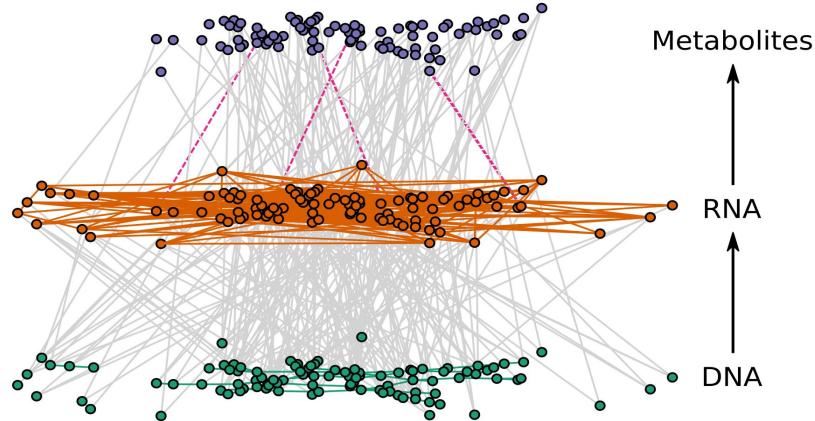


# Lecture 0: Introduction to Applied Research in Health Data Science

CSCI6410/4148 & EPAH6410

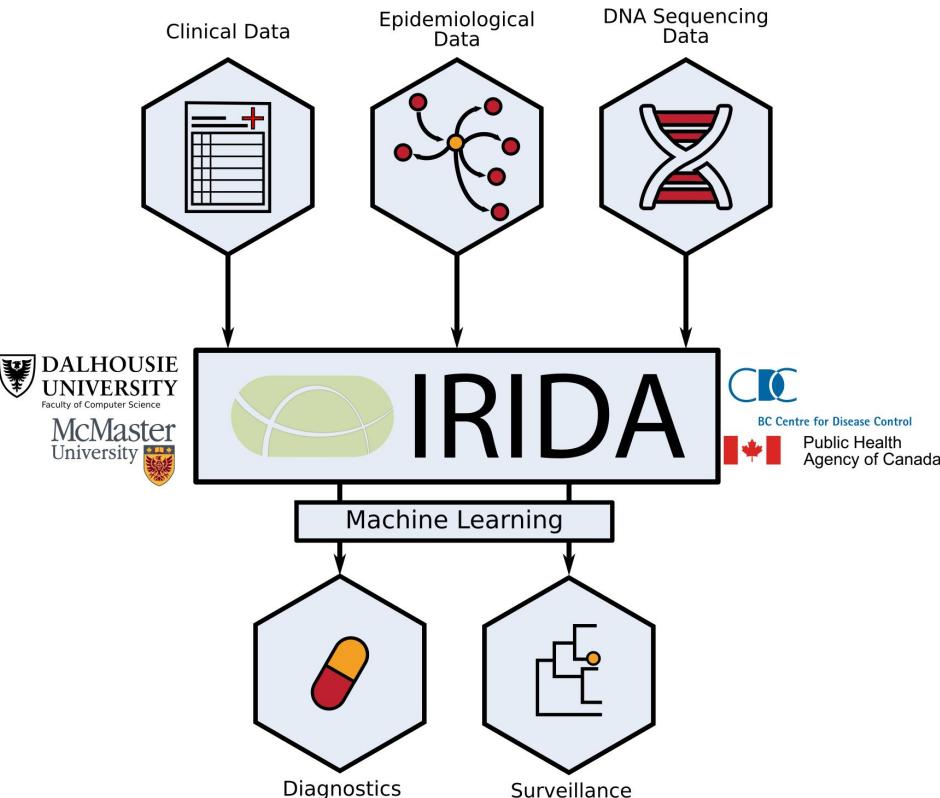
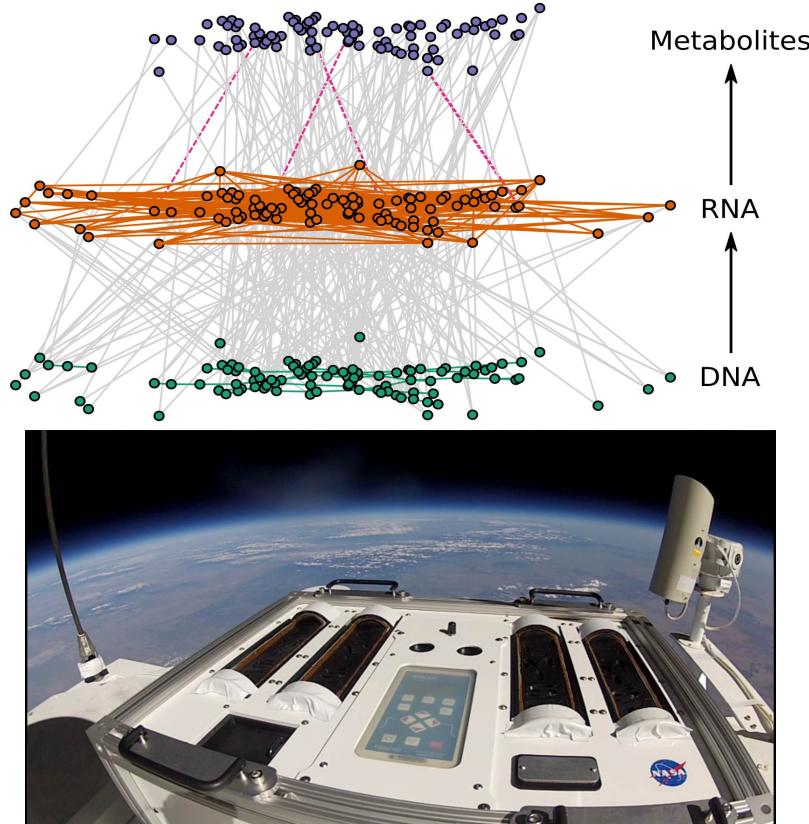
Finlay Maguire ([finlay.maguire@dal.ca](mailto:finlay.maguire@dal.ca))  
TA: Ehsan Baratnezhad ([ethan.b@dal.ca](mailto:ethan.b@dal.ca))

# Why am I teaching this course?



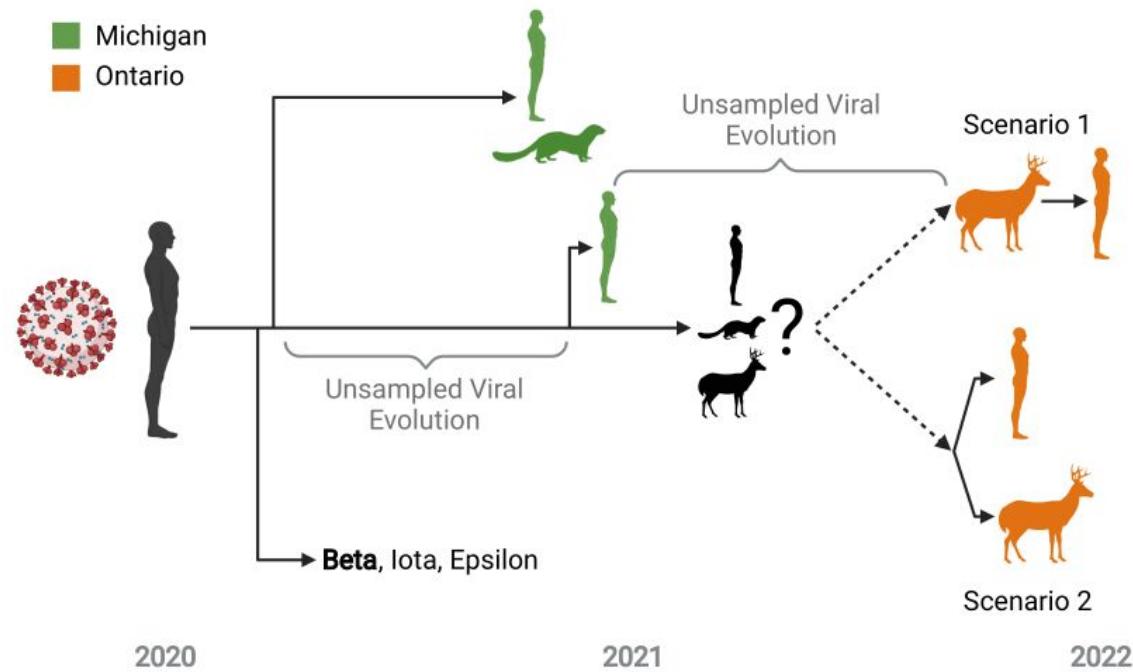
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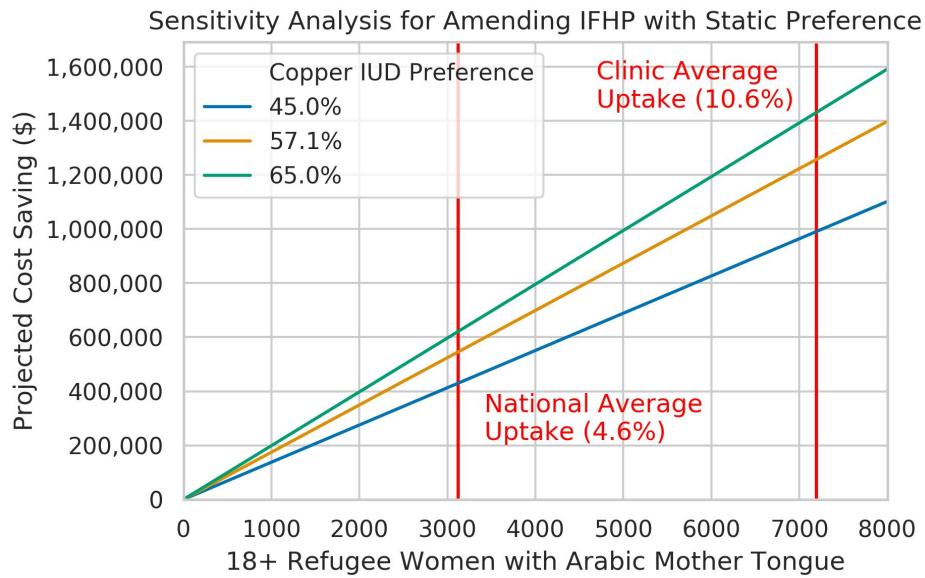
- **PhD (Bioinformatics):** using large noisy datasets to understand how microbial systems and mechanisms evolve.
- **Postdoc (Genomic Epidemiology):** using large noisy datasets to better diagnose, track and predict infectious diseases.

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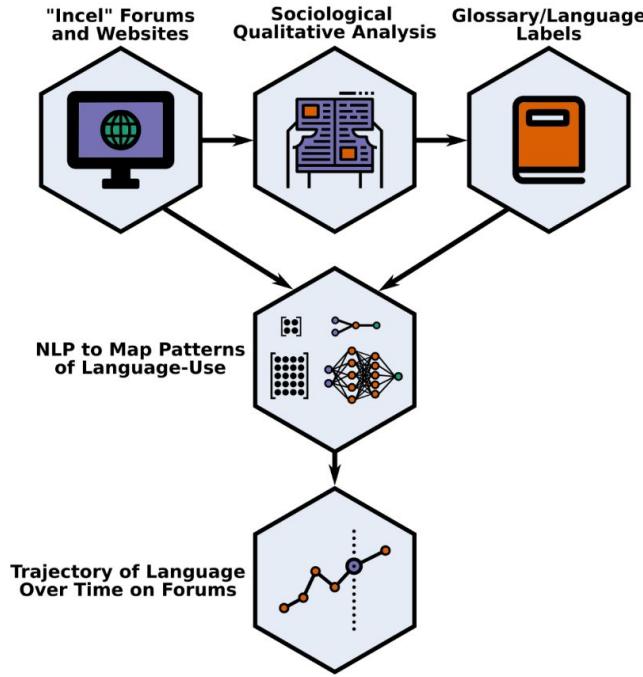


- **Research group:** using large noisy datasets:
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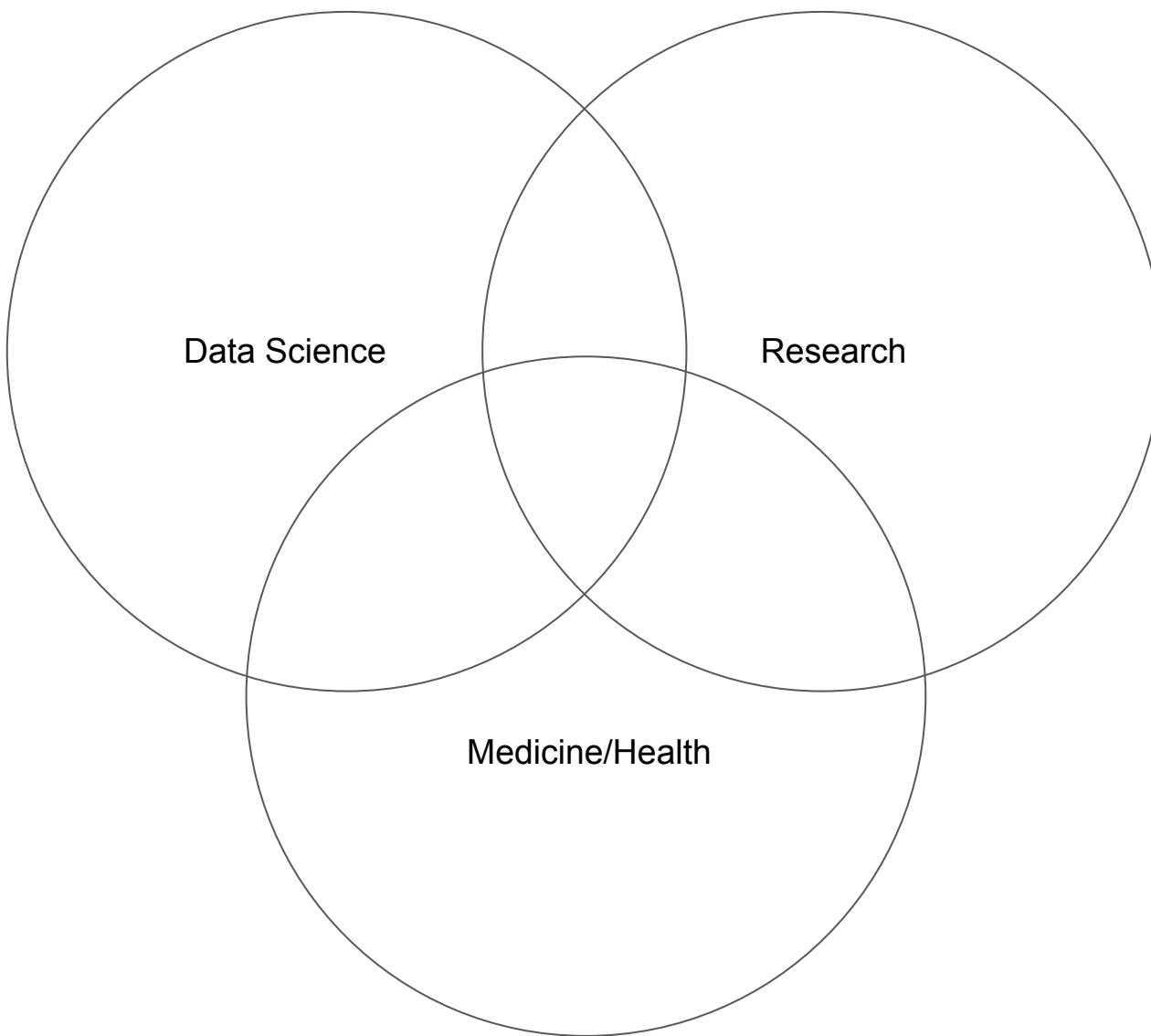
Modelling “Incel” Online Radicalisation via NLP



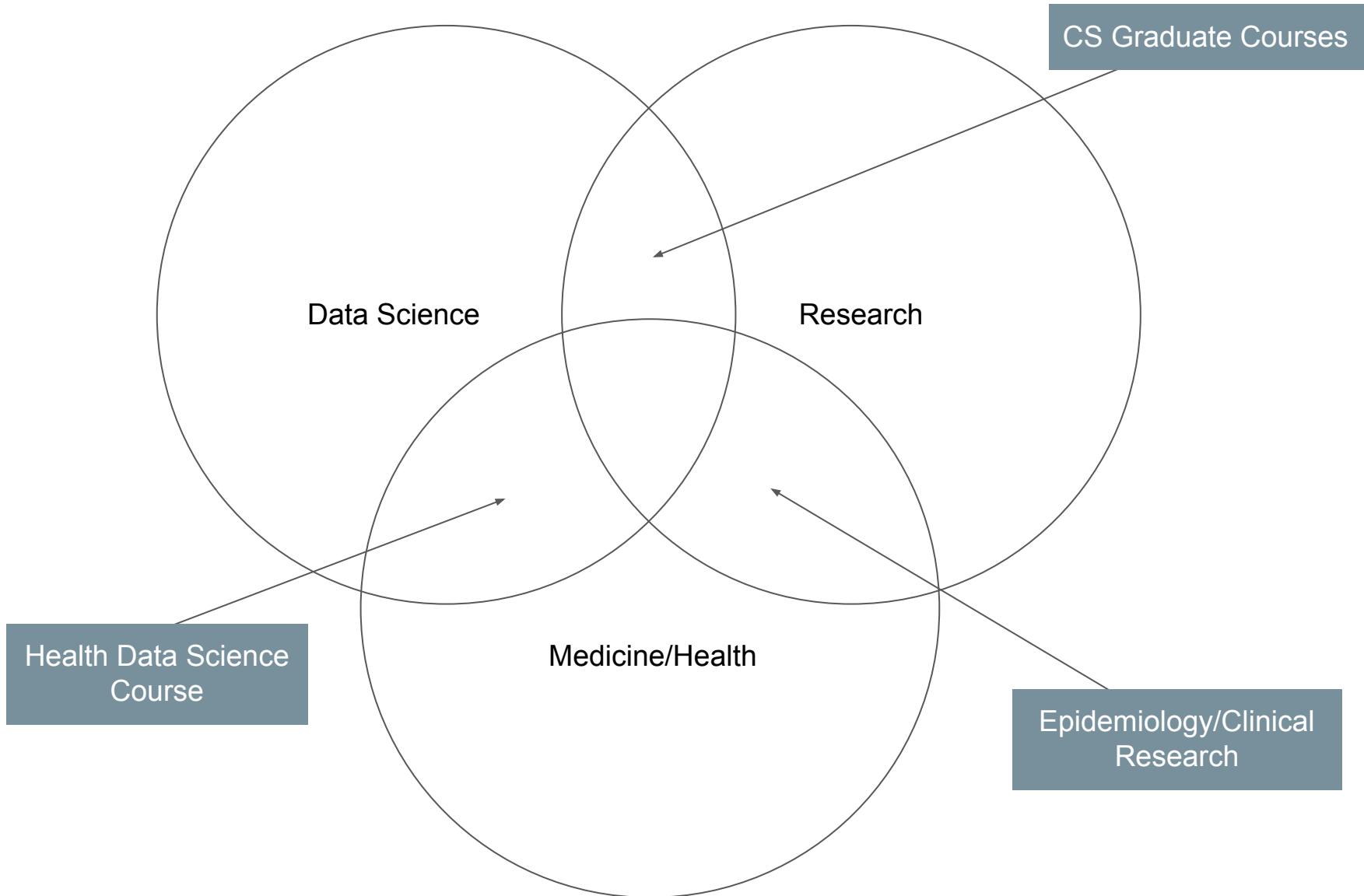
- **Research group:** using large noisy datasets:
  - Genomic epidemiology of infectious disease: **SARS-CoV-2, AMR**
  - Collaborations on socially/health focused problems: **refugee health, incel radicalisation, health inequality**

# Overview of course

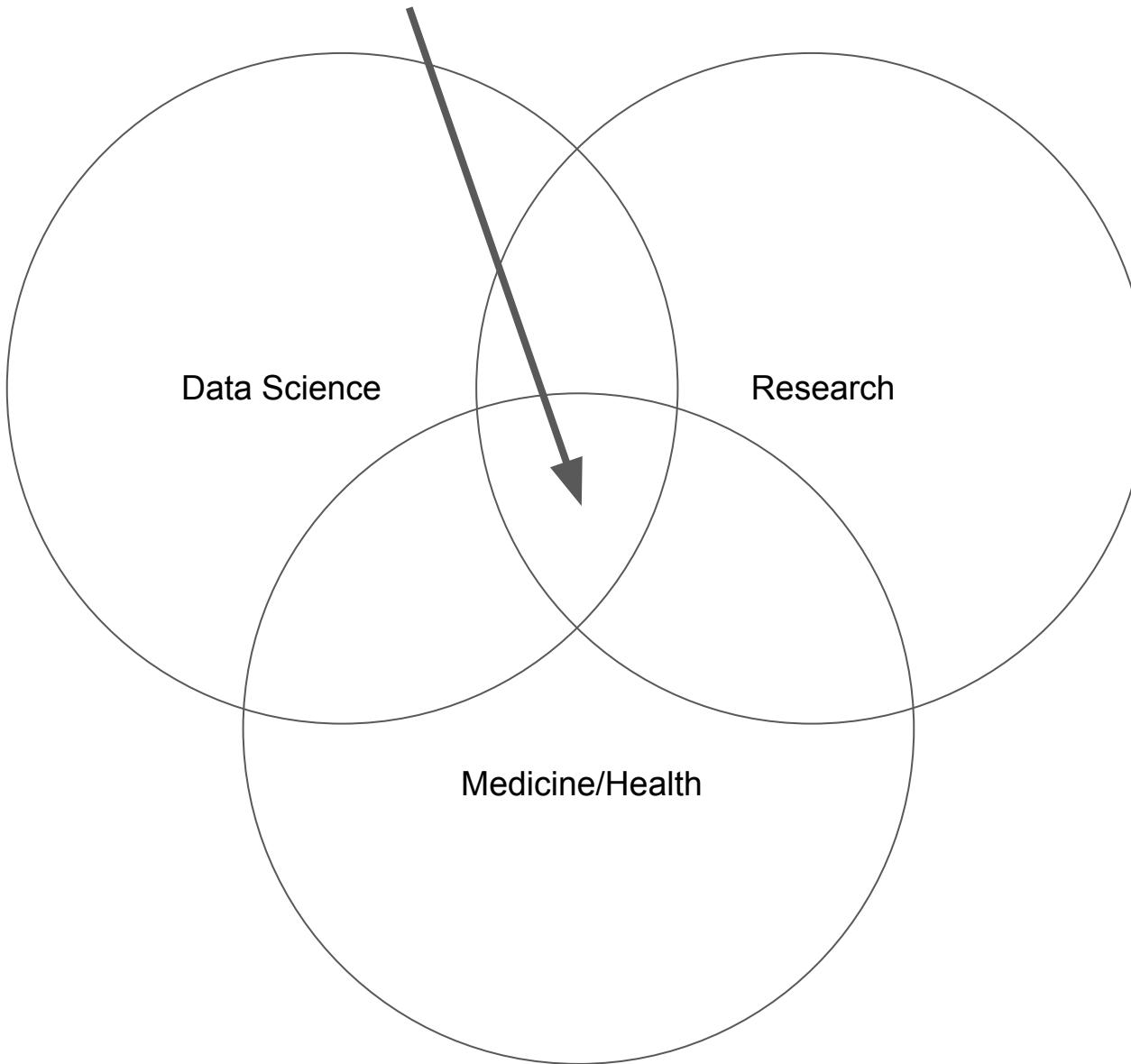
# Applied Research in Health Data Science



# Applied Research in Health Data Science



# Applied Research in Health Data Science



# Learning Outcomes

1. Understand the **4 principal sources and data types** of medical data:
  - a. longitudinal databases (tabular)
  - b. electronic medical records (structured, semi-structured, and unstructured text)
  - c. radiological imaging (image)
  - d. physiological (signal and time-series)

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5. Critically **appraise research literature** in health data science.
6. Combine these skills to develop high-quality collaborative health data science **research proposals**

# What is not covered in this course

- **Breadth/depth** of each data science method: *each could be multiple graduate CS courses*

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- **Breadth/depth** of medical research: *again could be a whole PhD program*
- True **messiness** of real data: *provide tools but experience is invaluable*
- Some important forms of medical data (e.g., genomics): see **CSCI4181/6810, EPAH6052 (partially)**, come speak to me if interested in this specifically.

# Course Structure

## Overview of data types & analysis methods:

- **Lectures** (Monday/Wednesday)

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(CSCI4148: drop lowest scoring assignment)

```
dens <- density(data, n = npts)
dx <- dens$x
dy <- dens$y
if(add == TRUE)
  plot(0., 0, main = "", xlab = "", ylab = "")
  if(orientation == "horizontal")
    dx2 <- (dx - min(dx)) / max(dx)
    x[1.]
    dy2 <- (dx - min(dx)) / max(dy)
    y[1.]
    seqbelow <- rep(y[1.], length(dx))
    if(Fill == T)
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## Research in health data science:

- **Journal Club** (Wednesday/Friday)

2 papers per week, randomly assigned rota for leading discussion of paper with rest of class.

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Paper presentation (10%)

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<https://www.coursera.org/learn/r-programming>

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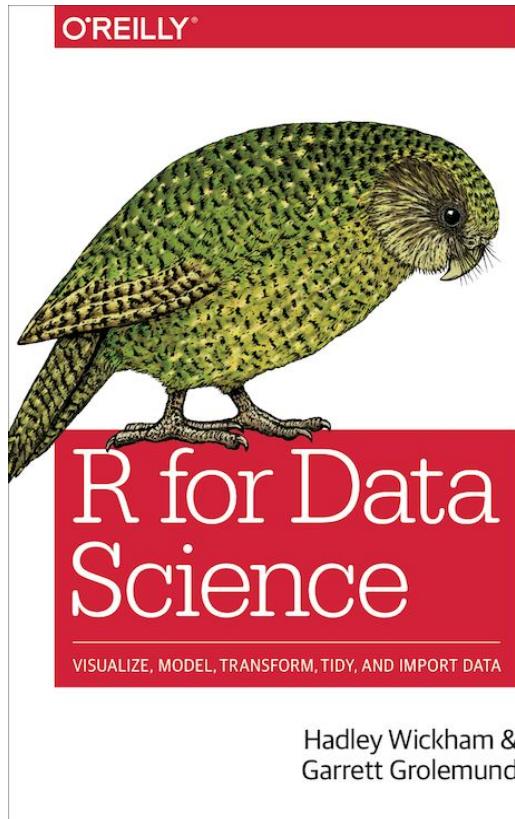
- **Class** (Wednesday/Friday)

Assessment:

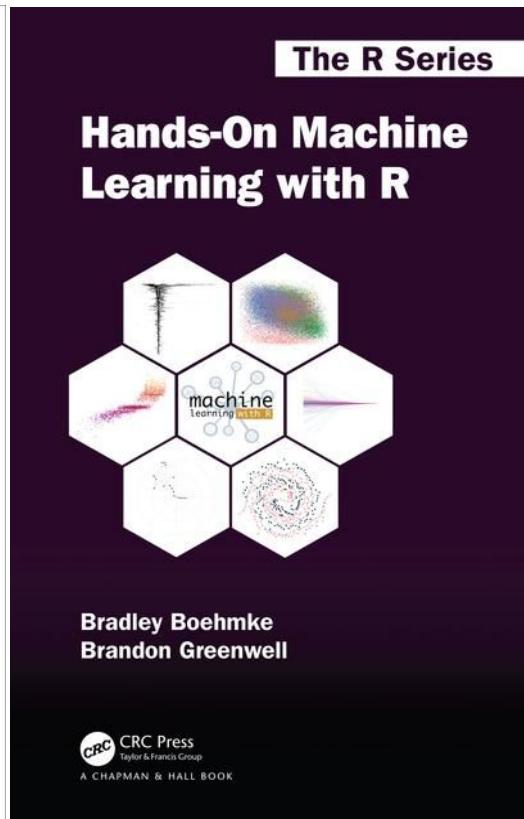
Presentation last full week of class (25%)

Submitted final day of class (15%)

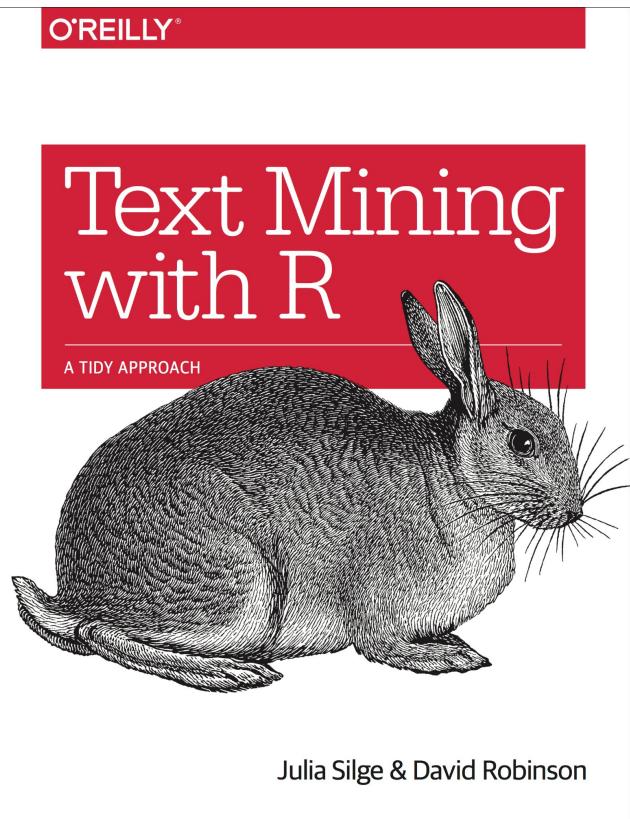
# Course Materials



<https://r4ds.had.co.nz/>



<https://bradleyboehmke.github.io/HOML/>



<https://www.tidytextmining.com/>

# Course Website



CSCI6410/CSCI4148/EPAH6410: Applied Research in Health Data Science / Summer 2023-2024

## Updates

- New Lecture is up: Lecture 0 - Introduction to health data science [[slides](#)]

**[https://maguire-lab.github.io/health\\_data\\_science\\_research\\_2025/](https://maguire-lab.github.io/health_data_science_research_2025/)**

# Course Website



Dalhousie University  
**CSCI6410/CSCI4148/EPAH6410: Applied Research in Health Data Science**  
Summer 2024-2025

HOME SCHEDULE LECTURES PRACTICALS PROPOSAL LITERATURE

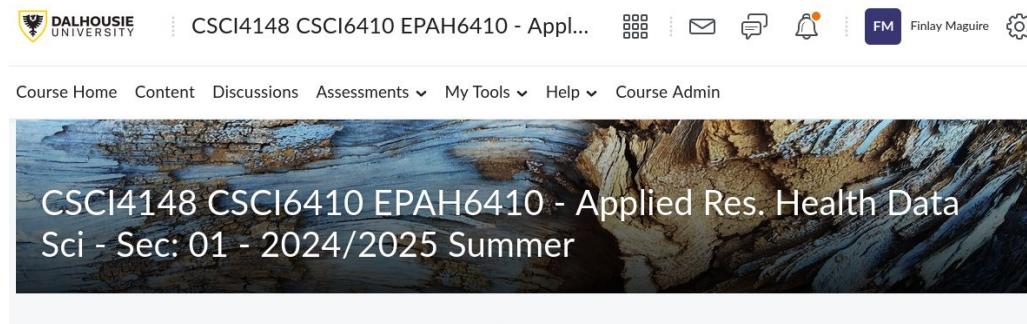
**CSCI6410/CSCI4148/EPAH6410: Applied Research in Health Data Science** / Summer  
2024-2025

## Course Description

This course is an introduction to the application of data science methods to health data within interdisciplinary research contexts. Students will be introduced to the main types of health data and their principal analysis methods while developing key research skills specific to effectively working at the intersection of medicine and computer science. This will encompass developing technical skills in the robust/reproducible analysis of data from medical databases, radiological imaging, electronic medical records, and physiological time-series data. Students will also gain specific training in developing interdisciplinary health data science research proposals including key considerations such as research ethics, data legislation, knowledge translation, and effective collaboration.

## 2024 Course Details

**[https://maguire-lab.github.io/health\\_data\\_science\\_research\\_2025](https://maguire-lab.github.io/health_data_science_research_2025)**



DALHOUSIE UNIVERSITY CSCI4148 CSCI6410 EPAH6410 - Appl... Finlay Maguire

Course Home Content Discussions Assessments My Tools Help Course Admin

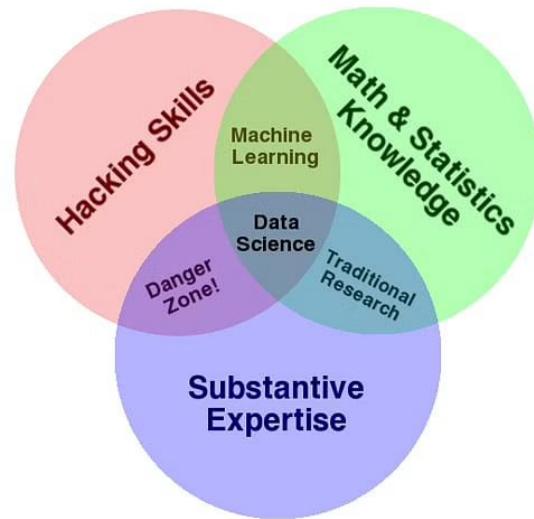
CSCI4148 CSCI6410 EPAH6410 - Applied Res. Health Data Sci - Sec: 01 - 2024/2025 Summer

## Grades/Submissions:

**<https://dal.brightspace.com/d2l/home/385844>**

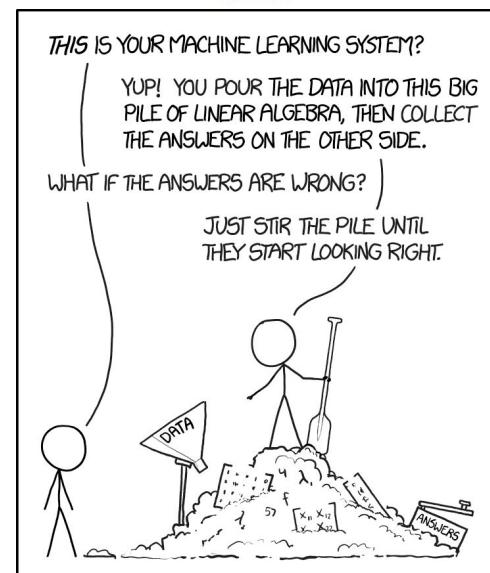
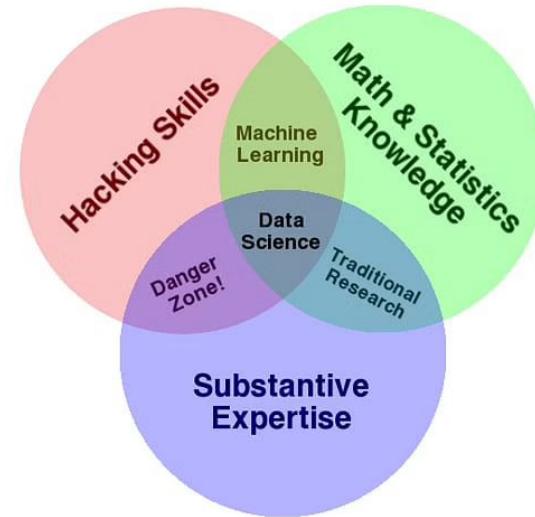
What is ~~health~~ data science?

# Data Science: *Data-intensive interdisciplinary approaches to understand and predict with secondary/live data*



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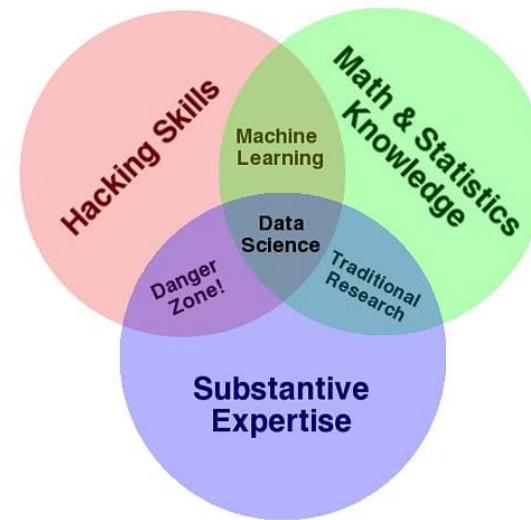
A range of partial and totally overlapping terms:



# Data Science: *Data-intensive interdisciplinary approaches to understand and predict with secondary/live data*

A range of partial and totally overlapping terms:

- Data Analytics
- Data Engineering
- Data Mining
- {Health,Bio,Medical}Informatics
- Database Analysis
- Business Intelligence
- Epidemiology
- Statistics
- **Machine Learning**
- Pattern Recognition
- Predictive Analytics
- Quantitative Researcher
- Scientist
- Analyst
- Algorithmic Modeling



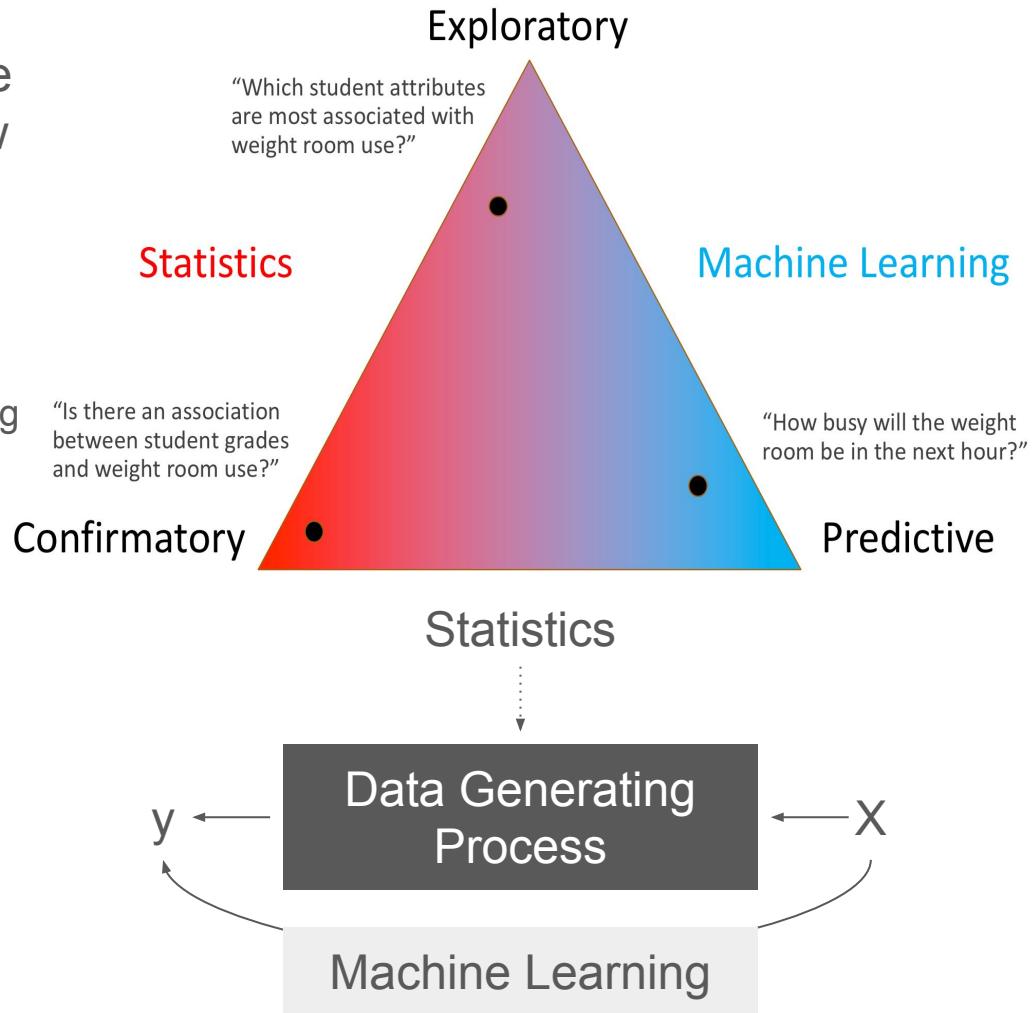
So, it is just statistics?

# Data Science/ML vs Statistics

- Many shared methods
- Difference in focus/priorities/culture

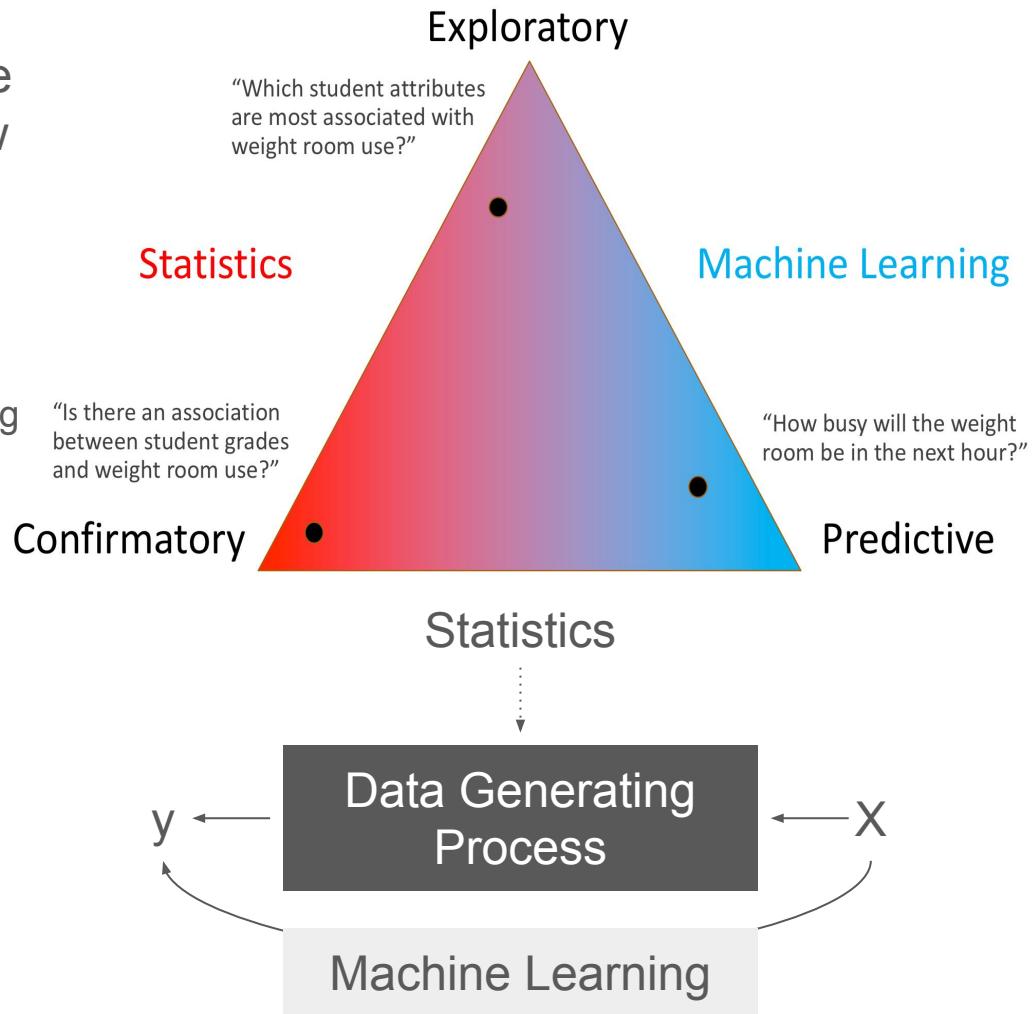
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- Statistics ~ tries to understand how outcome was generated by data
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- Alternative framing:
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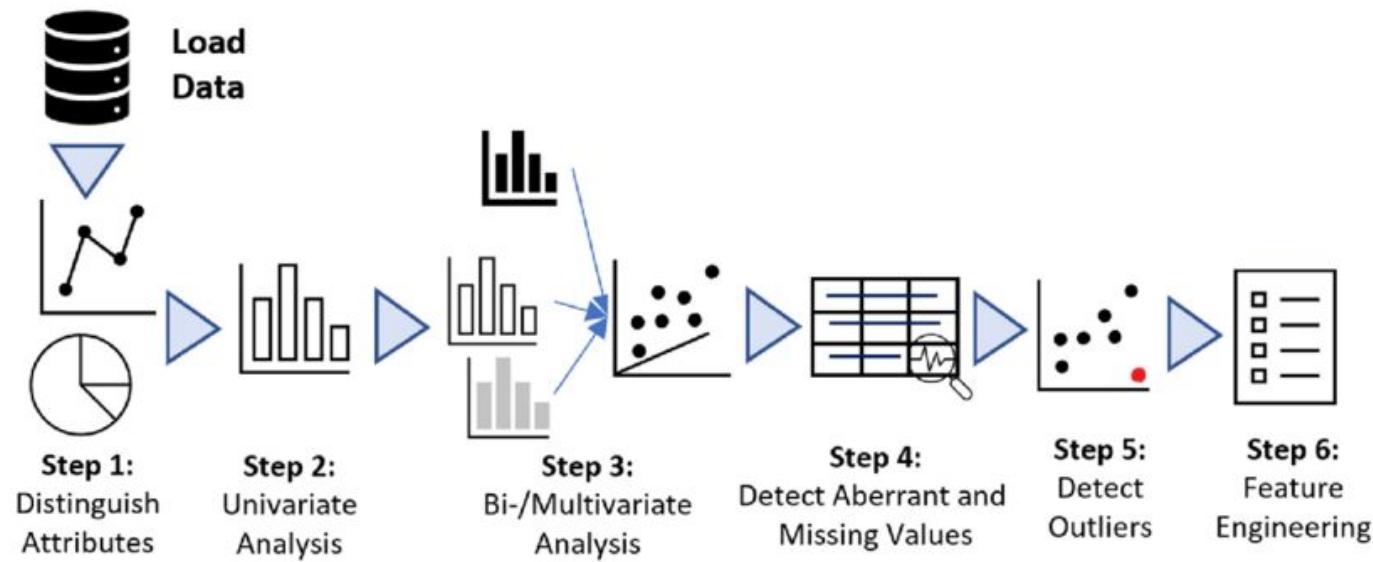


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  - Statistics ~ tries to understand how outcome was generated by data
  - ML infers/learns a process for linking data to outcome
  - Alternative framing:
    - Data Modelling vs Algorithmic Modelling
  - DS/ML Pitfalls (can be):
    - Less rigorous/principled
    - Prone to reinventing the wheel
  - DS/ML Benefits (can be):
    - More flexible
    - Less prescriptive/intimidating



# Data science centers exploratory data analysis

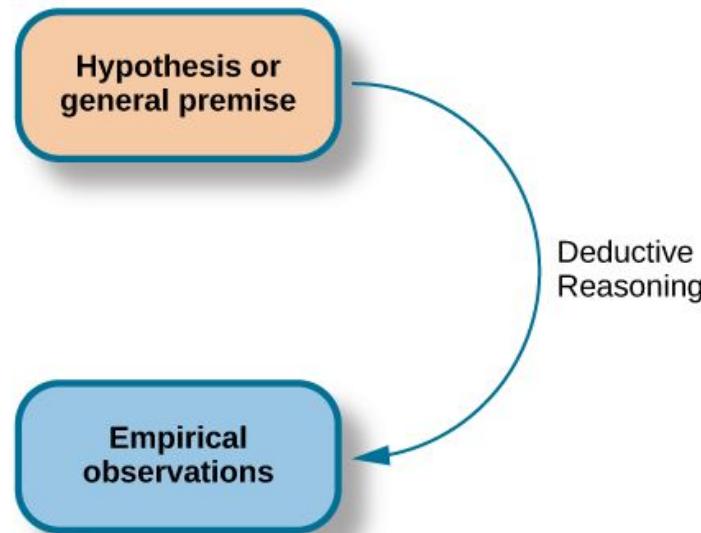


# Data science supports inductive approaches

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## Deductive:

- “Condition X, causes Y”
- Collect data
- Perform (typically) frequentist statistical tests
- Reject or confirm null hypothesis



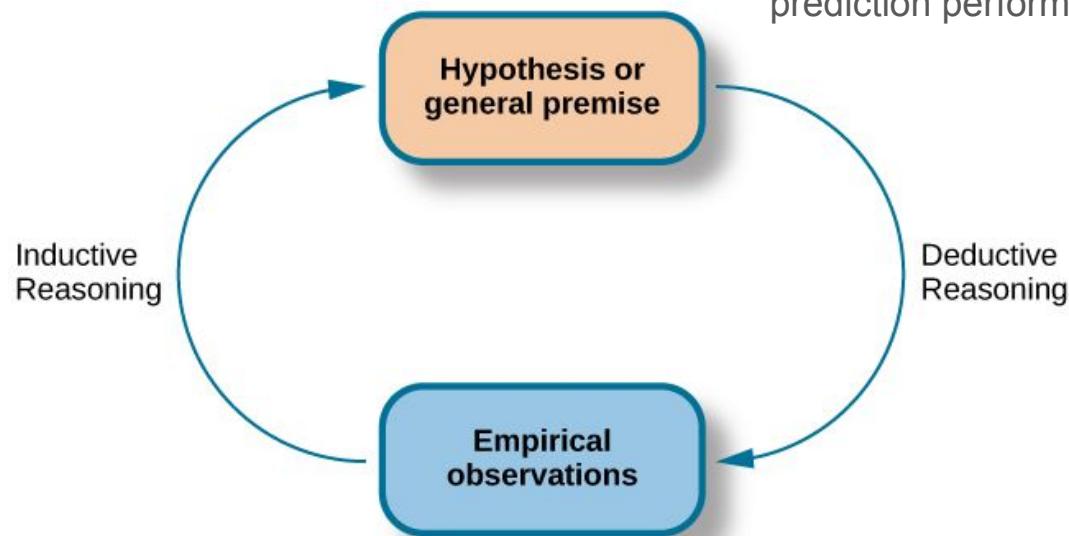
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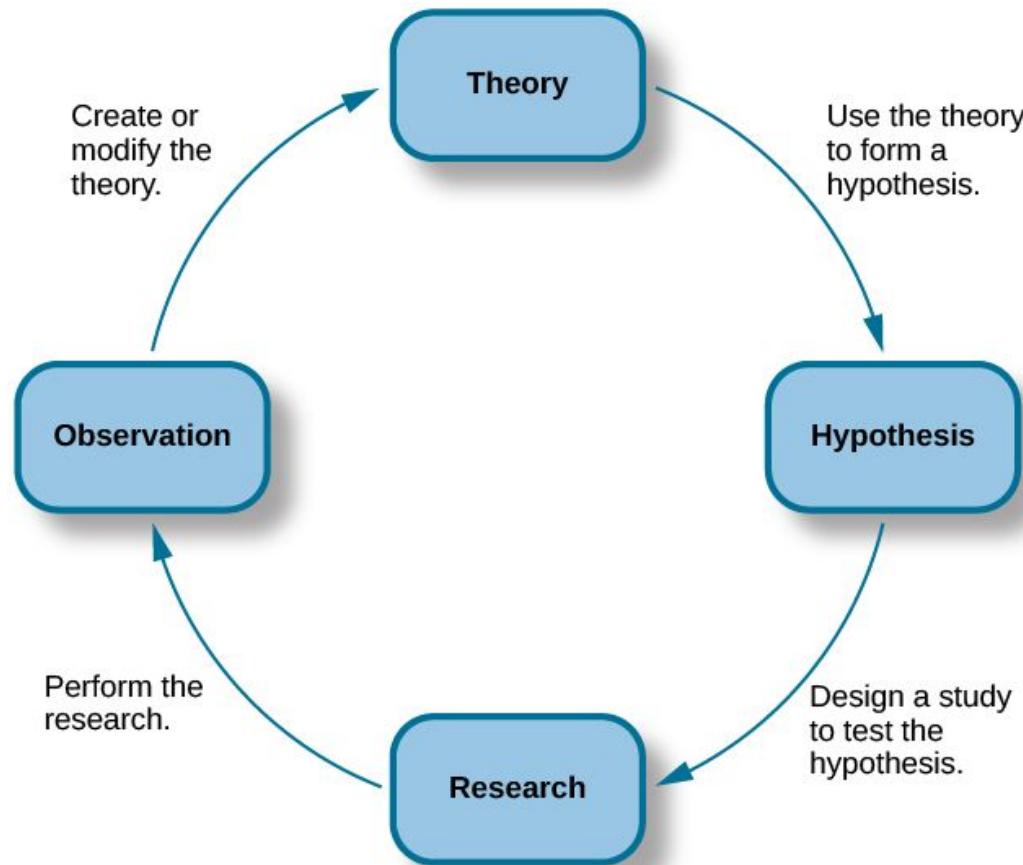
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## Inductive:

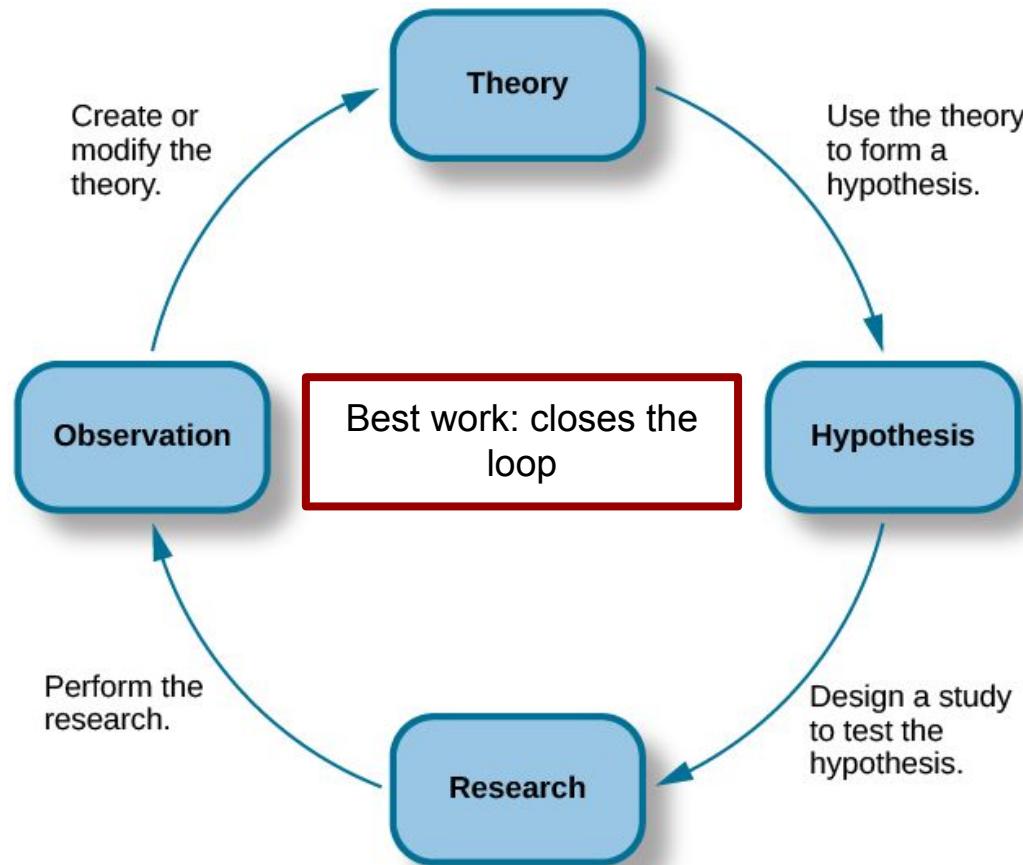
- Collect data
- Identify patterns in the data
- Observe X and Y seem connected somehow
- Quantify strength of association e.g., prediction performance



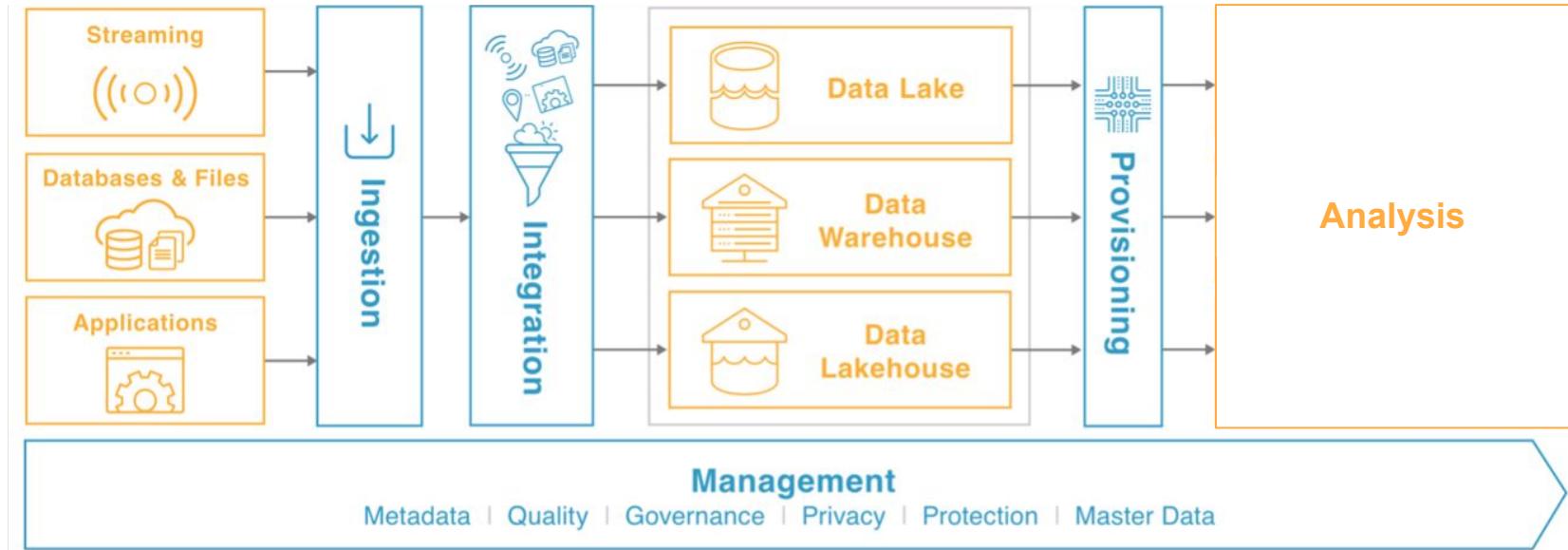
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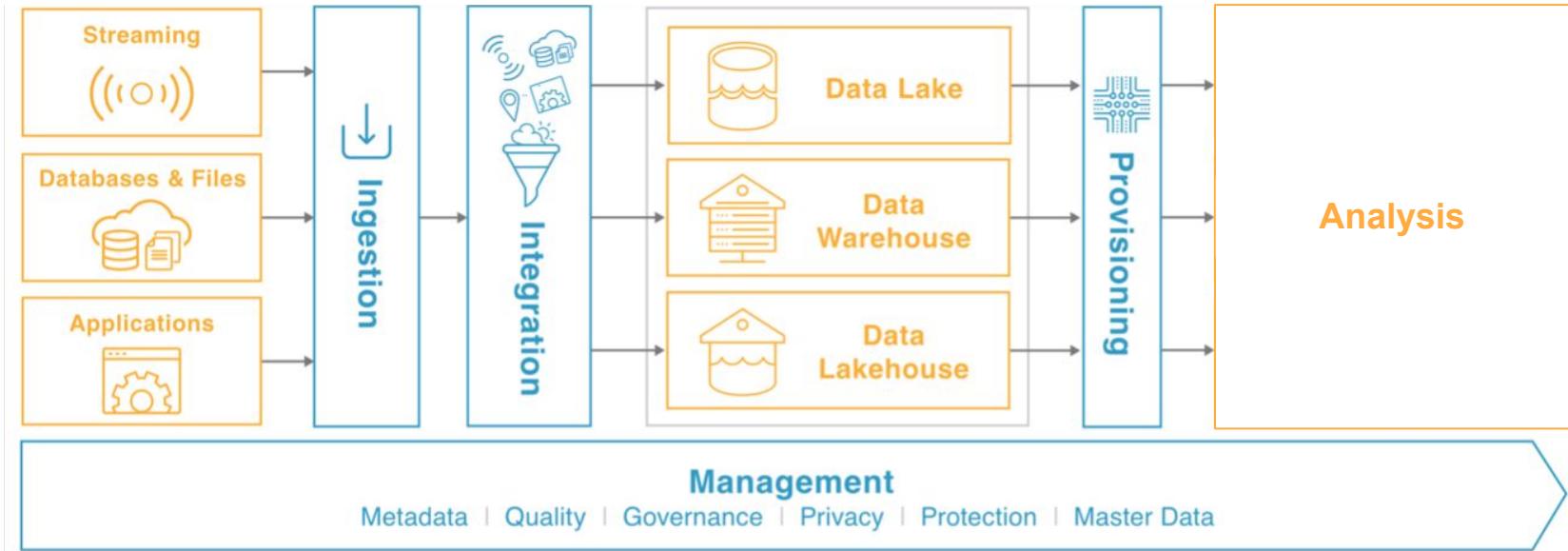


# Data science is integrated into a data ecosystem

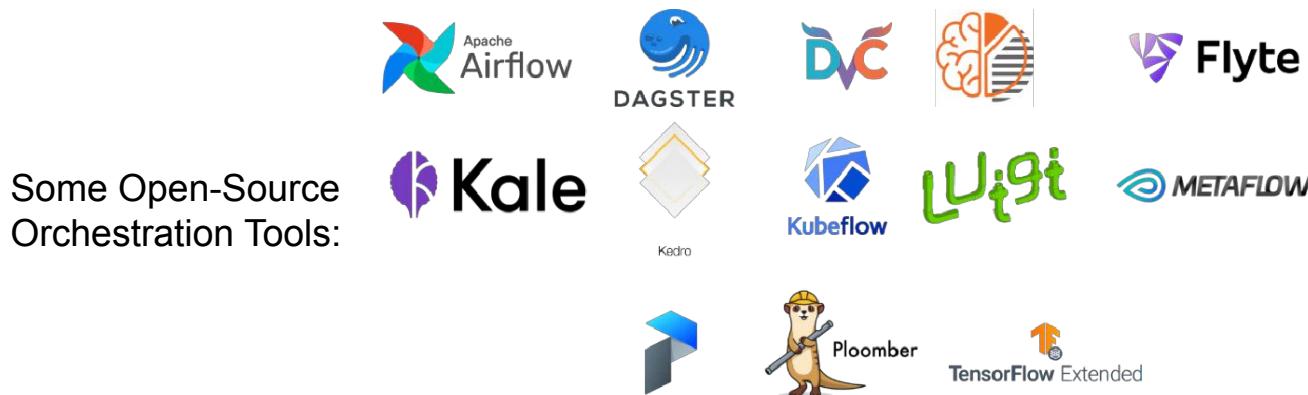


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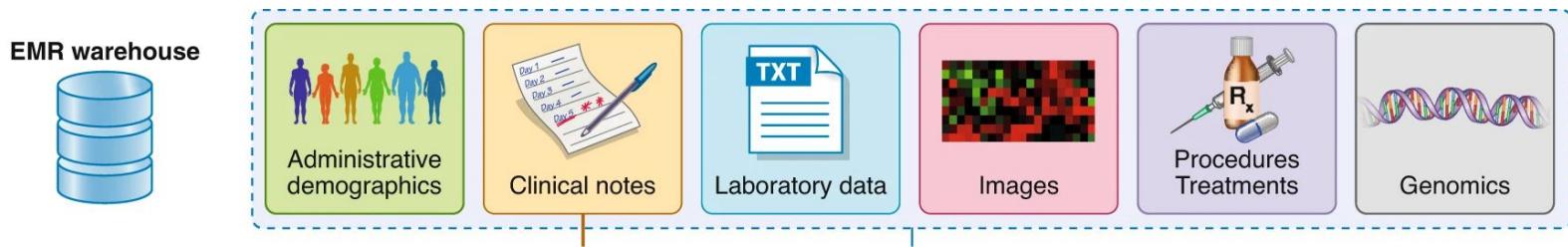


Some Open-Source  
Orchestration Tools:

<https://ploomber.io/blog/survey/>

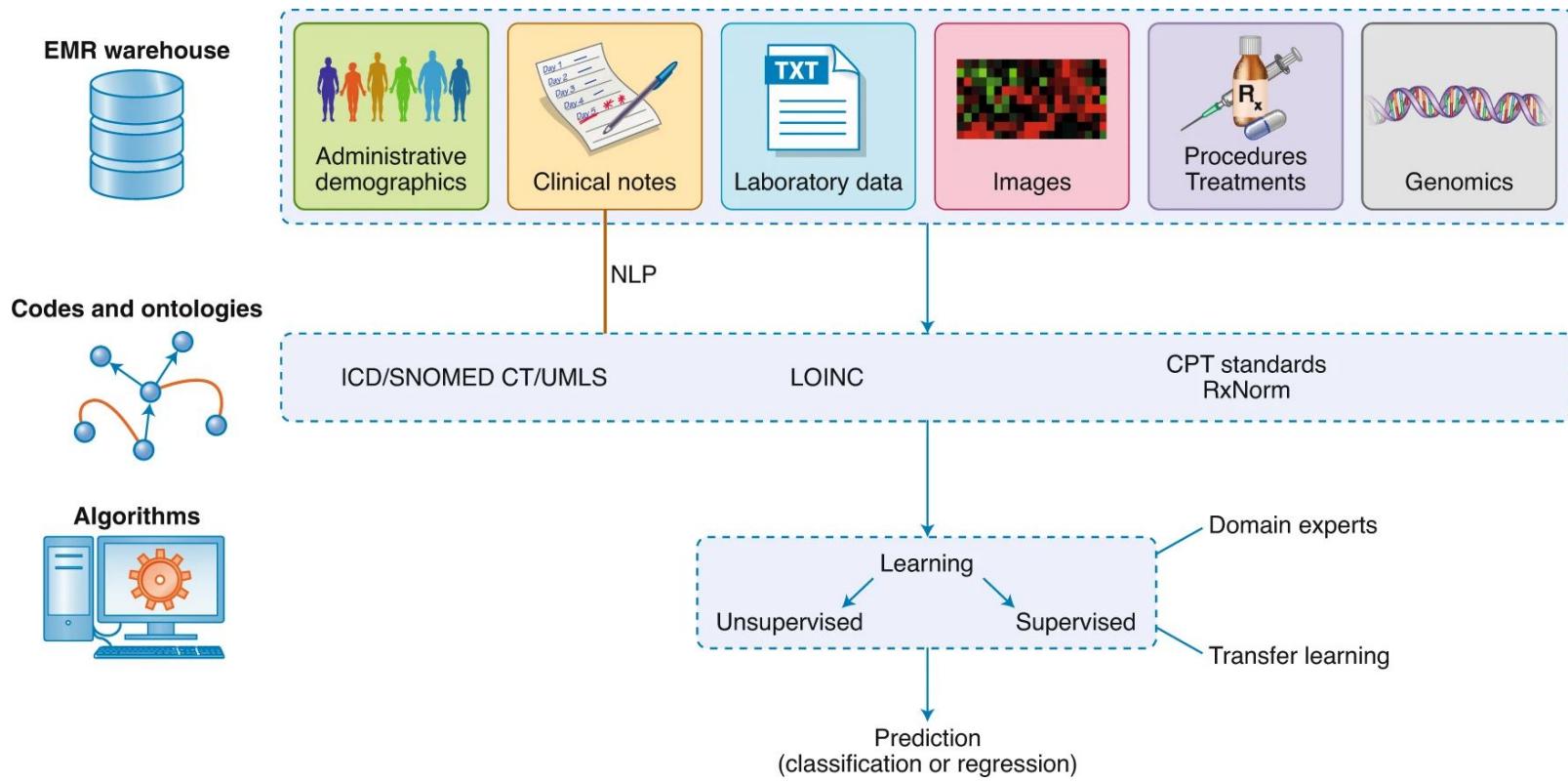
OK, what is **Health** Data Science?

# Data Science applied to Health Data



Why “health data” instead of “medical data”: health encompasses medical (**contentious**)

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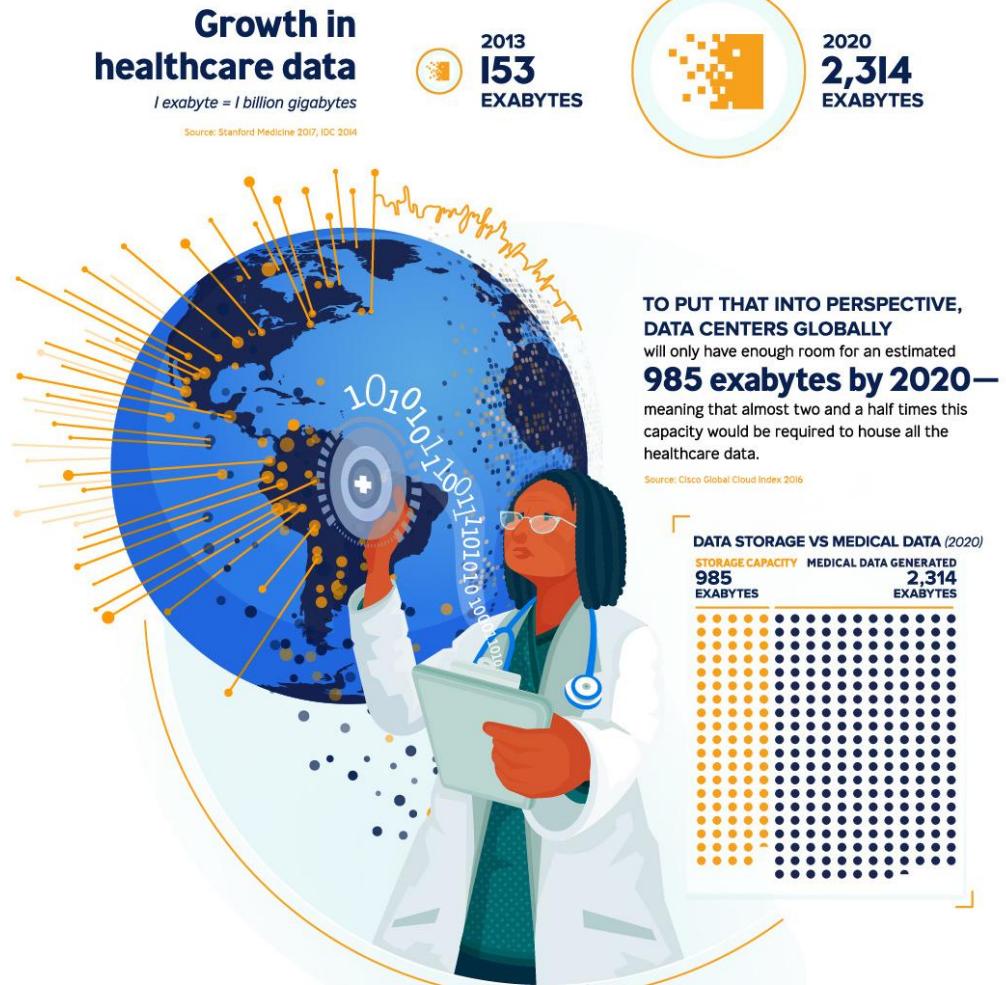


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# Opportunity of Health Data Science

Benefits (and pitfalls!) of data science in general combined with:

- Huge amounts of health data

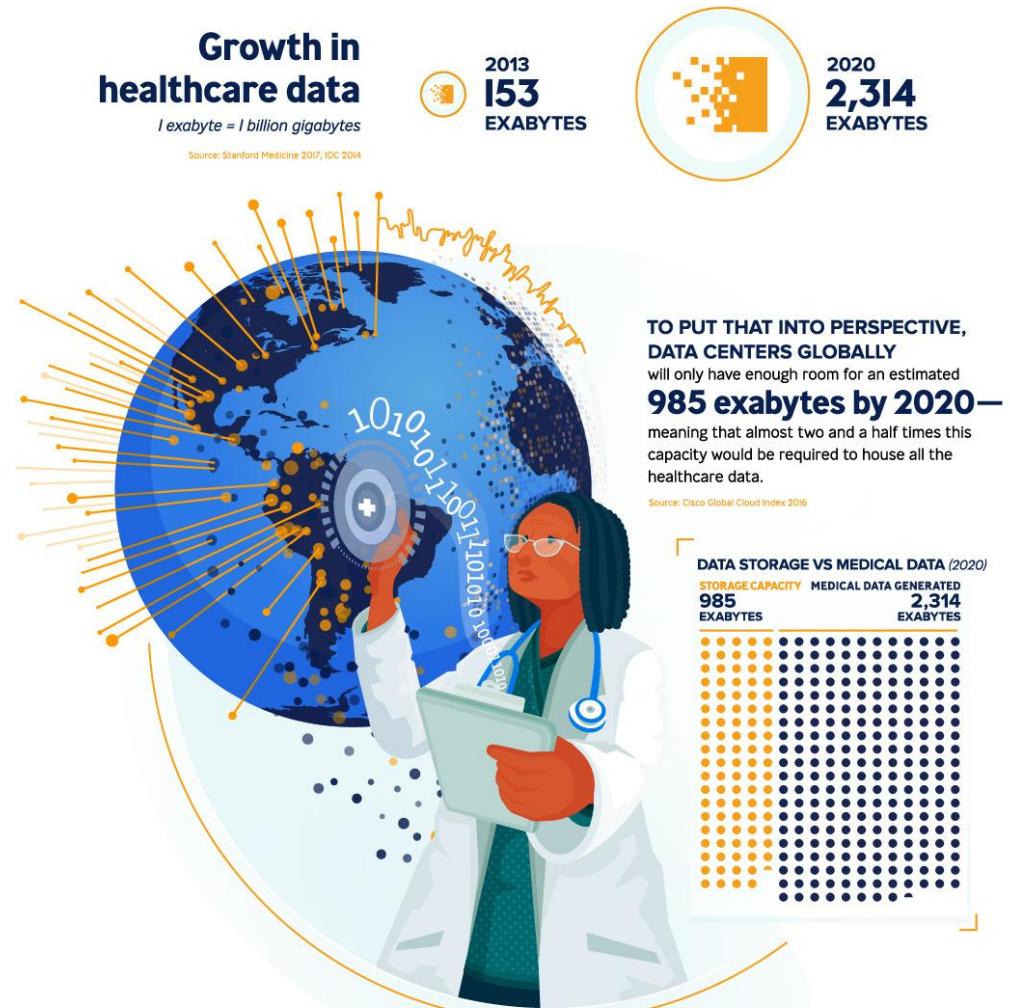


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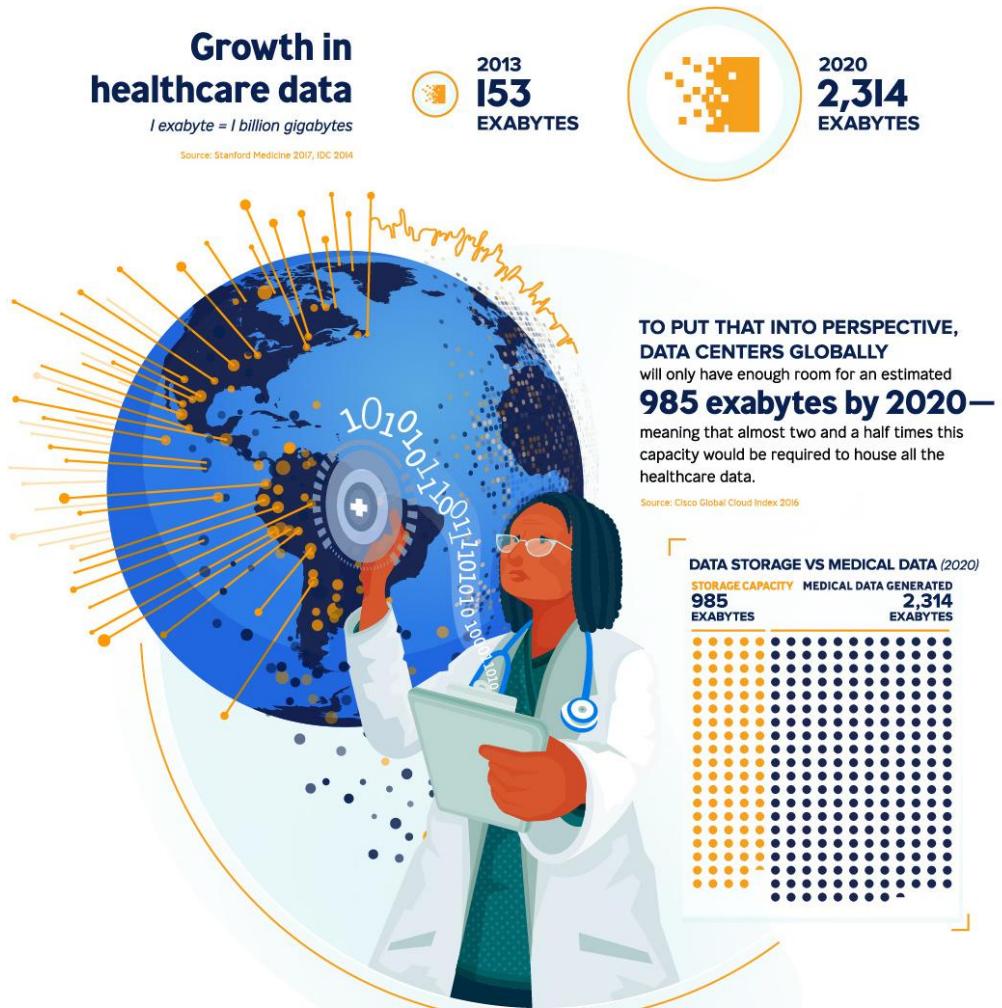


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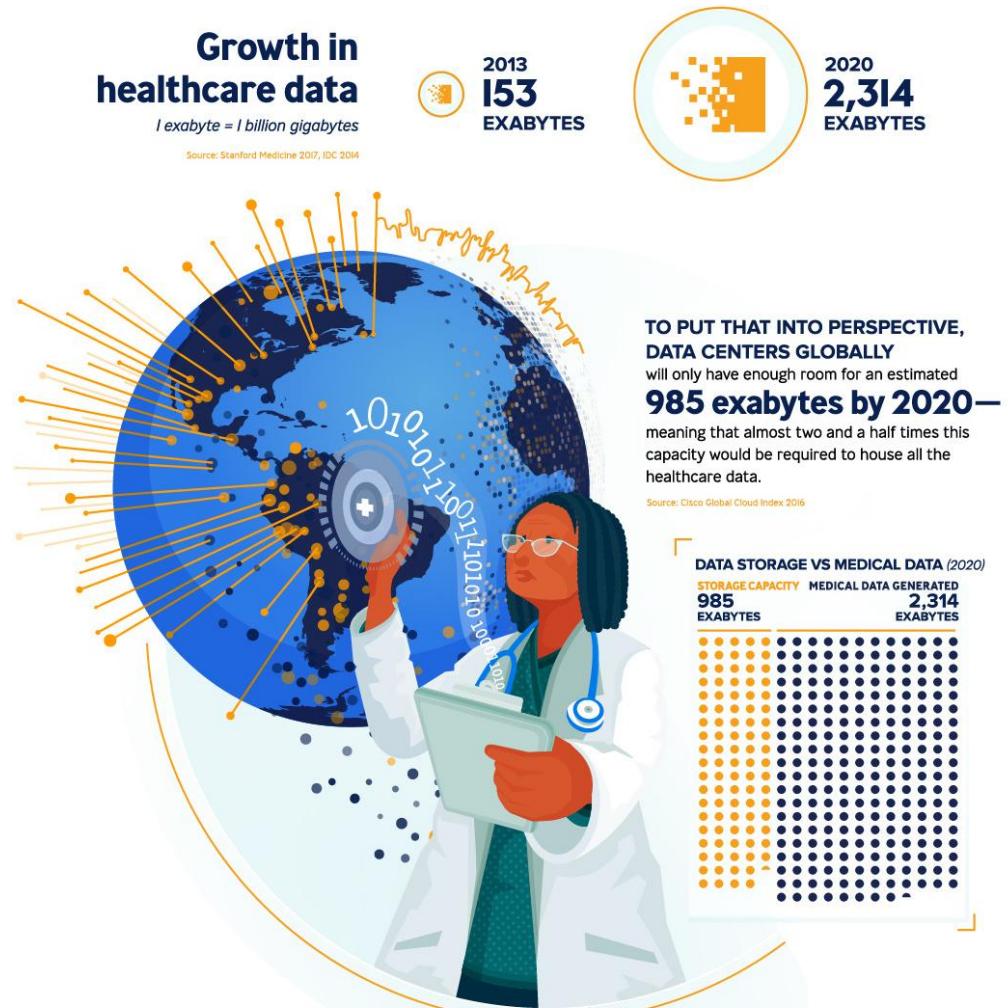


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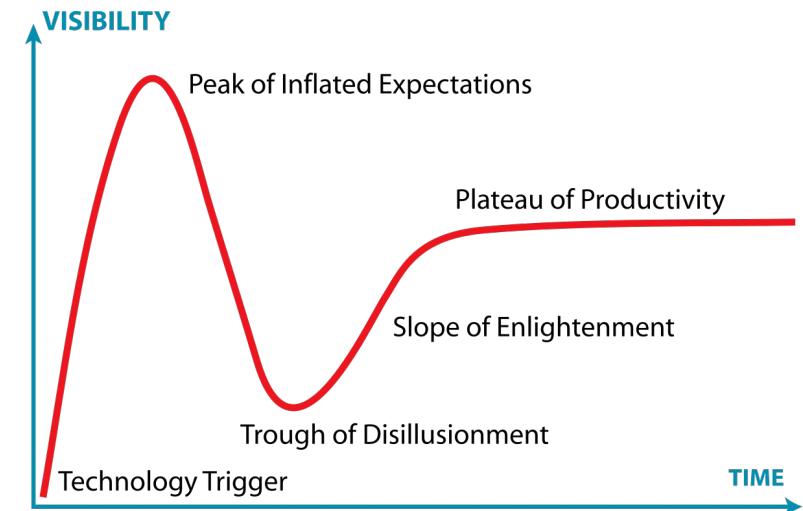
- Huge amounts of health data
- Many **interesting and important problems**
- Many domain experts desperate for data-related help with these problems
- Relative few skilled data science practitioners



<https://www.visualcapitalist.com/big-data-healthcare/>

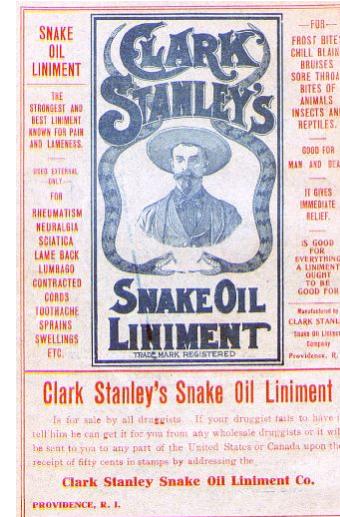
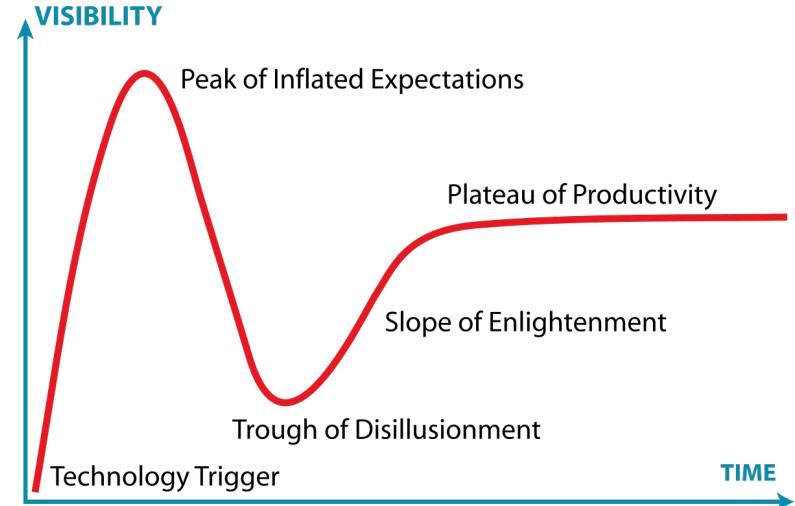
# (Some) Challenges of Health Data Science

- Lots of hype



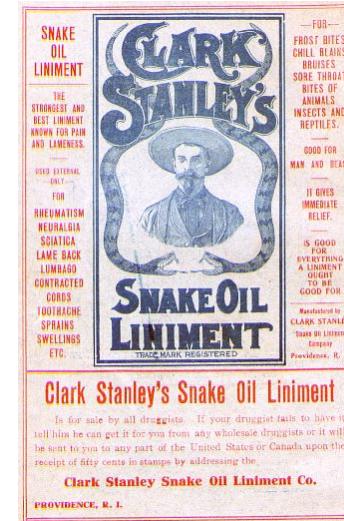
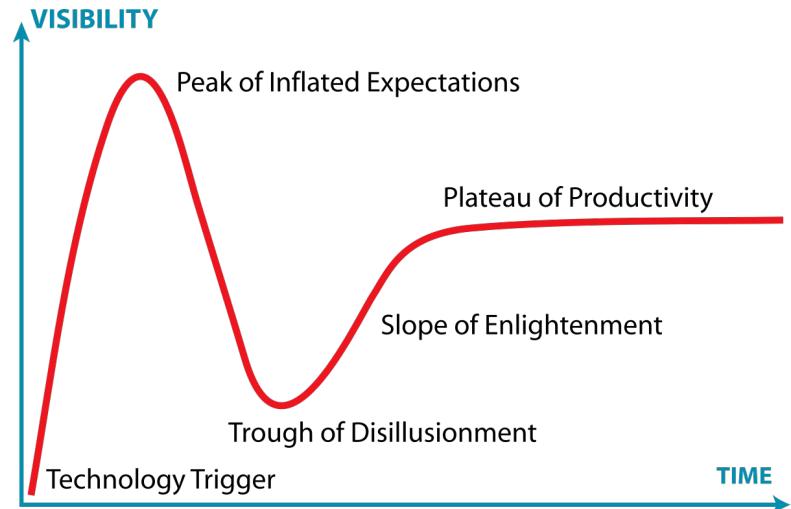
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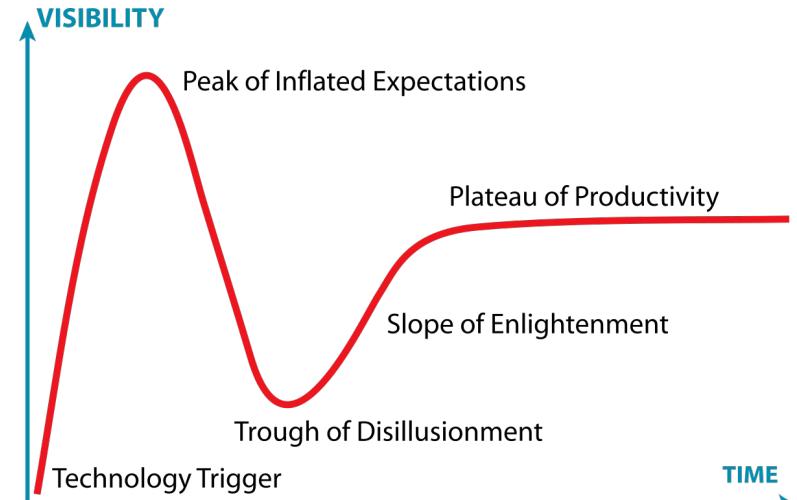
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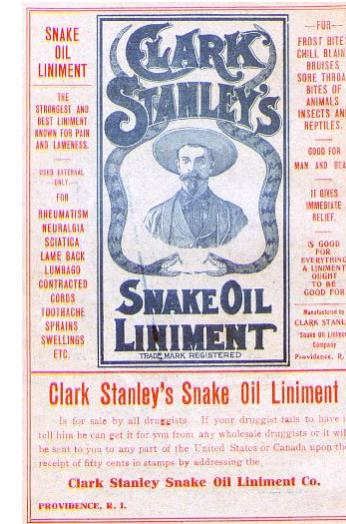


# (Some) Challenges of Health Data Science

- Lots of hype
- Lots of grifters
- Data quality issues
- Contextual/Metadata quality issues
- Regulatory challenges
- Influence of US health system
- Ethical pitfalls
- Treatment to the mean
- Knowledge Translation and Operations: **Hard**



<https://www.r-bloggers.com/2019/08/new-course-learn-advanced-data-cleaning-in-r/>

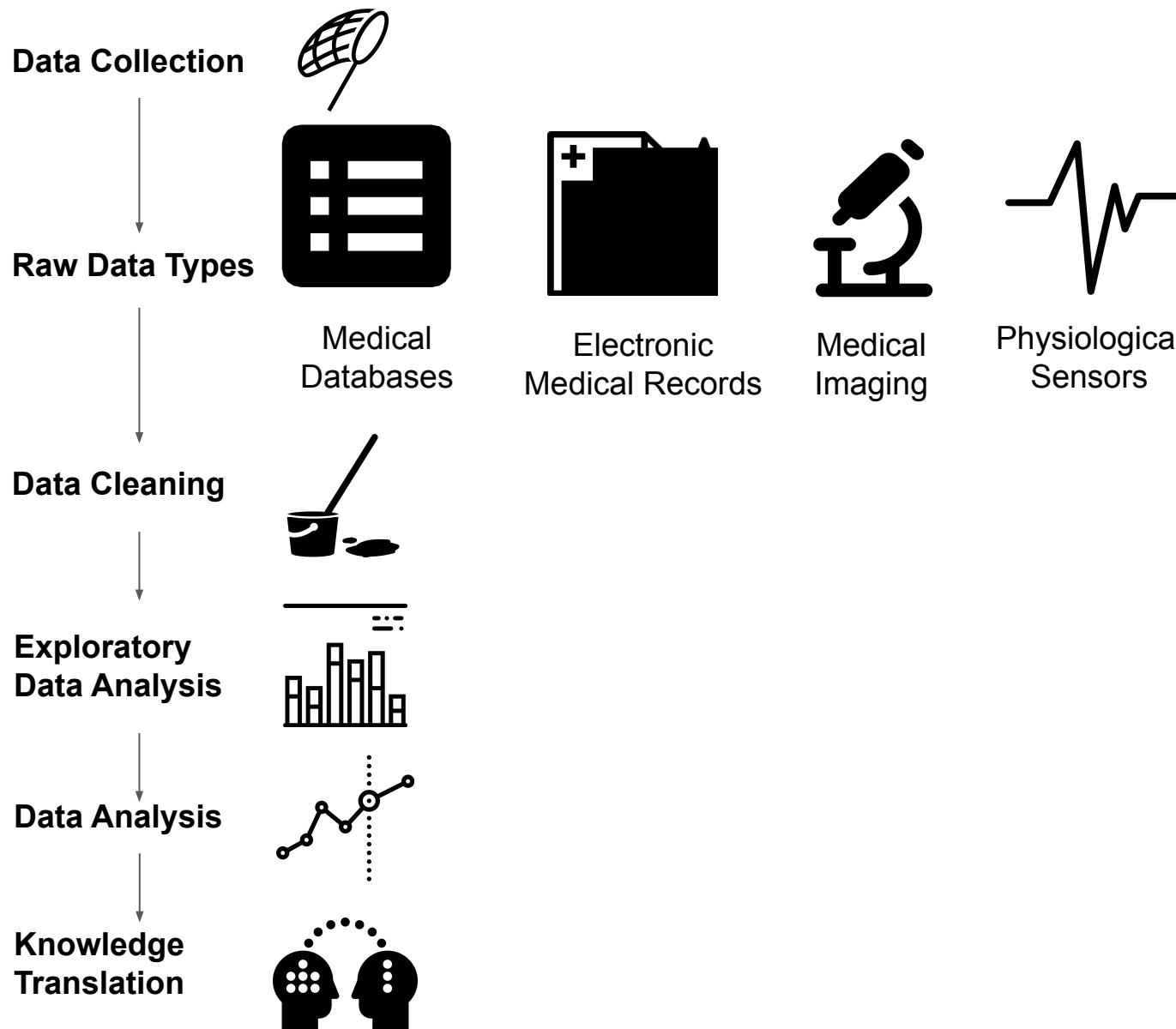


[https://upload.wikimedia.org/wikipedia/commons/9/94/Gartner\\_Hype\\_Cycle.svg](https://upload.wikimedia.org/wikipedia/commons/9/94/Gartner_Hype_Cycle.svg)

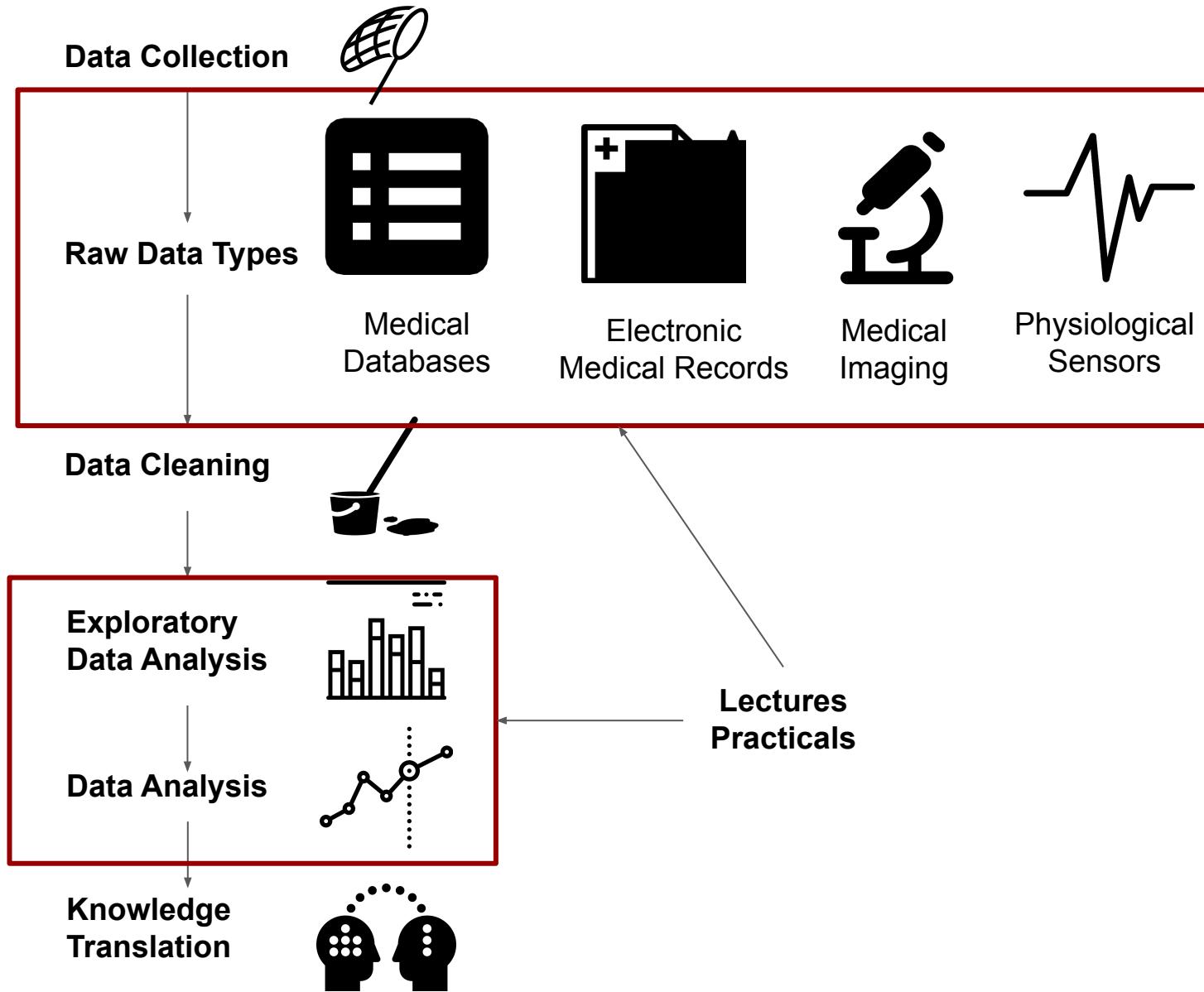
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What parts of health data science will this course cover?

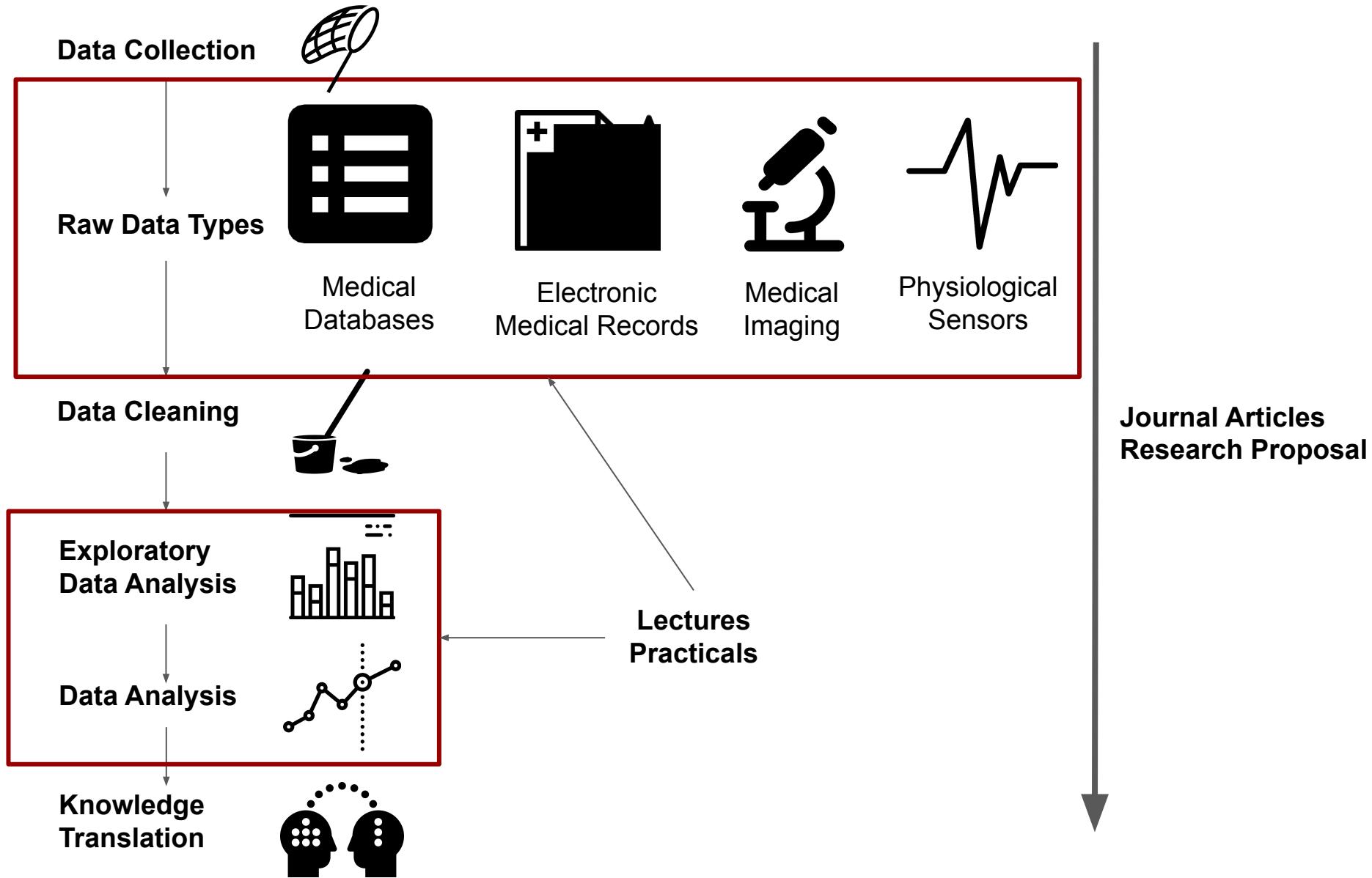
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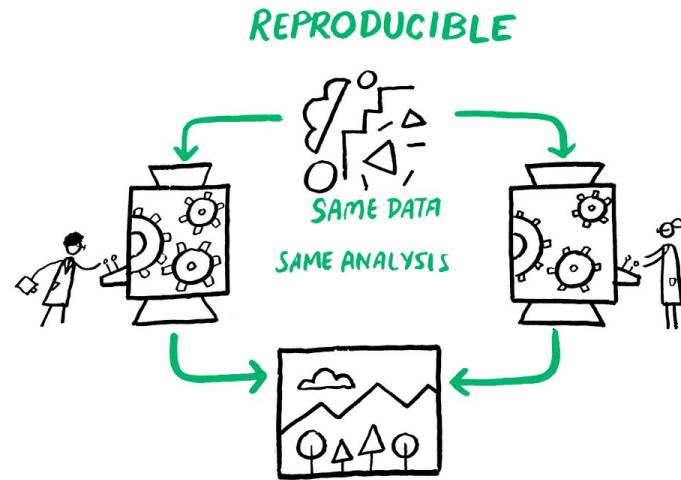
Let's take a 5 minute break!

# Tools for Reproducible Health Data Science

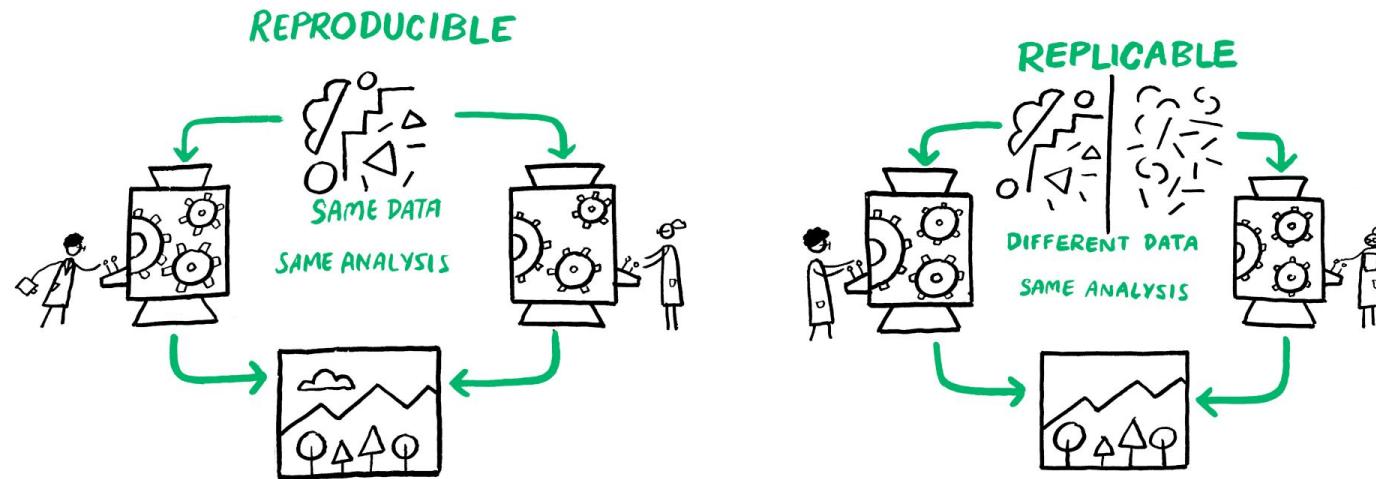
Rstudio, Rmarkdown, Git

Why do we care about reproducibility?

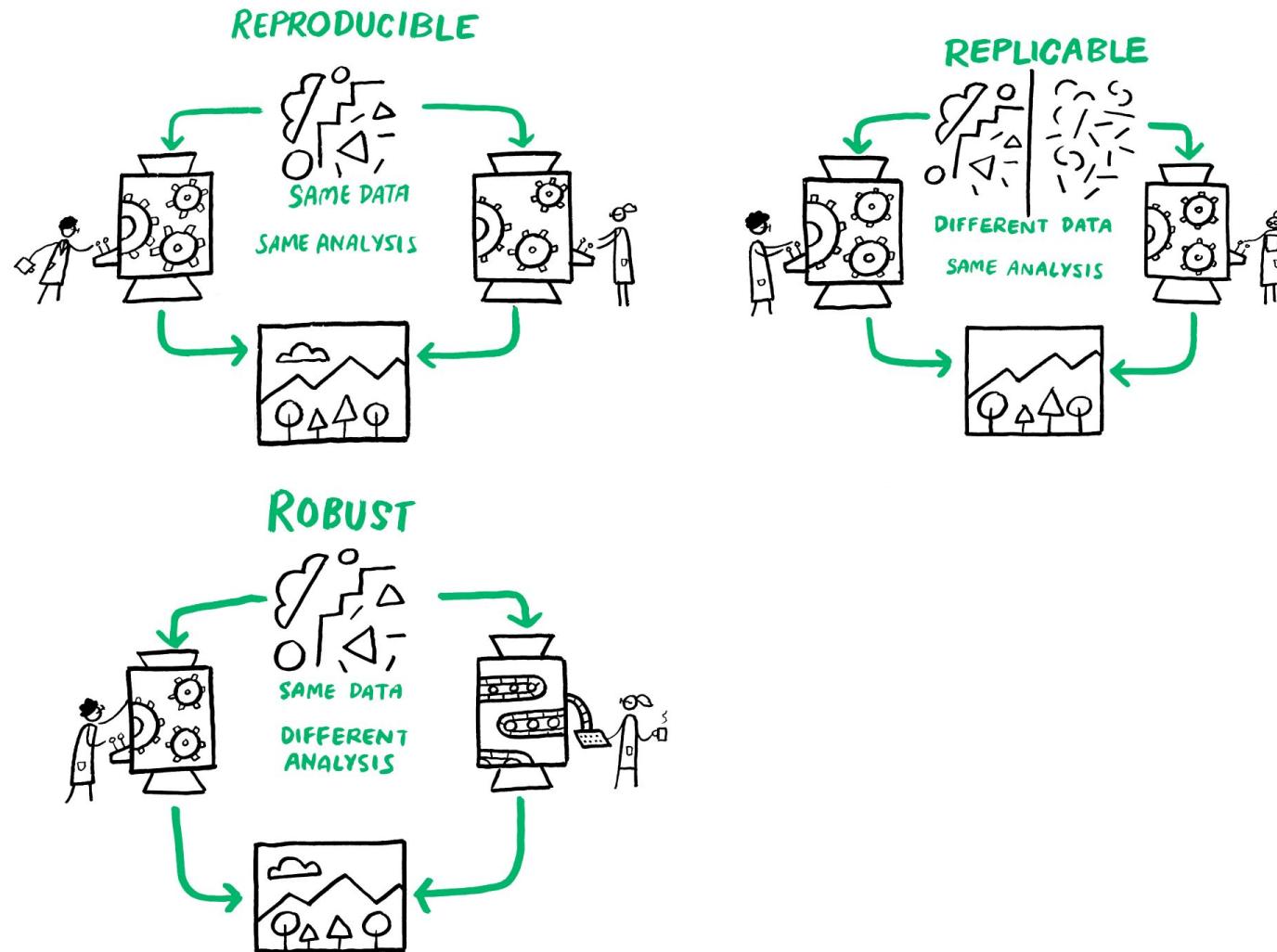
# Reproducibility should be the bare minimum



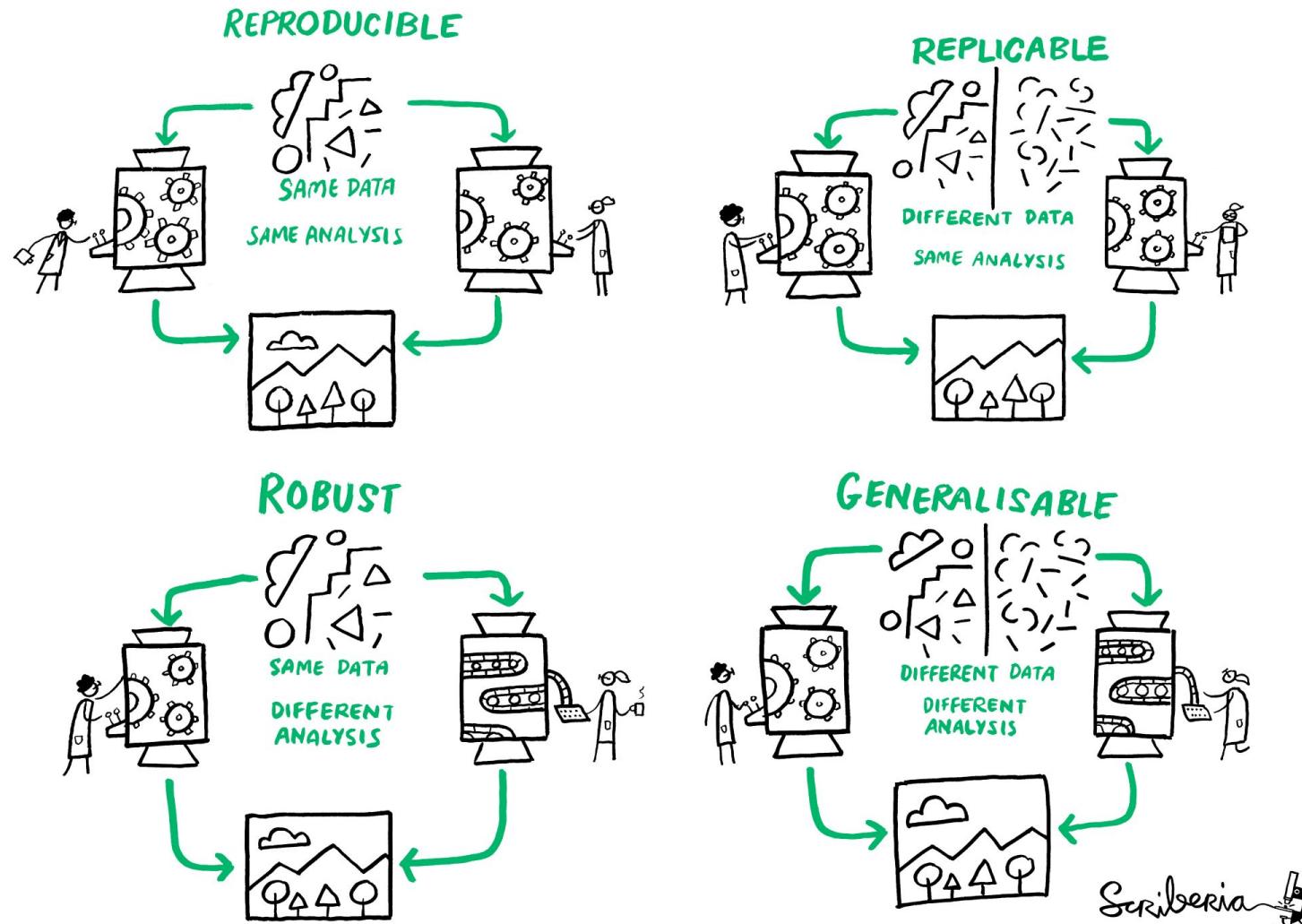
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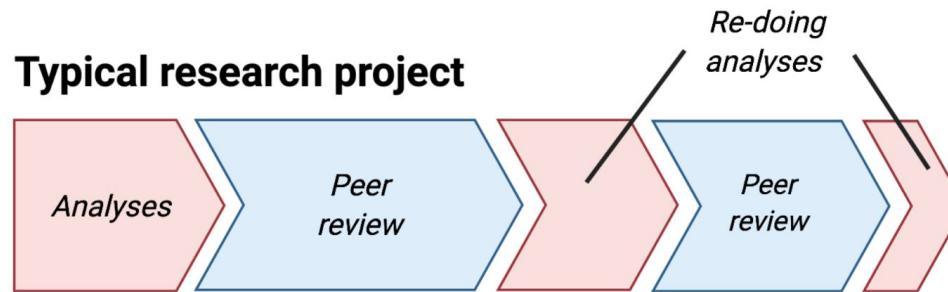
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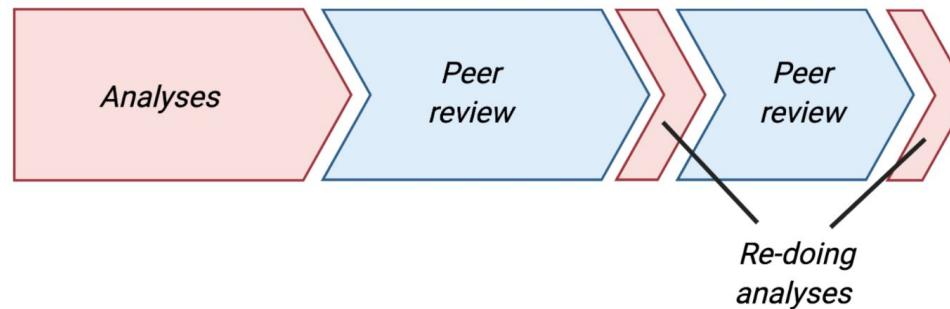
# Reproducibility should be the bare minimum



# Makes your own life easier



## Research project using reproducible practices



@dsquintana

[oliviergimenez.github.io/reproducible-science-workshop](http://oliviergimenez.github.io/reproducible-science-workshop)

What do we need to do to have reproducible research?

# Reproducibility checklist

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- Script every interaction with data:
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  - Formatting datasets
  - Cleaning data
  - Exploratory data analysis
  - Main analyses
  - Report generation

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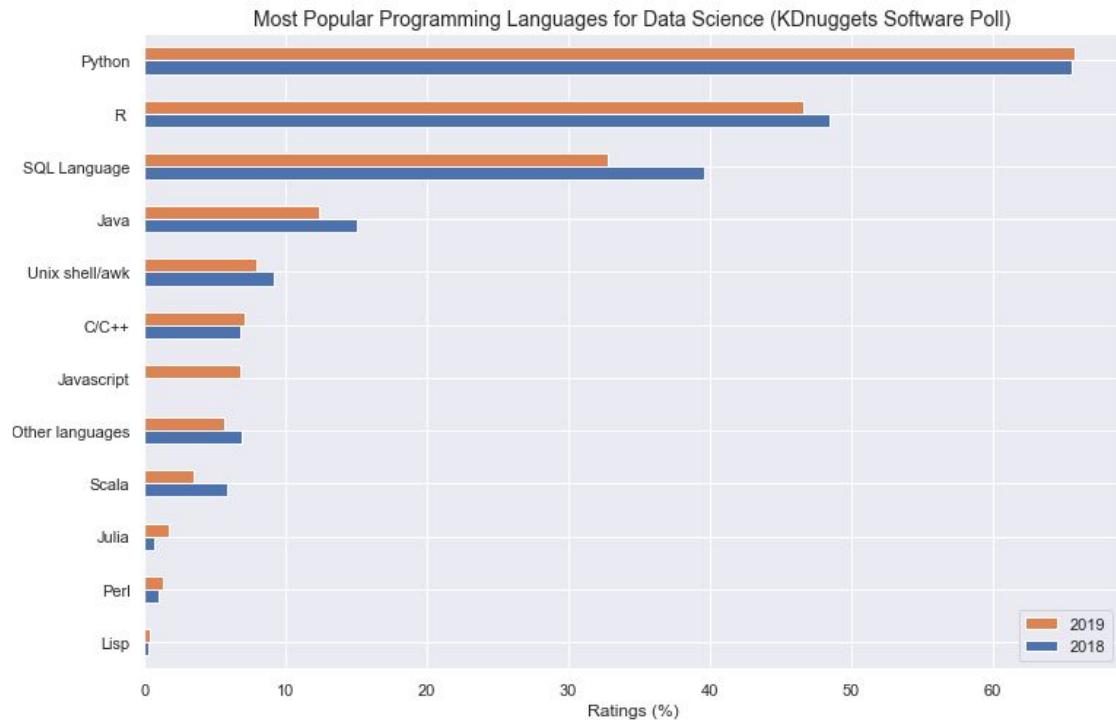
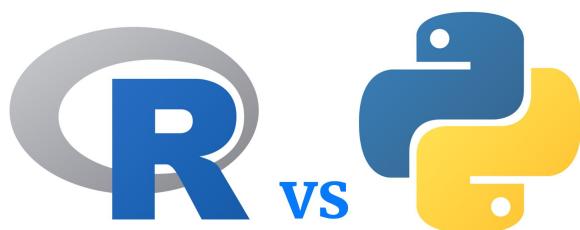
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- Use a random seed
- Keep track of the exact version of every library/program you use

How do we actually do these things?

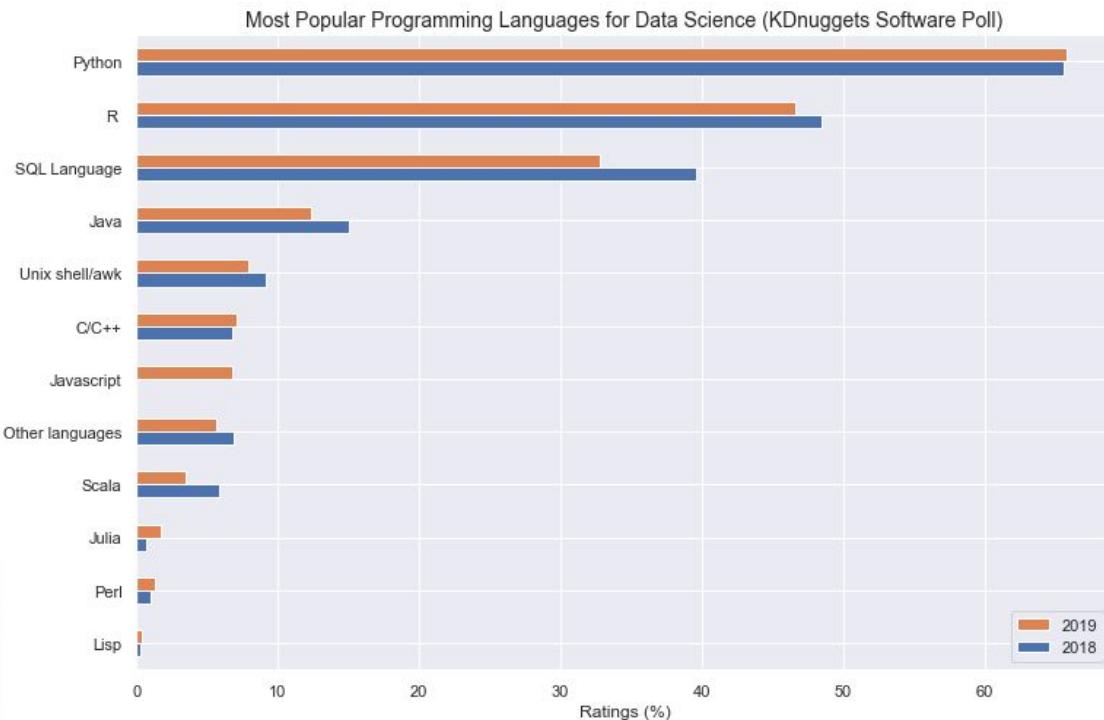
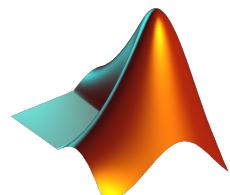
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<https://www.kdnuggets.com/2019/05/poll-top-data-science-machine-learning-platforms.html>

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# Use a data science focused IDE: Rstudio

`set.seed()`  
`sessionInfo()`

The screenshot shows the RStudio interface with the following components:

- Code Editor:** The "flights-example.R" script is open, displaying R code for loading the "nycflights13" dataset and creating a boxplot. The code includes imports for `nycflights13`, `lubridate`, `dplyr`, and `ggplot2`. It then filters the data to get daily counts, adds a weekday column, and creates a boxplot titled "Number of 2013 New York Flights Each Weekday".
- Console:** Shows the execution of the R code, including the creation of a tibble and the resulting boxplot.
- Environment:** The "daily" dataset is listed, showing 365 observations of 3 variables: date (Date[1:365]), n (int [1:365]), and wday (Ord.factor w/ 7 levels "Sun"<"Mon"<"Tue"<...: 3).
- Plots:** A boxplot titled "Number of 2013 New York Flights Each Weekday" is displayed, showing the distribution of flights per weekday. The x-axis is labeled "Weekday" and includes categories for Sun, Mon, Tue, Wed, Thu, Fri, and Sat. The y-axis is labeled "Flights" and ranges from 700 to 1000. The plot shows that flight volumes are highest on Monday and Friday, and lowest on Saturday.

# Use notebooks to document analyses: Rmarkdown/Quarto

The screenshot shows the RStudio interface with an Rmarkdown notebook open. The left pane displays the Rmd file content, and the right pane shows the generated HTML output.

**Rmd File Content:**

```
1 ---  
2 title: "Viridis Notebook"  
3 output: html_notebook  
4 ---  
5  
6 ```{r include = FALSE}  
7 library(viridis)  
8 ```  
9  
10 The code below demonstrates two color palettes in the viridis package. Each plot displays a contour map of the Maunga Whau volcano in Auckland, New Zealand.  
11  
12 ## Viridis colors  
13  
14 ```{r}  
15 image(volcano, col = viridis(200))  
16 ```
```

**Generated HTML Output:**

## Viridis Notebook

The code below demonstrates two color palettes in the [viridis](#) package. Each plot displays a contour map of the Maunga Whau volcano in Auckland, New Zealand.

### Viridis colors

```
image(volcano, col = viridis(200))
```

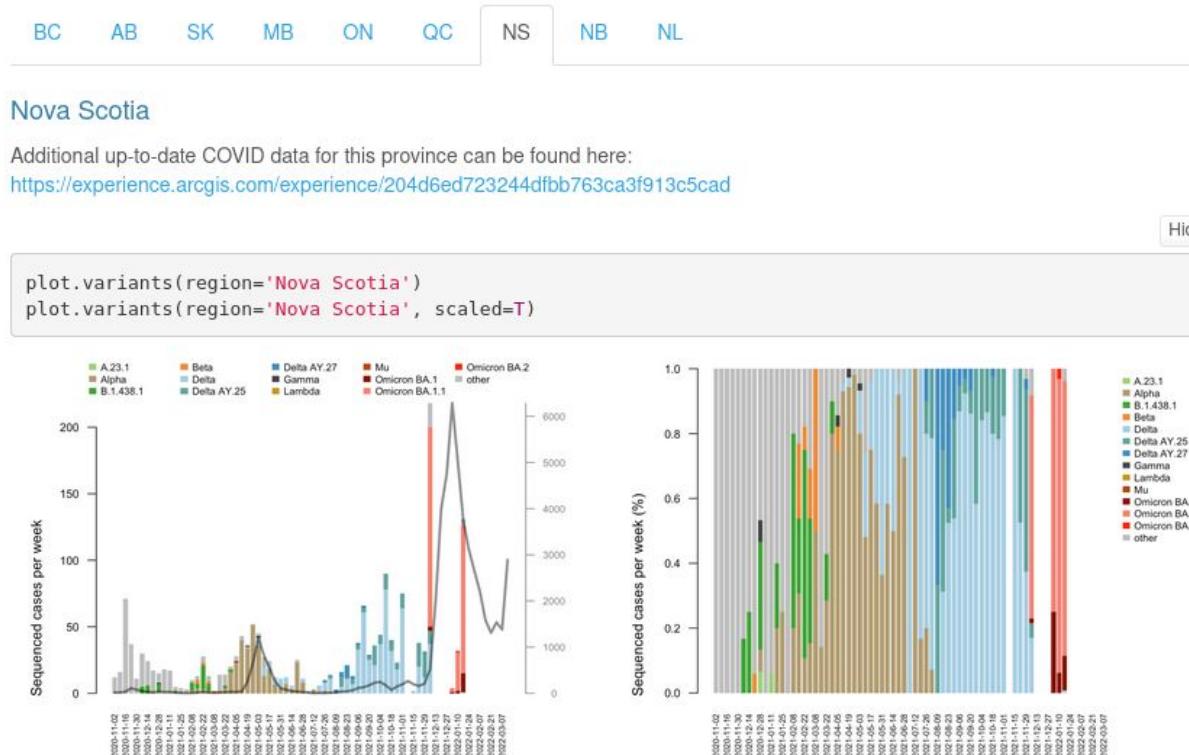
A contour plot of the Maunga Whau volcano in Auckland, New Zealand, using the Viridis color palette. The plot shows a central peak in yellow/green transitioning through green, blue, and purple towards the edges. The x-axis ranges from 0.0 to 1.0, and the y-axis ranges from 0.0 to 1.0.

### Magma colors

A contour plot of the Maunga Whau volcano in Auckland, New Zealand, using the Magma color palette. The plot shows a central peak in bright yellow transitioning through orange, red, and dark red/purple towards the edges. The x-axis ranges from 0.0 to 1.0, and the y-axis ranges from 0.0 to 1.0.

# Use notebooks to document analyses: Rmarkdown/Quarto

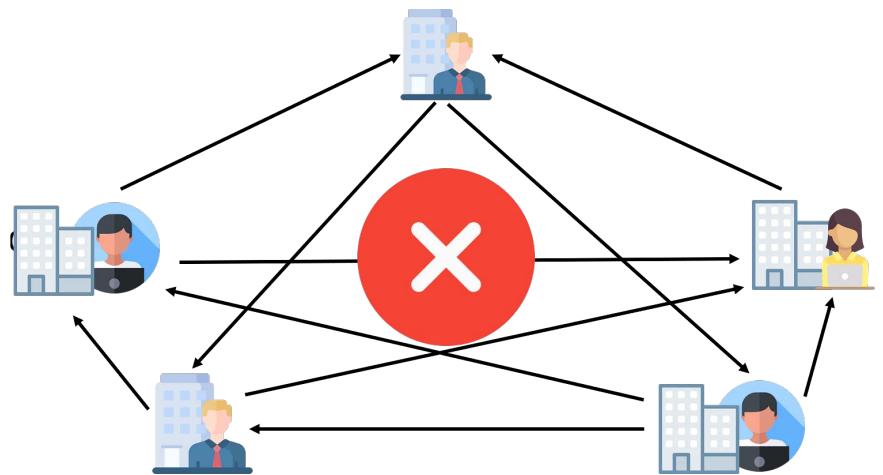
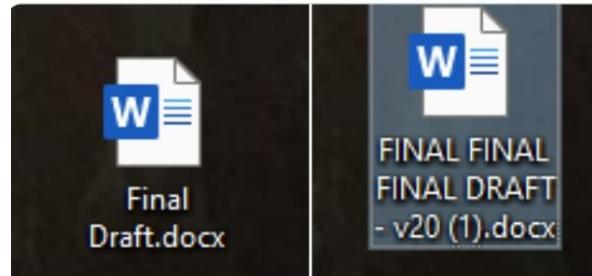
settings). Therefore, from this time onward, case counts are likely underestimated and the sequenced virus diversity is not necessarily representative of the virus circulating in the overall population.



<https://covarr-net.github.io/duotang/duotang.html#>

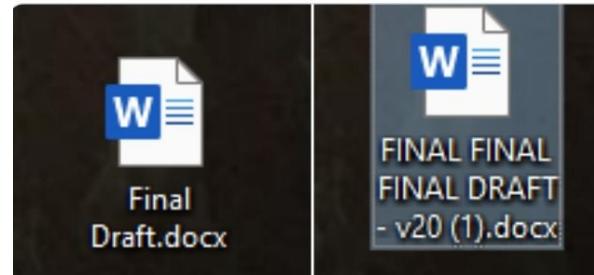
# Use standard version control systems

- Ever had a nightmare of versioning even when just you?
- Add more people and the chaos grows exponentially!



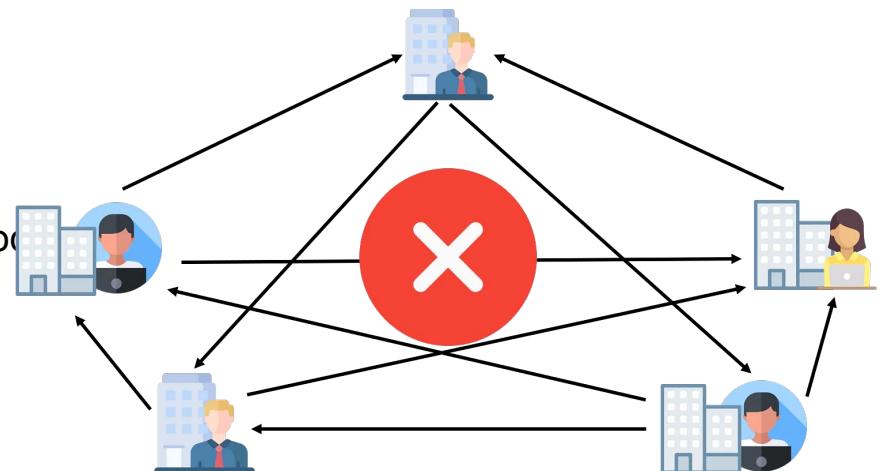
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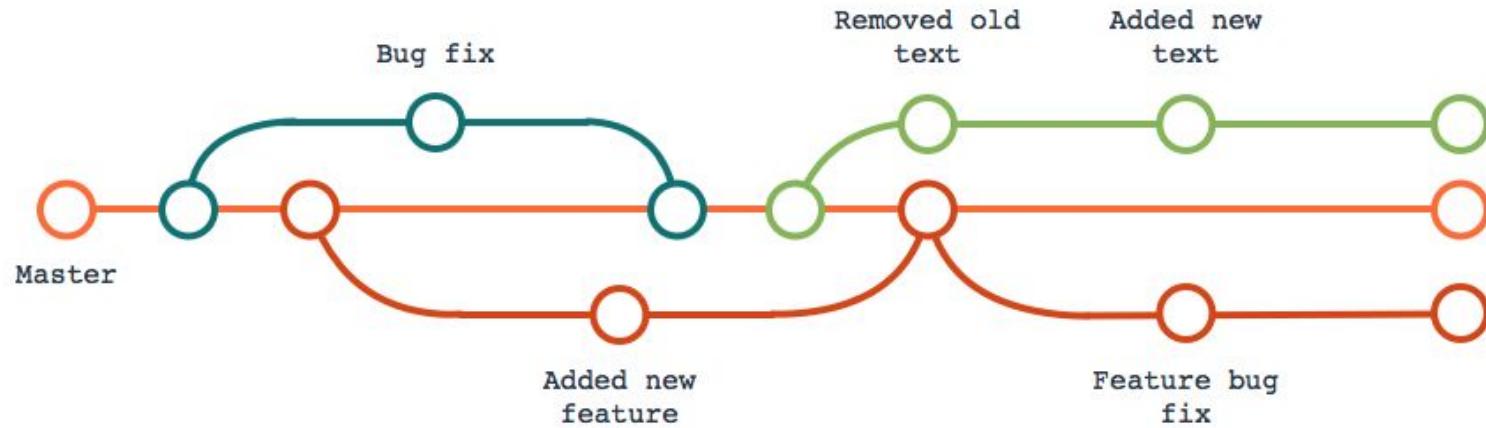


Version control let's you:

- Revert mistakes
- Acts as a comprehensive backup
- Let's you maintain multiple versions of your analysis
- Let's you compare different versions of your code
- Track down the who/what broke the analysis
- Work out why you did something in the past
- Build on someone else's work
- Share your own work
- Experiment without risk

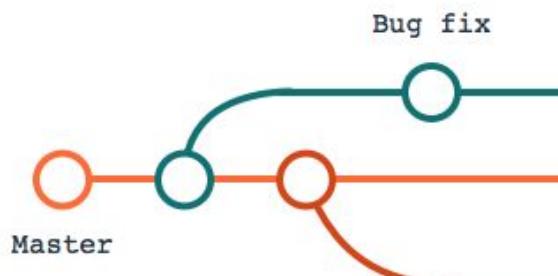


# Git Version Control



- Most popular
- Decentralised
- Designed for
- GitLab/GitHub Services

# Git Version Control

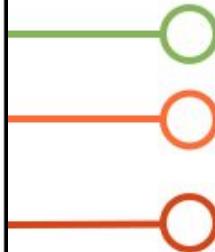


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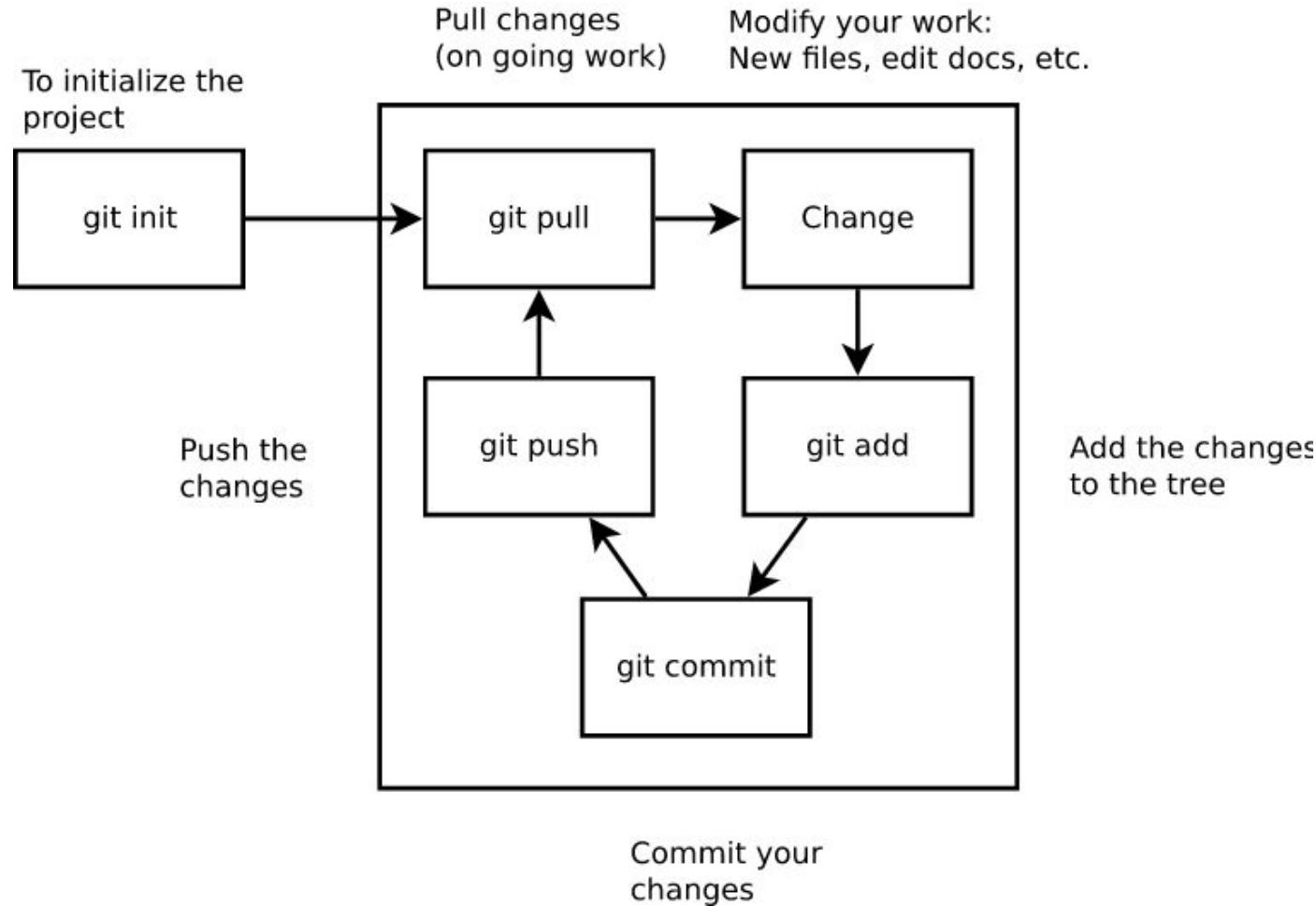
THIS IS GIT. IT TRACKS COLLABORATIVE WORK ON PROJECTS THROUGH A BEAUTIFUL DISTRIBUTED GRAPH THEORY TREE MODEL.

COOL. HOW DO WE USE IT?

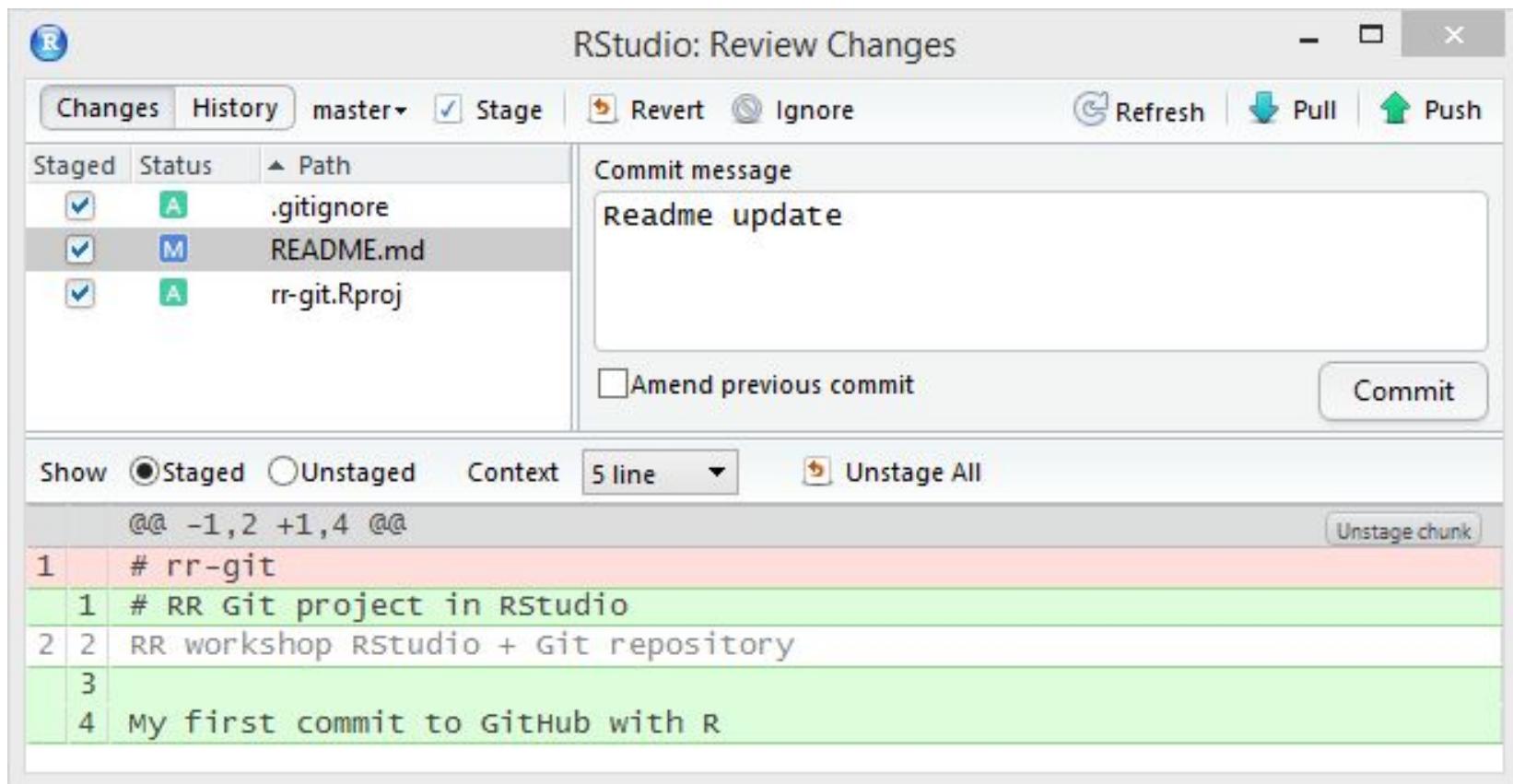
NO IDEA. JUST MEMORIZE THESE SHELL COMMANDS AND TYPE THEM TO SYNC UP.  
IF YOU GET ERRORS, SAVE YOUR WORK ELSEWHERE, DELETE THE PROJECT, AND DOWNLOAD A FRESH COPY.



# Git Workflow



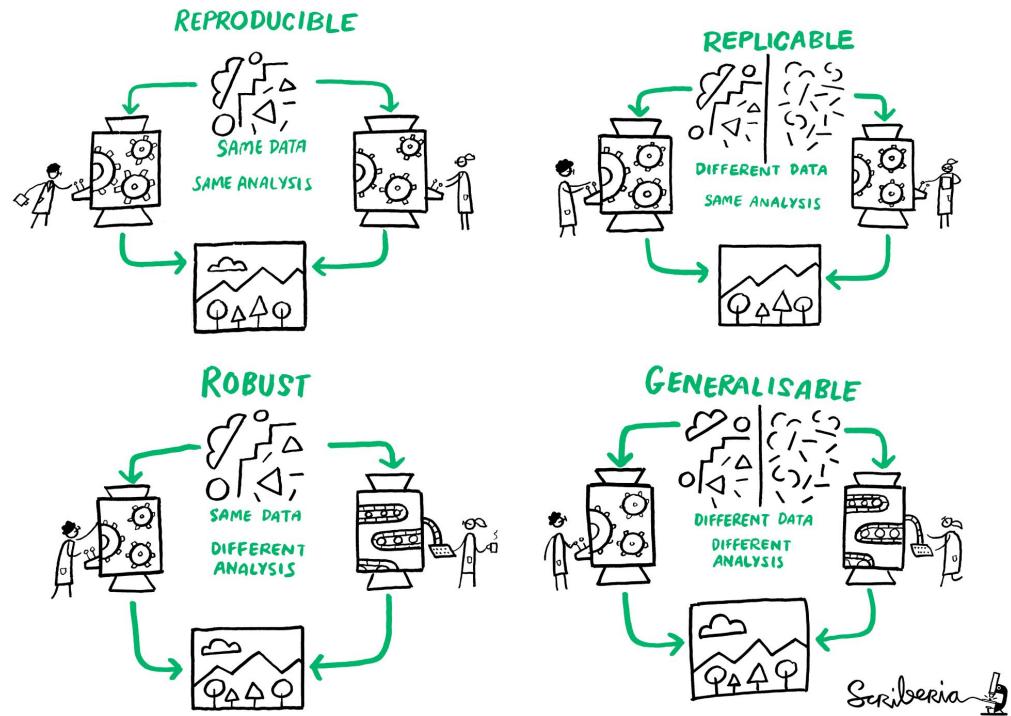
# Git is integrated into Rstudio!



# Combine Git+Rmd Notebooks for Reproducibility

1. Add analysis to notebook
2. Add changes to git
3. Find out you made a mistake
4. Revert changes

1. Share notebook with collaborator
2. They make changes
3. You make changes
4. Merge changes into single analysis



# Summary

- Overview of course: Database/EMR/Imaging/Signal
- Main assessments: practicals, journal article presentations, research proposal
- Data science is statistics with an EDA/Inductive/Data-focused Spin
- Health Data Science is a massive and growing area with lots of opportunity and challenges
- R is a powerful and useful tool for health data science
- Reproducibility is vital to good ~~health data~~ science
- Rstudio, Rmarkdown notebooks and Git based version control facilitate that reproducibility

# Friday's Practical

- Will go over the practical use of R, Rstudio, Rmd Notebooks, Git
- Try and install rstudio, git, and rmarkdown beforehand.
- 1st practical will not contribute to your course grade

# Wednesday's Journal Articles

- **Reproducibility in machine learning for health research:  
Still a ways to go**

[Matthew B. A. McDermott](#) [Shirly Wang](#) [Nikki Marinsek](#) [Rajesh Ranganath](#) [Luca Foschini](#) [Marzyeh Ghassemi](#)

Science Translational Medicine • 24 Mar 2021 • Vol 13, Issue 586 • [DOI: 10.1126/scitranslmed.abb1655](#)

- **A Beginner's Guide to Conducting Reproducible Research**

[Jesse M. Alston](#), [Jessica A. Rick](#) First published: 15 January 2021 <https://doi.org/10.1002/bes2.1801>