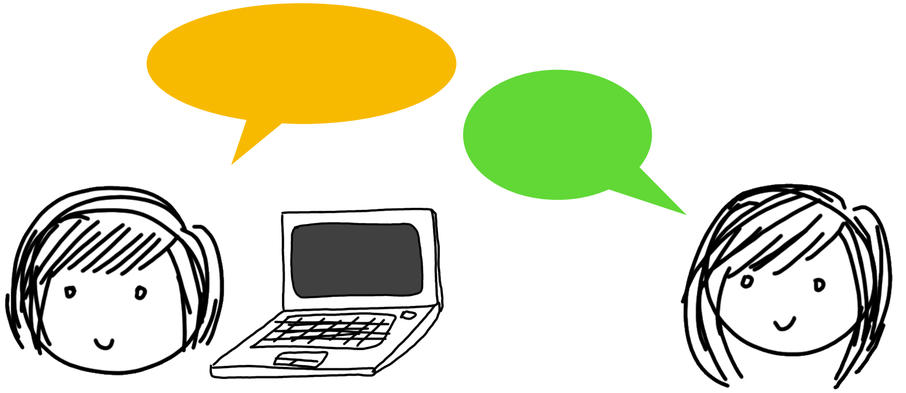
Thursday: 6-7pm (Yeonji in Milstein 503)

Prof Megjhani’s office hours are during this class (MW 1-2)

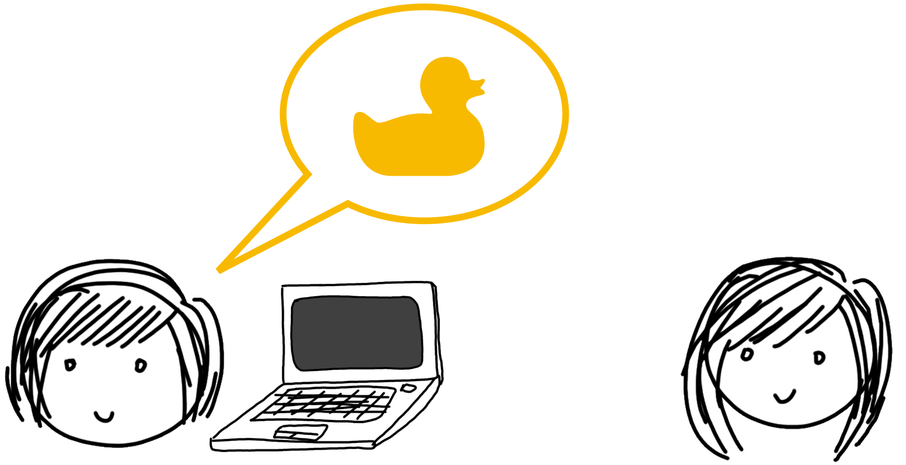
Course Policies

Collaboration

- Even though homeworks are individual, you may discuss problems with each other
  - However, you must write solutions on your own.
  - *Do not share solutions!*
- You are encouraged to try problems on your own first before discussing with others
  - You will learn much more this way!
  - It's okay if it doesn't work at first! You learn a lot talking through issues with others to figure out why something doesn't work



Here we see Carol discussing problems with Alice and writing up solutions on her own



When she gets stuck, she talks through her code and thought process with Alice, also known as "rubber ducking"

Generative AI Usage

- This course is meant to build your programming skills, so it is generally not advised to use generative AI tools
  - We want you to build intuition about what's going in the code, how to write it, and how to fix common issues!
  - The most productive use would be to use it as a support tool to explain code snippets
- In particular, **you may *not* submit code or text that is primarily AI-generated**
  - Doing so may result in a failing grade for the assignment and/or course
  - As a rule of thumb, **do not submit anything that you could not have reasonably written yourself**





Gemini

ChatGPT

Don't do it!
I will be very sad and take it personally

Regrades

- Regrade requests must be submitted **within 1 week** of your grade being received
    - We will not consider any regrades after this timeframe
    - Do not wait until the end of the semester to tell us if something was marked incorrectly!
- If you request a regrade, please provide sufficient information for why you think something was marked incorrectly
    - To combat abuse, we reserve the right to lower your grade if the original grading was found to be too generous

Any questions about the syllabus?

Let’s think about data

What is Data Science?

Data science allows us to draw useful conclusions from large and diverse data sets through:

- Exploration: Identifying patterns and trends using data
- Inference: Drawing reliable conclusions using statistics
- Prediction: Making informed guesses about patterns using models

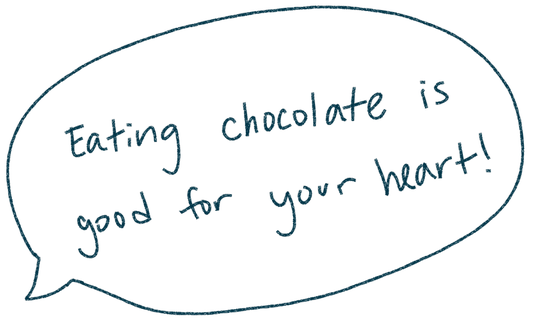
Before we get into programming, let's talk a bit about this.
What kinds of conclusions can we (or can we not) draw?

Cause and Effect

A link between chocolate and health



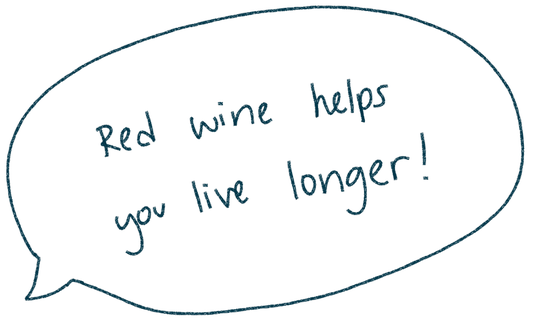




A link between red wine and health







A link between cats and grades





Observational Studies

Definition: A study in which researchers / scientists make conclusions based on *observed data* in which they had no hand in generating

- Individuals: study subjects, participants, units

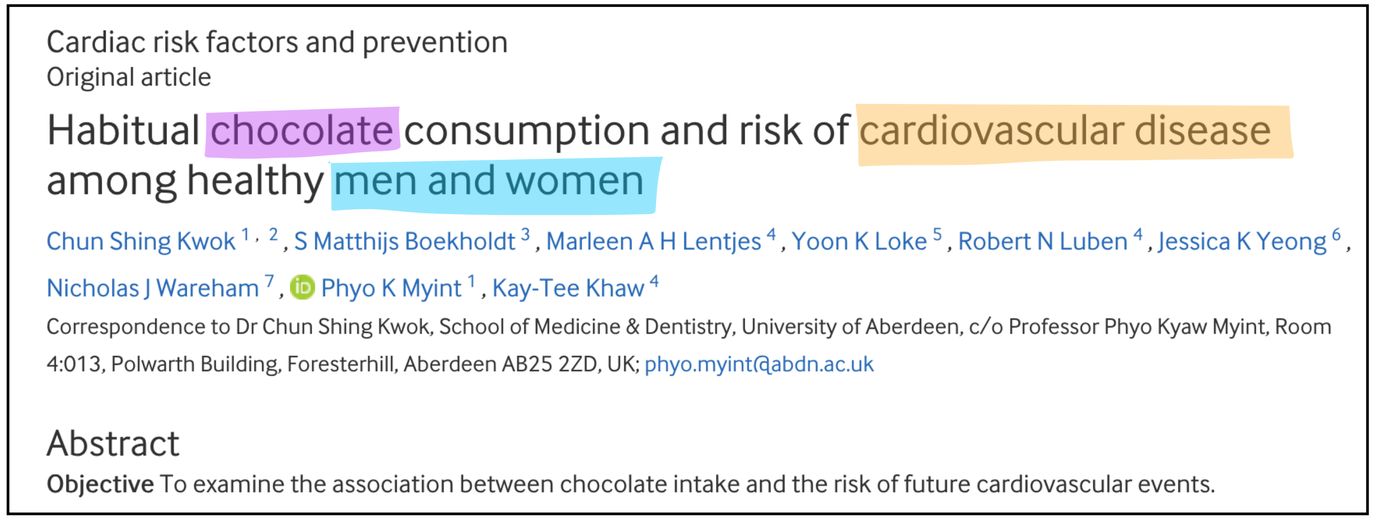
- Treatment: factor of interest

- Outcome: result of treatment

Observational Studies

Definition: A study in which researchers / scientists make conclusions based on *observed data* in which they had no hand in generating

- Individuals: study subjects, participants, units → people
- Treatment: factor of interest → chocolate consumption
- Outcome: result of treatment → heart health



Cardiac risk factors and prevention
Original article

Habitual chocolate consumption and risk of cardiovascular disease among healthy men and women

Chun Shing Kwok [1, 2], S Matthijs Boekholdt [3], Marleen A H Lentjes [4], Yoon K Loke [5], Robert N Luben [4], Jessica K Yeong [6], Nicholas J Wareham [7], Phyo K Myint [1], Kay-Tee Khaw [4]

Correspondence to Dr Chun Shing Kwok, School of Medicine & Dentistry, University of Aberdeen, c/o Professor Phyo Kyaw Myint, Room 4:013, Polwarth Building, Foresterhill, Aberdeen AB25 2ZD, UK; phyo.myint@abdn.ac.uk

Abstract

Objective To examine the association between chocolate intake and the risk of future cardiovascular events.

Source: https://heart.bmj.com/content/101/16/1279

Association and Causality

Association: Any relation between the treatment and the outcome

Causality: if the treatment causes the outcome to occur

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Association and Causality

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heart health

Causality: if the treatment causes the outcome to occur

Is there an association between chocolate consumption and heart disease?
According to this study, yes ☺

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Abstract

Objective To examine the association between chocolate intake and the risk of future cardiovascular events.

Conclusions Cumulative evidence suggests that higher chocolate intake is associated with a lower risk of future cardiovascular events, although residual confounding cannot be excluded. There does not appear to be any evidence to say that chocolate should be avoided in those who are concerned about cardiovascular risk.

https://doi.org/10.1136/heartjnl-2014-307050

Association and Causality

eating chocolate

Association: Any relation between the treatment and the outcome

heart health

Causality: if the treatment causes the outcome to occur

Is there an association between chocolate consumption and heart disease? According to this study, yes ☺

Does eating chocolate lead to a reduction in heart disease? Well... that's harder to say...

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Confounding Factors

Definition: In observational studies, underlying difference(s) between two groups other than the treatment (that make it difficult to identify causality)

It's possible that people who like to eat chocolate do something else that offers heart protection, like eat a wide variety of healthful foods. One of the interesting things about this research is that participants in the non-chocolate group had higher average weight, more artery-damaging inflammation, more diabetes, were less physically active and had diets with the least amount of fat compared to chocolate eaters.

By Howard E. LeWine, MD, Chief Medical Editor, Harvard Health Publishing; Editorial Advisory Board Member, Harvard Health Publishing

Source: https://www.health.harvard.edu/blog/sweet-dreams-eating-chocolate-prevents-heart-disease-201506168087

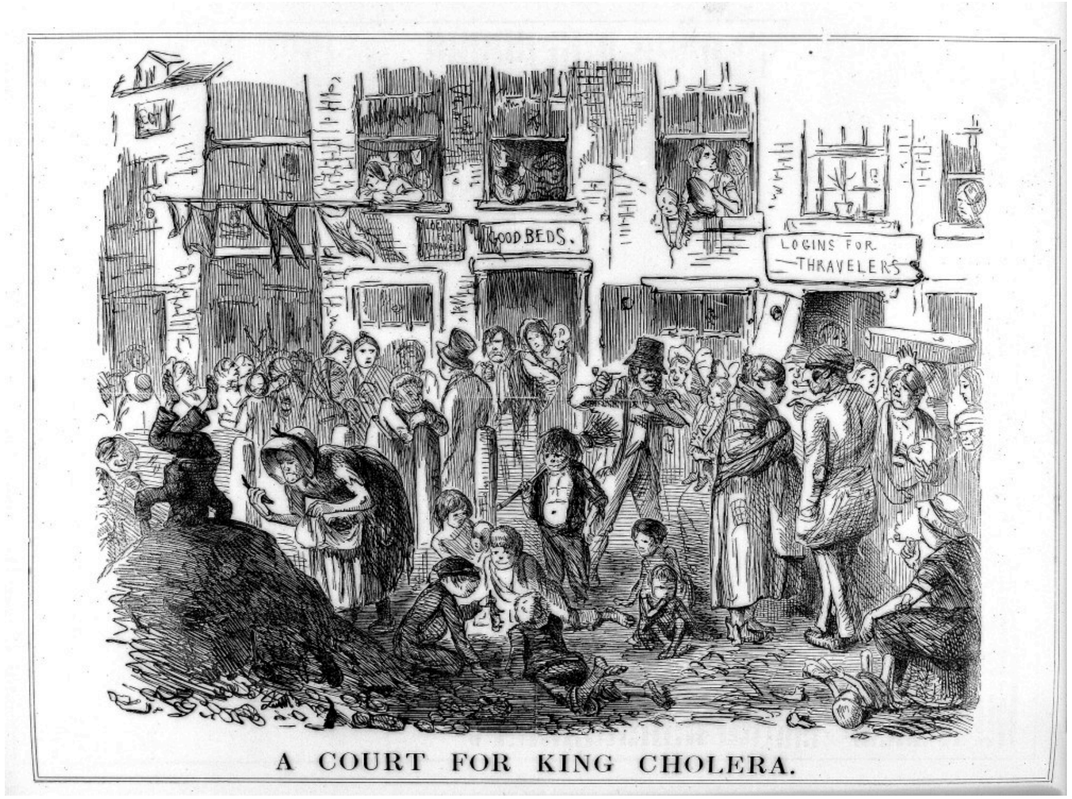
In general, observational studies are not enough to determine causation

Association, Causation, and Early Data Science

London 1850s: Cholera Epidemic

- Large migration into London in the 1700-1800s, leading to overcrowding

- What's causing cholera to spread?



A COURT FOR KING CHOLERA.

https://www.sciencemuseum.org.uk/objects-and-stories/medicine/cholera-victorian-london

Miasma

- ‘Bad air’ given off by waste and rotting matter
  - Believed to the main source of how infectious disease spread
  - Potential remedies: “Fly to clean air”, “pocket full of posies”, “fire off barrels of gunpowder”
- Popular medical theory of the time
  - Florence Nightingale (founder of modern nursing)
  - Edwin Chadwick (Commissioner of the Board of Health)



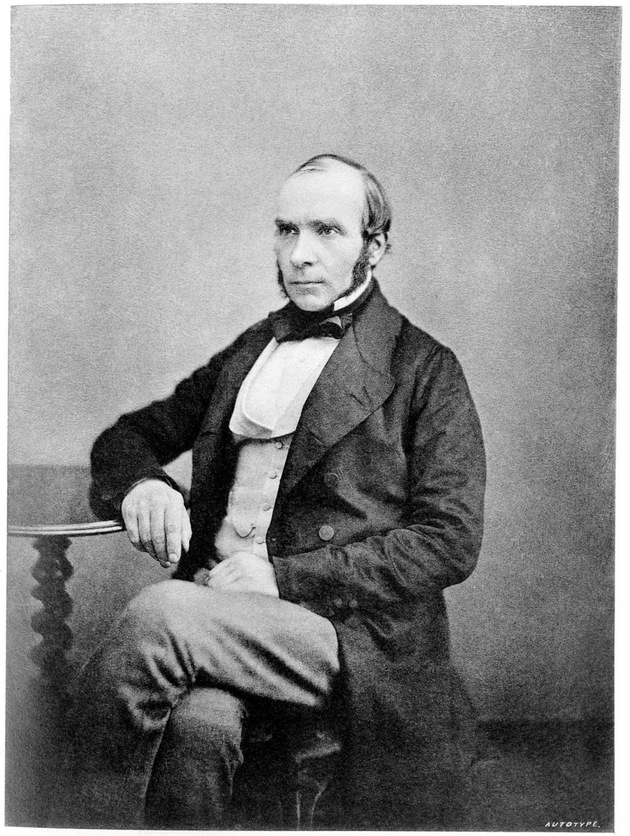
By Robert Seymour - Cholera "Tramples the victors & the vanquished both." U.S. National Library of Medicine Digital Collections., Public Domain, https://commons.wikimedia.org/w/index.php?curid=117446532

John Snow (1813 - 1858)

- English physician
- Used data and visualizations to understand why cholera was spreading in the way that it was
  - Noticed people could be in close proximity without the same outcomes



not this dude



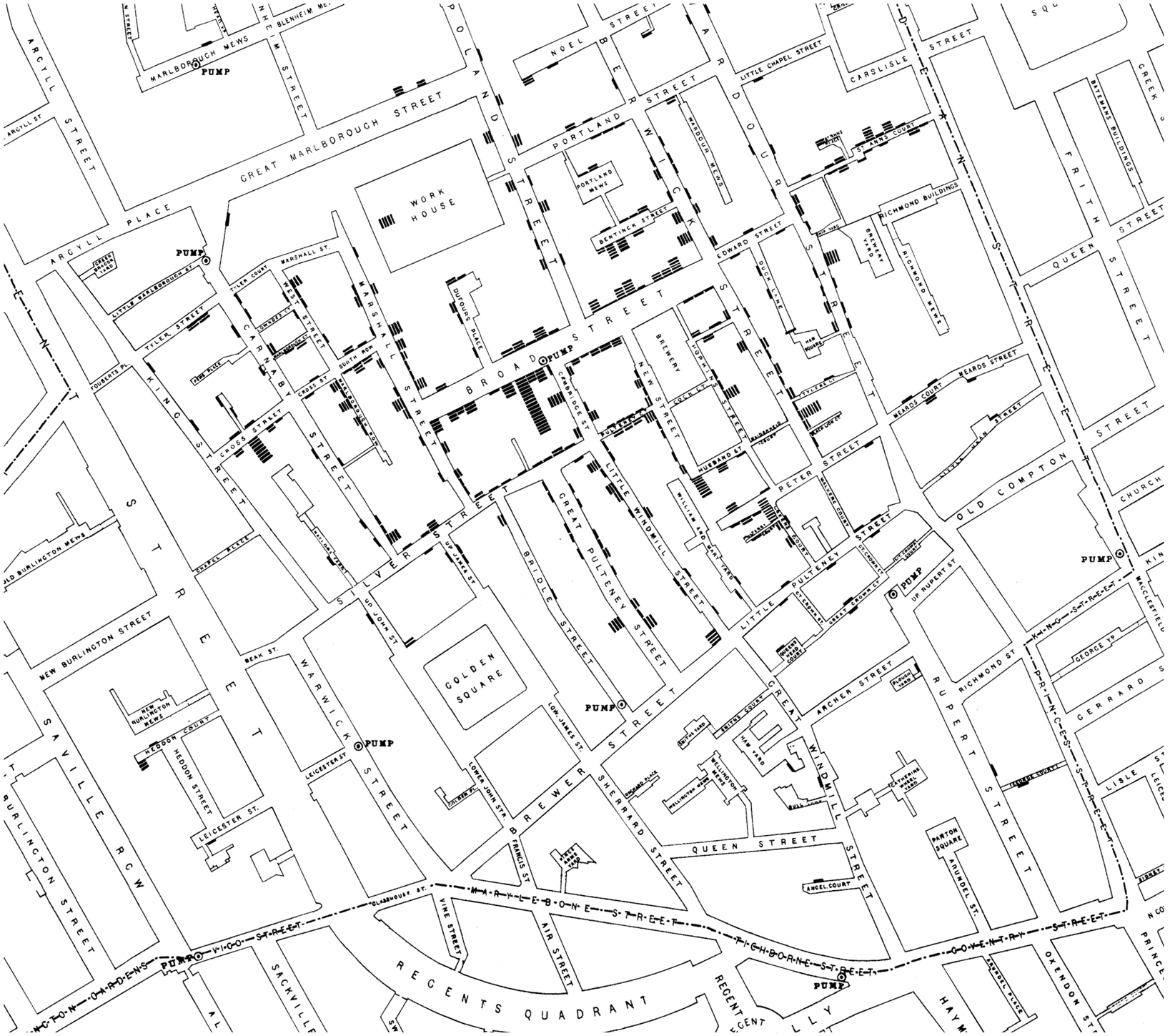
John Snow

(Autotype from a Presentation Portrait, 1856, and Autograph facsimile.—B. W. R.)

https://wellcomecollection.org/works/dkk5vx46

Mapping the Disease

- Snow went around SOHO in London and counted people who died at each address
  - Each black bar represents a death at that address
- Do you notice anything?

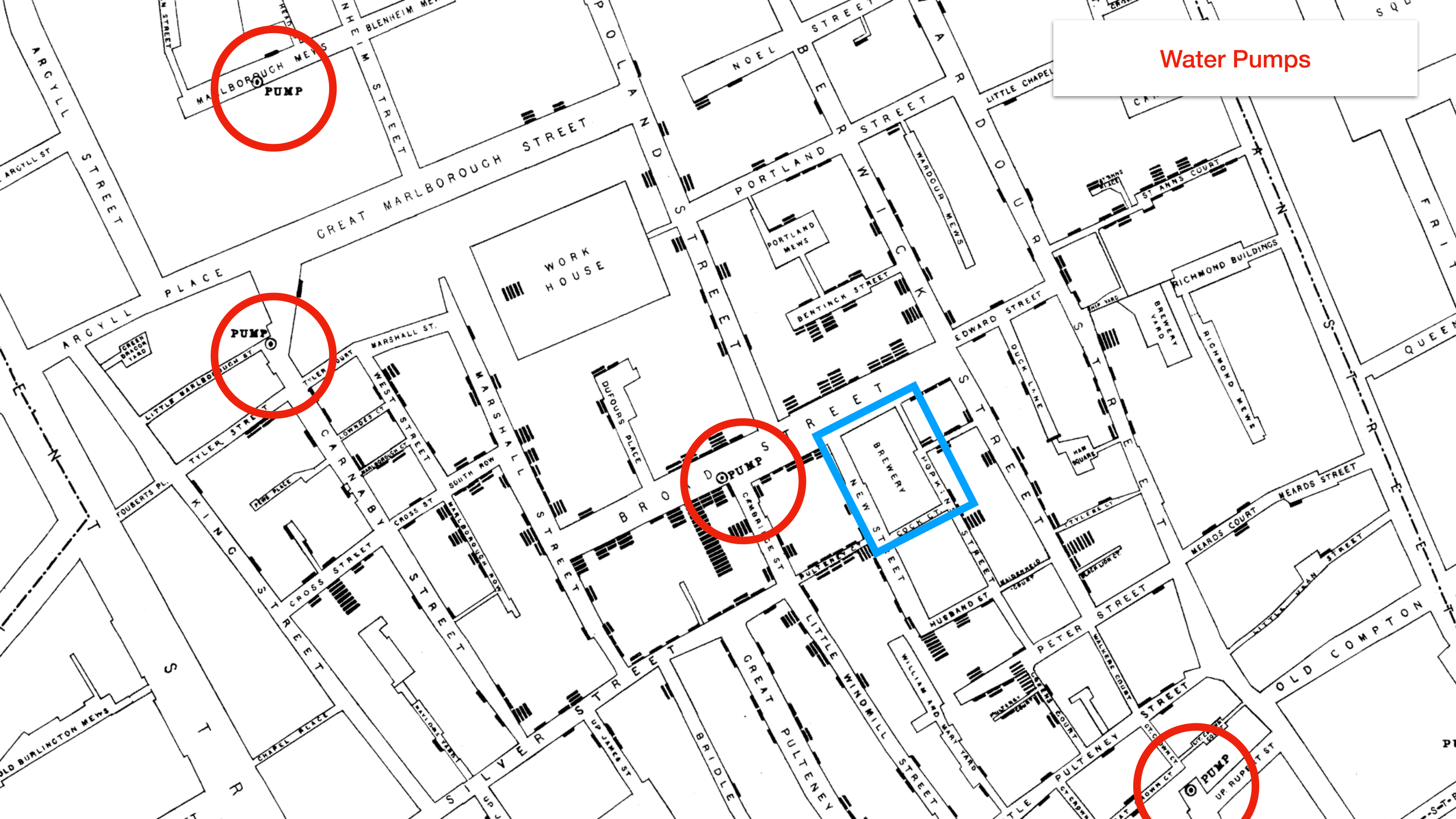



GREAT MARLBOROUGH STREET
ARGYLL PLACE
ARGYLL STREET
LITTLE MARLBOROUGH ST.
GREEN DRAGON YARD
PUMP
TYLER STREET
FOUBERTS PL.
KINGS STREET
TYLER COURT
MARSHALL ST.
CARNABY STREET
WORK HOUSE
DUFOURS PLACE
BROAD STREET
PUMP
PORTLAND STREET
PORTLAND MEWS
BENTINCK STREET
WARDOUR MEWS
EDWARD STREET
DUCK LANE
HAM SQUARE
BREWERY YARD
RICHMOND BUILDINGS
RICHMOND MEWS
ST ANNS COURT
QUEEN
FRITH
REGENT
CROSS STREET
CHAPEL PLACE
NEW BURLINGTON MEWS
NEW BURLINGTON STREET
BEAK ST.
WARWICK
SILVER STREET
UP JAMES ST
UP JOHN ST
GOLDEN SQUARE
BRIDLE STREET
GREAT PULTENEY STREET
LITTLE WINDMILL STREET
CAMBRIDGE ST
NEW STREET
BREWERY
HOPKINS STREET
HUSBAND ST
WILLIAM AND MARY YARD
PETER STREET
WALKERS COURT
LITTLE PULTENEY STREET
GREAT CROWN CT
QUEENS HEAD COURT
PUMP
UP RUPERT ST
RICHMOND ST
PLOUGH YARD
OLD COMPTON
MEARDS COURT
MEARDS STREET
REGENT STREET


BROAD STREET
PUMP
BREWERY
NEW STREET
HOPKINS STREET
COCK CT
CAMBRIDGE ST
FULTHENE
HUSBAND ST
LITTLE WINDMILL ST
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KING STREET
CROSS STREET
GREAT PULTENEY STREET
LITTLE WINDMILL STREET
PETER STREET
OLD COMPTON
RICHMOND BUILDINGS
EDWARD STREET
NOEL STREET
PORTLAND MEWS
BENTINCK STREET
WARDOUR MEWS
DUFOURS PLACE
CARNABY STREET
NEWCASTLE STREET
DUKE STREET
NEW STREET
BREWERY
DUCK LANE
RICHMOND MEWS
BREWERY YARD
ST ANNS COURT
HEARDS COURT
HEARDS STREET
OLD BURLINGTON MEWS
CHAPEL PLACE
TYLER STREET
LITTLE MARLBOROUGH ST
GREEN DRAGON YARD
MARLBOROUGH ROW
SOUTH ROW
HUSBAND ST
WILLIAM AND MARY YARD
WALKERS COURT
PULTENEY COURT
UP JAMES ST
UP RUPERT ST


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Water Pumps
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RICHMOND MEWS
HAM SQUARE
SHIP YARD
GREEN DRAGON YARD
LITTLE MARLBOROUGH ST
TYLER STREET
TYLER COURT
MARLBOROUGH PLACE
MARLBOROUGH CT
LOWNDES CT
WEST STREET
CANNON
SOUTH ROW
MARLBOROUGH ROW
CROSS ST
TAYLORS STREET
UP JAMES ST
BRIDLE
NOEL STREET
LITTLE CHAPEL
ST ANNS YARD
FRI
QUEEN
UP RUPERT ST

Broad Street Pump

- Snow got pump handle removed
  - It was later discovered a cesspit had been leaking into the well
- Observational study
  - Snow did not control the pump or the people
  - Association was strong, but he could not prove causation

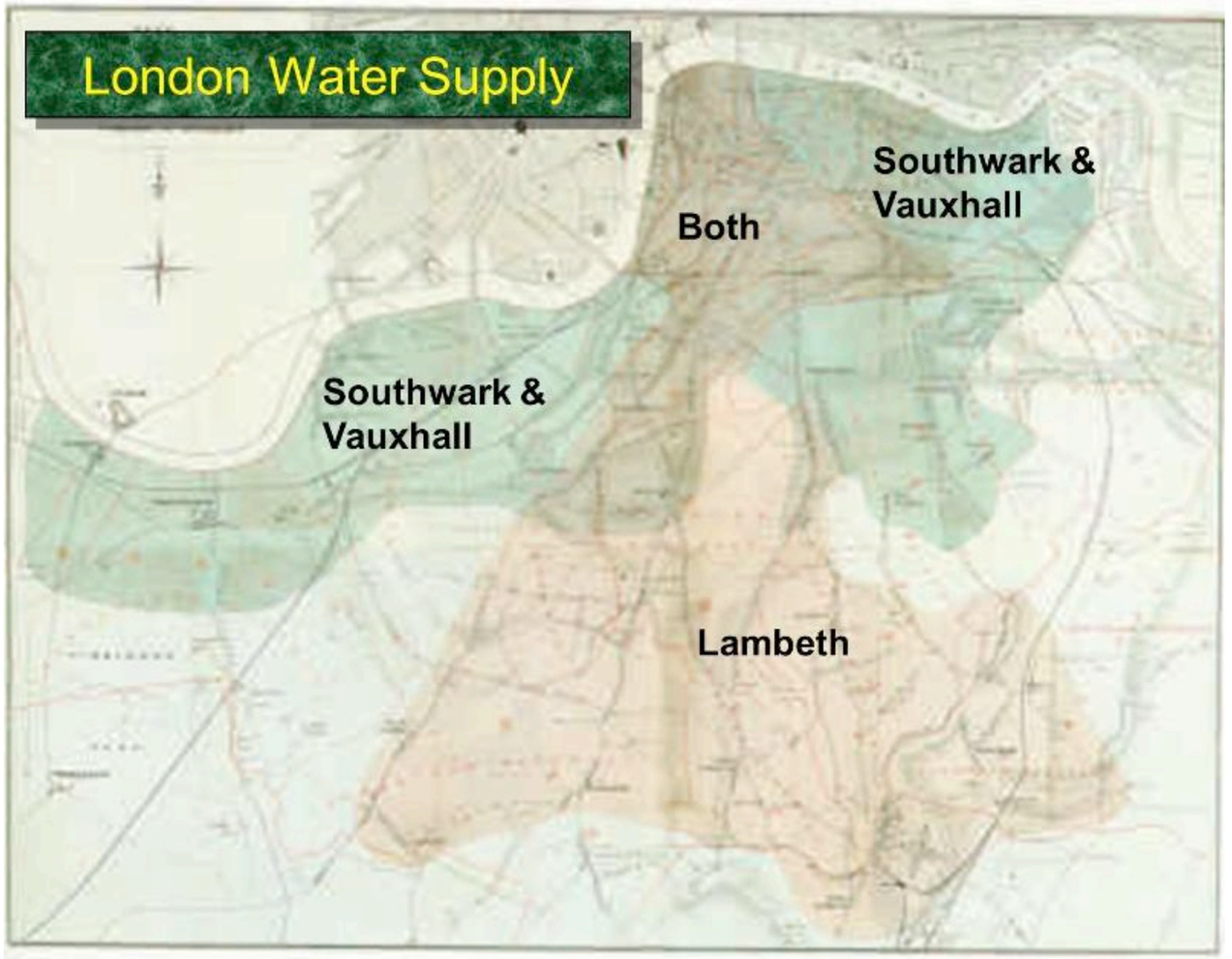


Showing Causation

Snow investigated cases in an area served by two water companies

- Southwark and Vauxhall's intake was in heavily polluted area of the Thames

- Lambeth's water intake was in a less polluted area upstream



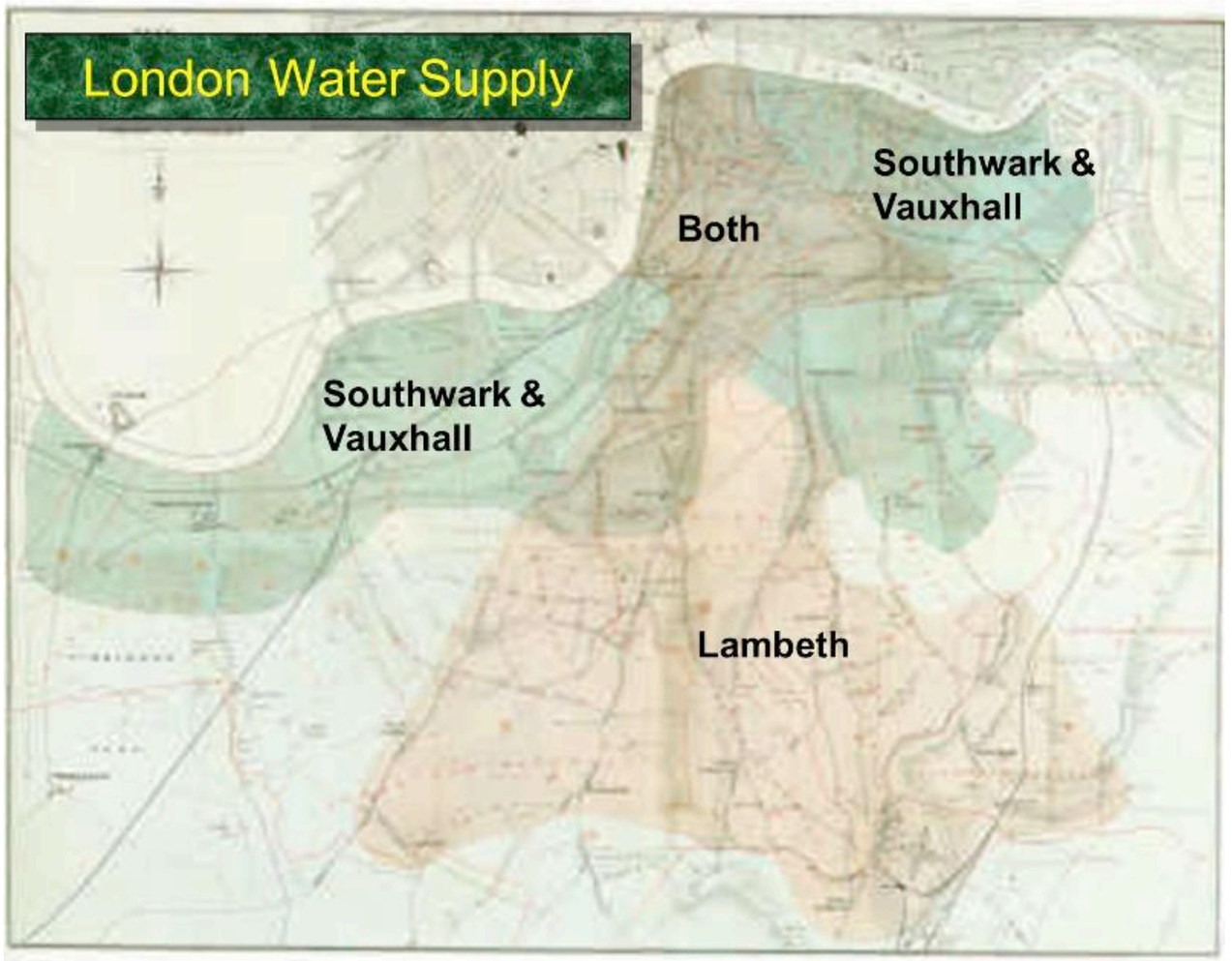
Snow's "Grand Experiment"

Treatment group: S&V

Control group: Lambeth

"… there is no difference whatever in the houses or the people receiving the supply of the two Water Companies, or in any of the physical conditions with which they are surrounded…"

Two groups are similar except for the treatment



Snow’s “Grand Experiment”

Deaths From Cholera Epidemic in Districts of London Supplied by Two Water Companies Over 7 Weeks, 1854

Water Supply Company	Number of Houses	Deaths From Cholera	Cholera Deaths per 10,000 Houses
Southwark and Vauxhall	40,046	1,263	315
Lambeth	26,107	98	37
Rest of London	256,423	1,422	59

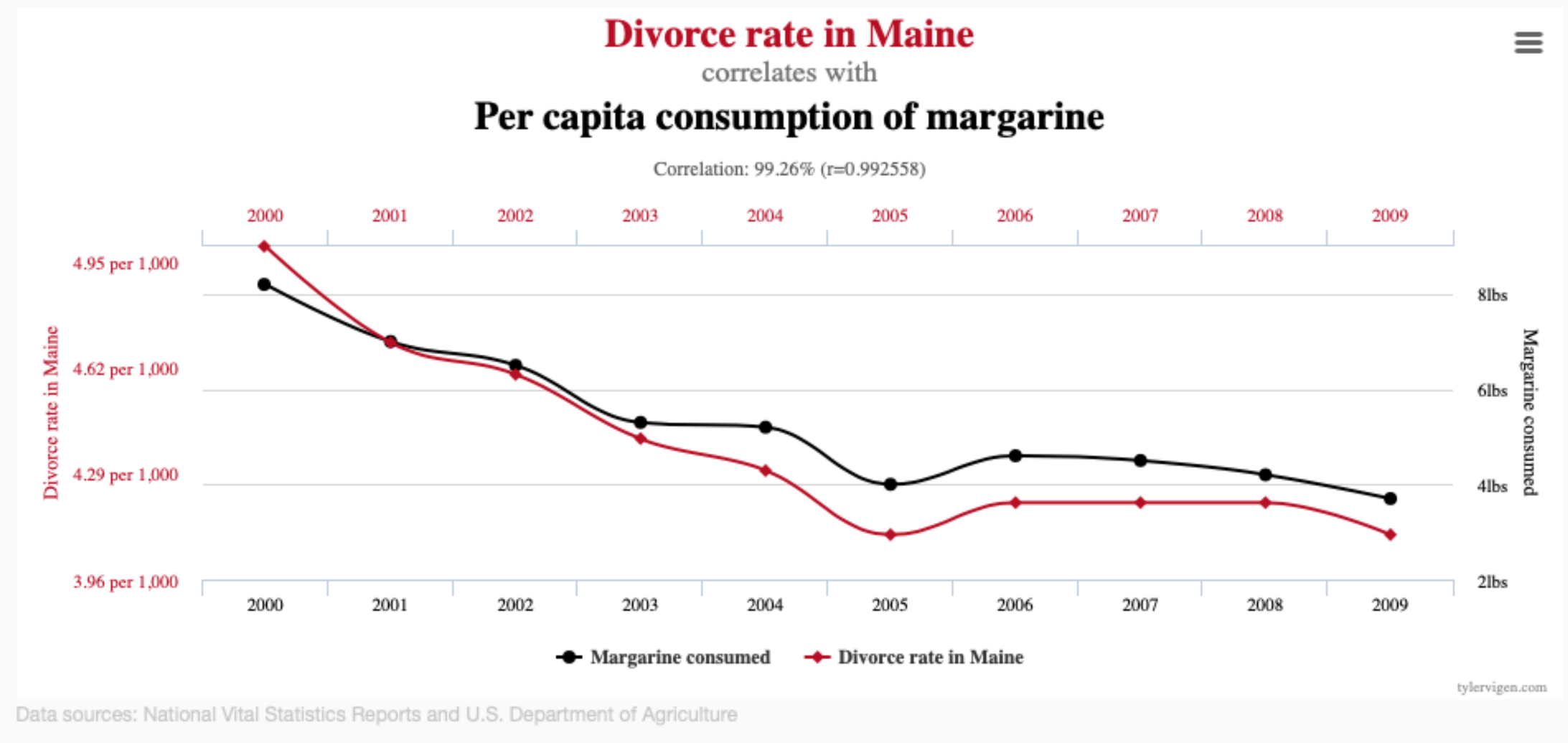
Key to Establishing Causality

- Treatment group: Receives the treatment

- Control group: Does not receive the treatment

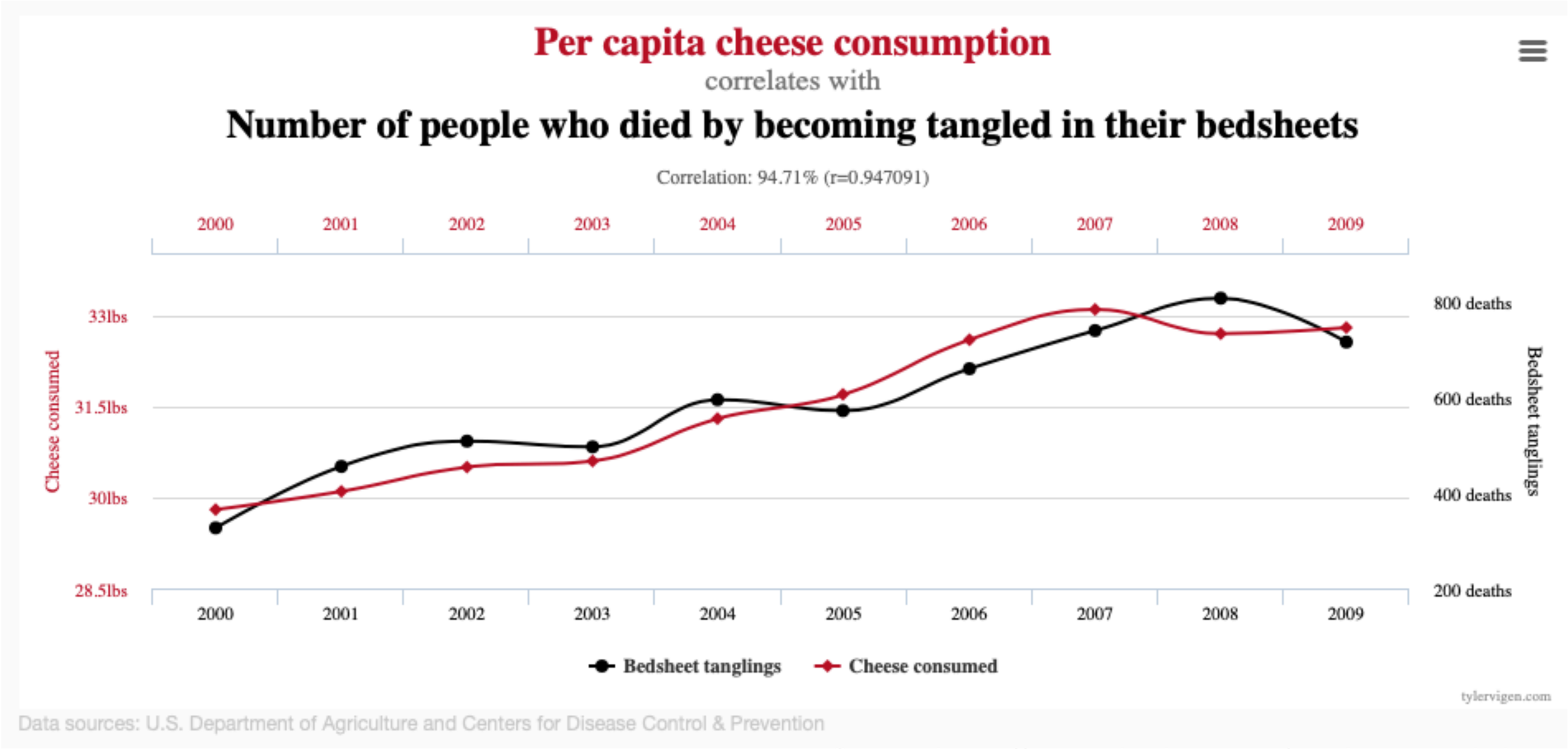
If the treatment and control groups are *similar apart from the treatment*, then differences between the outcomes in the two groups can be ascribed to the treatment

Confounding Factors / Spurious Correlations



Source: https://www.tylervigen.com/spurious-correlations

Confounding Factors / Spurious Correlations



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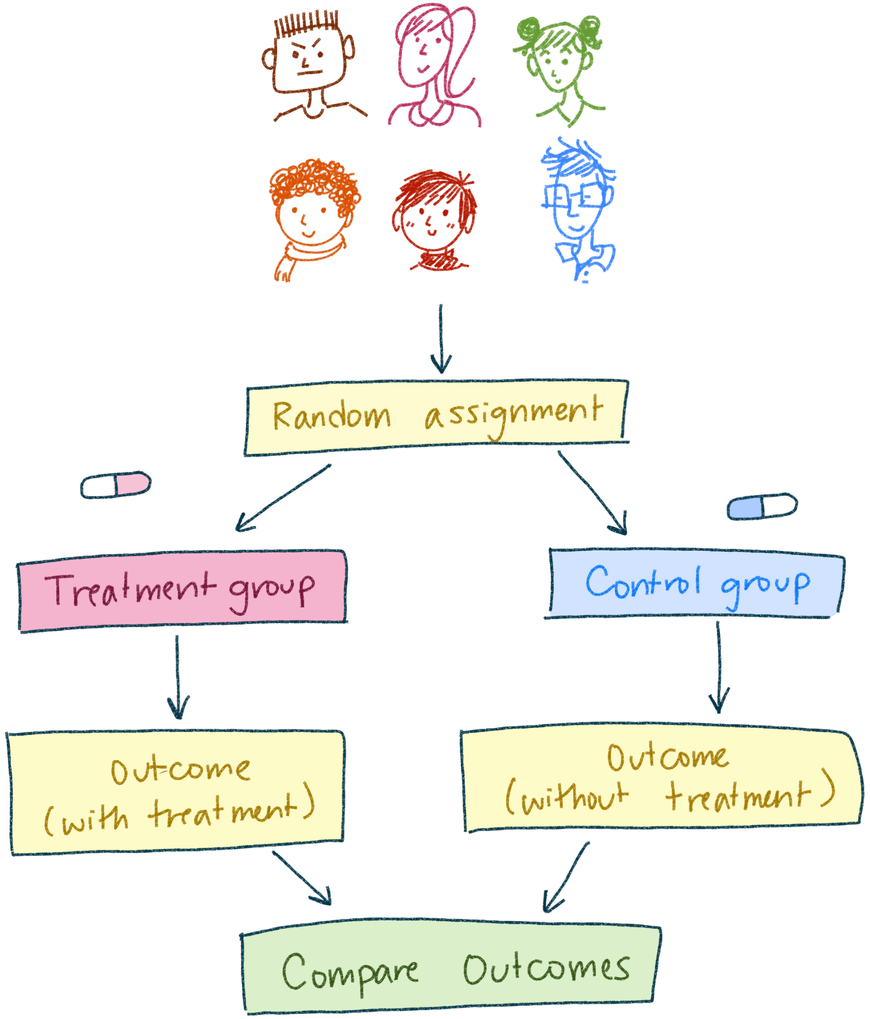
How to determine causation vs random correlation?

Randomization!

- If you assign individuals to treatment and control at random, then the two groups are likely to be similar apart from the treatment.

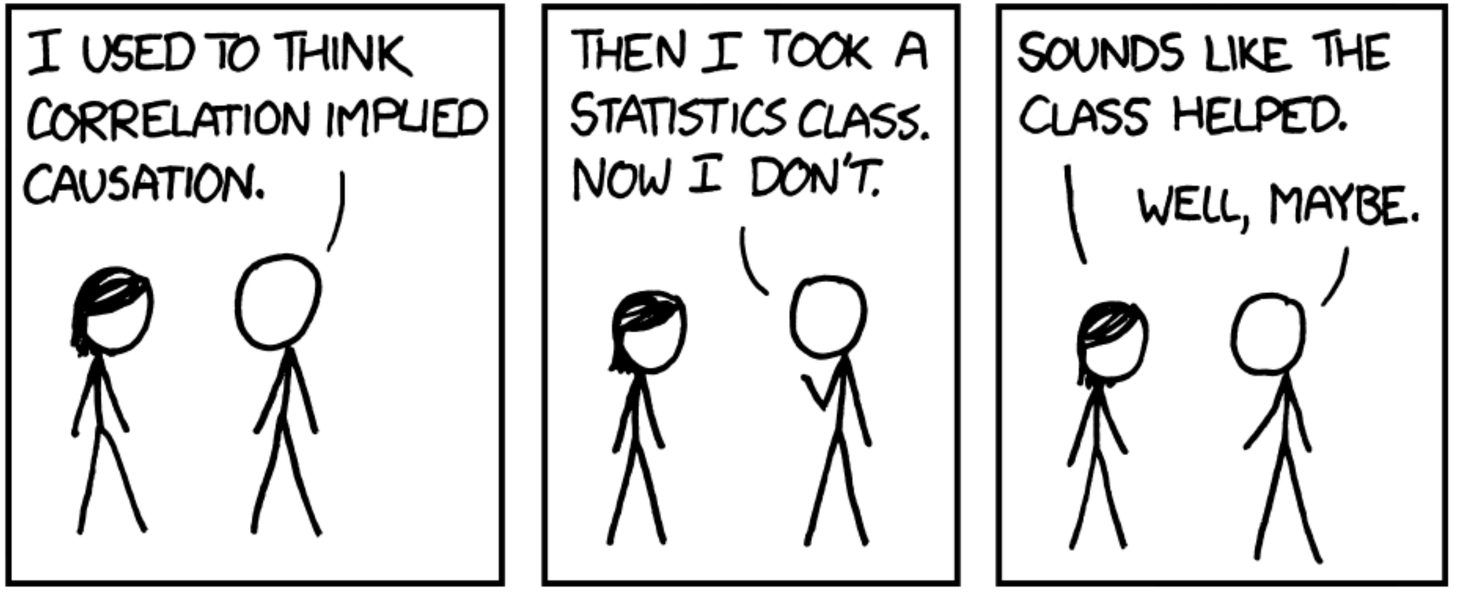
- Known as a **Randomized Controlled Experiment** or **Randomized Controlled Trial (RCT)**

- You can account (mathematically) for variability in the assignment



Correlation

|< < Prev Random Next > >|



|< < Prev Random Next > >|

https://xkcd.com/552/

Next Class

- Intro to Python: Expressions and Data Types
  - Bring your laptops if you want to follow along :)
- Remember: Labs start next week!!