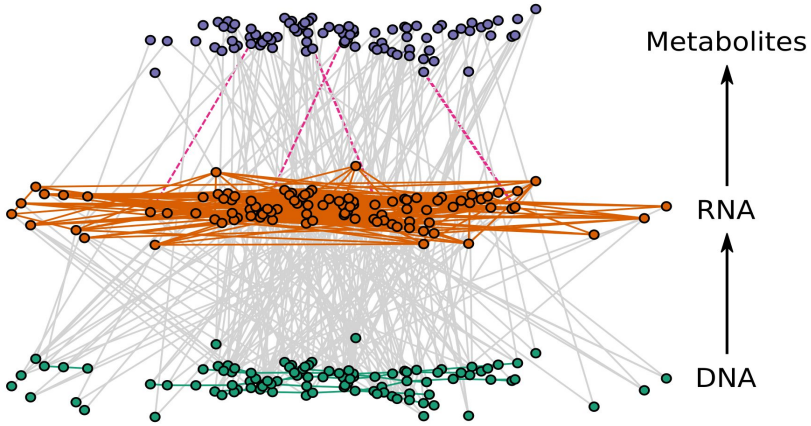
Lecture 0: Introduction to Applied Research in Health Data Science

CSCI6410/4148 & EPAH6410

Finlay Maguire (finlay.maguire@dal.ca)
TA: Mehrana Calagari (m.calagari@dal.ca)

Why am I teaching this course?



- **PhD (Bioinformatics)**: using large noisy datasets to understand how microbial systems and mechanisms evolve.

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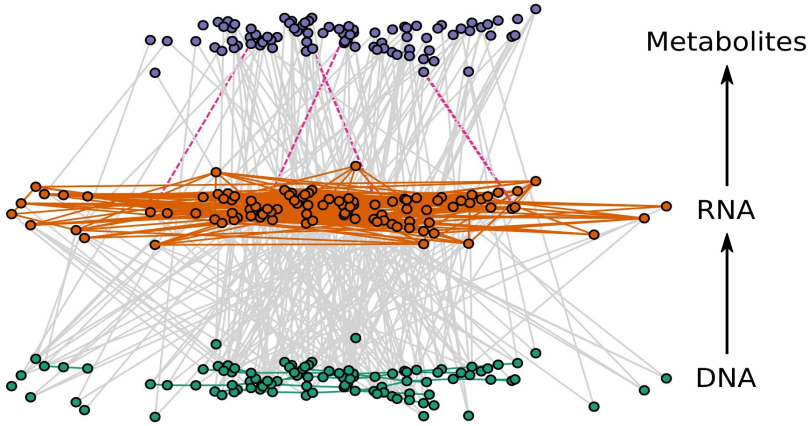

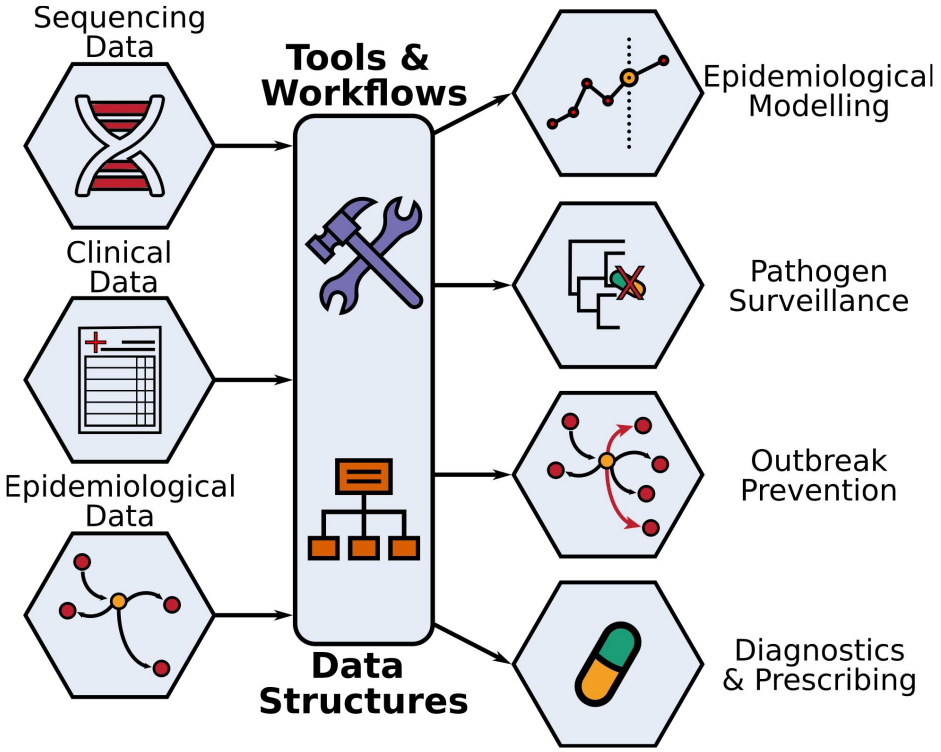

- **PhD (Bioinformatics)**: using large noisy datasets to understand how microbial systems and mechanisms evolve.
- **Research Group (Genomic Epidemiology)**: using large noisy datasets to better diagnose, track and predict infectious diseases.

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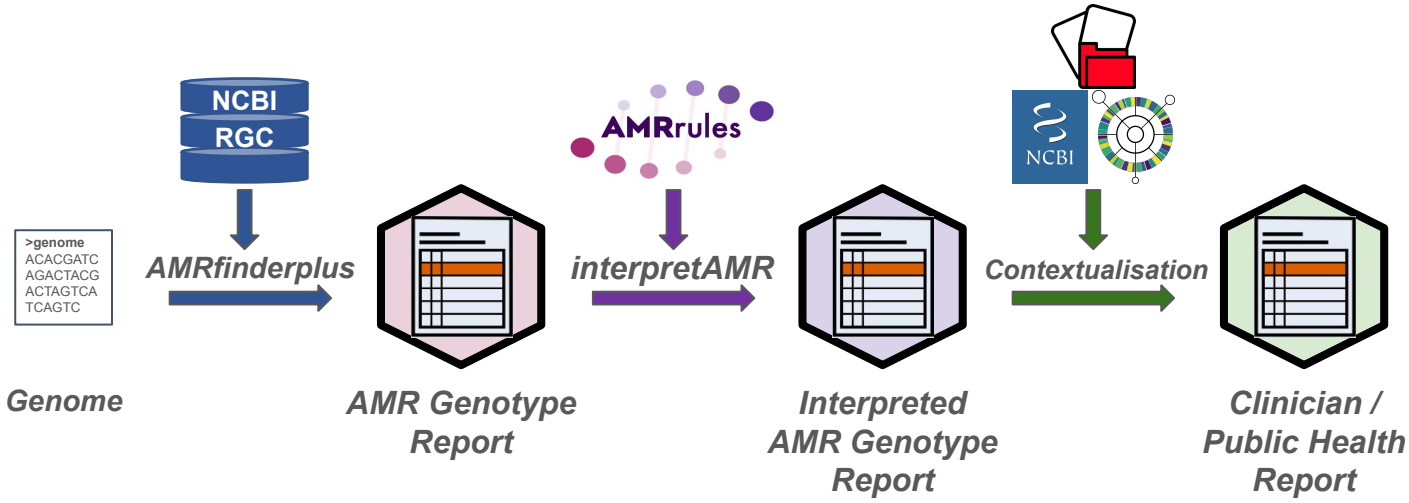

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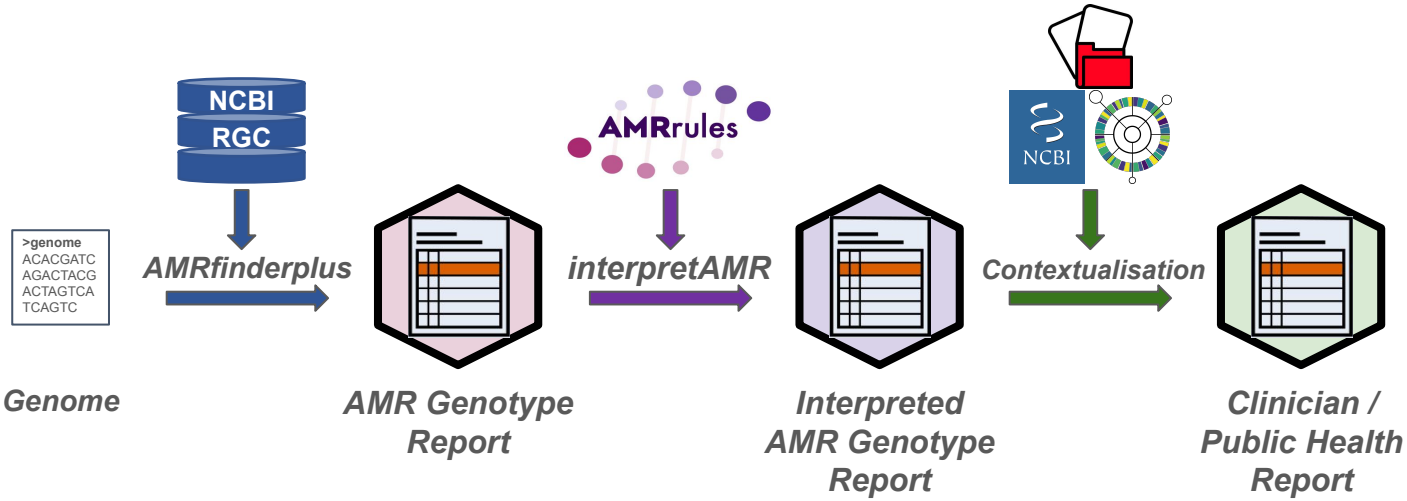

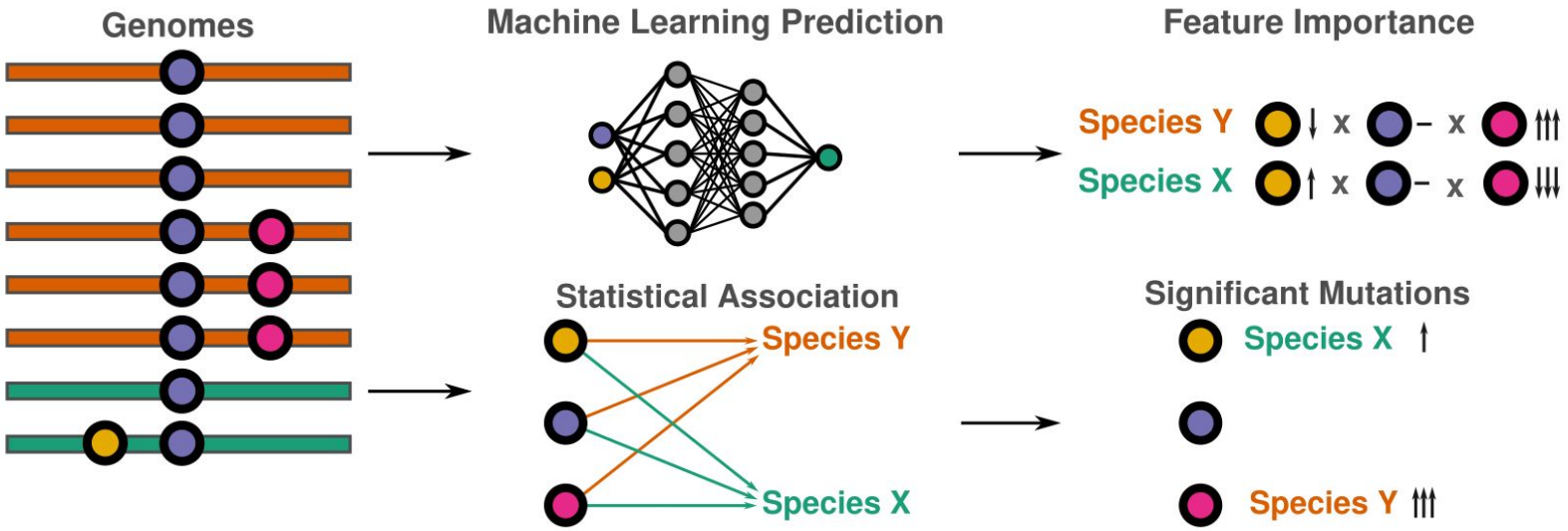

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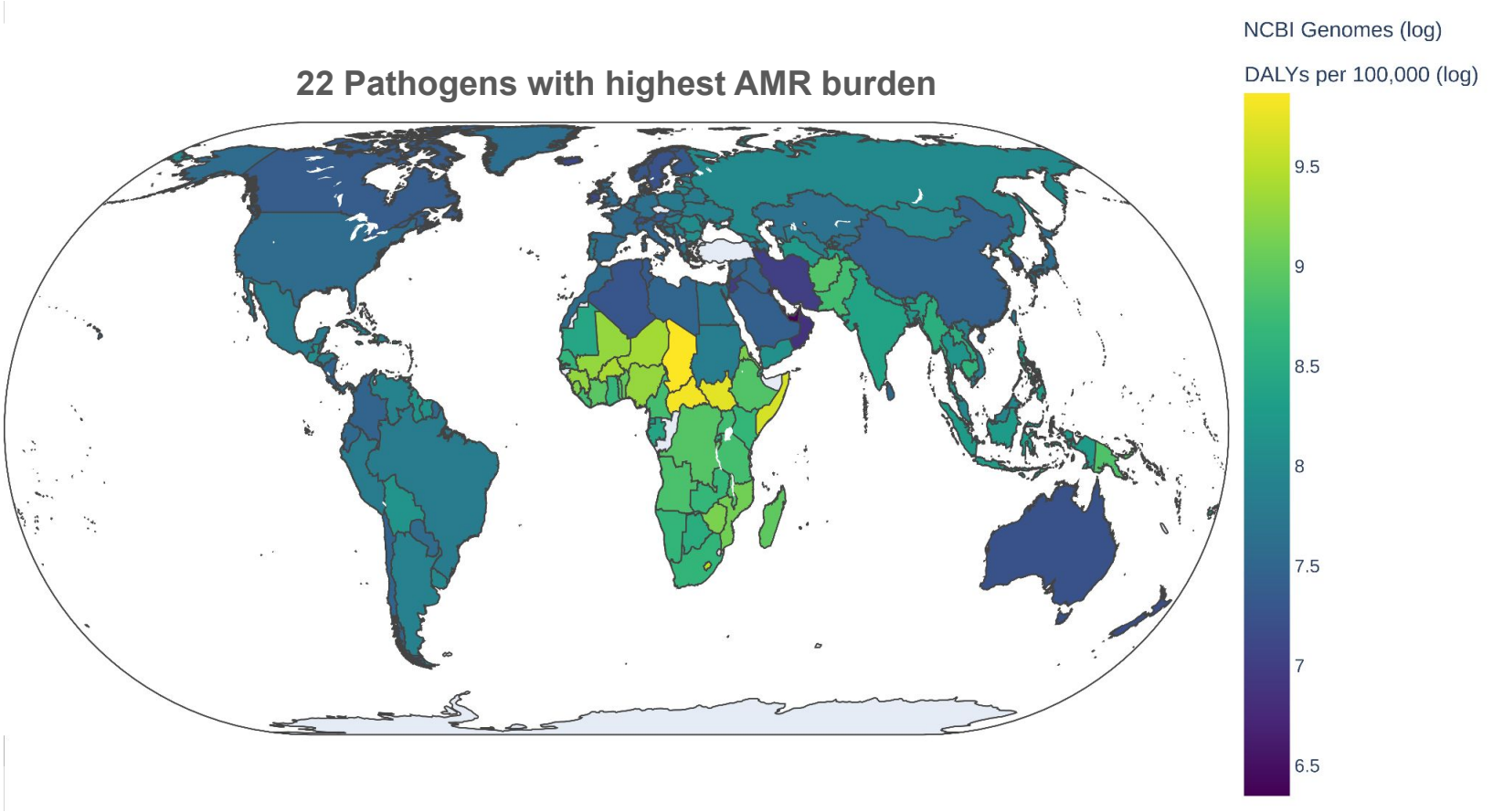

K. pneumoniae: 23,379,605 DALYs across 100 highest burden countries

Data from: Naghavi, Mohsen, et al. "Global burden of bacterial antimicrobial resistance 1990–2021: a systematic analysis with forecasts to 2050." The Lancet 404.10459 (2024): 1199-1226.

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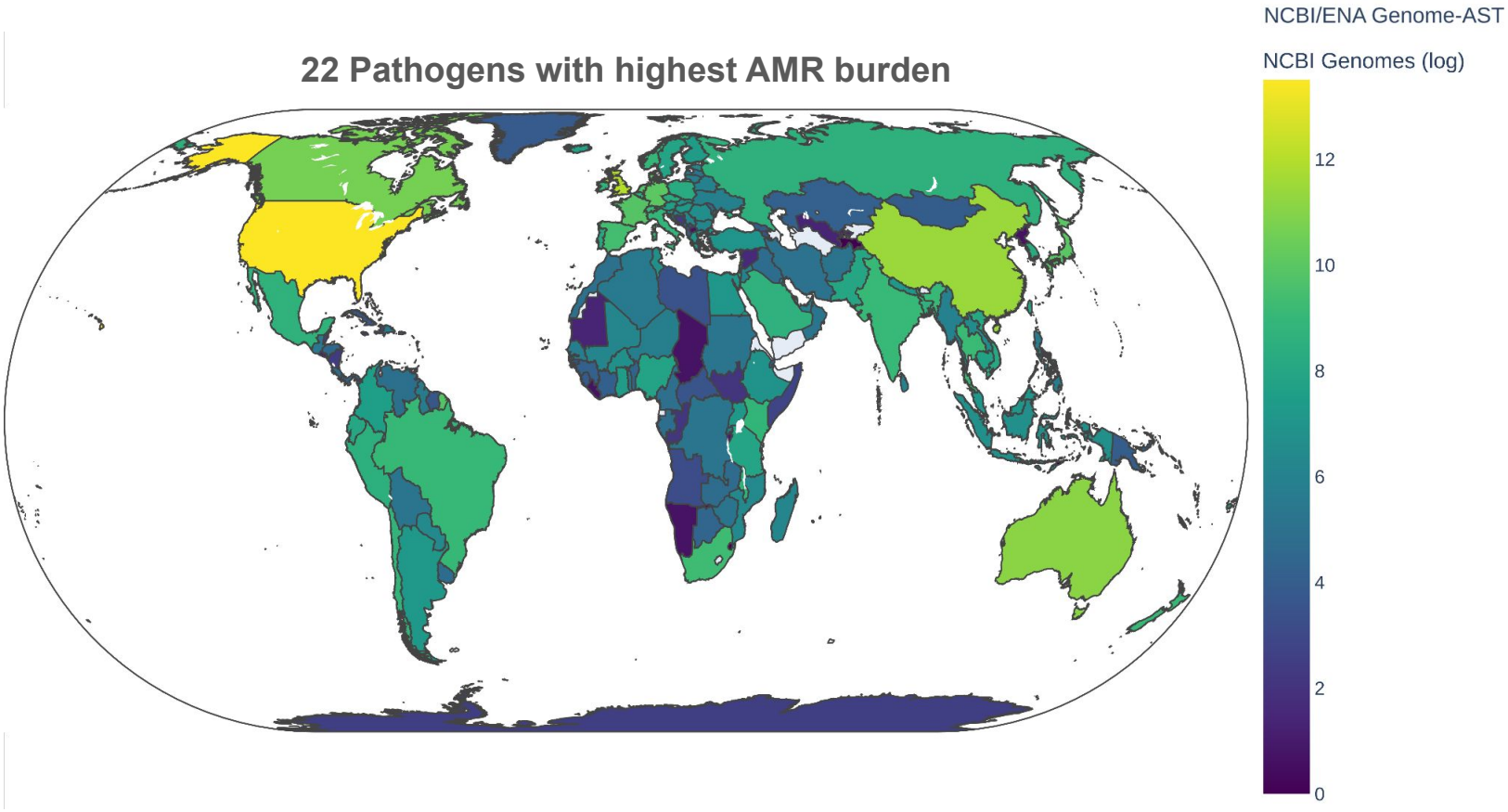
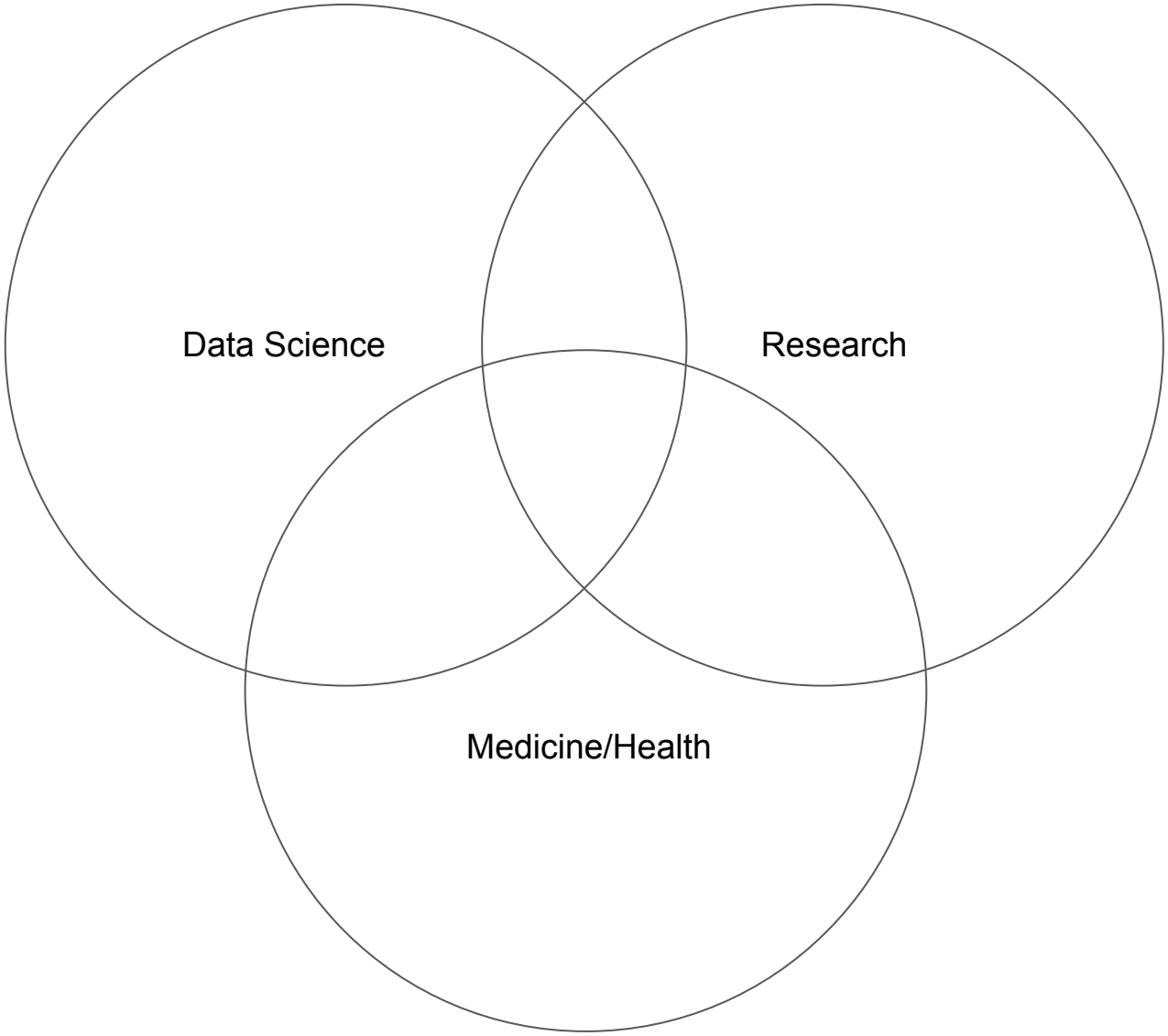


K. pneumoniae: 8,689/89,056 genomes from 100 highest burden countries

Data from: NCBI Datasets 2025-06-15 - O'Leary, Nuala A., et al. "Exploring and retrieving sequence and metadata for species across the tree of life with NCBI Datasets." Scientific data 11.1 (2024): 732.

Overview of course

Applied Research in Health Data Science



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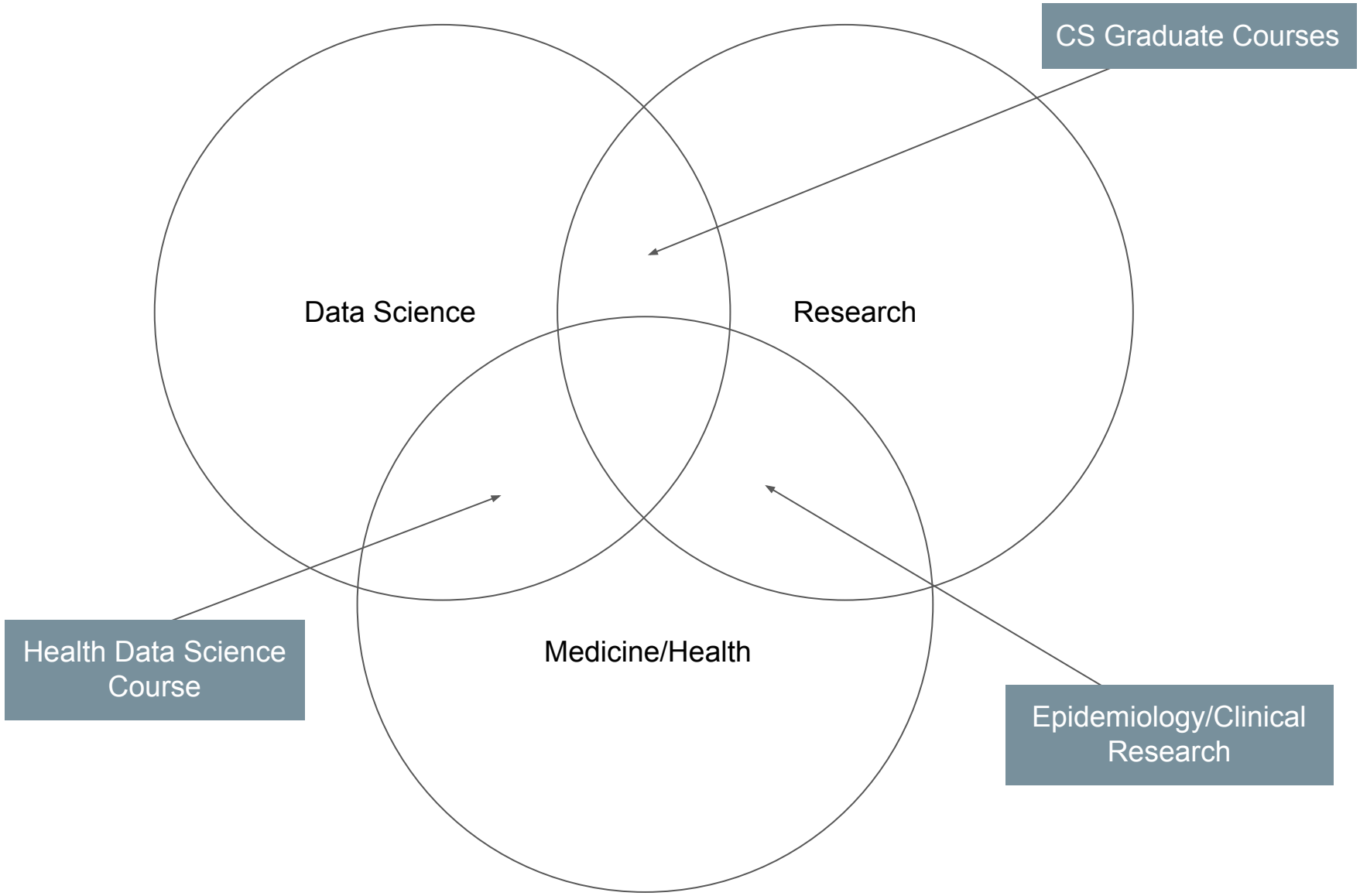

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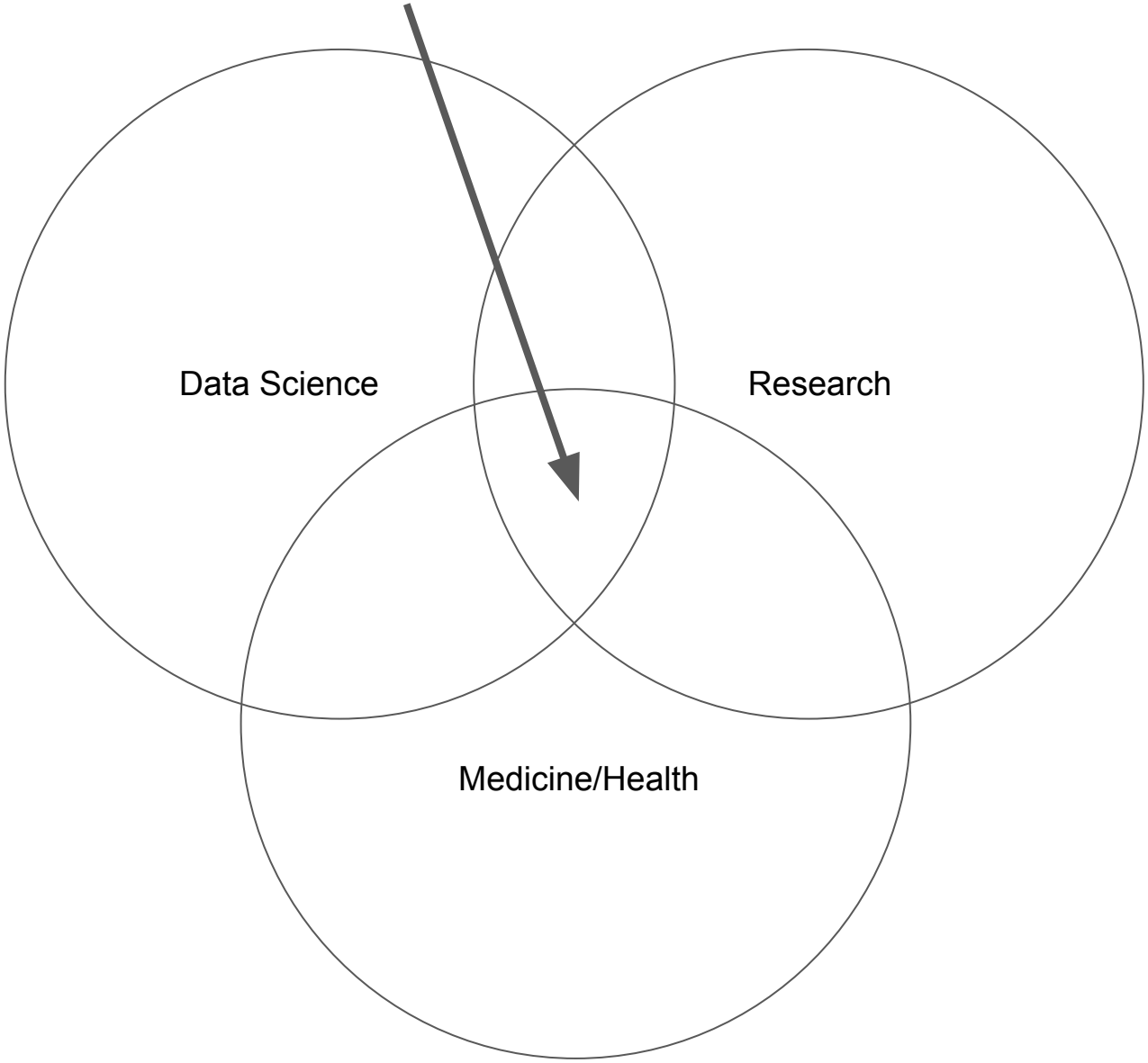

Learning Outcomes

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 each data science method: *each could be multiple graduate CS courses*
- **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, come speak to me if interested in this specifically.*

Course Structure

Overview of data types & analysis methods:

- **Lectures** (Monday/Wednesday)

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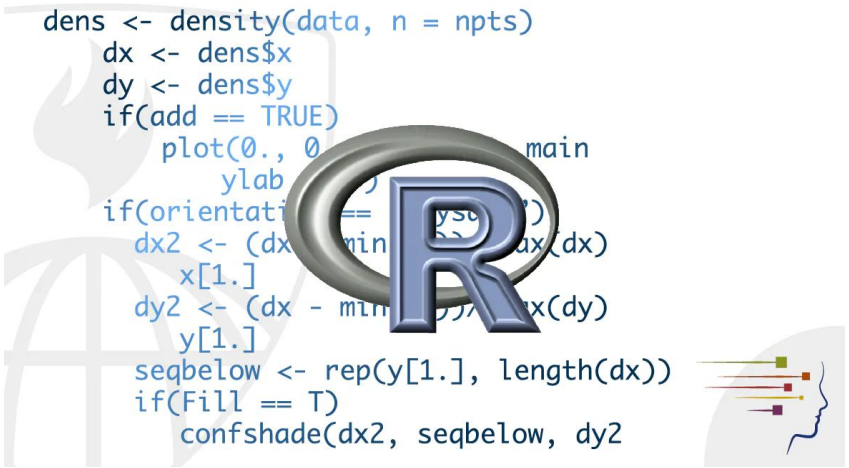
(CSCI4148: drop lowest scoring assignment)



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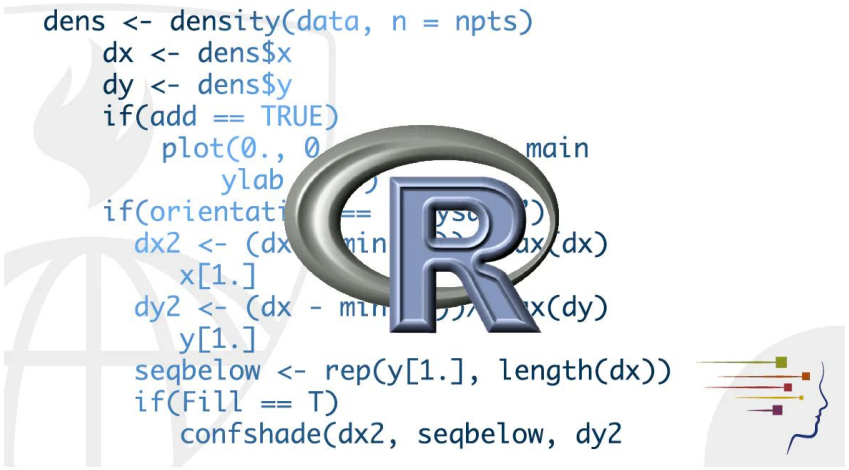

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2 papers per week, randomly assigned rota for leading discussion of paper with rest of class.

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Paper presentation (20%)

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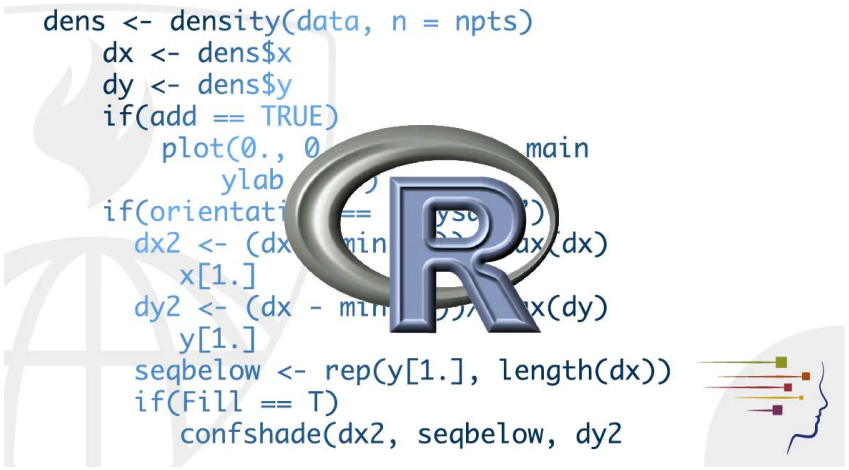

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Paper presentation (20%)

Participation in discussion (10%)

Development of a research proposal:

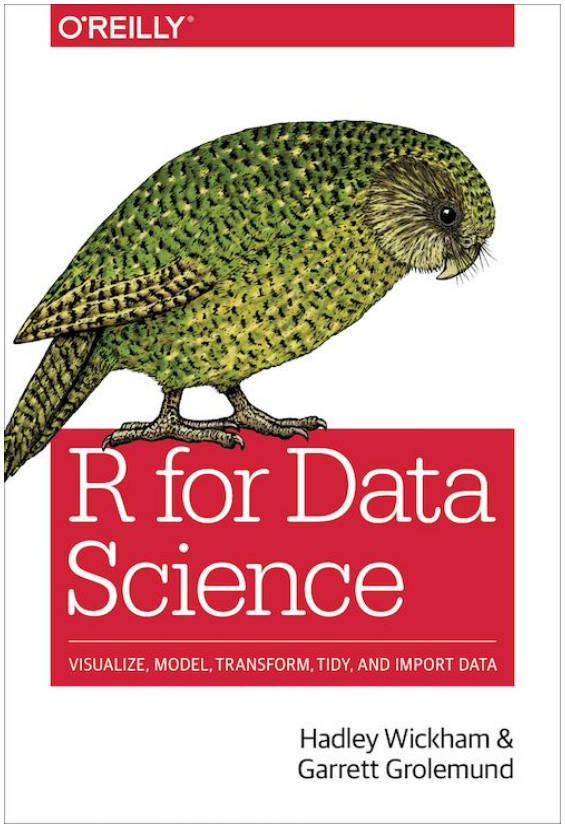
- **Class** (Wednesday/Friday)

Assessment:

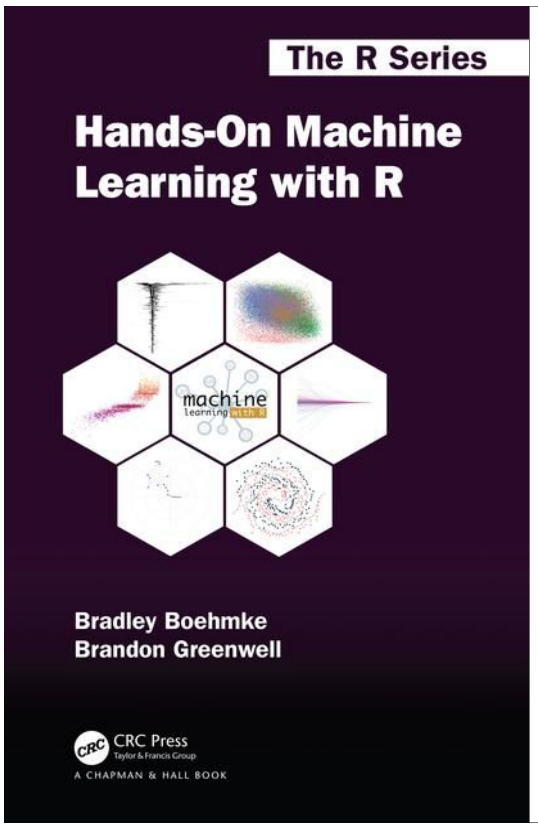
Presentation **last full week of class** (20%)

Submitted **final day of class** (20%)

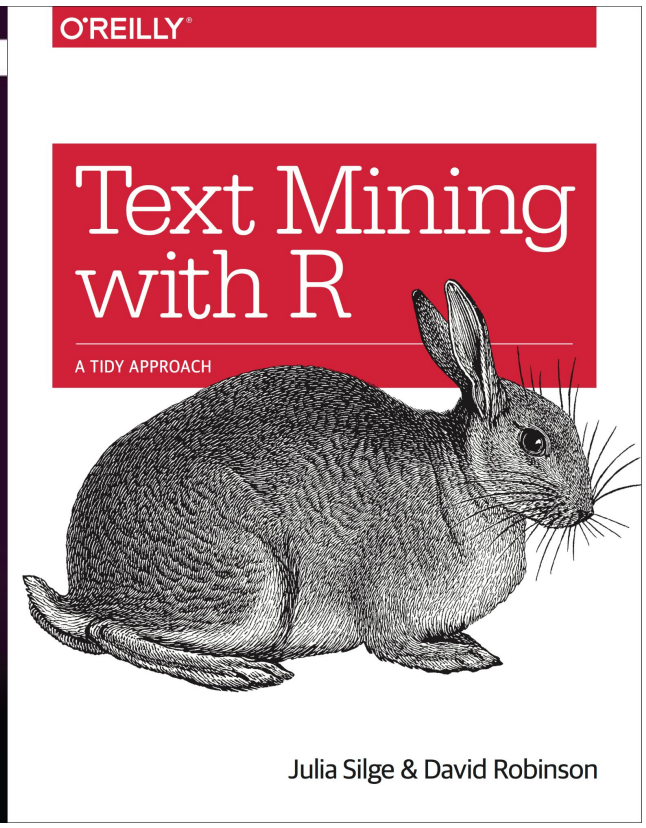
Course Materials



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



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



https://www.tidytextmining.com/

Course Website

https://maguire-lab.github.io/health_data_science_research_2026/

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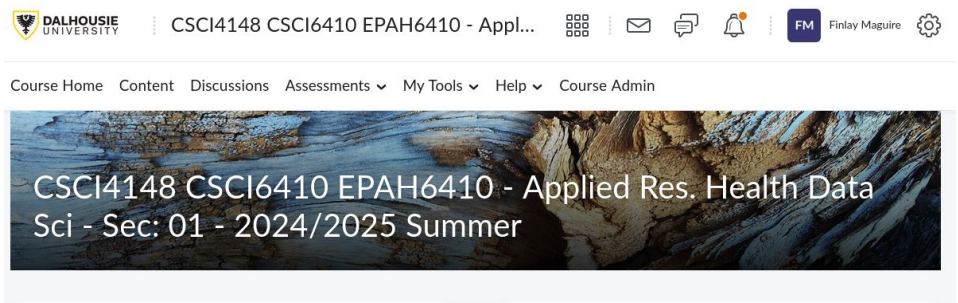
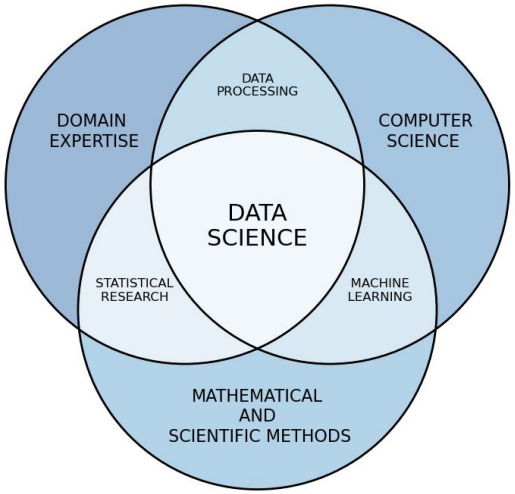


~~**Grades/Submissions: https://dal.brightspace.com/d2l/home/385844**~~

What is ~~health~~ data science?

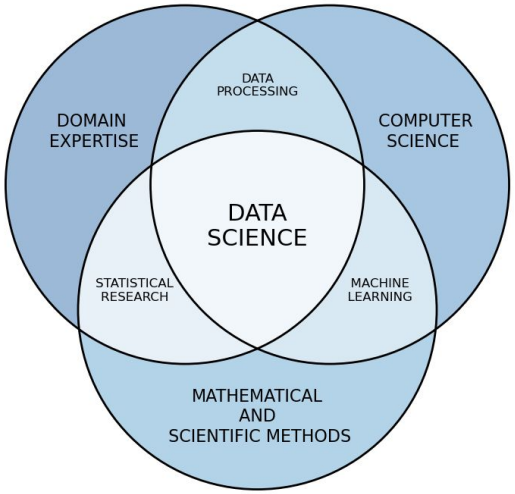
Data Science: *Data-intensive interdisciplinary approaches to understand and predict with secondary/live data*



http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram

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

A range of partial and totally overlapping terms:



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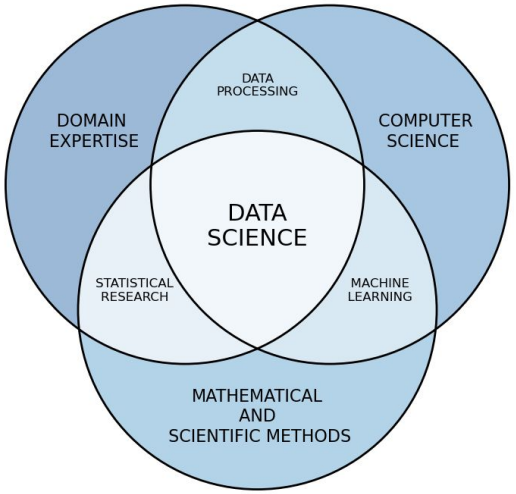
Data Science: *Data-intensive interdisciplinary approaches to understand and predict with secondary/live data*

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



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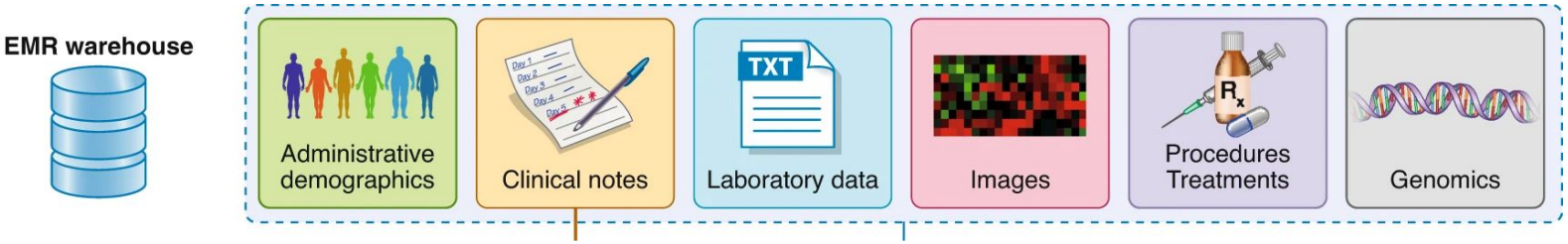
OK, what is **Health** Data Science?

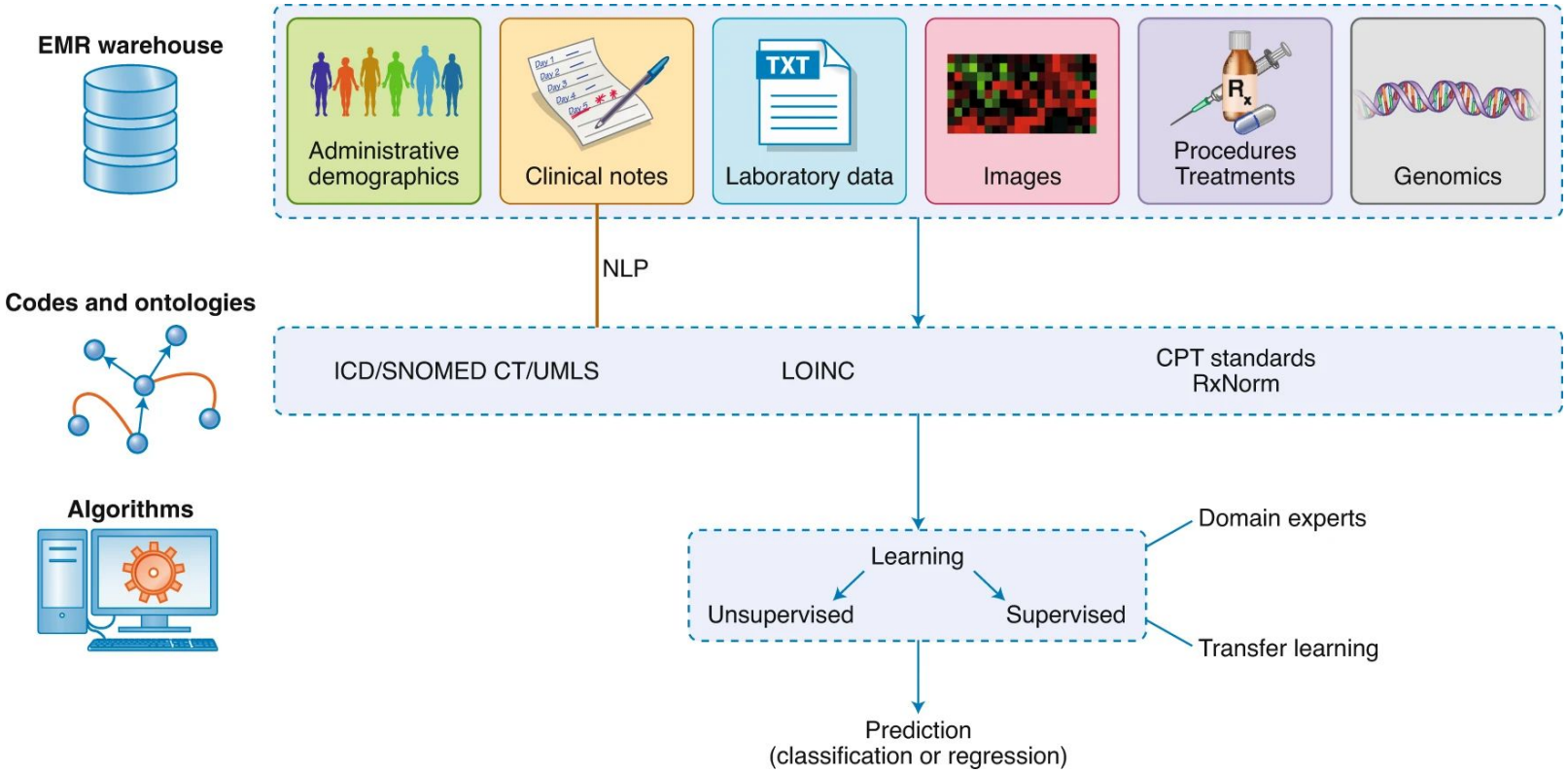
Data Science applied to Health Data



Why “health data” instead of “medical data”:

medical (being defined as MD-related”) ⊂ health ***- contentious***

Data Science applied to Health Data



https://www.nature.com/articles/s41588-020-0698-y/figures/2

Why “health data” instead of “medical data”:

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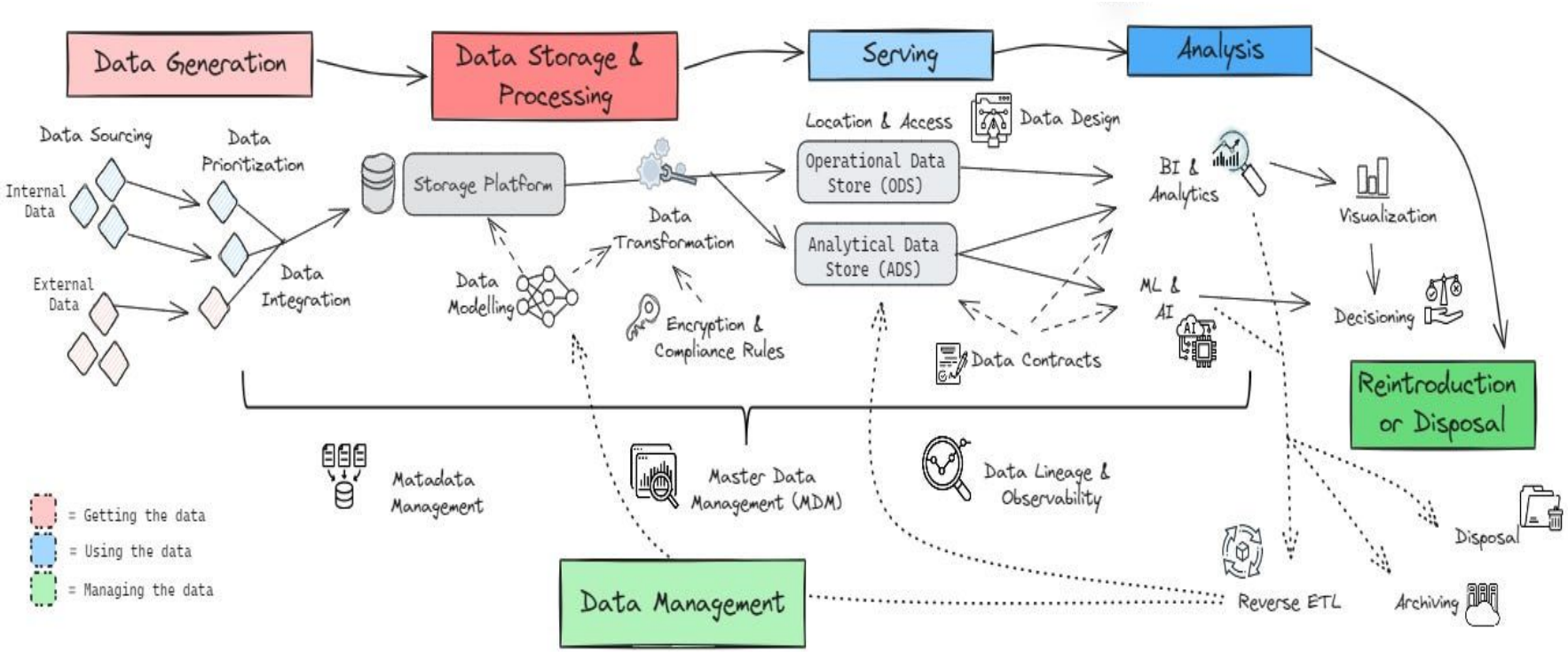
How does (health) data science (generally) differ from traditional epidemiology using secondary data?

Data science integrates within the wider data ecosystem



https://thedataecosystem.substack.com/p/issue-10-the-data-lifecycle
https://xkcd.com/2054/

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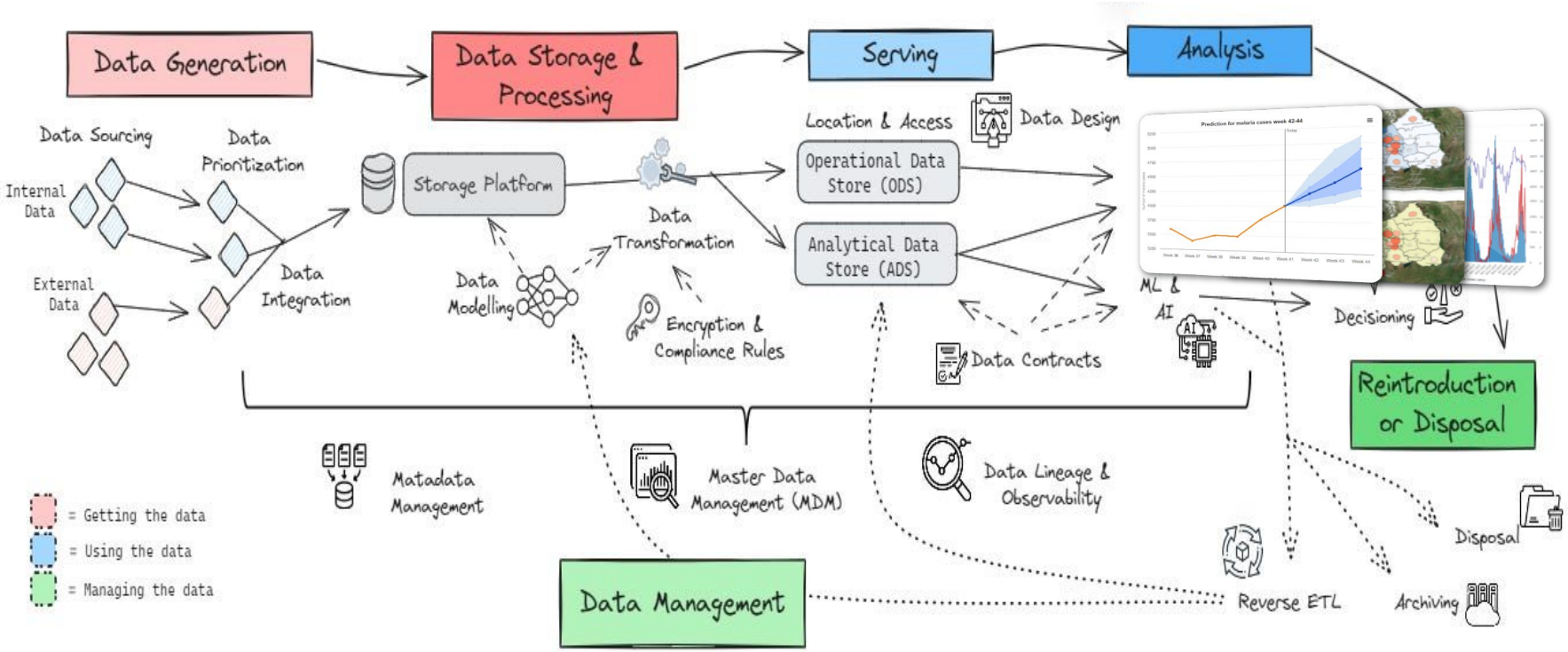

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Important as datafication pervades medicine (and more)

Medical Notes:
- 1-50MB

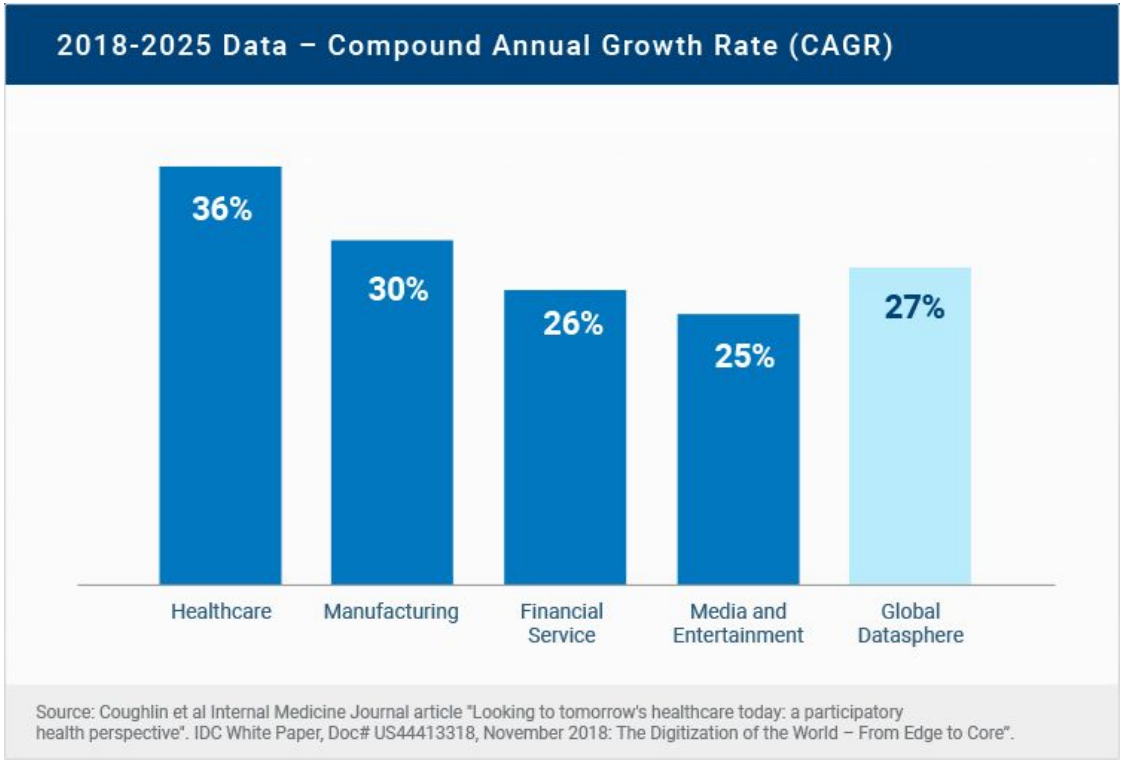
Laboratory Values:
- 10-2000MB

Physiological Sensors:
- 0.1-200GB

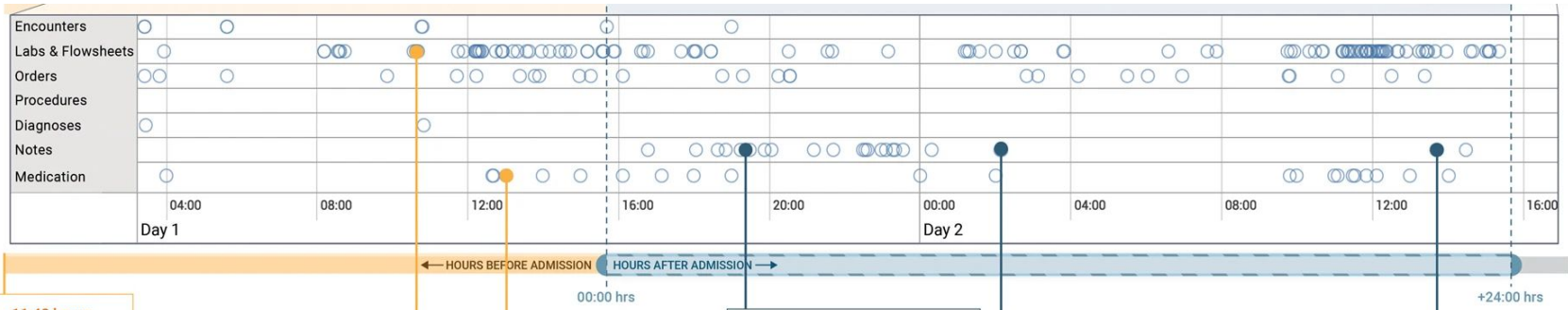
Genomics:
- 25-250GB

Medical Imaging:
- 0.1-10TB

Hospital:
- 0.5-50PB per day



Data Science handles unstructured and multi-modal data



−11:42 hours

Pegfilgrastim

-2:42 hours

Medication

Vancomycin, Metronidazole

+3:33 hours

Physician Note

"... PMH **of metastatic breast cancer, R lung malignant** effusion, and **R lung empyema** who presents with increased drainage from **R lung pleurx** tract ... "

+7:38 hours

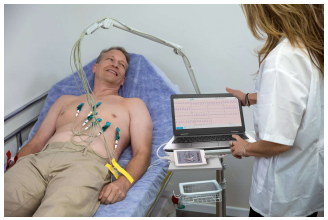
Radiology Report - CT CHEST ABDOMEN PELVIS

"... FINDINGS : CHEST LUNGS AND PLEURA: Redemonstration of a moderate **left pleural effusion**. **interval** removal of a right chest tube within a loculated **right pleural effusion** which contains foci of air. [..]. IMPRESSION: 1. Interval progression of disease in the chest and abdomen including **increased** mediastinal **lymphadenopathy, pleural/parenchymal** disease within the right lung, probable new hepatic metastases and subcutaneous nodule within the thorax [..]"

+22:47 hours

Pulmonary Consult Note

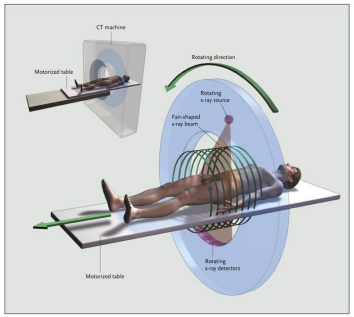
"... has a **complicated pleural space** that requires IR guidance. CT scan showing **increased loculted effusion** on R compared to date ..."

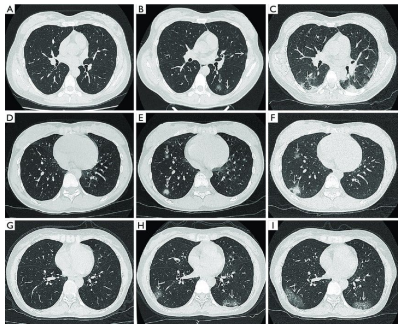


−3:23 hours

Nursing Flowsheet

NUR RS BRADEN SCALE SCORE : 22

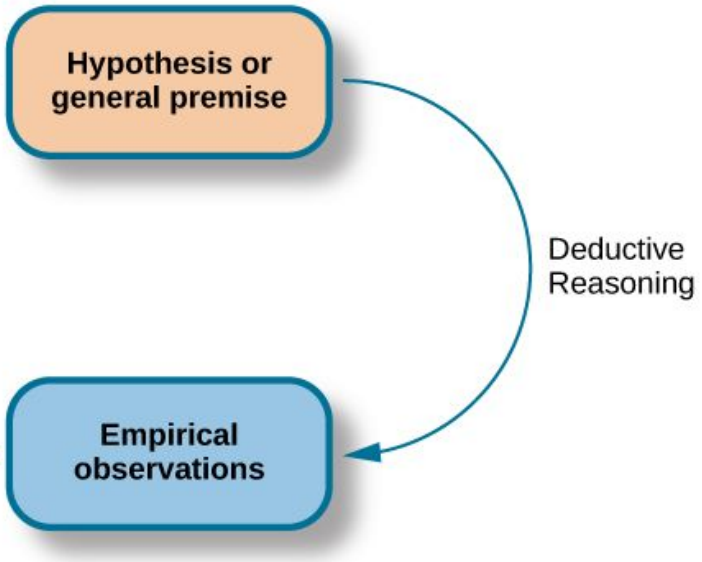




Data science supports inductive approaches

Deductive:

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



https://opened.cuny.edu/courseware/lesson/14/student/?task=3

Data science supports inductive approaches

Deductive:

- “Condition X, causes Y”
- Collect data
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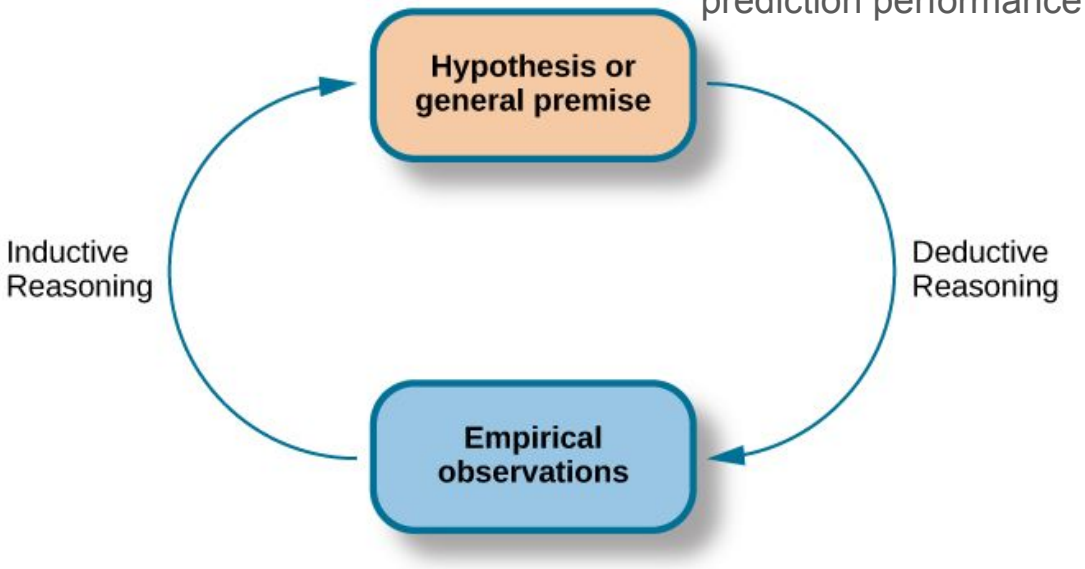
Inductive:

- 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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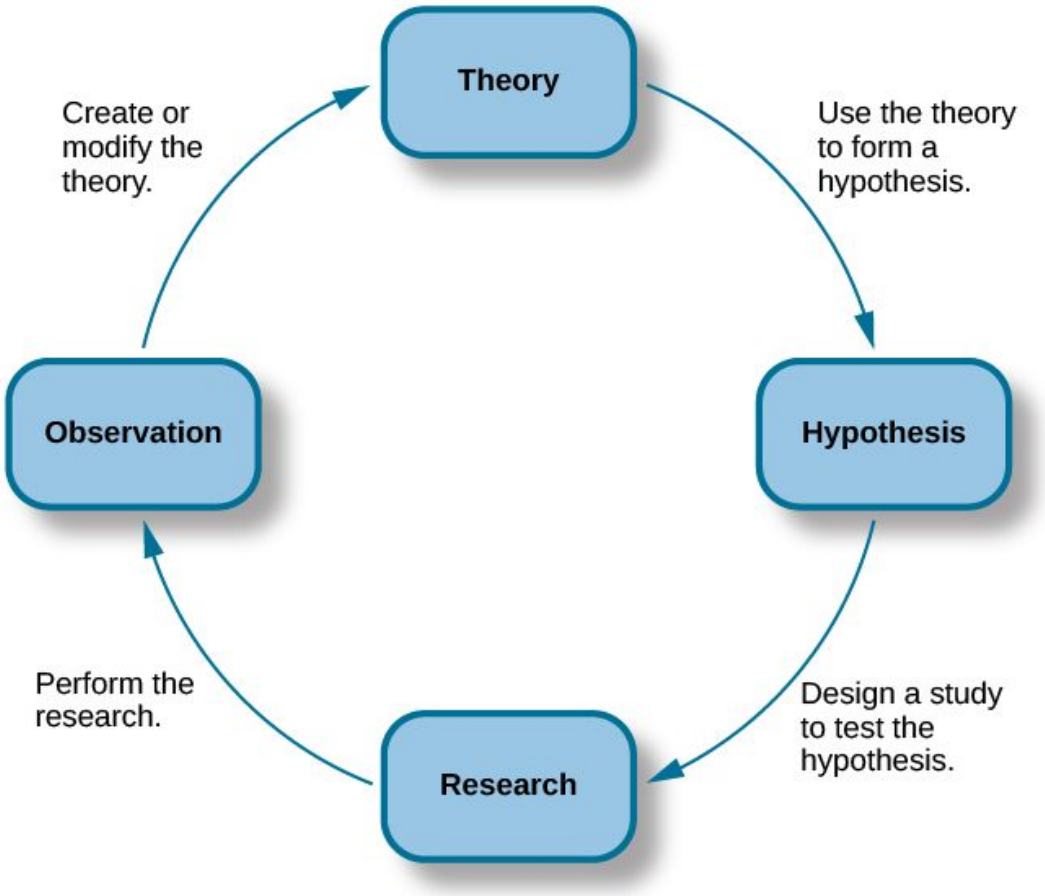
Data science aligns with knowledge cycle



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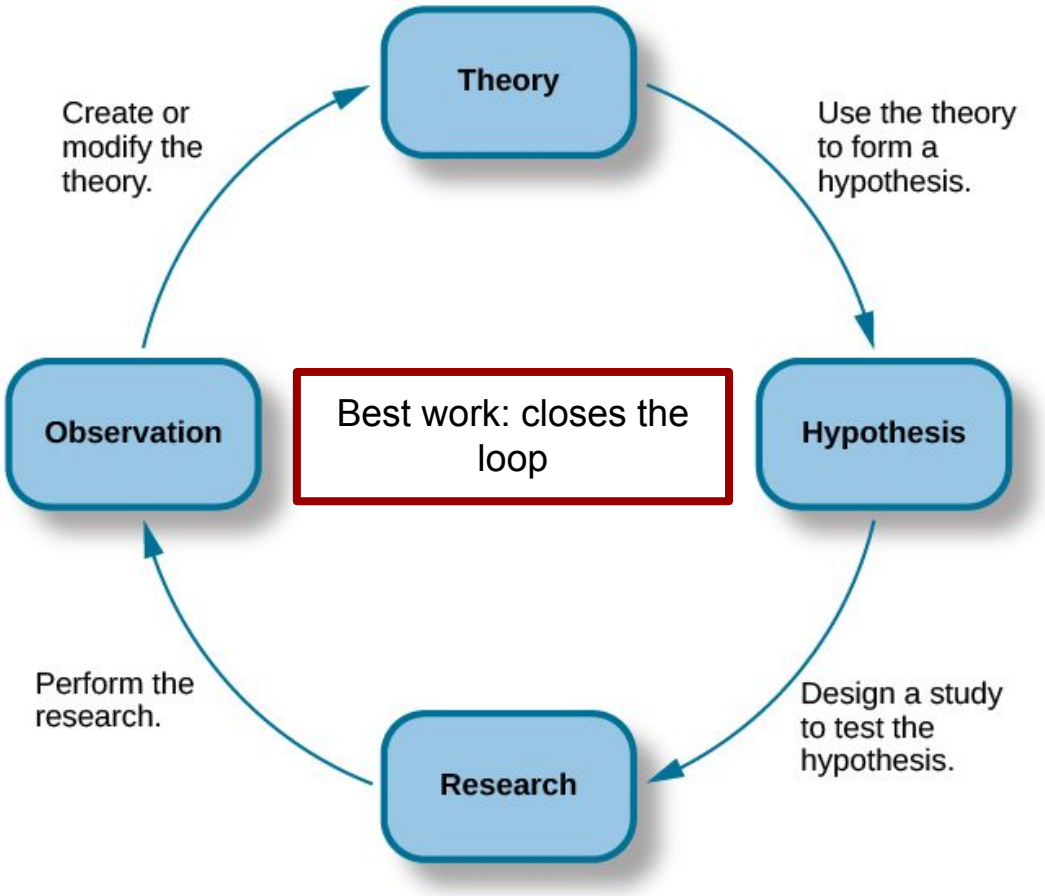

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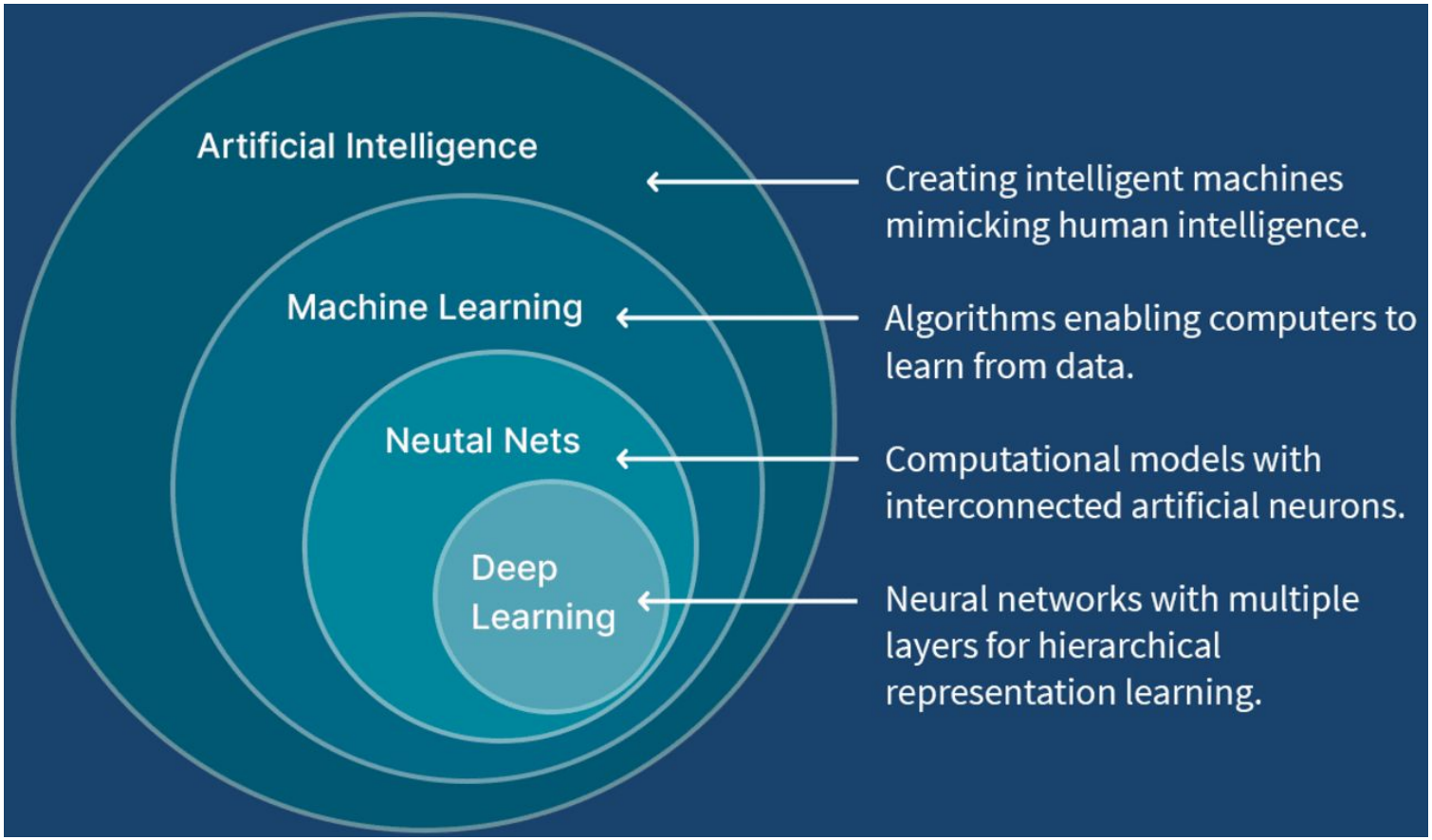
Most obvious difference: Data Science often is based in Machine Learning

Machine Learning is a subset of Artificial Intelligence



https://www.qlik.com/us/augmented-analytics/machine-learning-vs-ai

ML involves finding and using patterns in data

- “Machine Learning is the field of study that gives the computer the ability to learn without being explicitly programmed”

- “A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.”

- **T**ask *(play checkers)*
- **E**xperience *(data)*:
  - games played by the program (with itself)
- **P**erformance *(metric)*:
  - How often does it win

- *Training models which identify patterns in data*

https://xkcd.com/1838/

Is Machine Learning just a CS-flavoured rebrand of statistics?

Large overlap but difference in people and priorities

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

https://stats.stackexchange.com/questions/442128/machine-learning-vs-statistical-learning-vs-statistics

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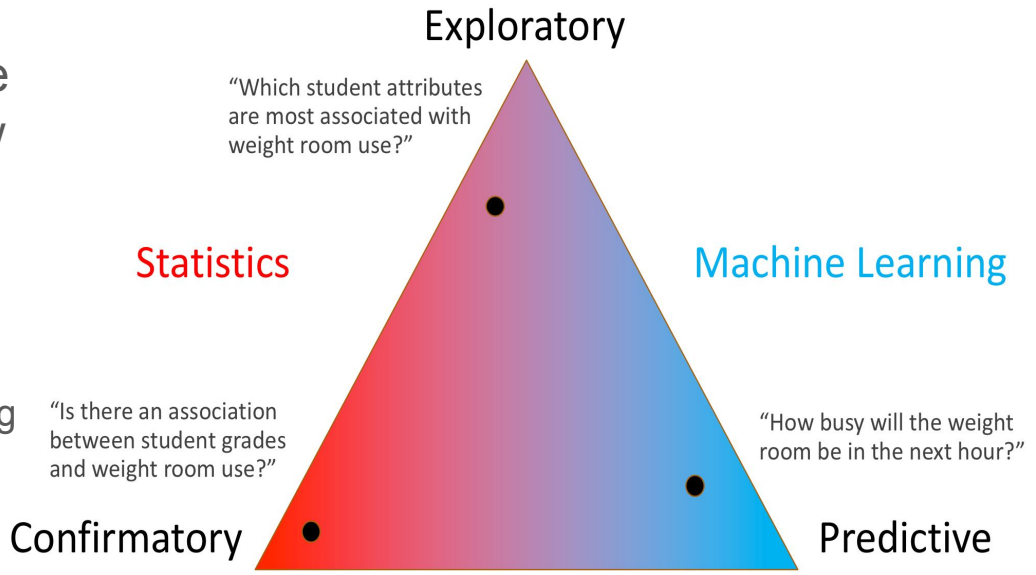

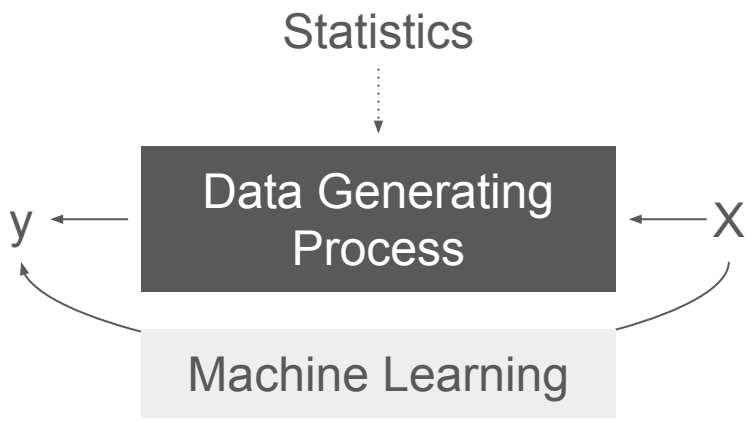

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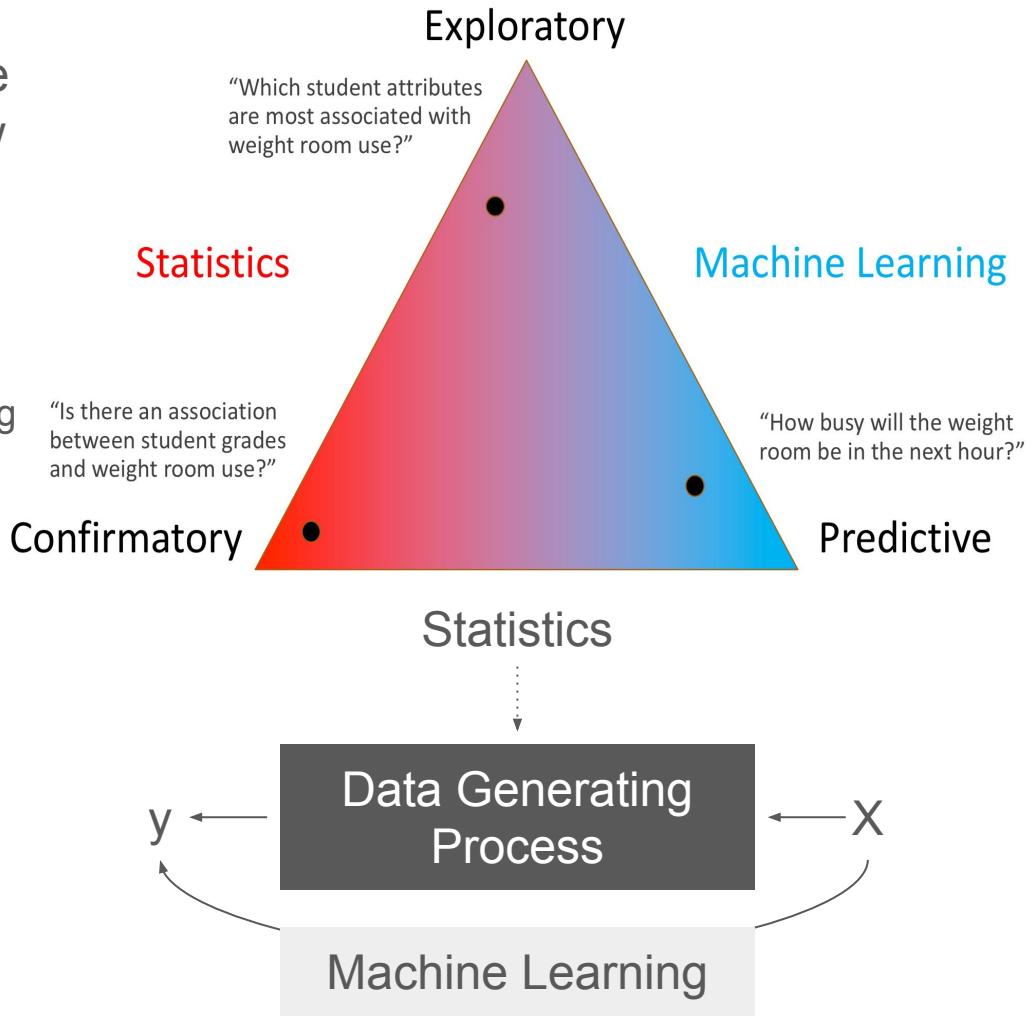
- DS/ML Pitfalls (can be):
  - Less rigorous/principled
  - Prone to reinventing the wheel
- DS/ML Benefits (can be):
  - More flexible
  - Less prescriptive/intimidating



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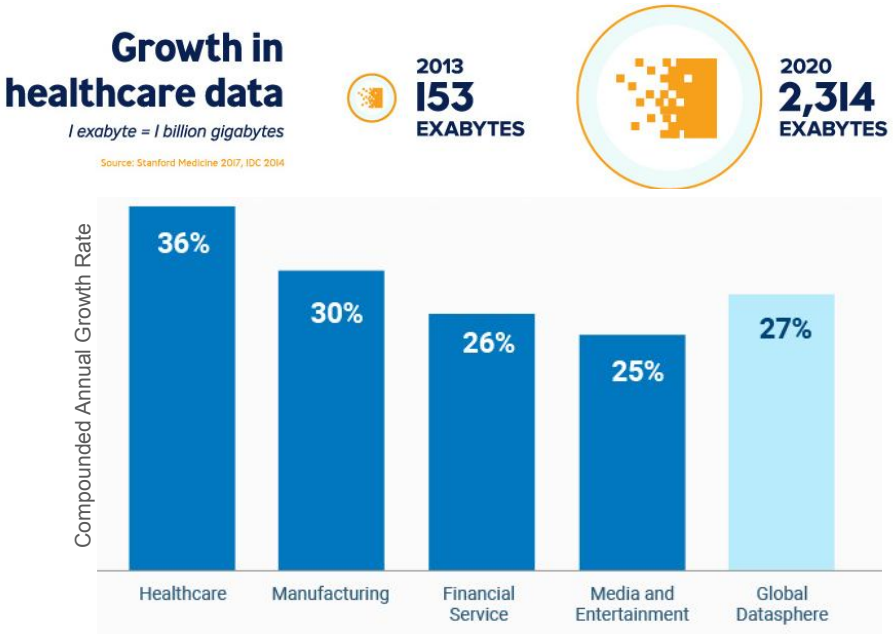
Why learn about Health Data Science research?

Opportunity of Health Data Science

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

- Huge amounts of health data



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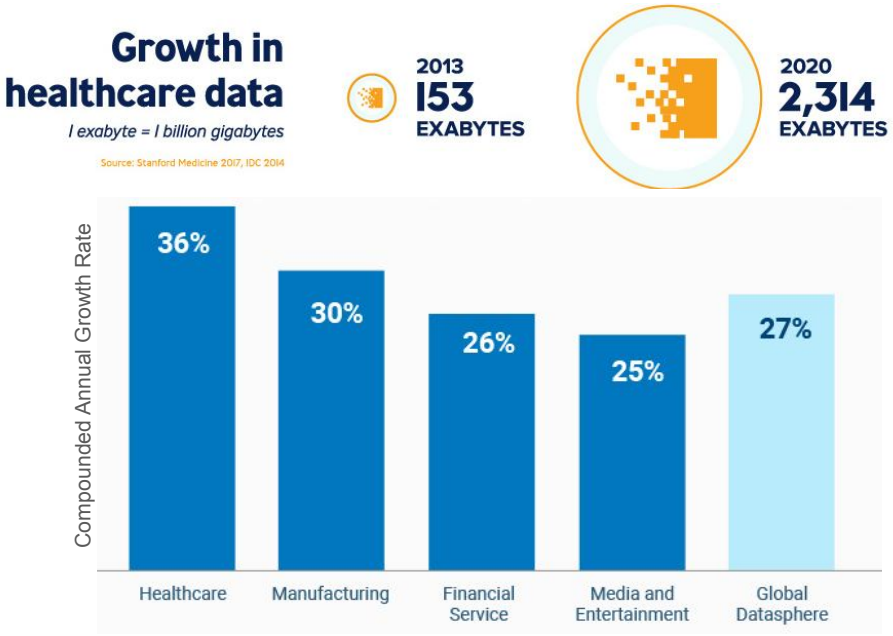

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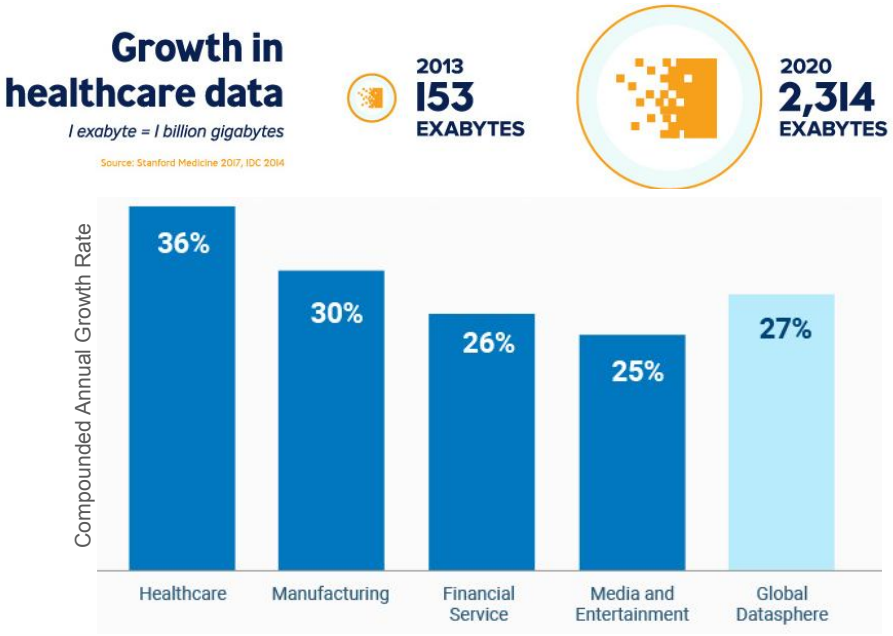

Opportunity of Health Data Science

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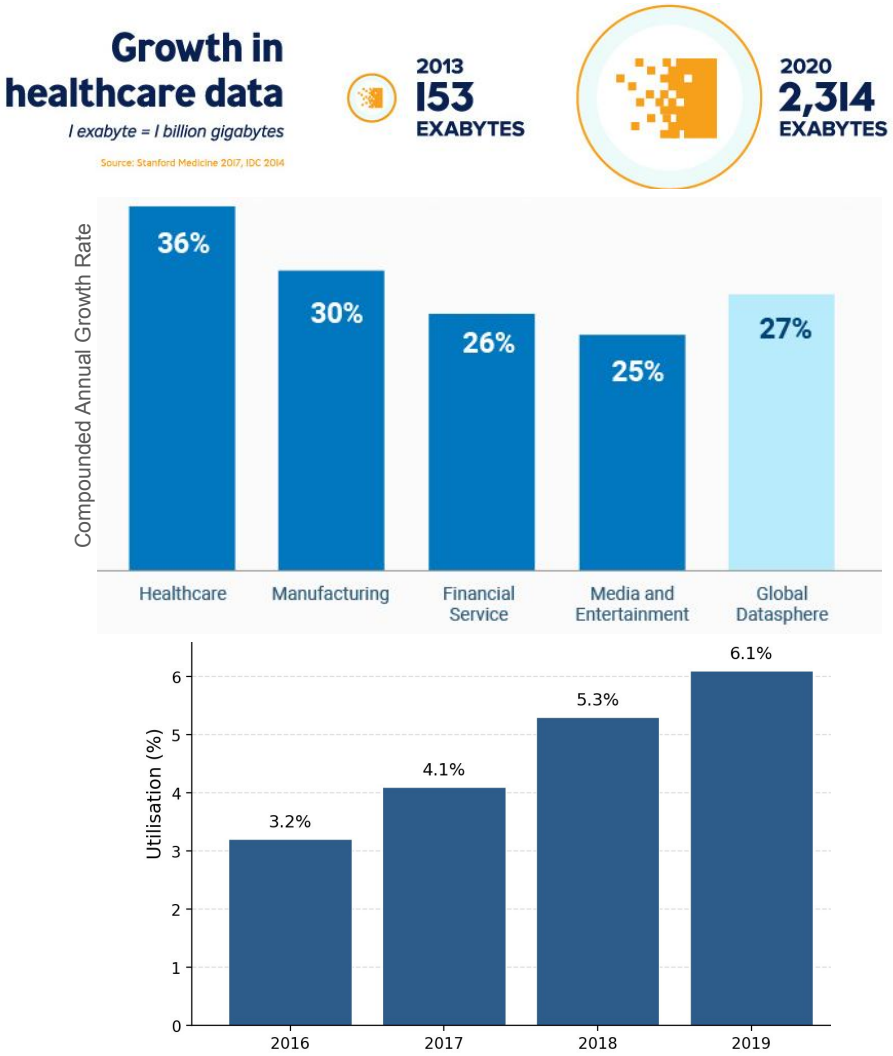
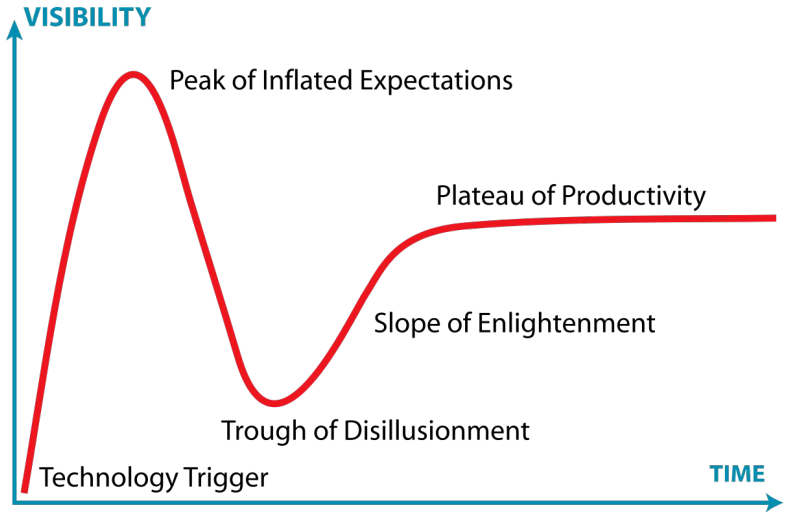
- Many **interesting** and **important problems**
- Many domain experts desperate for data-related help with these problems
- Relative few skilled data science practitioners



Xuanwu Hospital: % of staff requesting EMR data for research (Li et al., JMIR Med Inform 2021)

(Some) Challenges of Health Data Science

- Lots of hype



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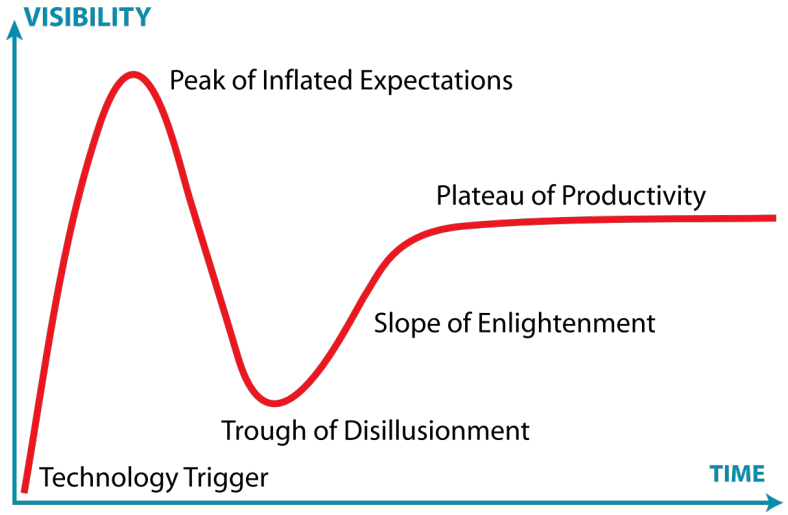
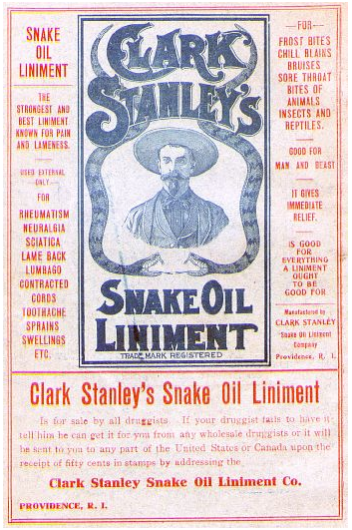
- Lots of hype
- Lots of grifters

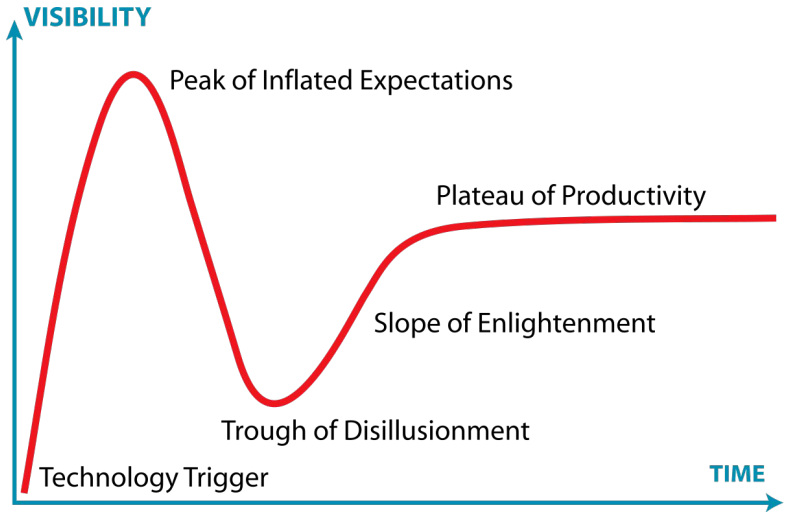


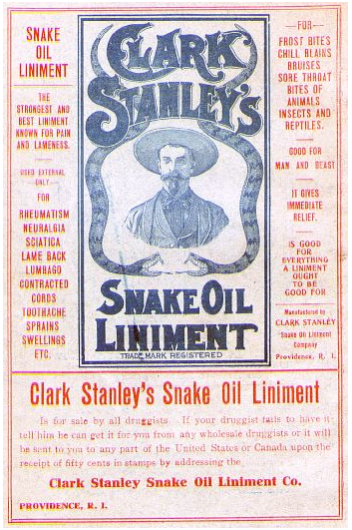


https://upload.wikimedia.org/wikipedia/commons/9/94/Gartner_Hype_Cycle.svg
https://commons.wikimedia.org/wiki/File:Clark_Stanley%27s_Snake_Oil_Liniment.png

(Some) Challenges of Health Data Science

- Lots of hype
- Lots of grifters
- Data quality issues
- Contextual/Metadata quality issues





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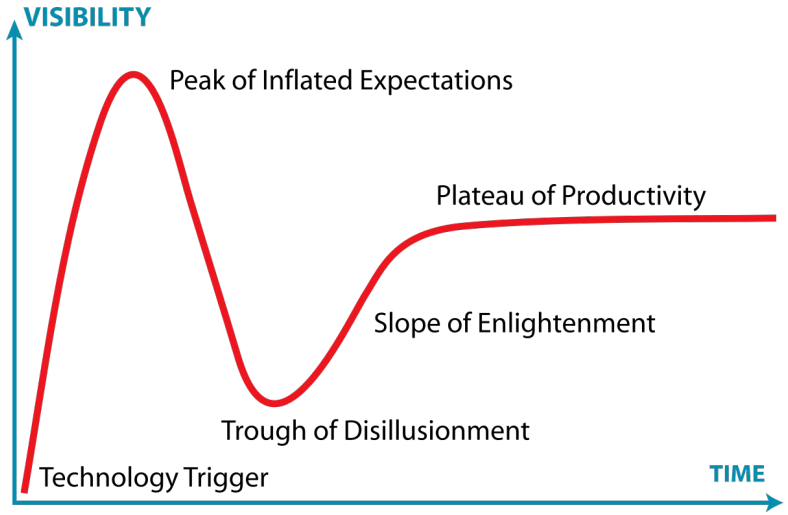
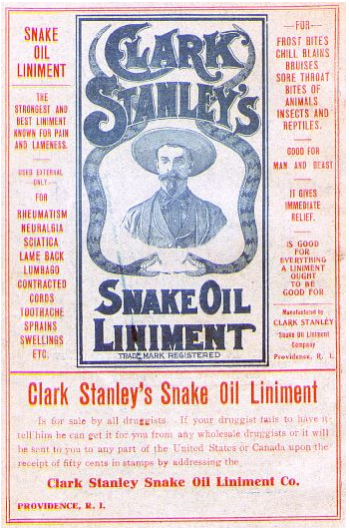
(Some) Challenges of Health Data Science

- 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/



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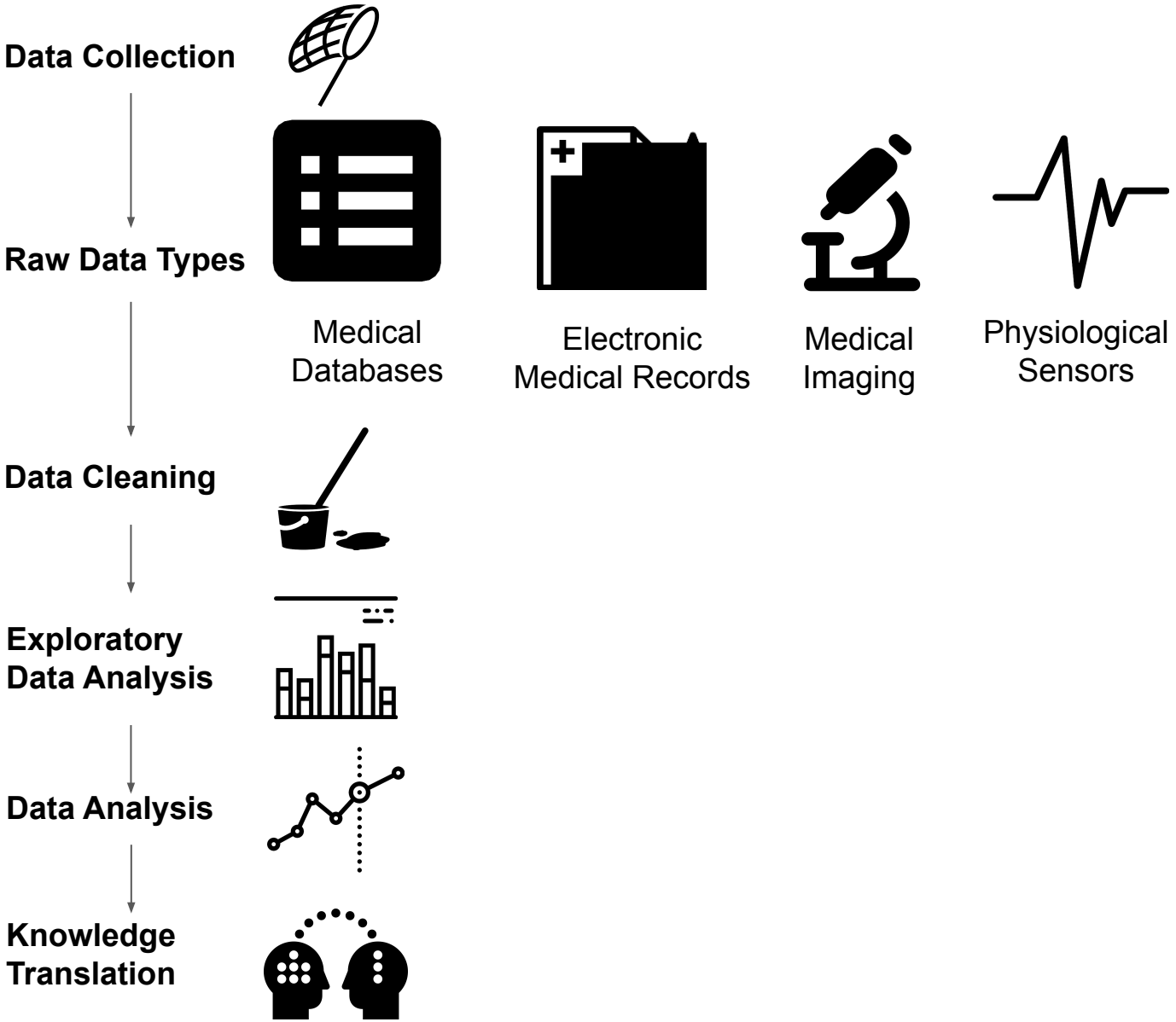

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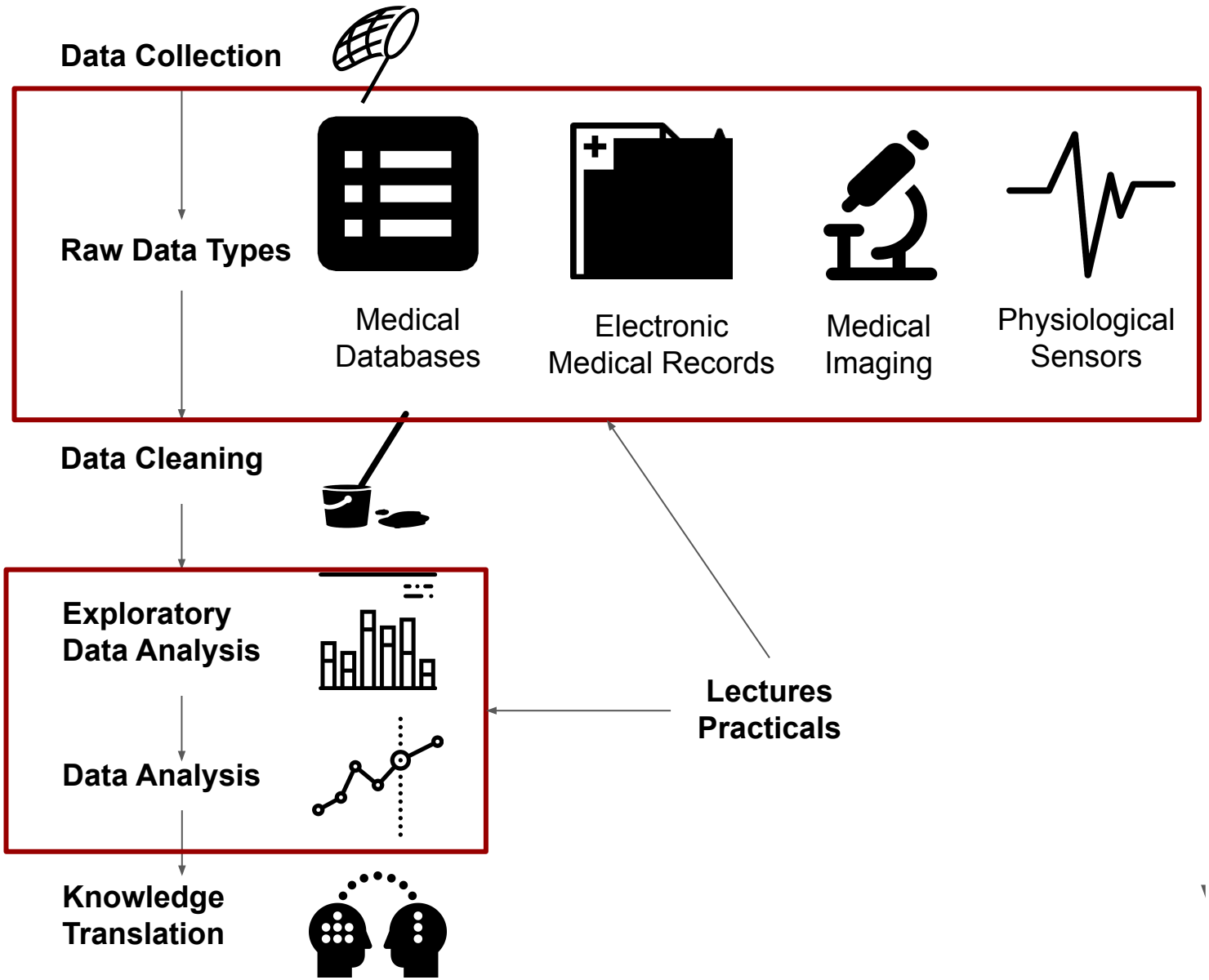

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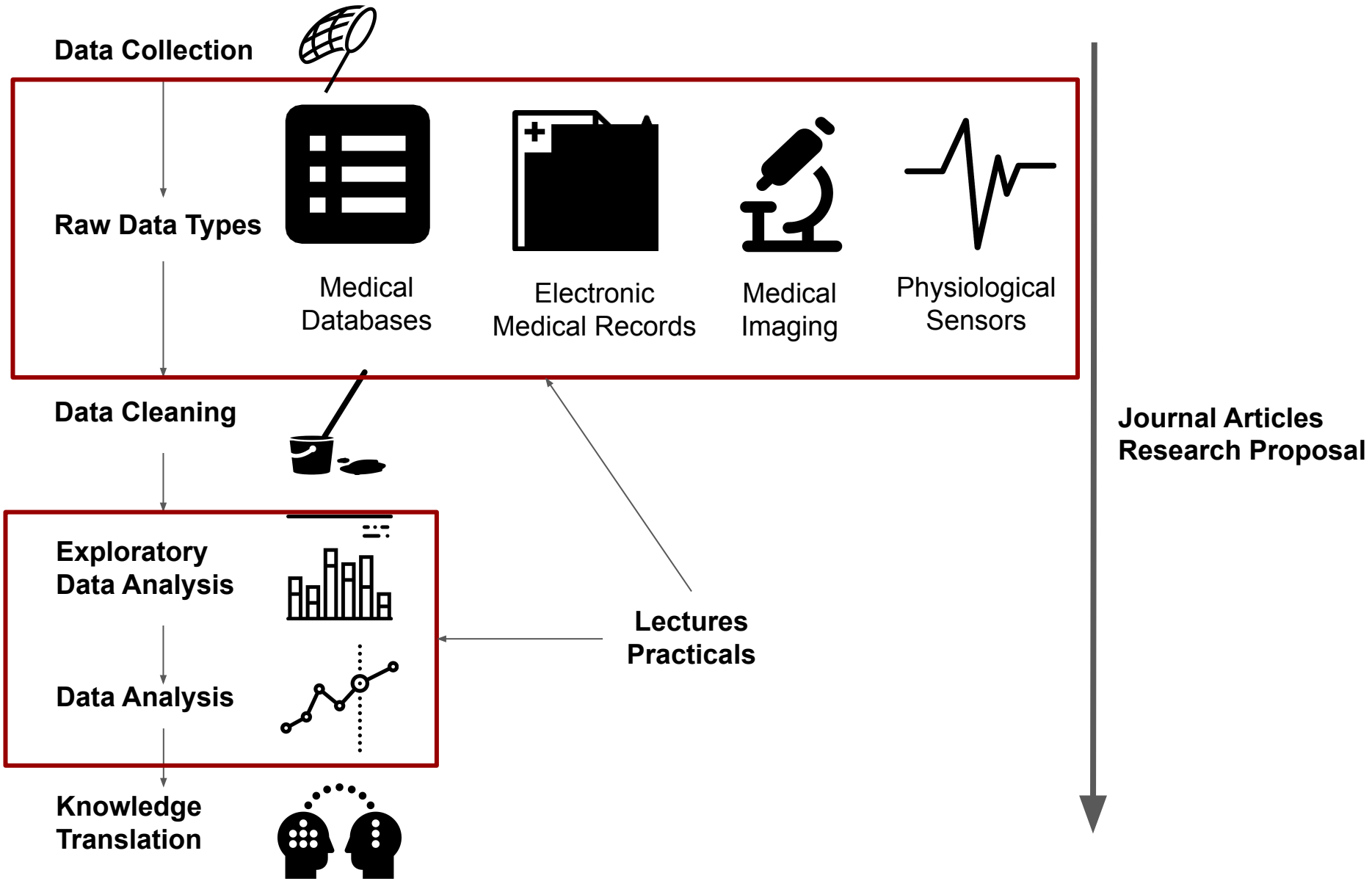


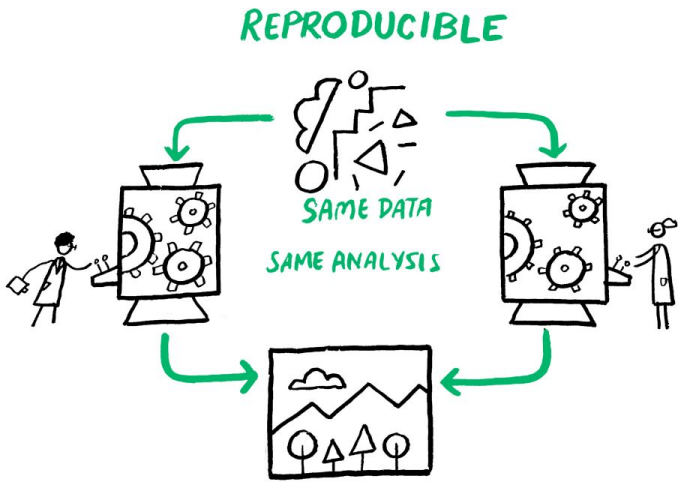
Let’s take a 5 minute break!

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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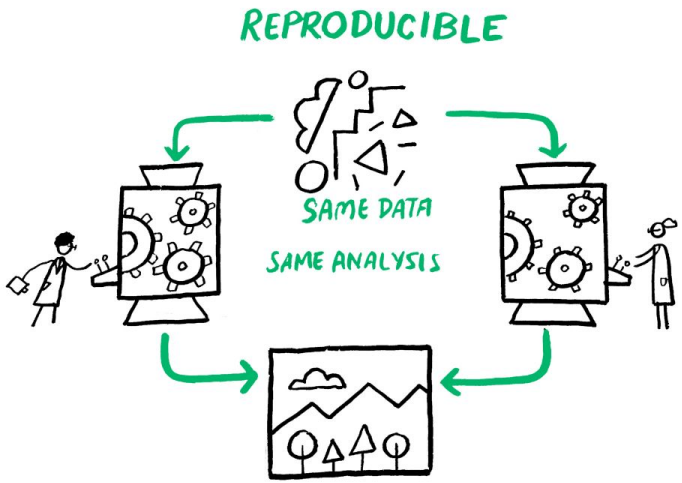

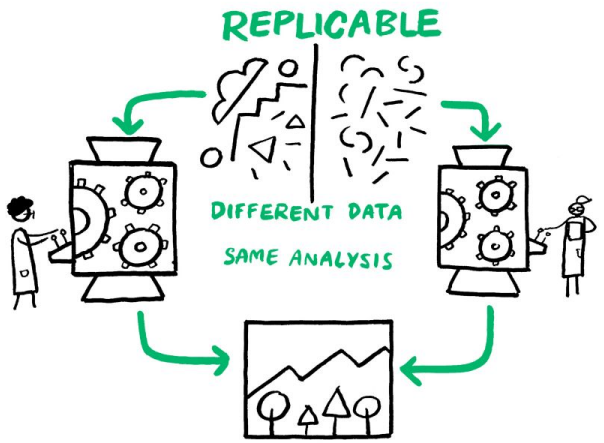

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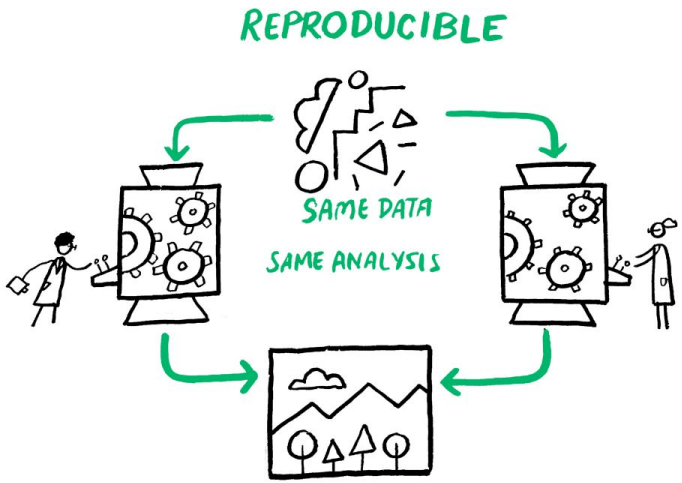

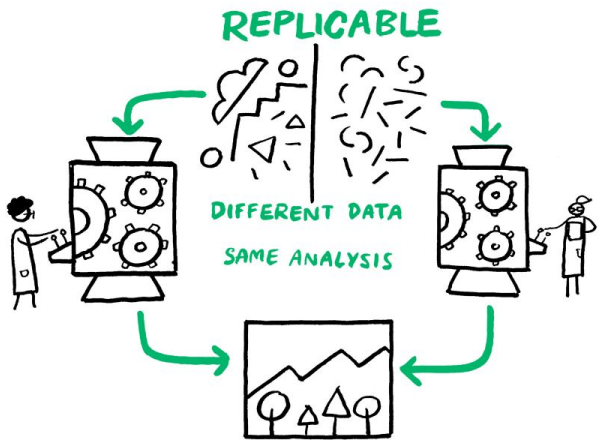

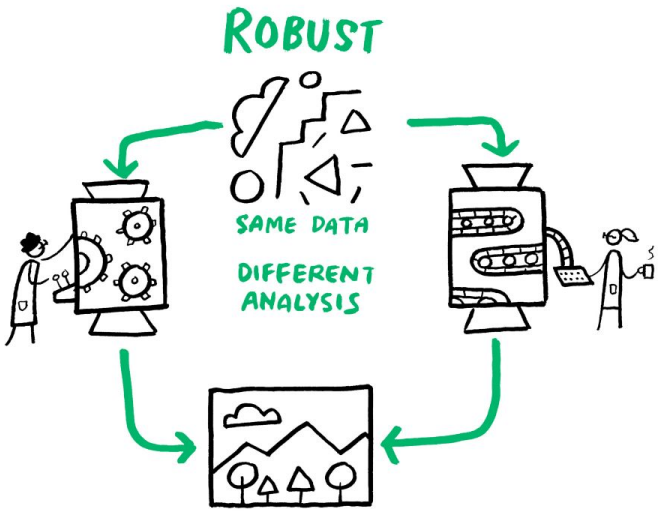

oliviergimenez.github.io/reproducible-science-workshop

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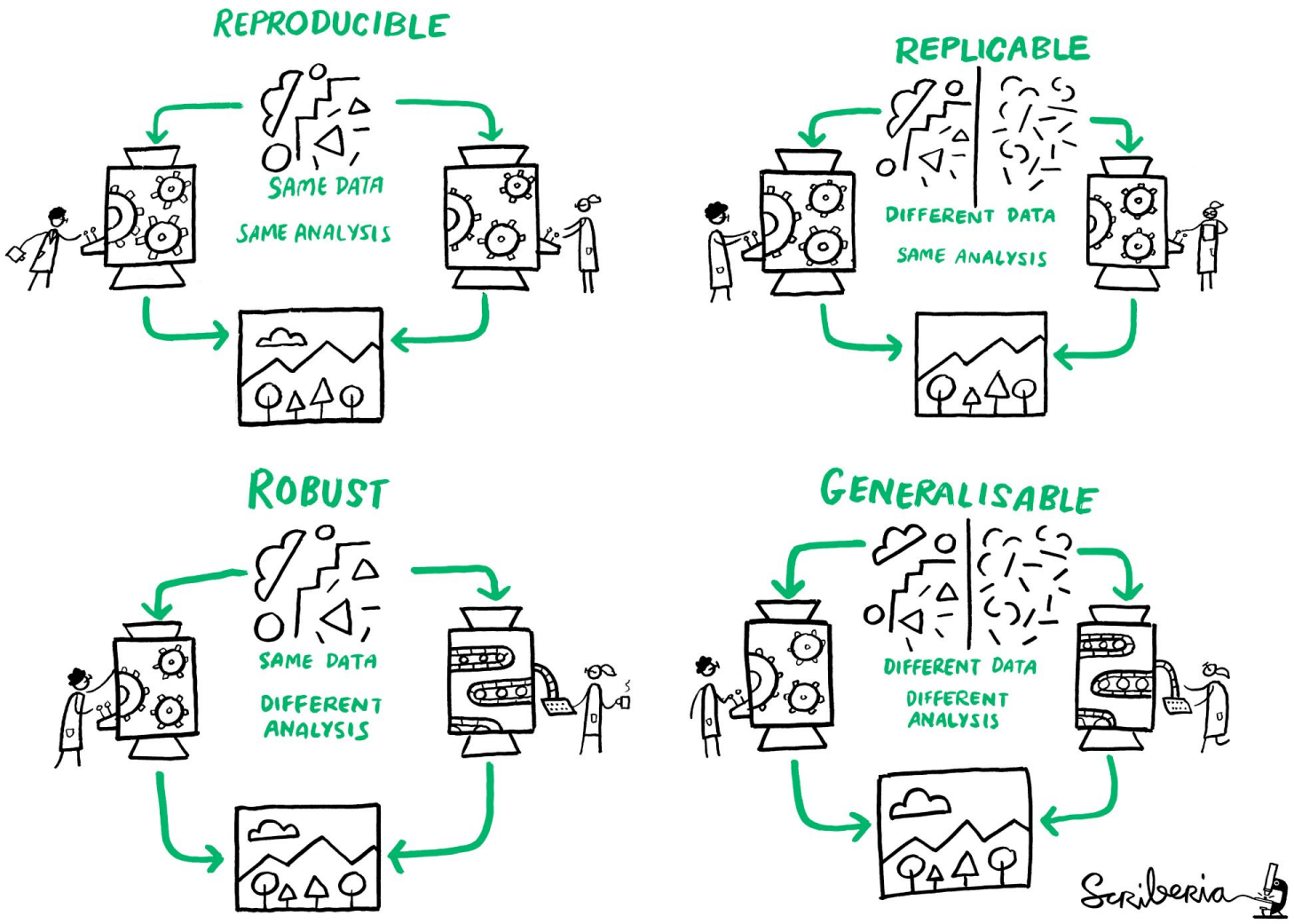
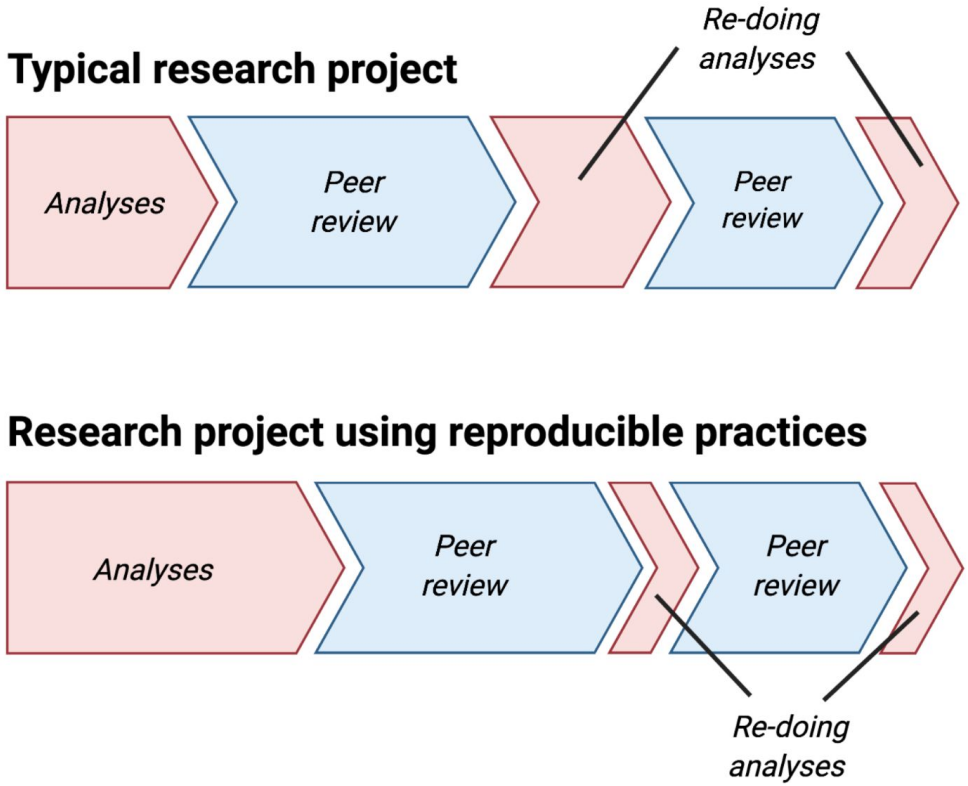


oliviergimenez.github.io/reproducible-science-workshop

Makes your own life easier



@dsquintana

oliviergimenez.github.io/reproducible-science-workshop

What do we need to do to have reproducible research?

Reproducibility checklist

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  - Main analyses
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- Keep track of the exact version of every library/program you use
- Remove hard-coded/system specific paths

How do we actually do these things?

Choose a language that makes it easy to do most/all of your analysis

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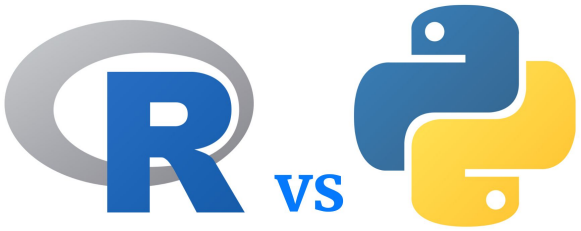

May 2026	May 2025	Change	Programming Language	Ratings	Change
1	1		Python	19.98%	-5.37%
2	3	↑	C	11.55%	+1.84%
3	4	↑	Java	7.94%	-1.37%
4	2	↓	C++	7.92%	-2.02%
5	5		C#	5.41%	+1.19%
6	6		JavaScript	3.08%	-0.60%
7	8	↑	Visual Basic	2.90%	+0.28%
8	12	⇈	R	1.77%	+0.31%
9	10	↑	SQL	1.57%	-0.33%
10	9	↓	Delphi/Object Pascal	1.44%	-0.85%

https://www.tiobe.com/tiobe-index/

2026 consolidation toward R for statistical:

- MATLAB #20
- SAS #28
- Wolfram/Mathematica: #50-100
- S #102
- SPSS #112
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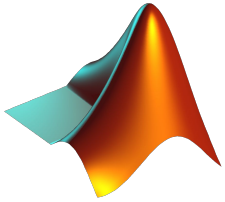

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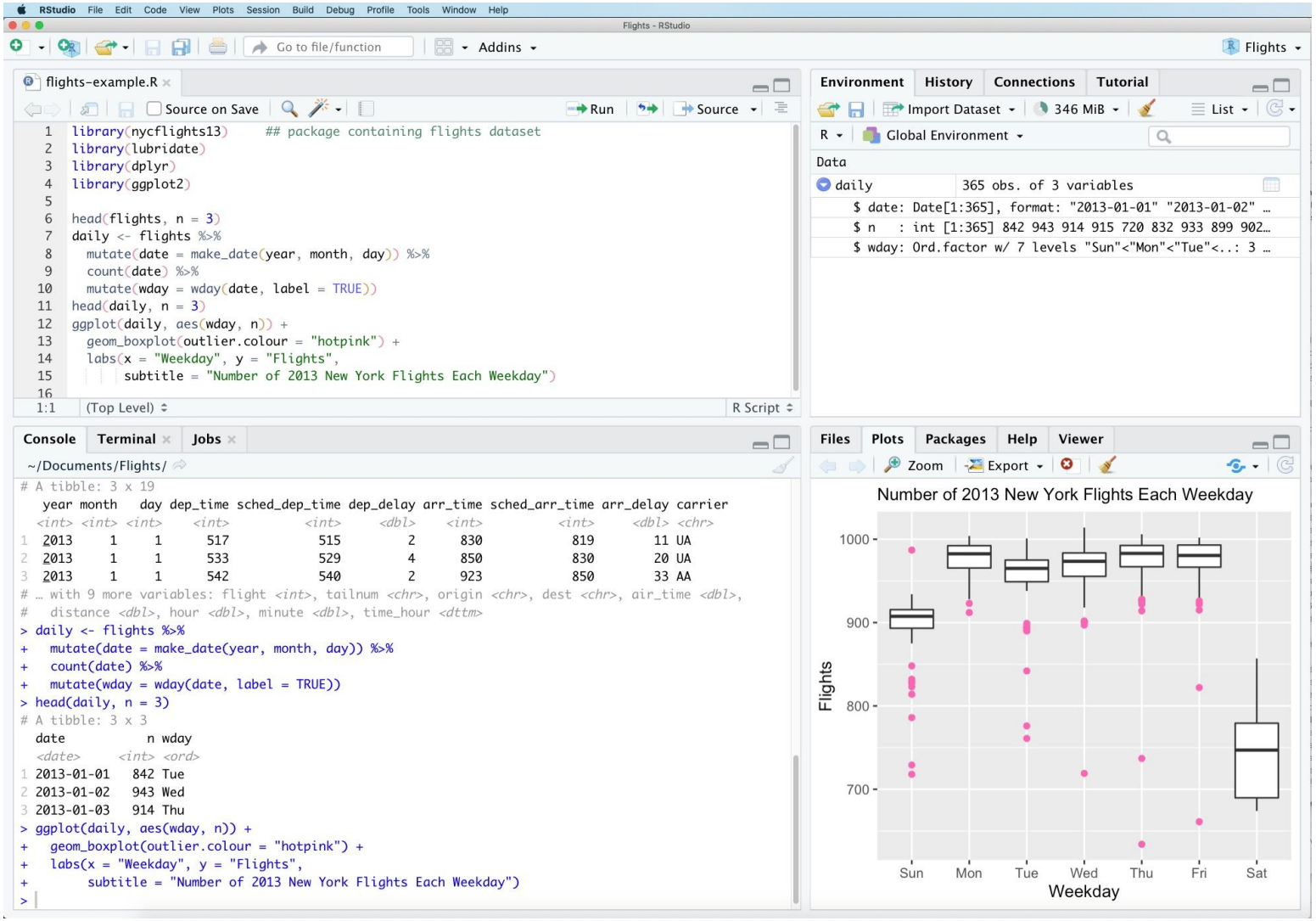
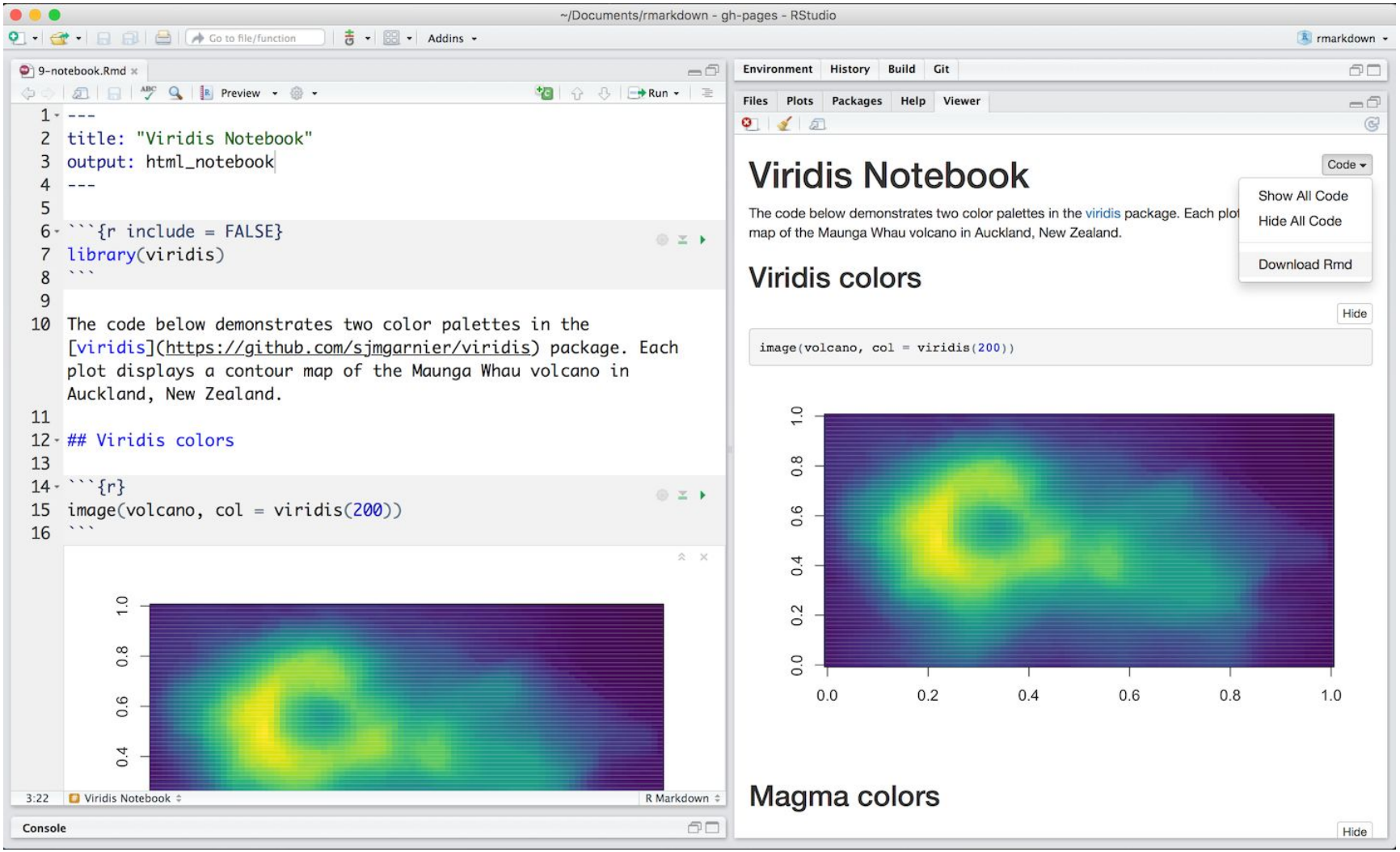
Use a data science focused IDE: Rstudio

.Rproj file
here()

set.seed()
sessionInfo()



Use notebooks to document analyses: Rmarkdown/Quarto



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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.

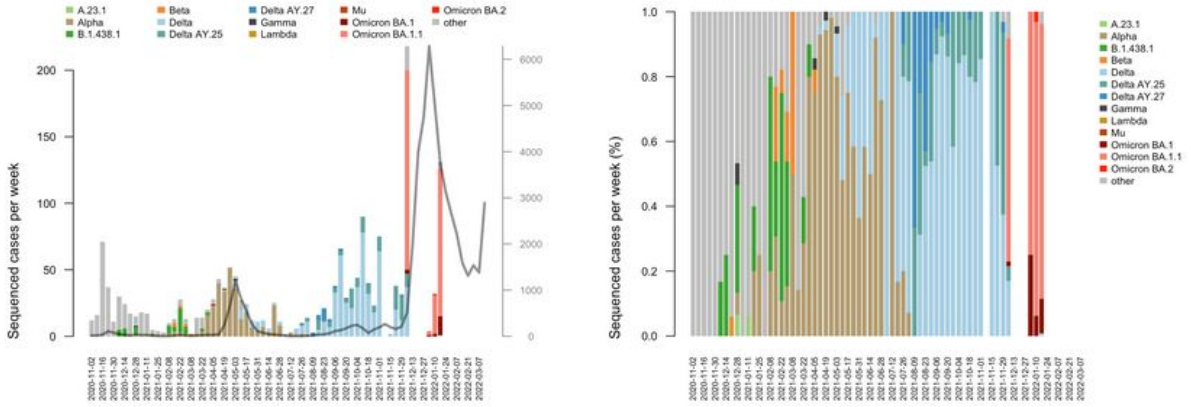
BC AB SK MB ON QC NS NB NL

Nova Scotia

Additional up-to-date COVID data for this province can be found here:
https://experience.arcgis.com/experience/204d6ed723244dfbb763ca3f913c5cad

Hide

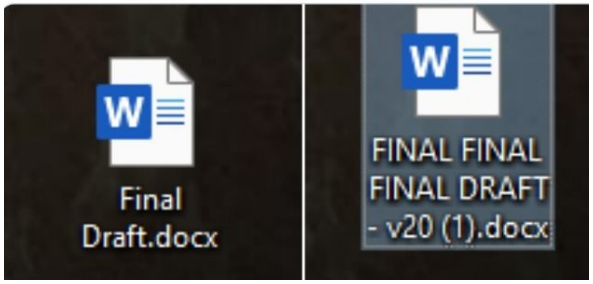
```
plot.variants(region='Nova Scotia')
plot.variants(region='Nova Scotia', scaled=T)
```

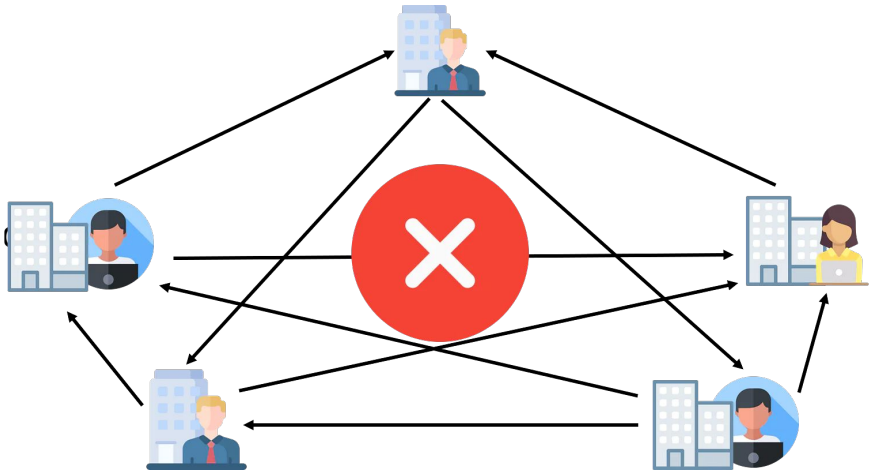


https://covarr-net.github.io/duotang/duotang.html#

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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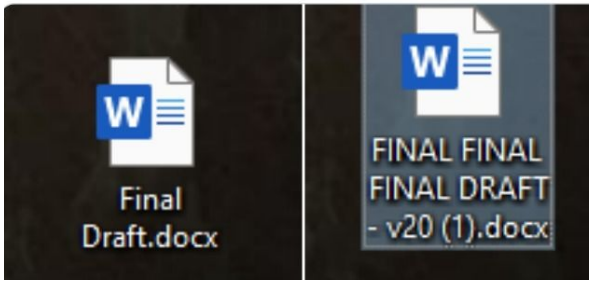
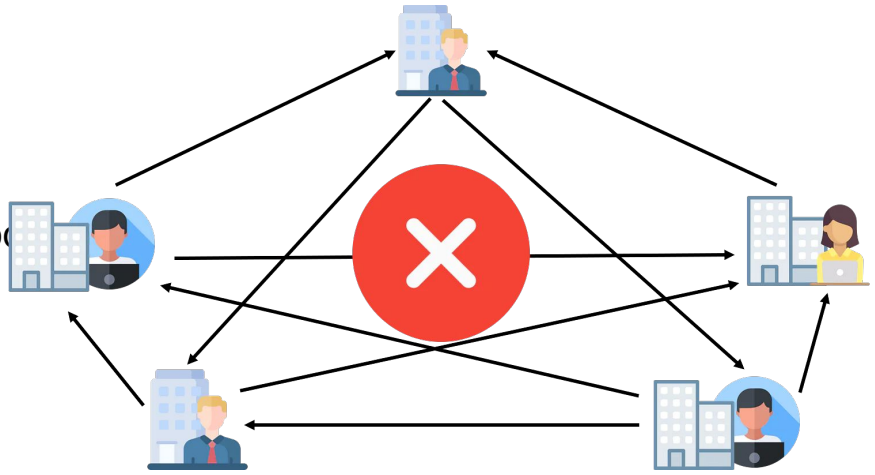
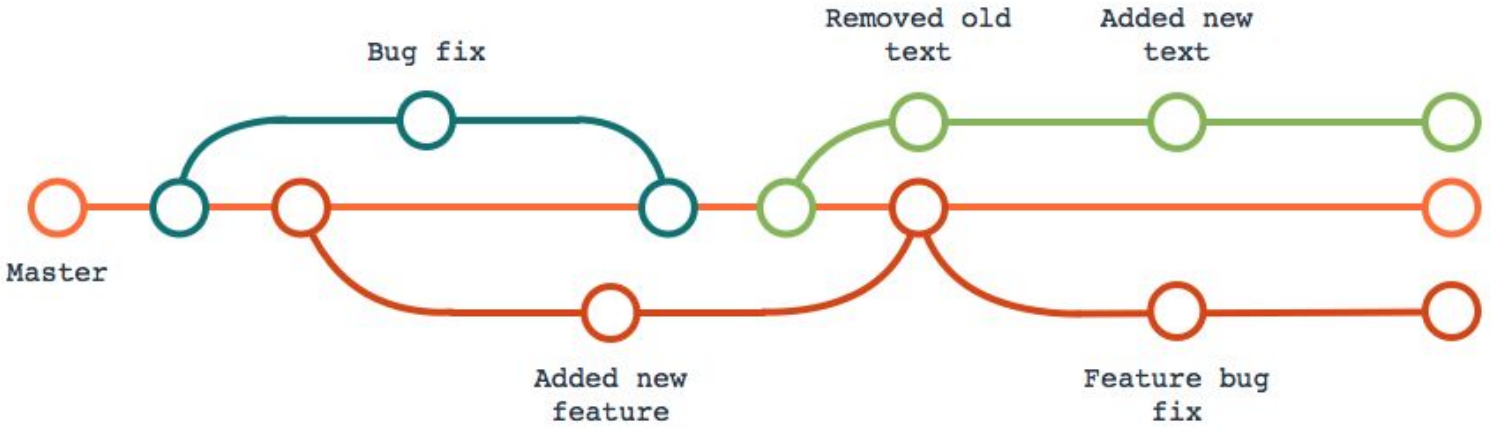


Version control let's you:

- Revert mistakes
- Acts as a comprehensive backup
- Let's you maintain multiple versions of your analysis
- Let's you compare different versions of your co
- 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
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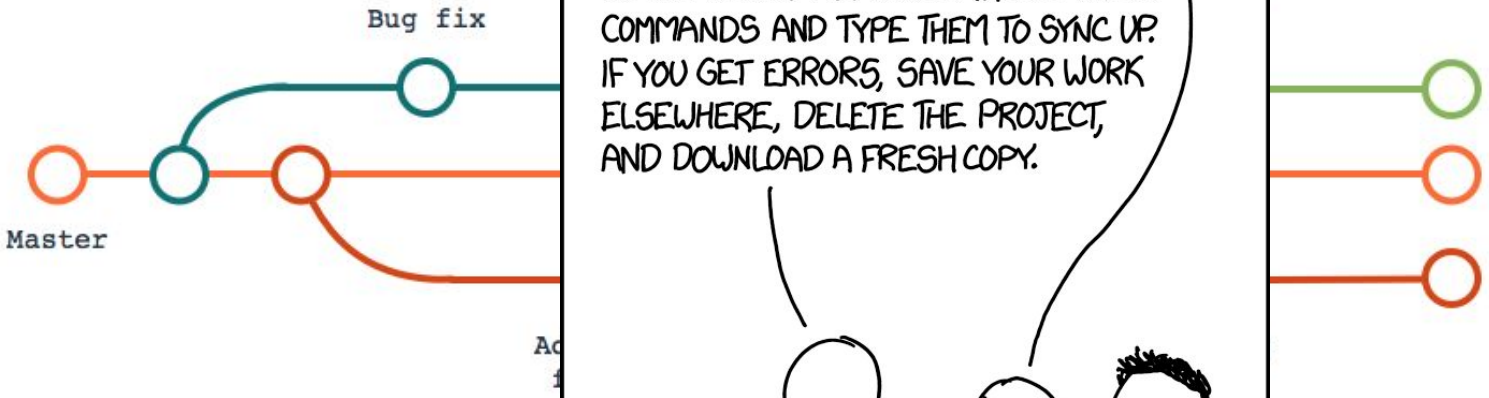

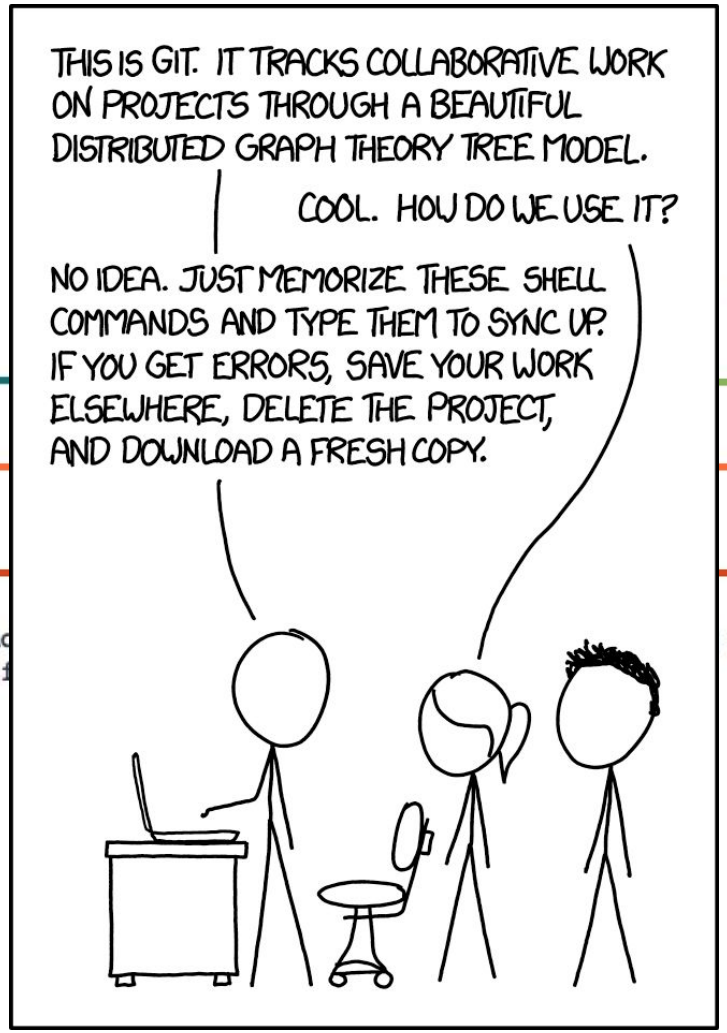

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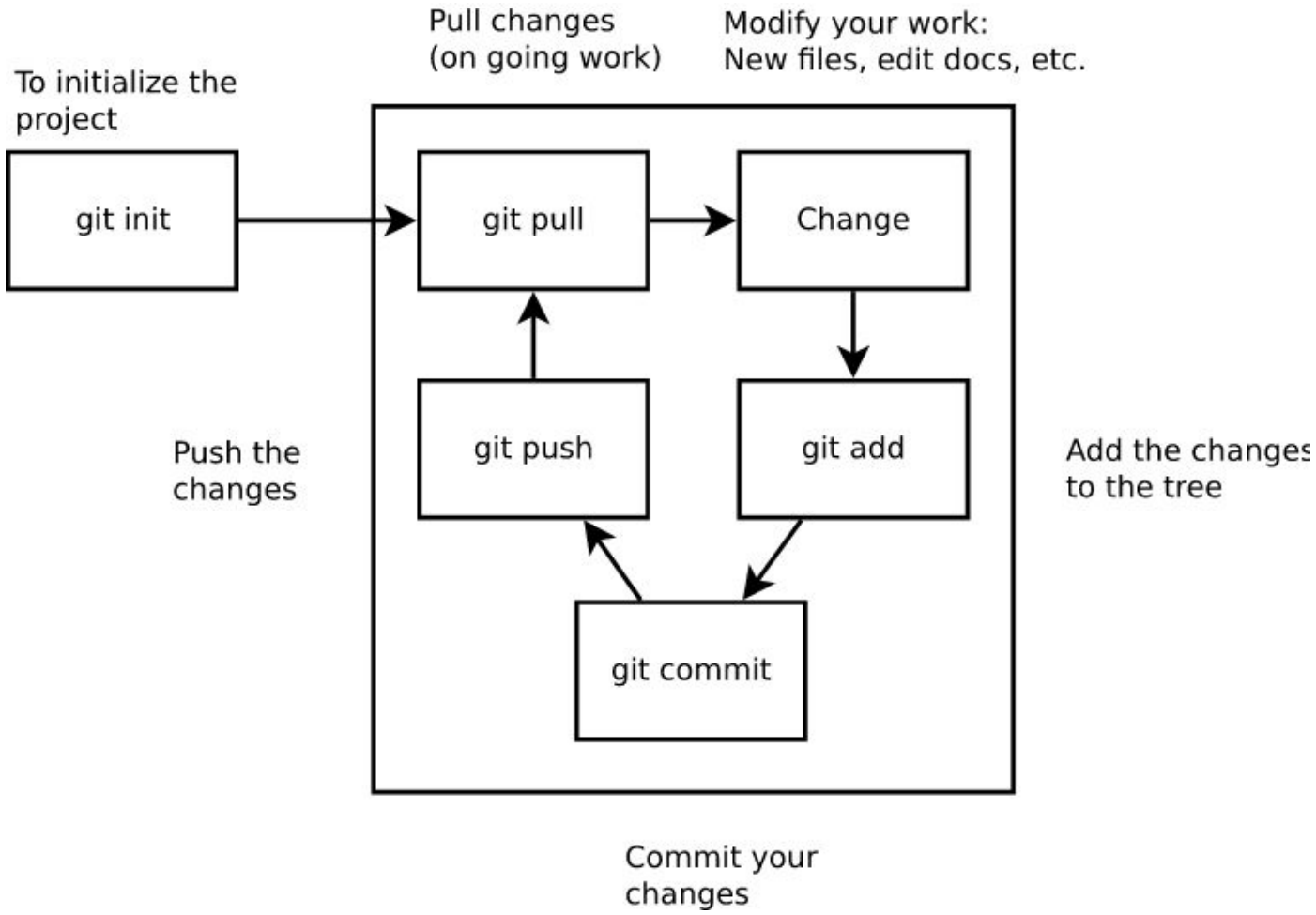
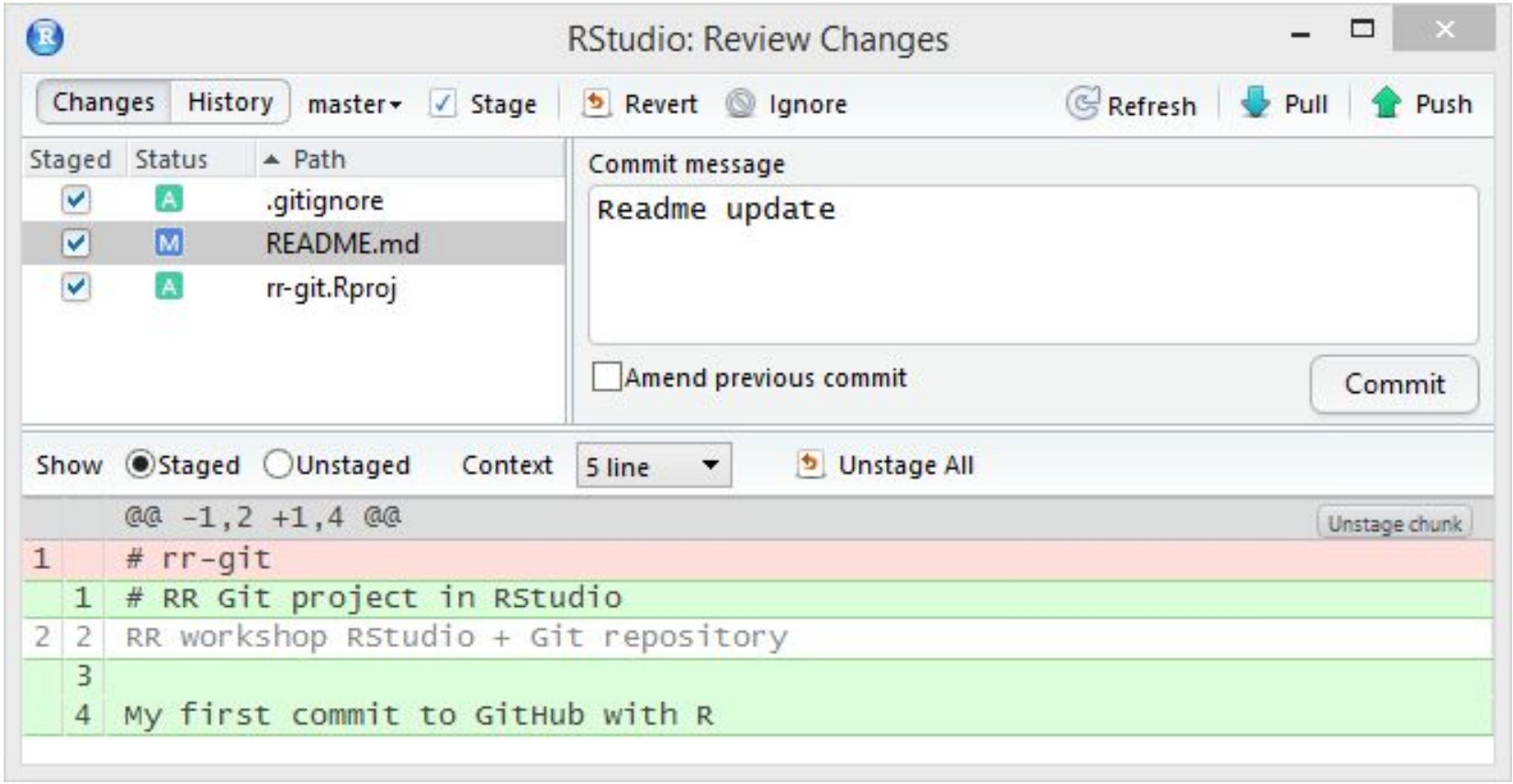
Git Workflow



https://uscbiostats.github.io/PM566/slides/02-version-control/slides.html#8

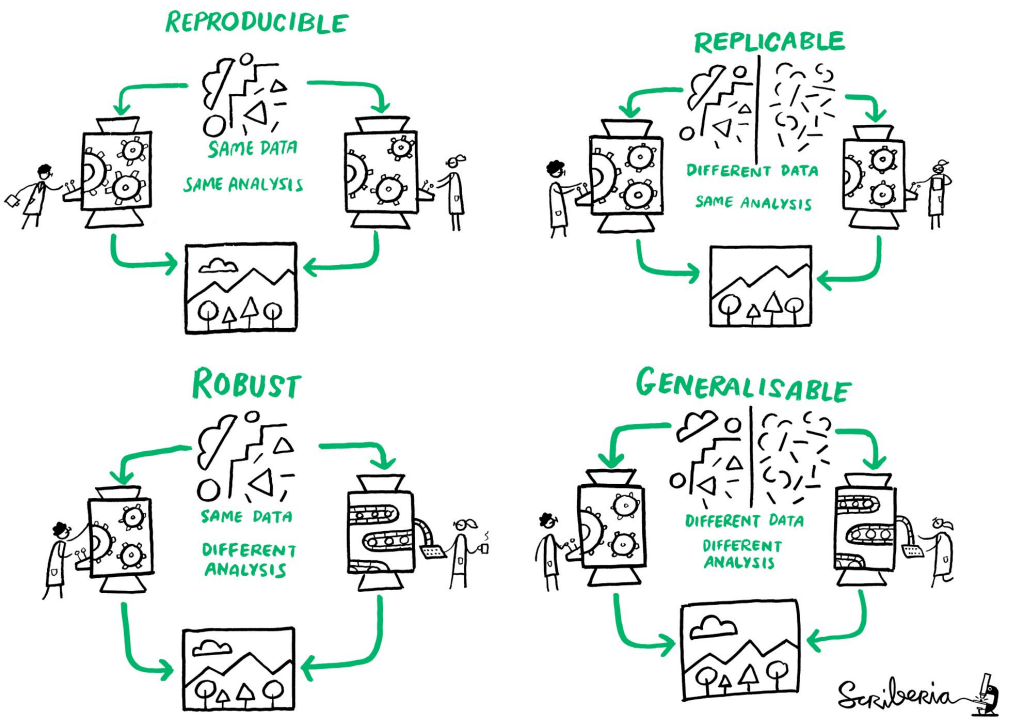
Git is integrated into Rstudio!



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

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

Challenges to the Reproducibility of Machine Learning Models in Health Care

Andrew L. Beam, Arjun K. Manrai, Marzyeh Ghassemi https://doi.org/10.1001/jama.2019.20866

JAMA • 28 January 2020 • Volume 323, Number 4

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

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