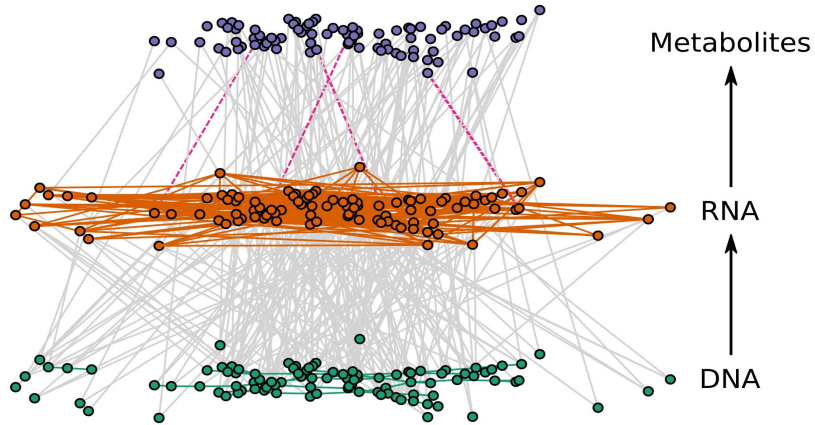


Lecture 0: Introduction to Applied Research in Health Data Science

CSCI6410/4148 & EPAH6410

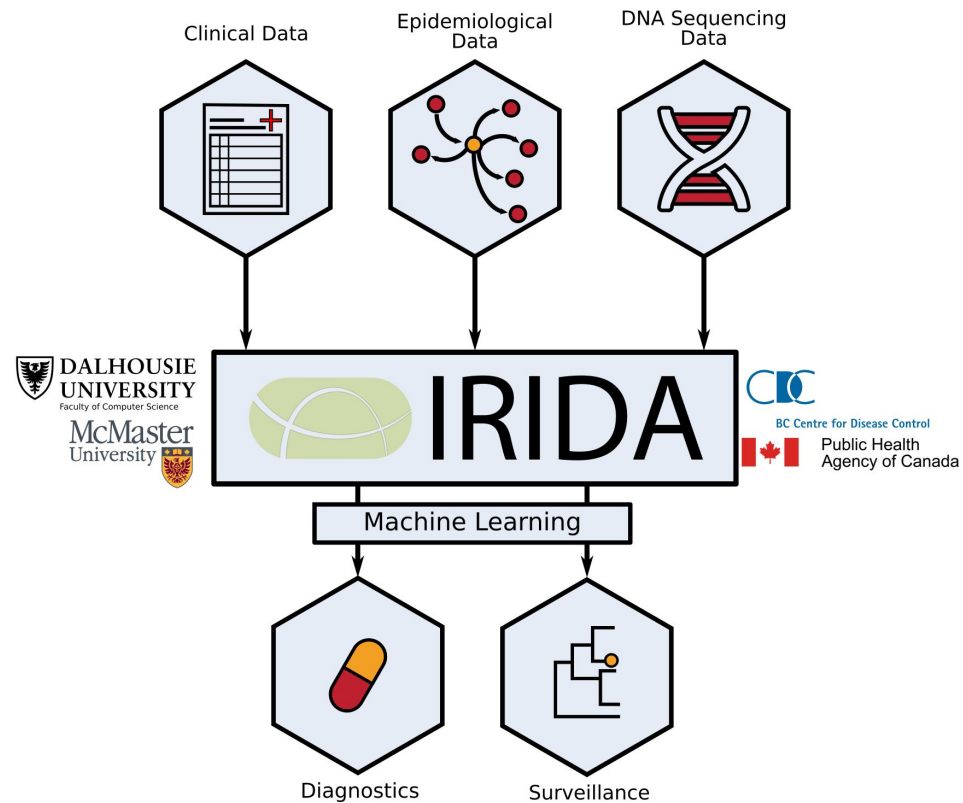
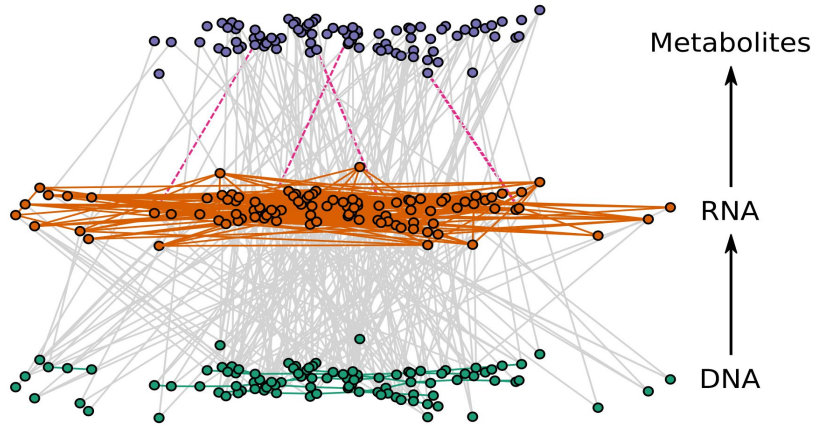
Finlay Maguire (finlay.maguire@dal.ca)
TA: Ehsan Baratnezhad (ethan.b@dal.ca)

Why am I teaching this course?



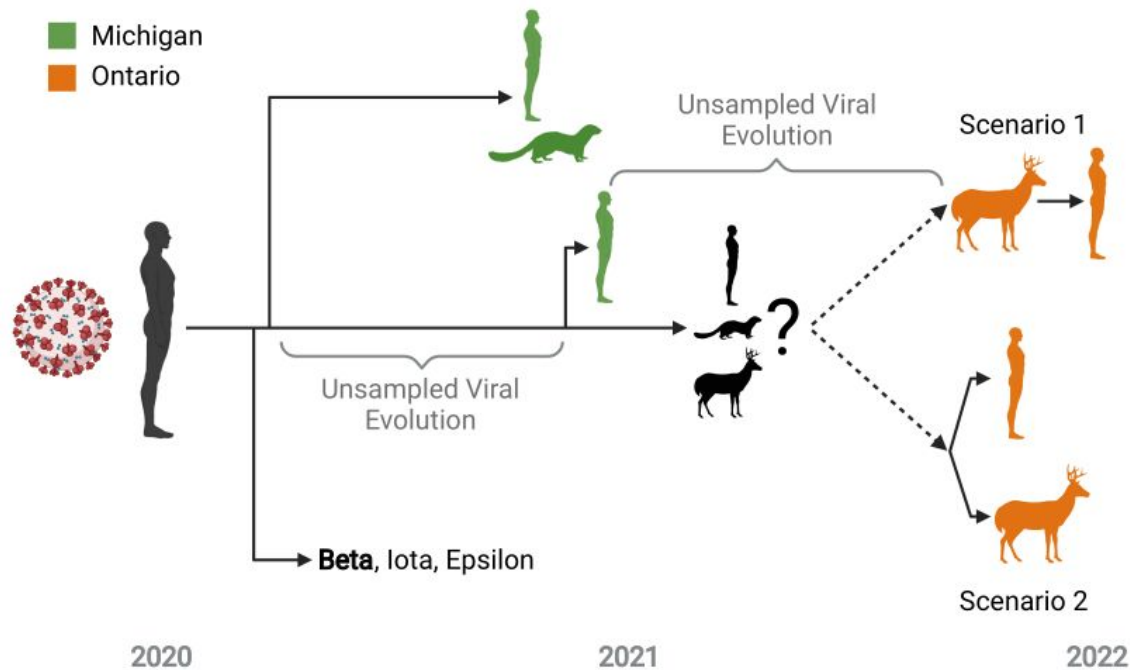
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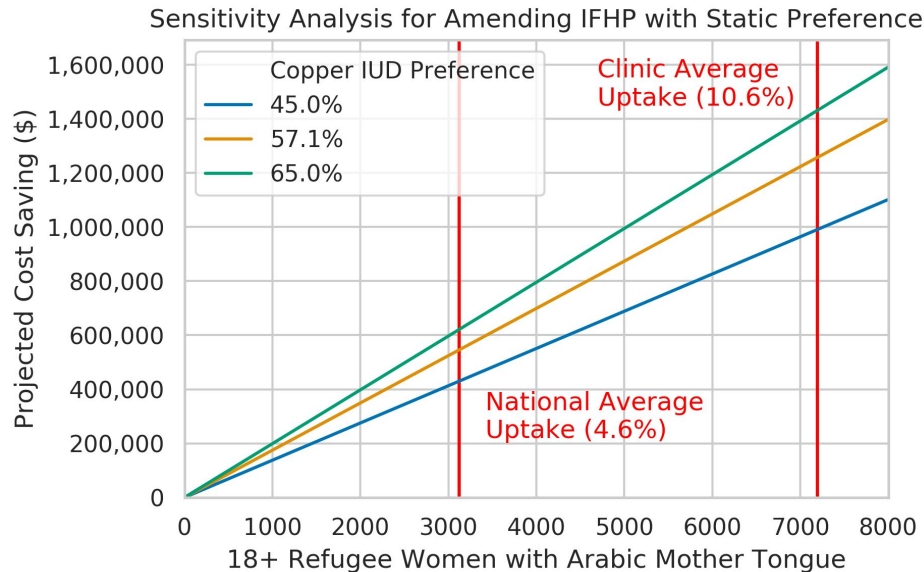
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- **Postdoc (Genomic Epidemiology)**: using large noisy datasets to better diagnose, track and predict infectious diseases.

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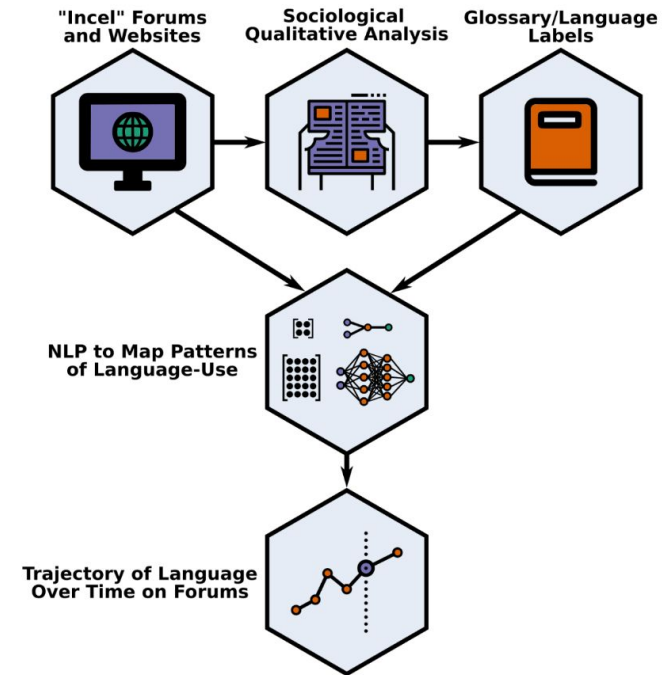


- **Research group:** using large noisy datasets:
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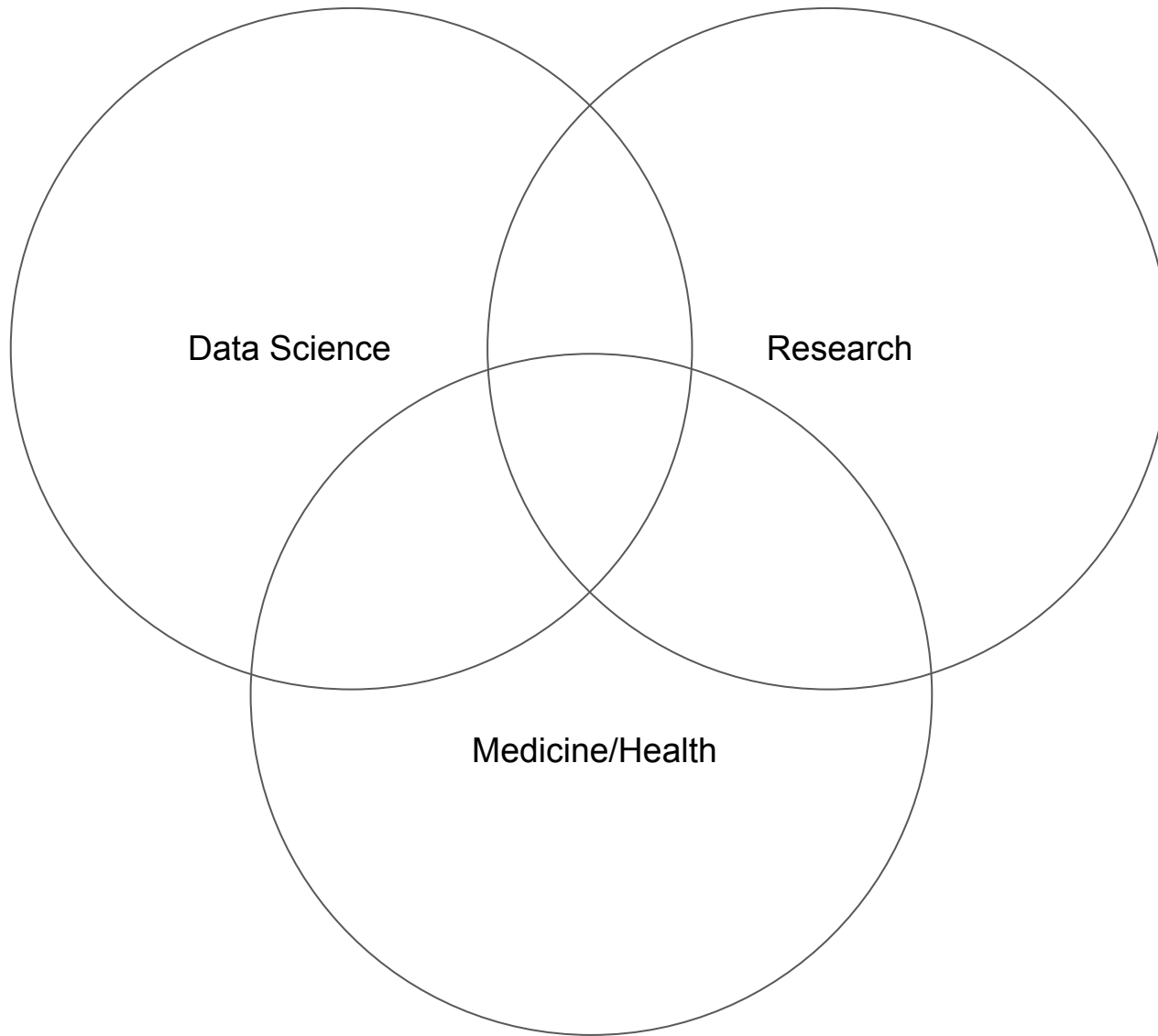
Modelling "Incel" Online Radicalisation via NLP



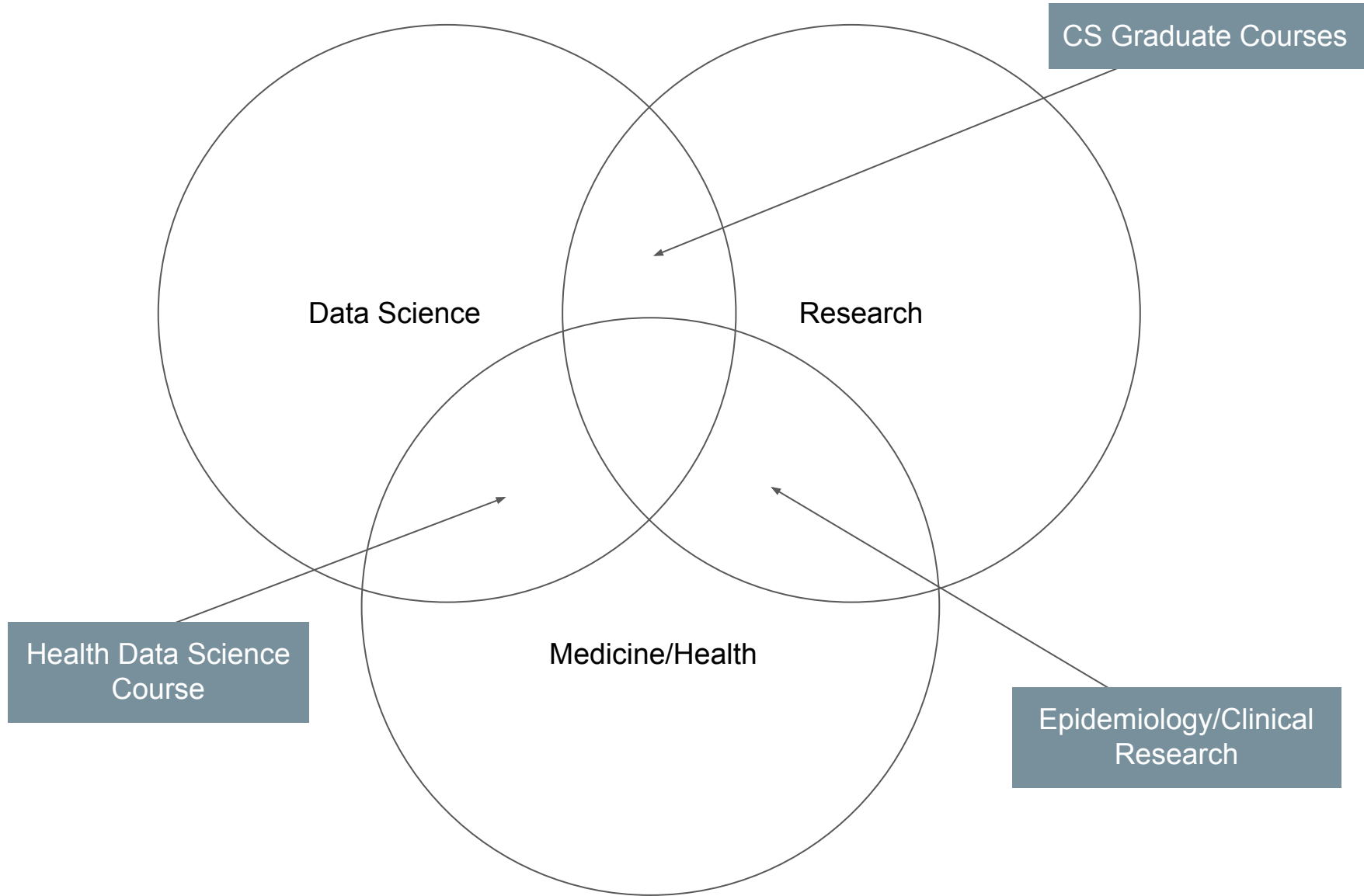
- **Research group:** using large noisy datasets:
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 - Collaborations on socially/health focused problems: **refugee health, incel radicalisation, health inequality**

Overview of course

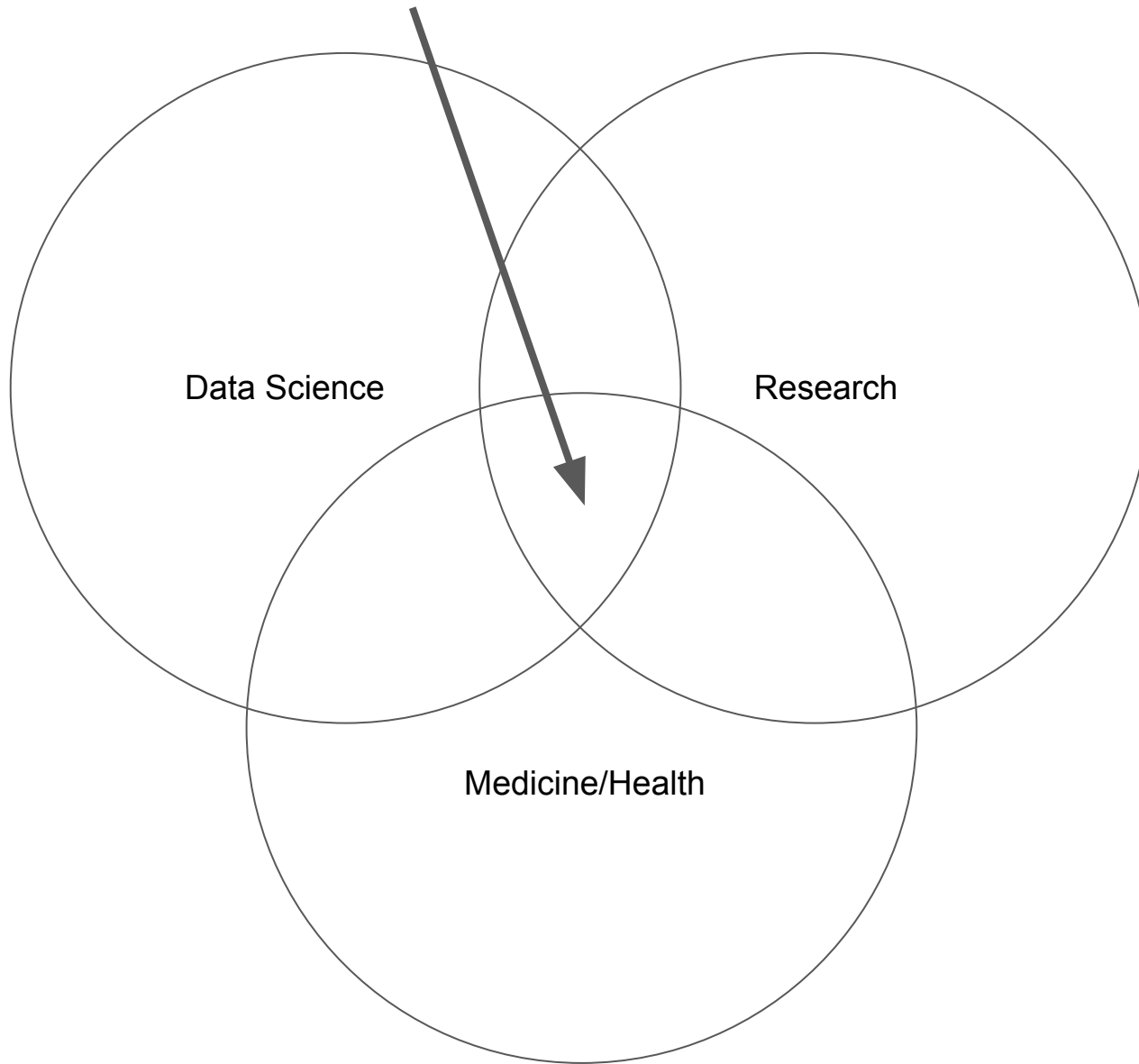
Applied Research in Health Data Science



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**

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- **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)

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dens <- density(data, n = npts)
dx <- dens$x
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if(add == TRUE)
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<https://www.coursera.org/learn/r-programming>

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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 (15%)

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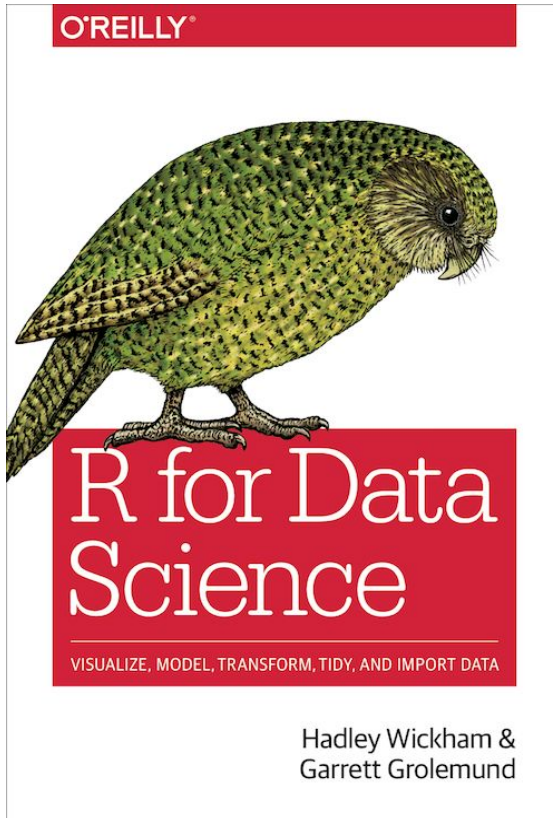
- **Class** (Wednesday/Friday)

Assessment:

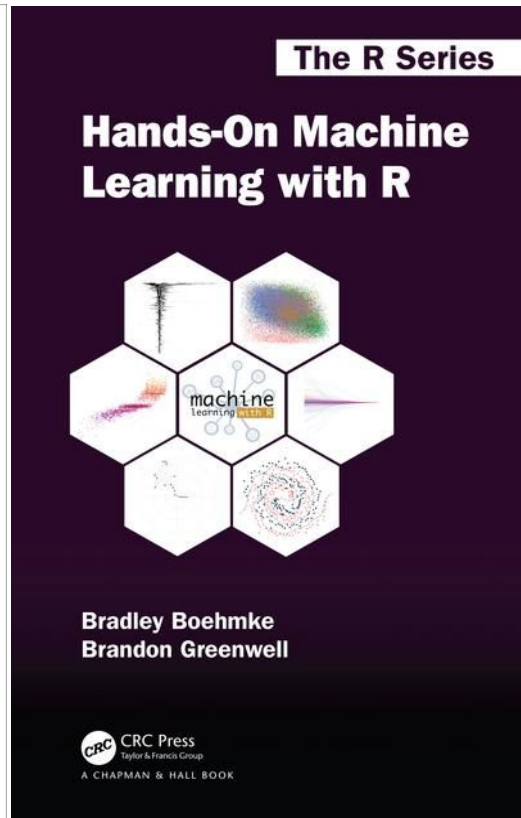
Presentation **last full week of class** (20%)

Submitted **final day of class** (15%)

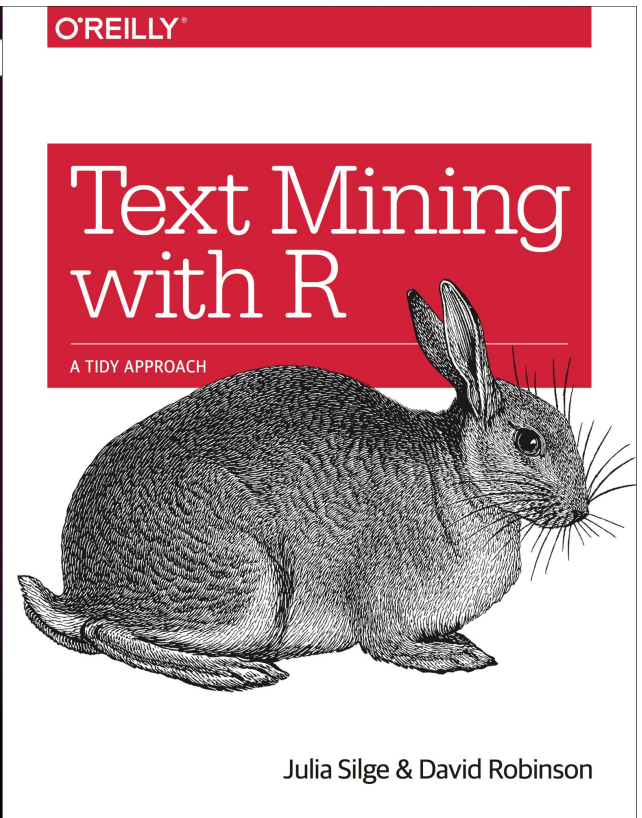
Course Materials



<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_2025/

Course Website



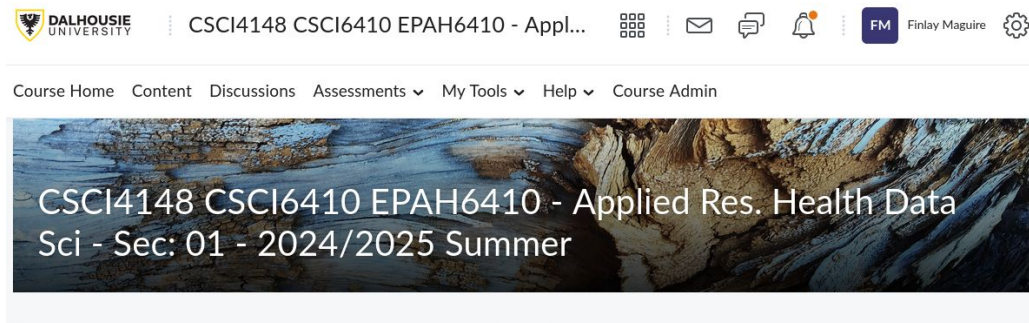
CSCI6410/CSCI4148/EPAH6410: Applied Research in Health Data Science / Summer 2024-2025

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

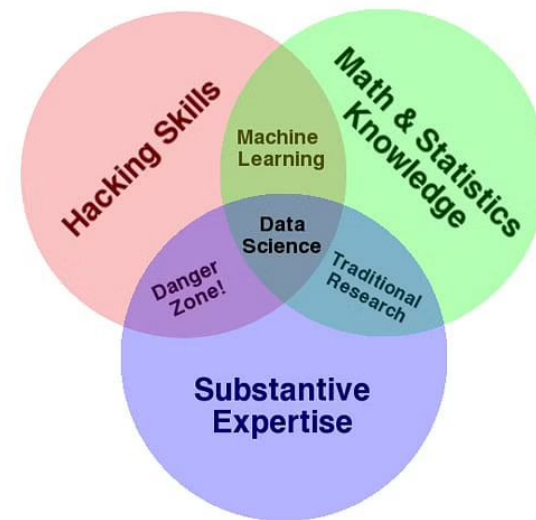


Grades/Submissions:

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

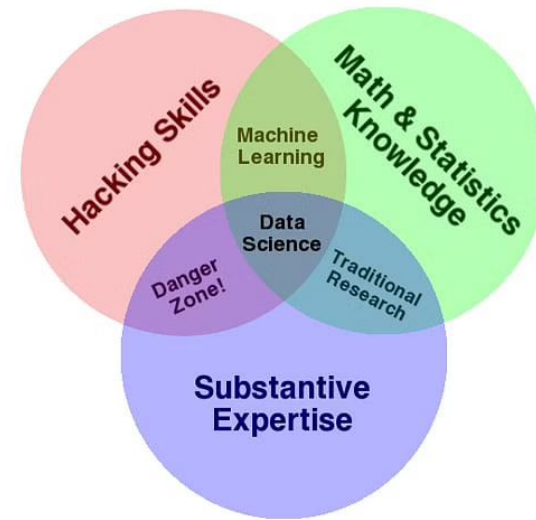
What is ~~health~~ data science?

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



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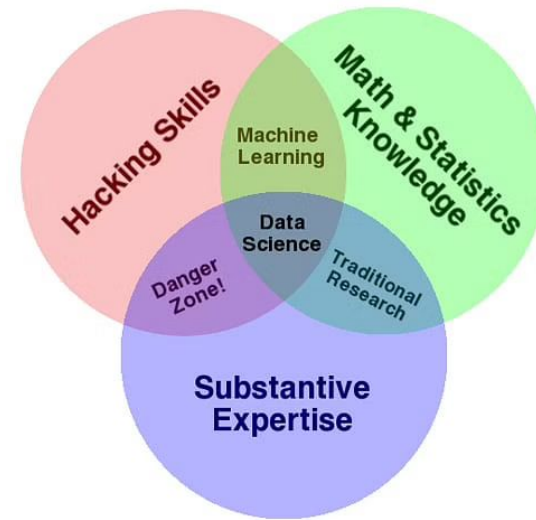
A range of partial and totally overlapping terms:



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



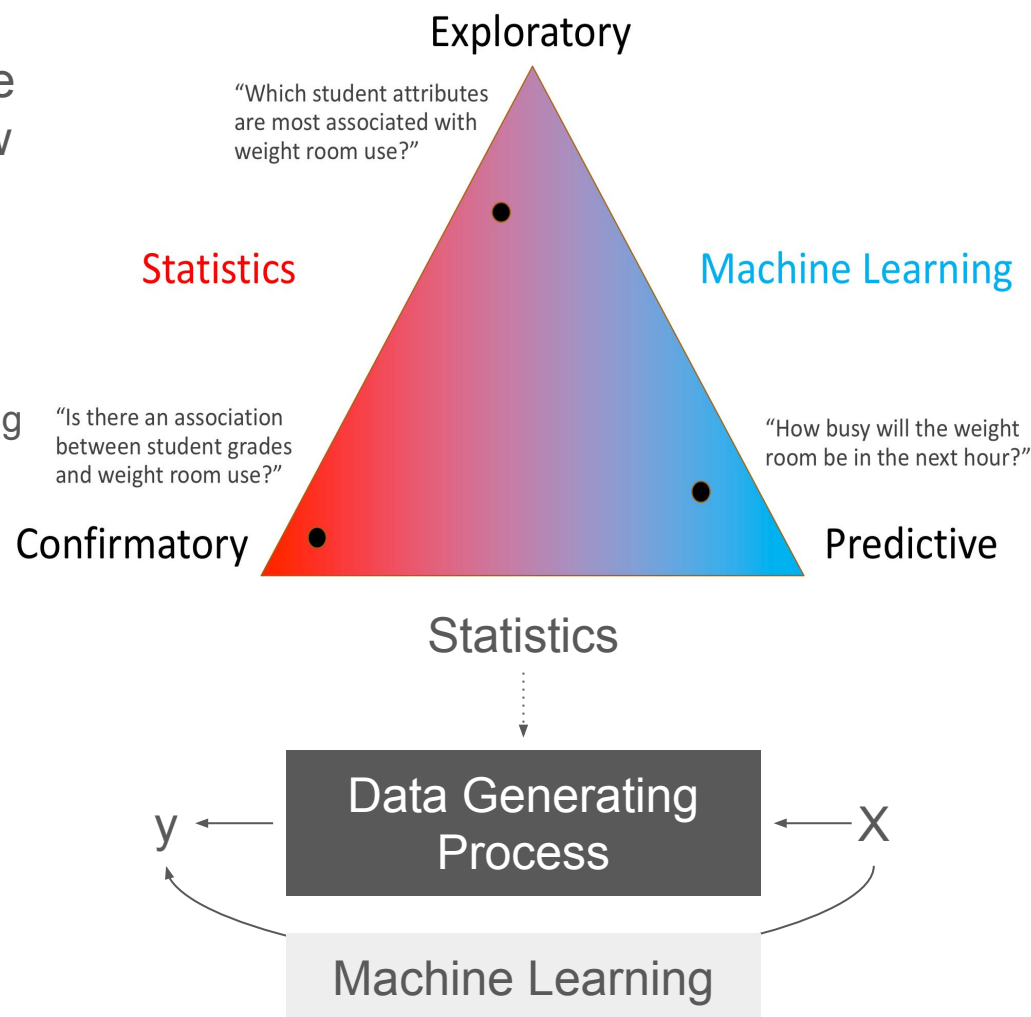
So, it is just statistics?

Data Science/ML vs Statistics

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

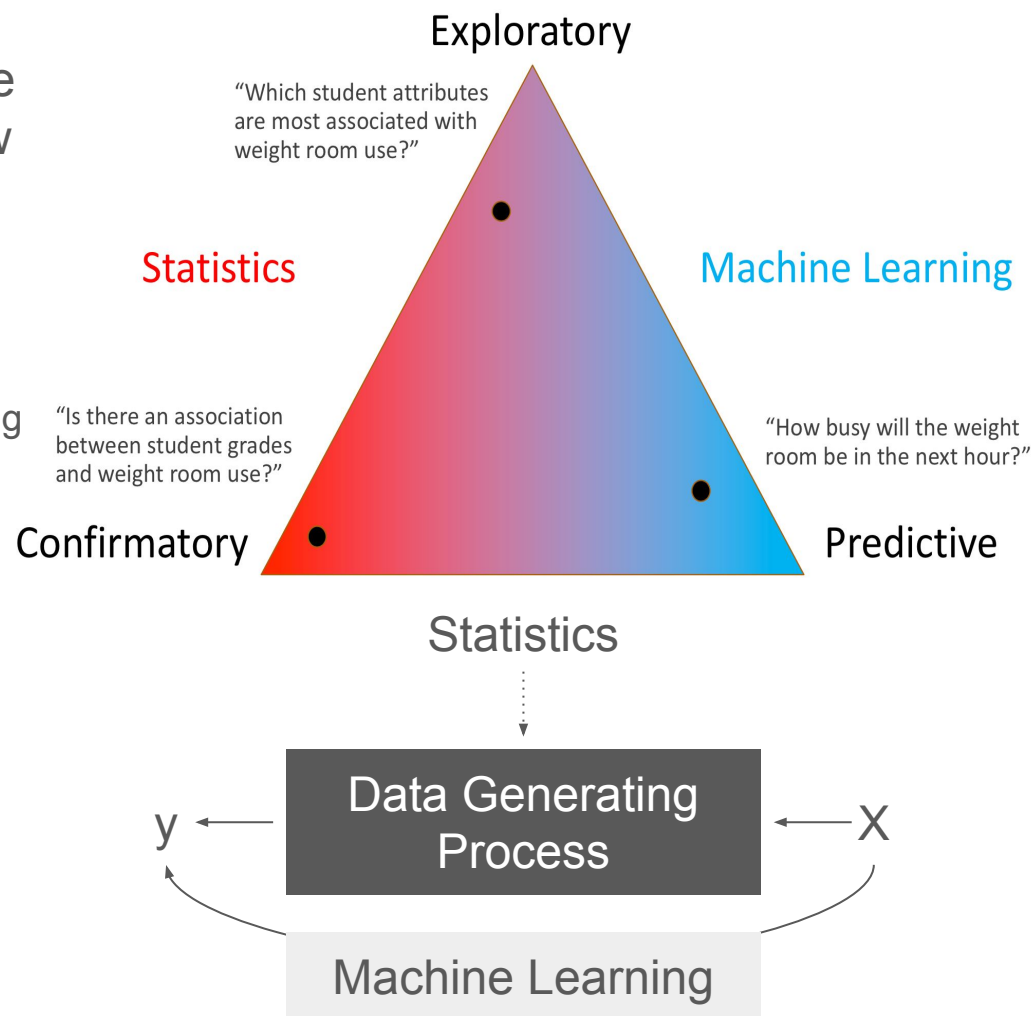
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 - Data Modelling vs Algorithmic Modelling

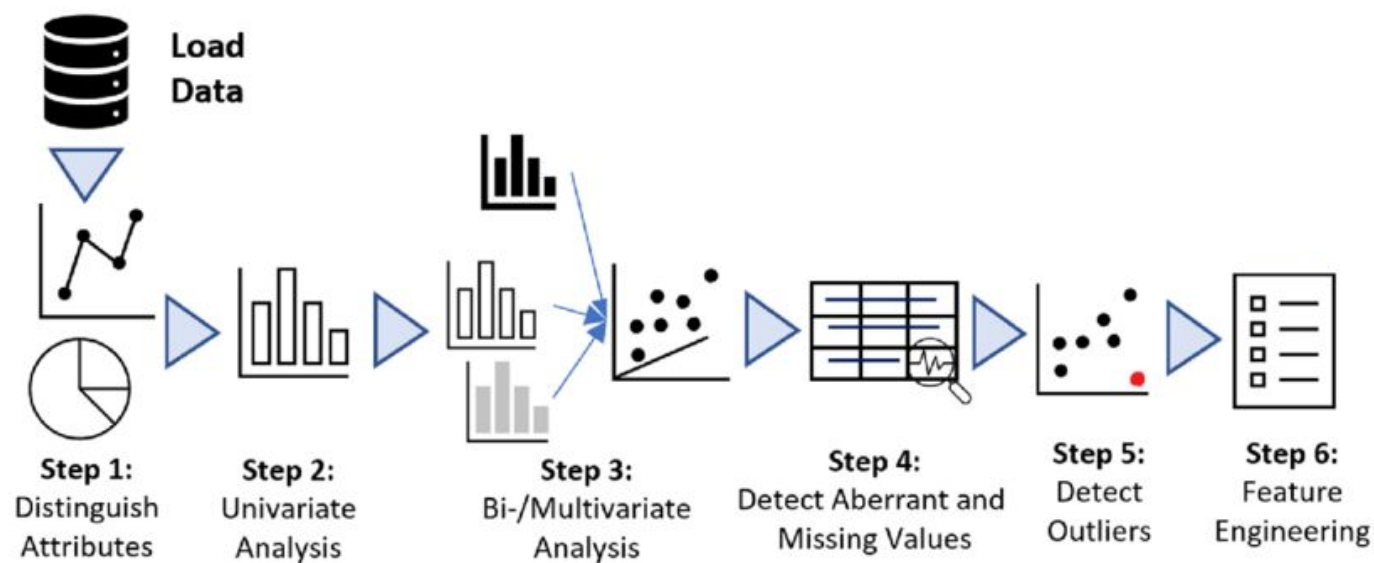


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- Alternative framing:
 - Data Modelling vs Algorithmic Modelling
- DS/ML Pitfalls (can be):
 - Less rigorous/principled
 - Prone to reinventing the wheel
- DS/ML Benefits (can be):
 - More flexible
 - Less prescriptive/intimidating



Data science centers exploratory data analysis

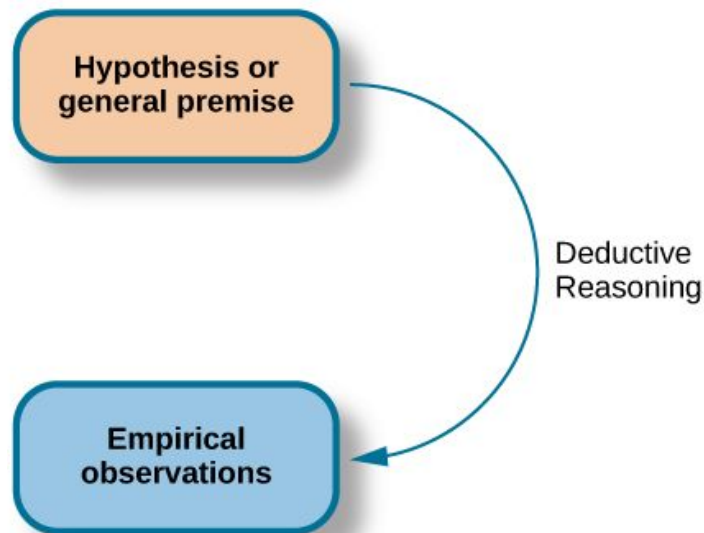


Data science supports inductive approaches

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Deductive:

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



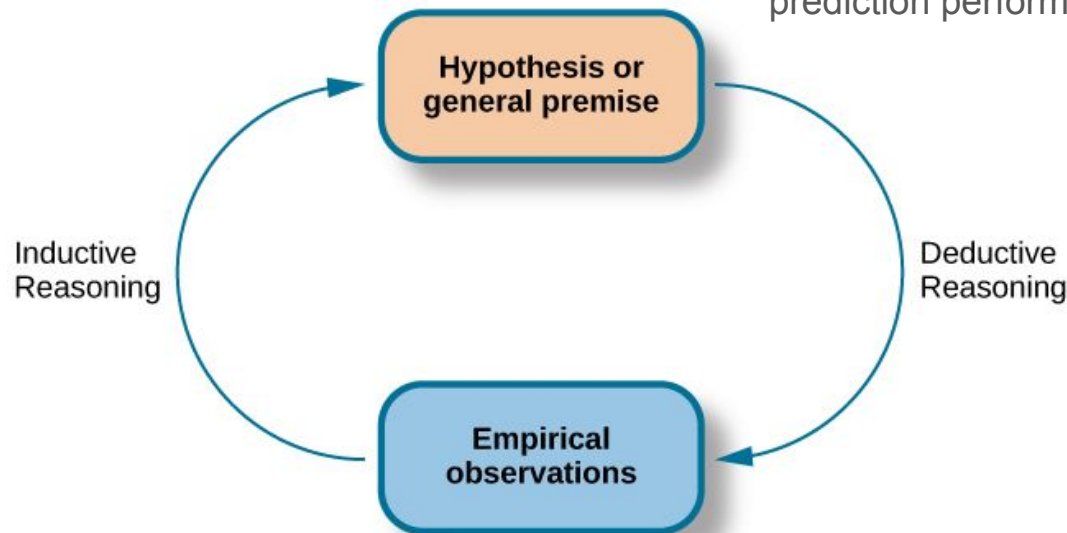
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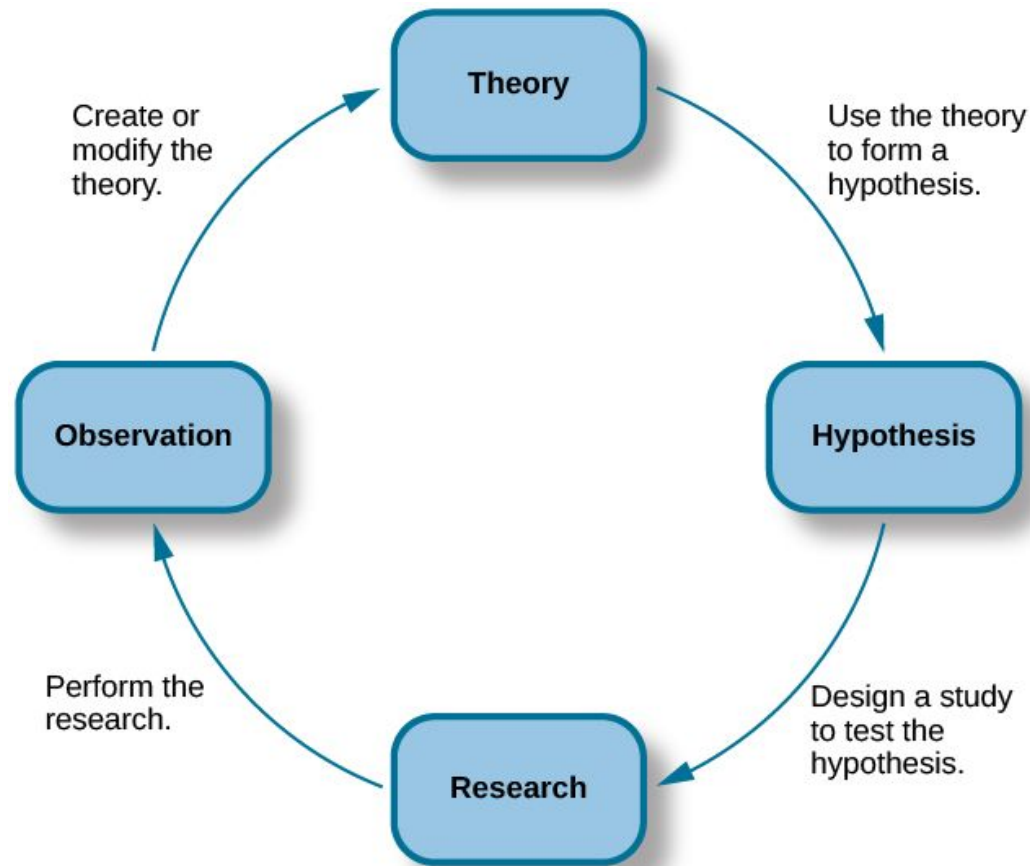
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Inductive:

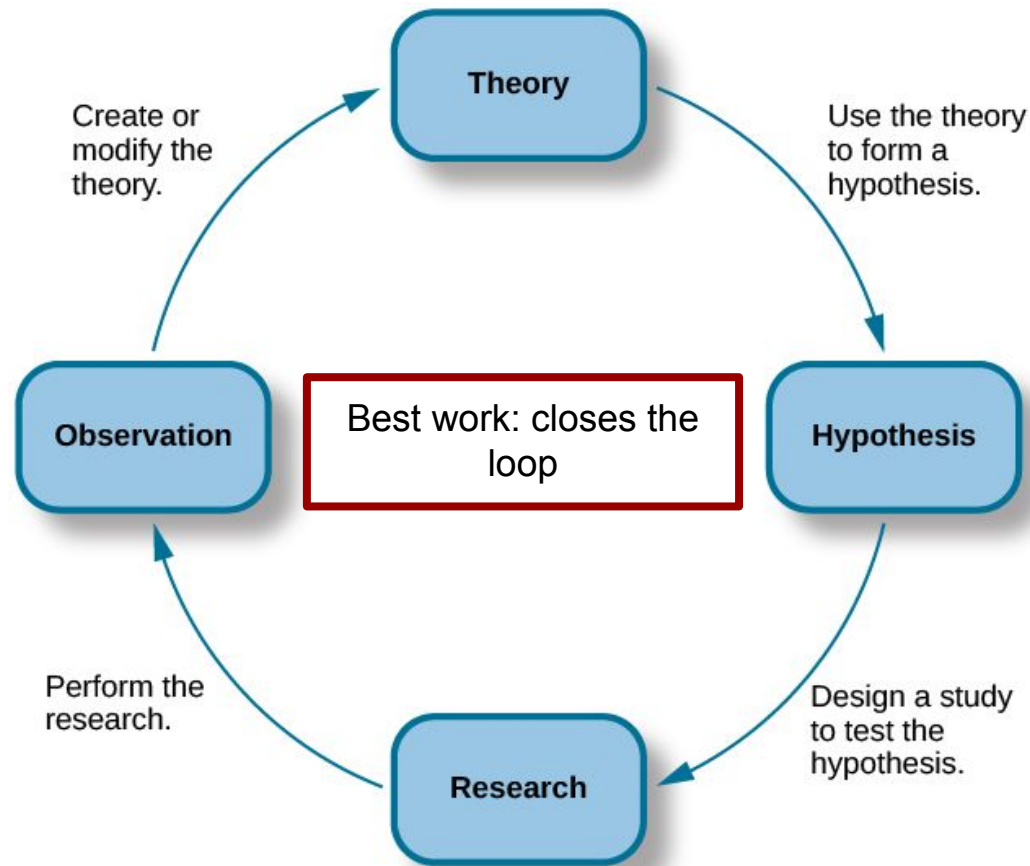
- Collect data
- Identify patterns in the data
- Observe X and Y seem connected somehow
- Quantify strength of association e.g., prediction performance



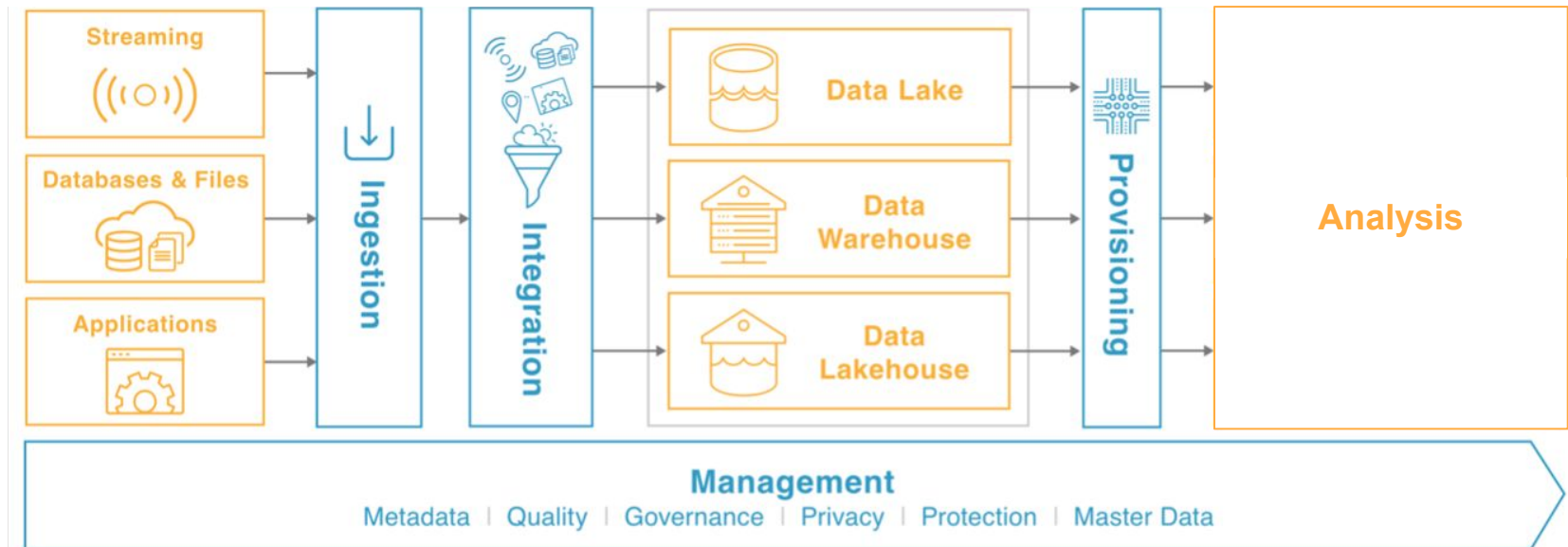
Data science aligns with knowledge cycle



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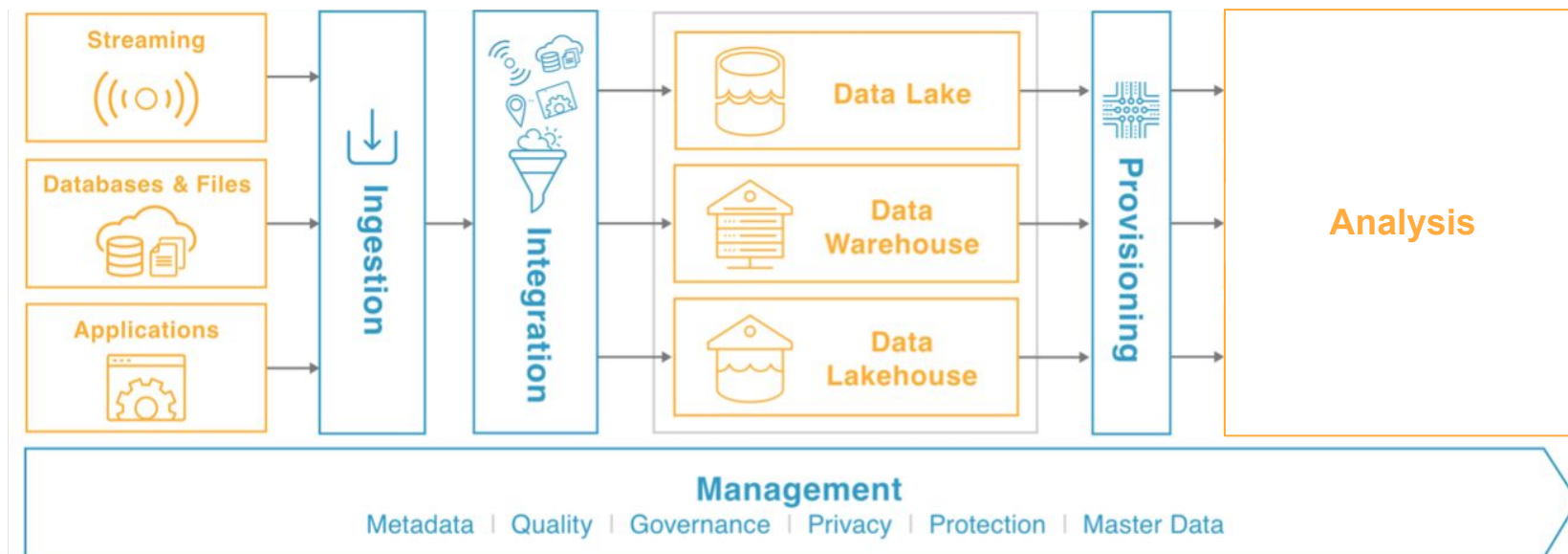


Data science is integrated into a data ecosystem



<https://www.2ndwatch.com/blog/what-is-a-data-pipeline-and-how-to-build-one/>

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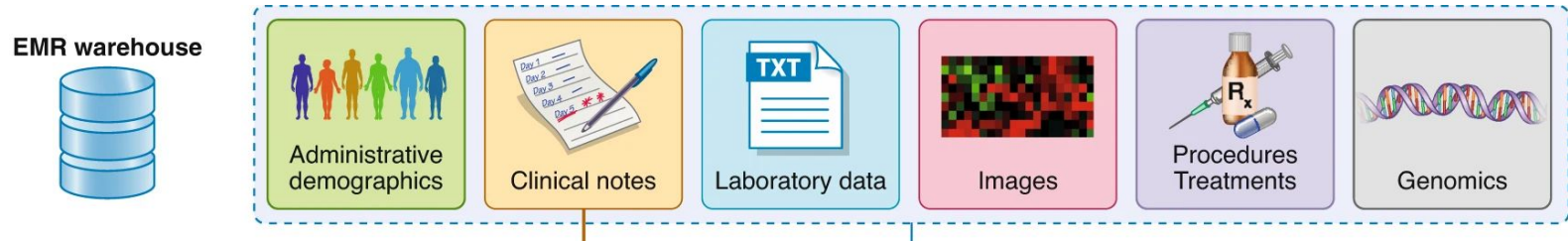
Some Open-Source
Orchestration Tools:



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

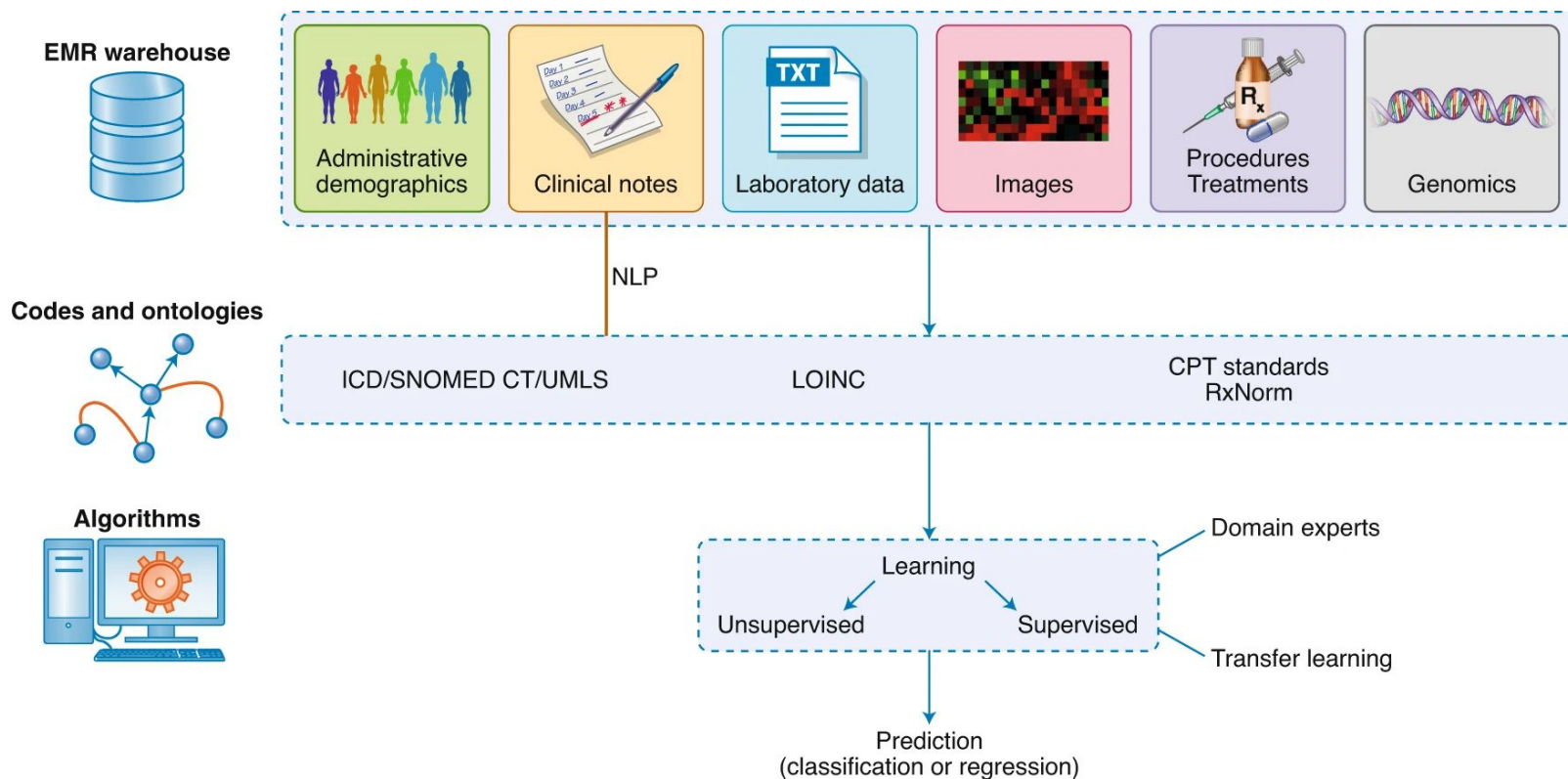
OK, what is **Health** Data Science?

Data Science applied to Health Data



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

Data Science applied to Health Data



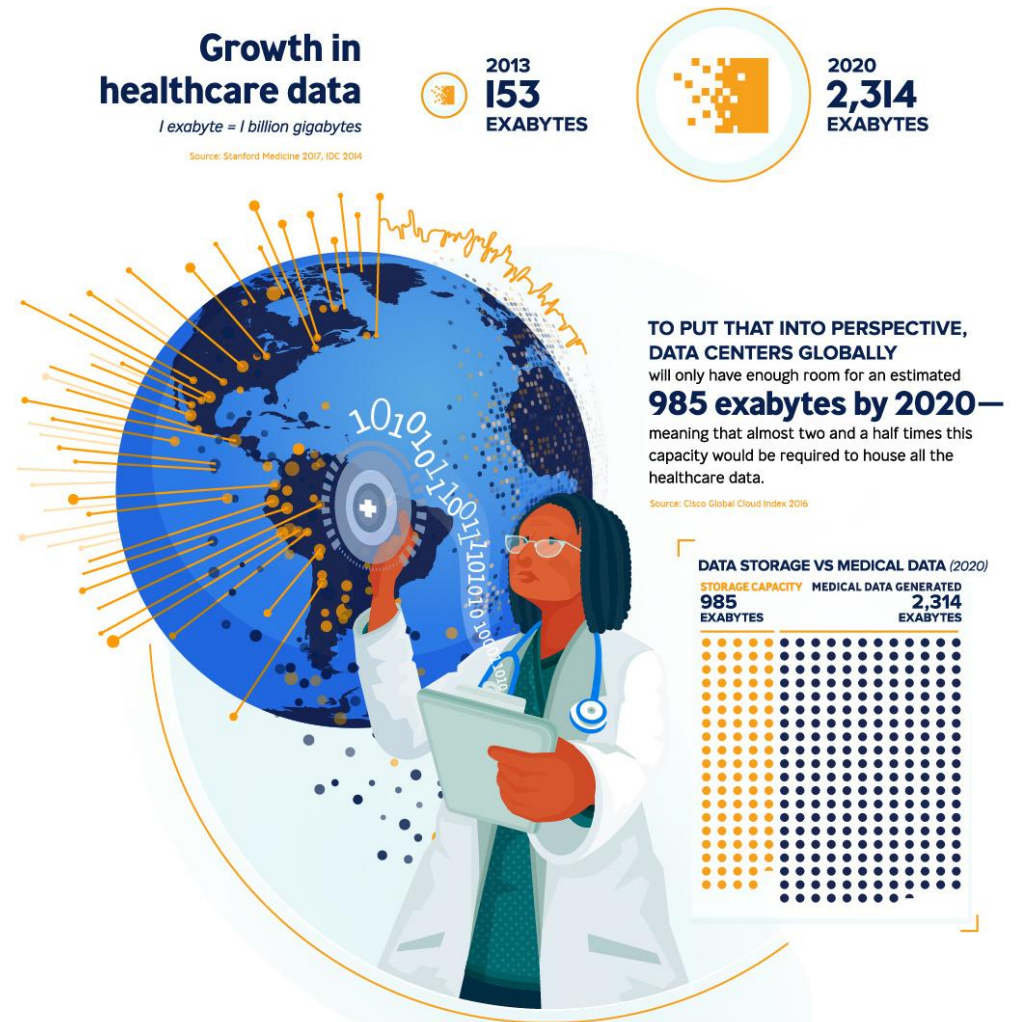
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Opportunity of Health Data Science

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

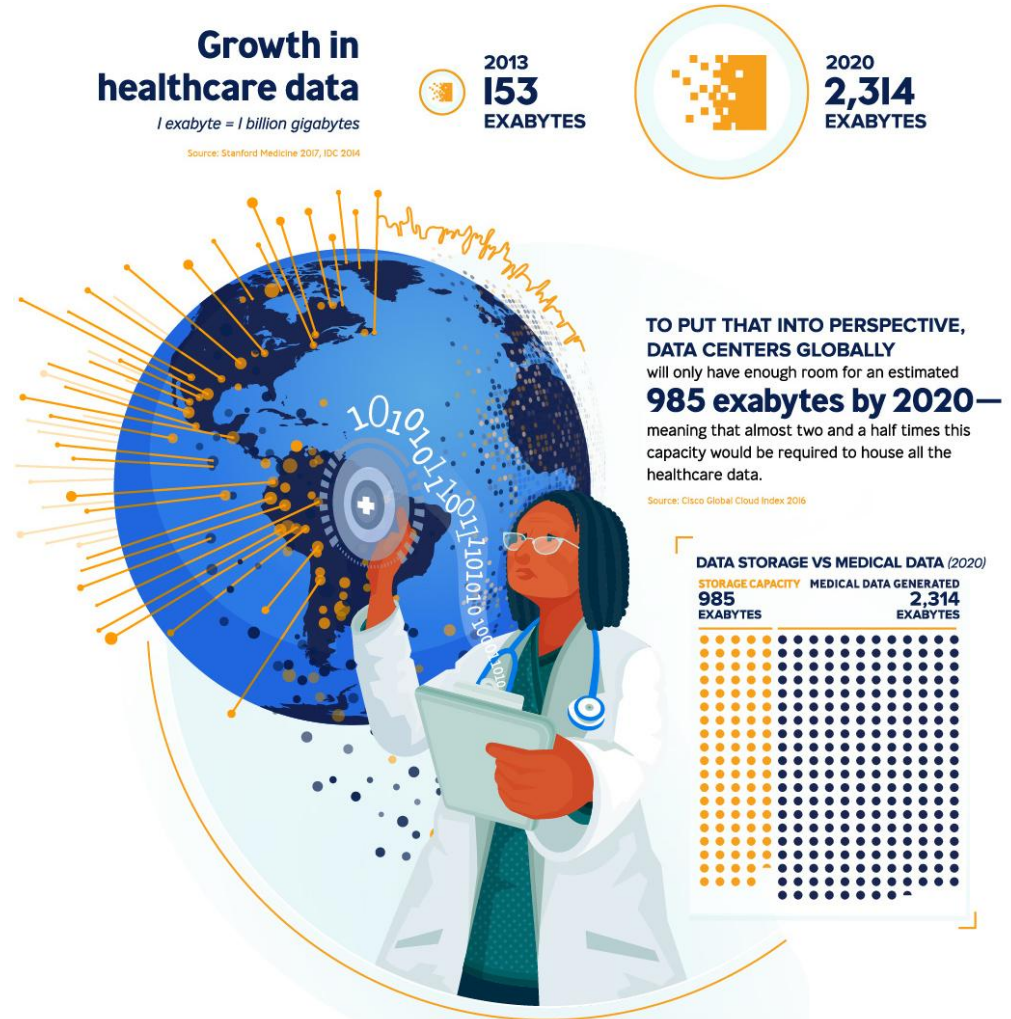
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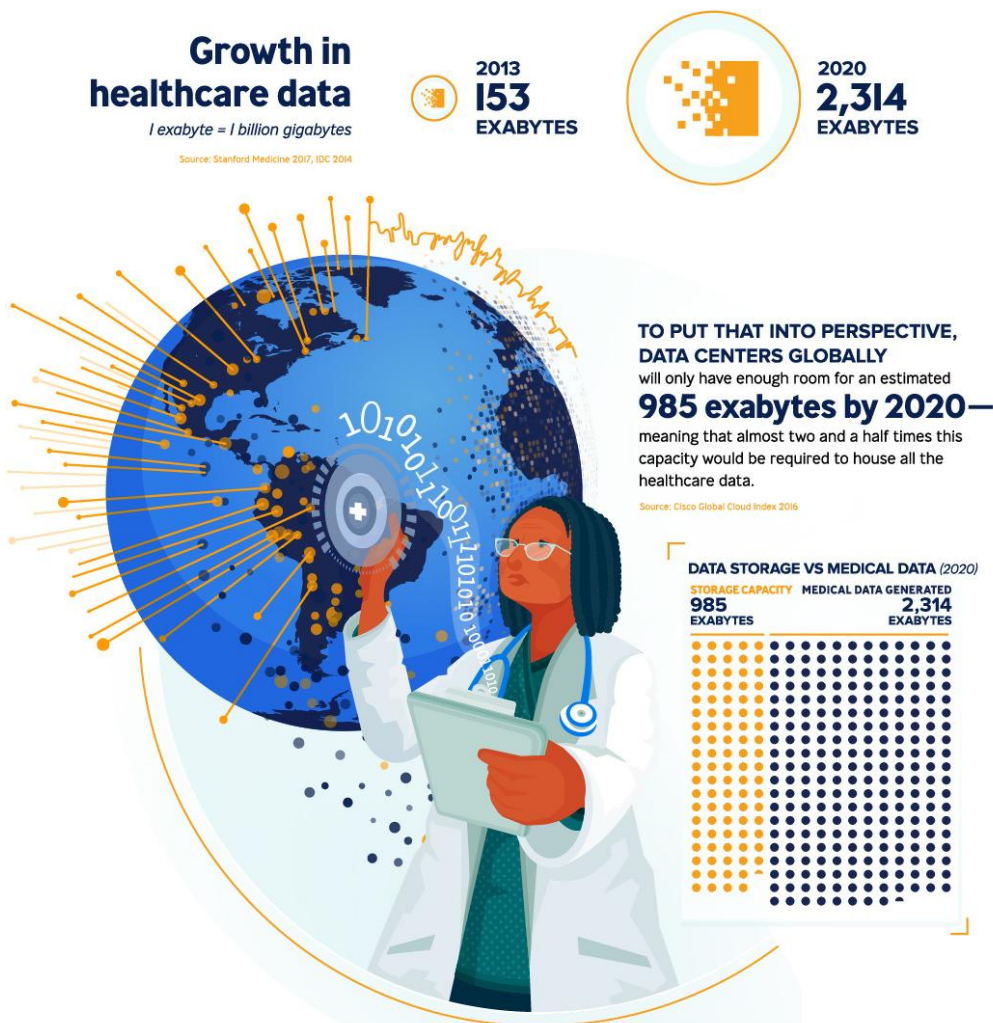
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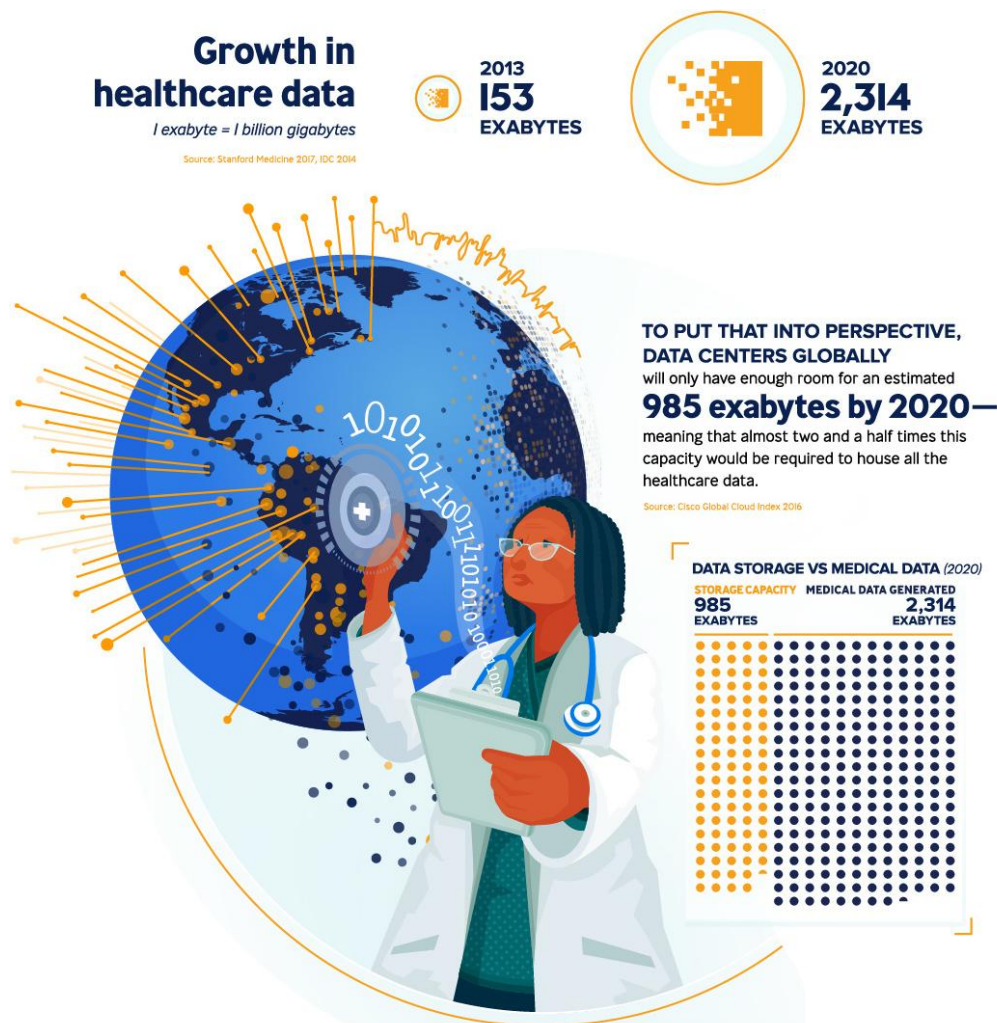
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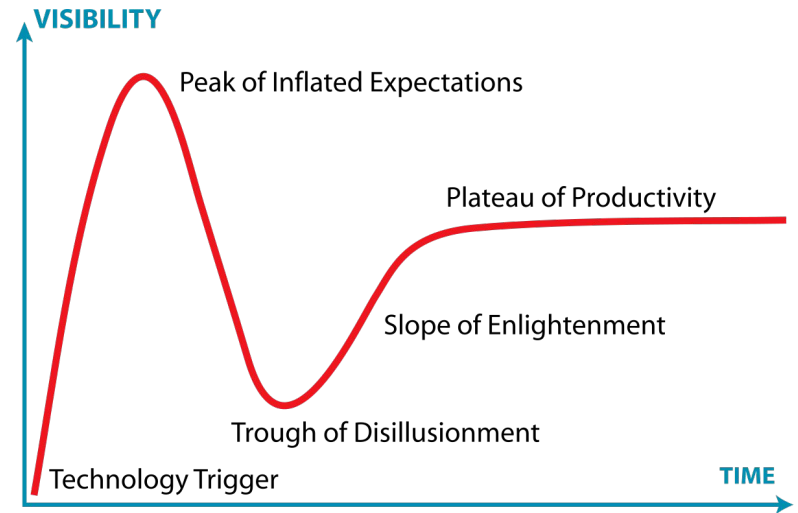
Benefits (and pitfalls!) of data science in general combined with:

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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



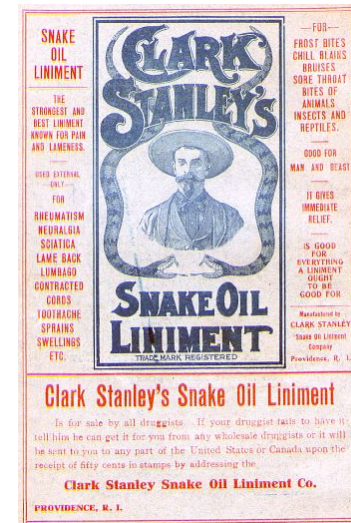
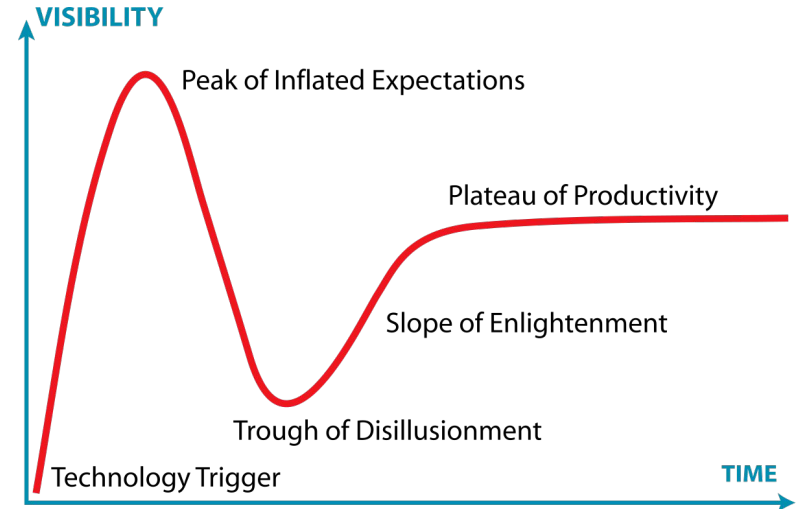
(Some) Challenges of Health Data Science

- Lots of hype



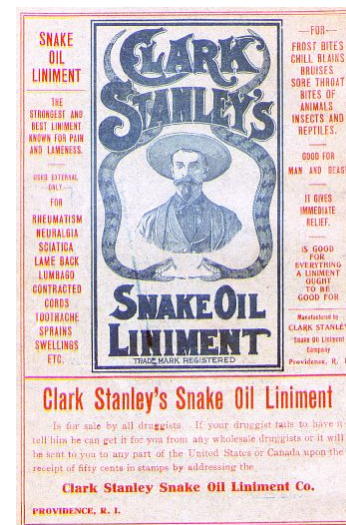
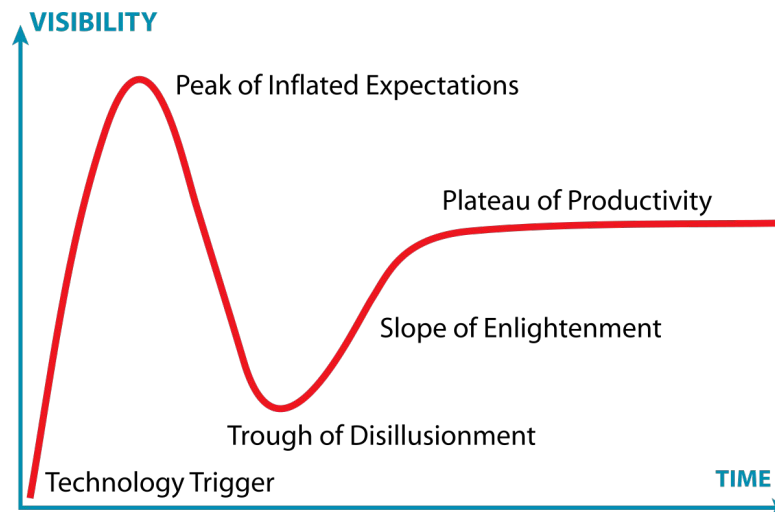
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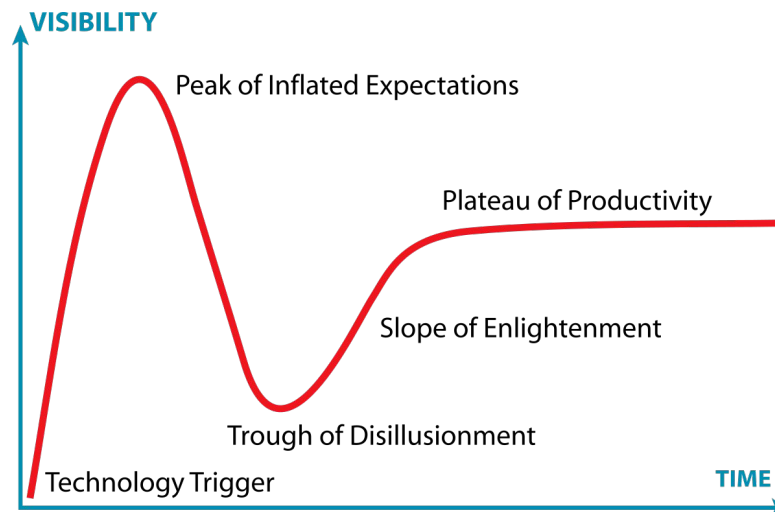
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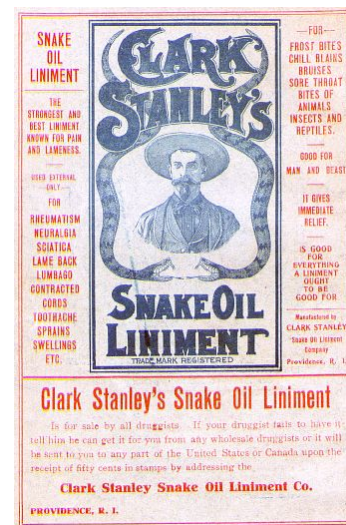


(Some) Challenges of Health Data Science

- 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**

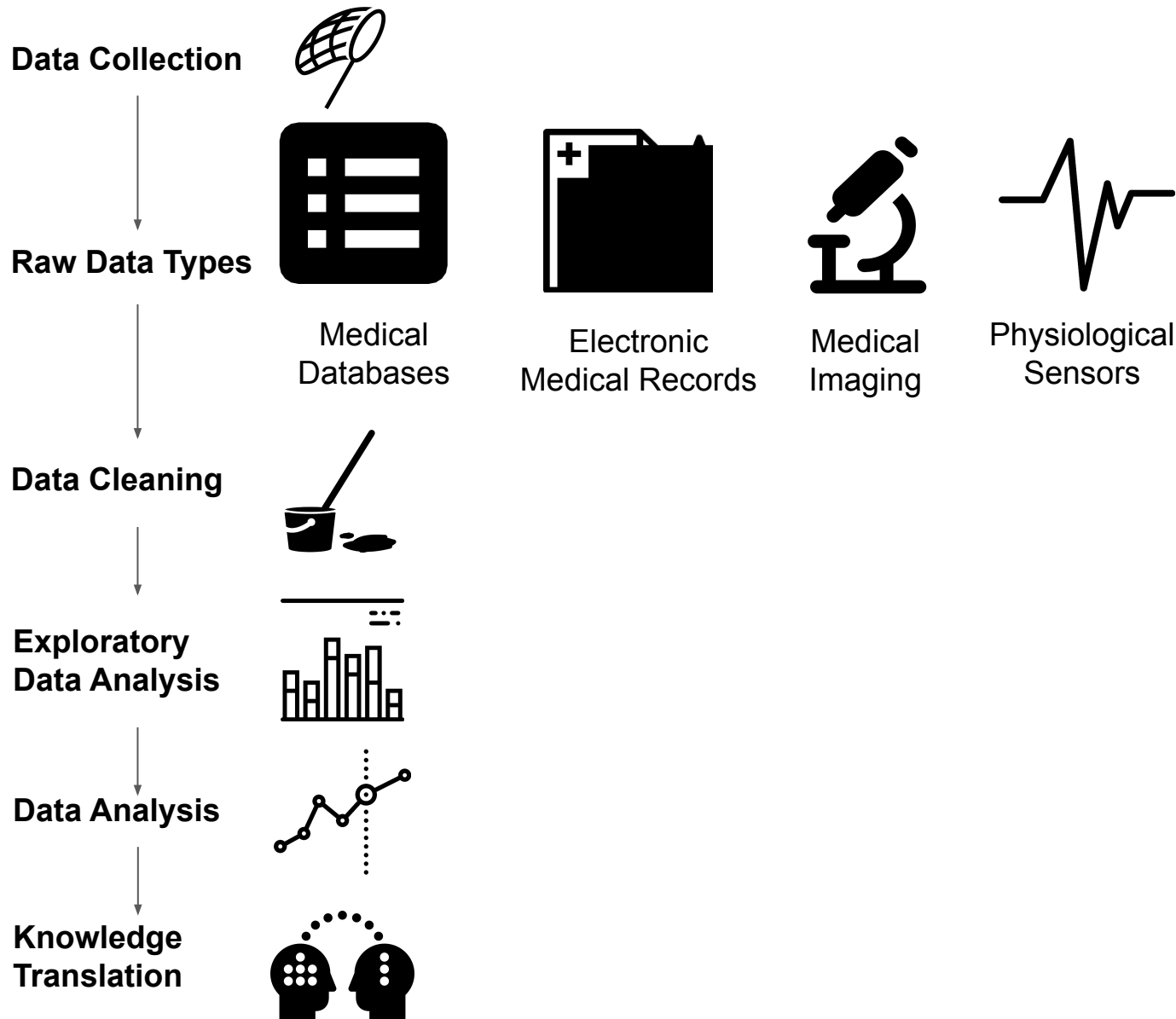


<https://www.r-bloggers.com/2019/08/new-course-learn-advanced-data-cleaning-in-r/>

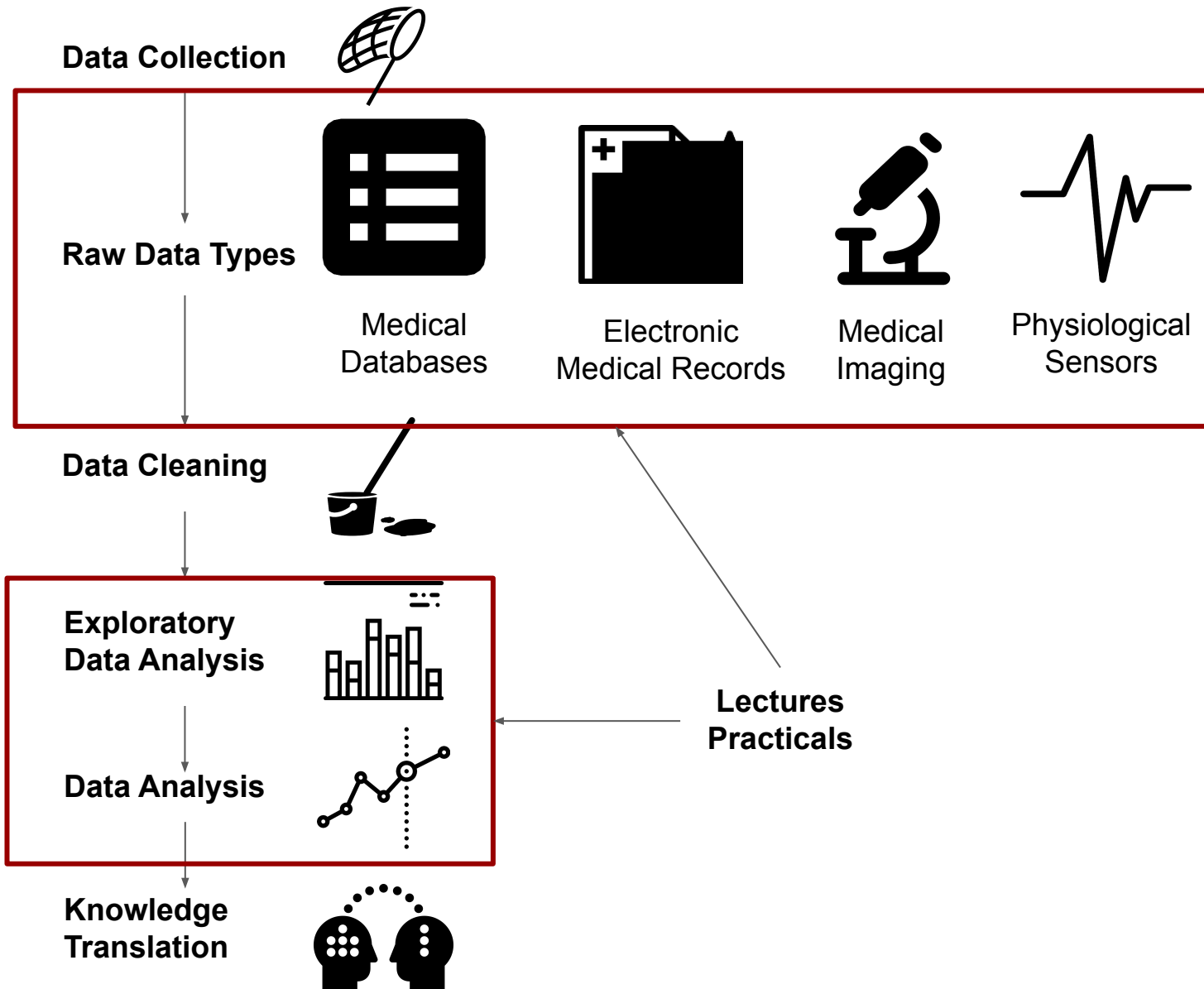


What parts of health data science will this course cover?

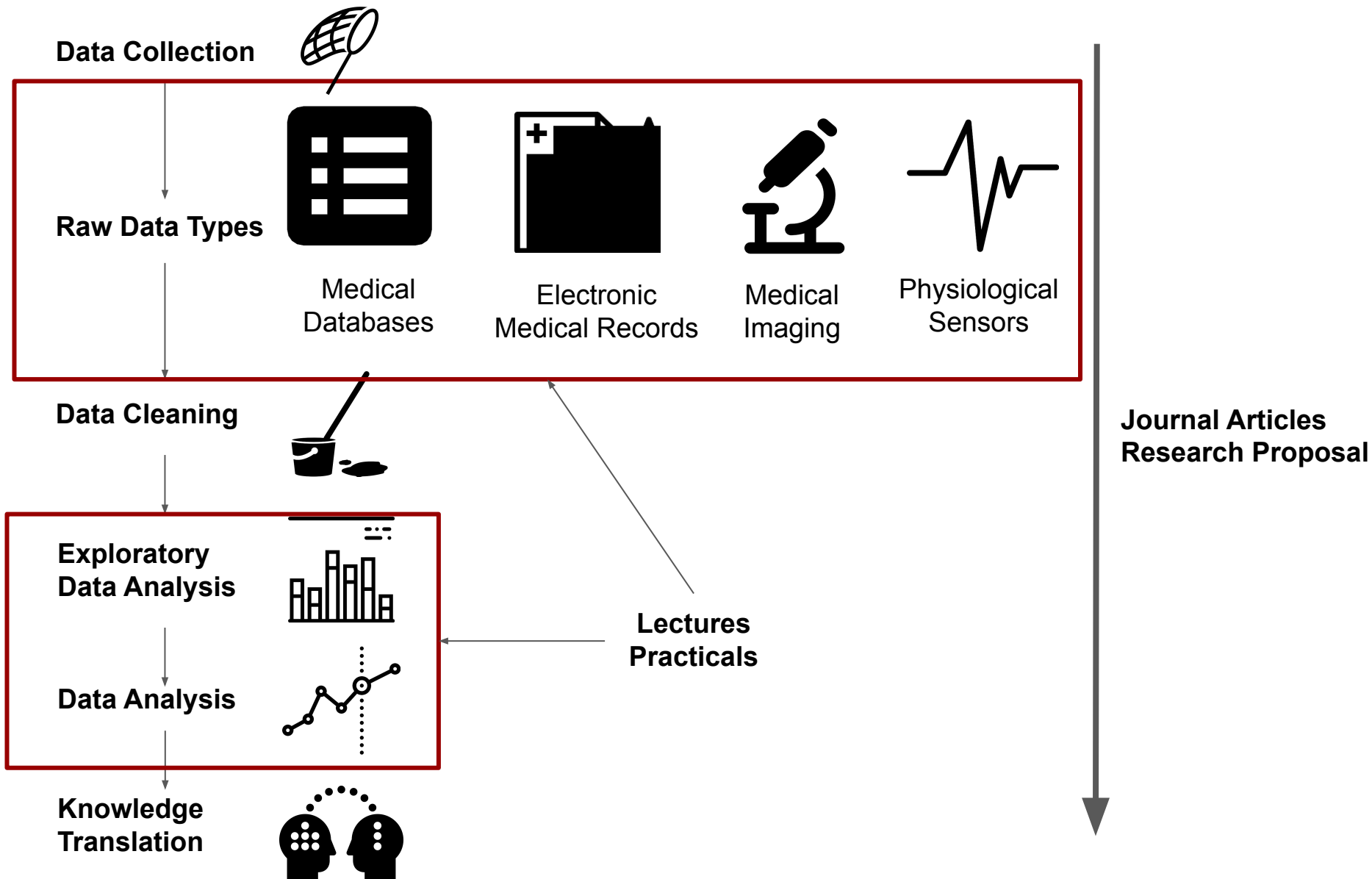
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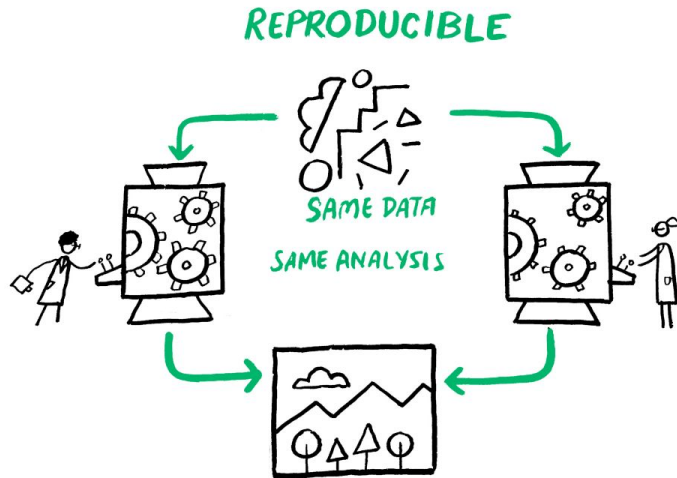
Let's take a 5 minute break!

Tools for Reproducible Health Data Science

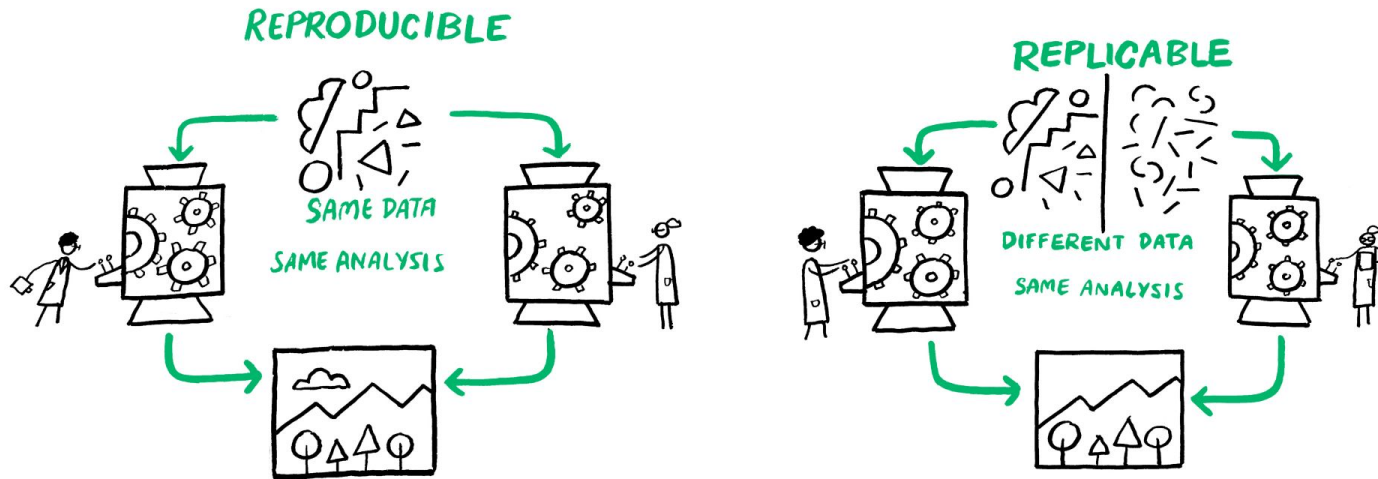
Rstudio, Rmarkdown, Git

Why do we care about reproducibility?

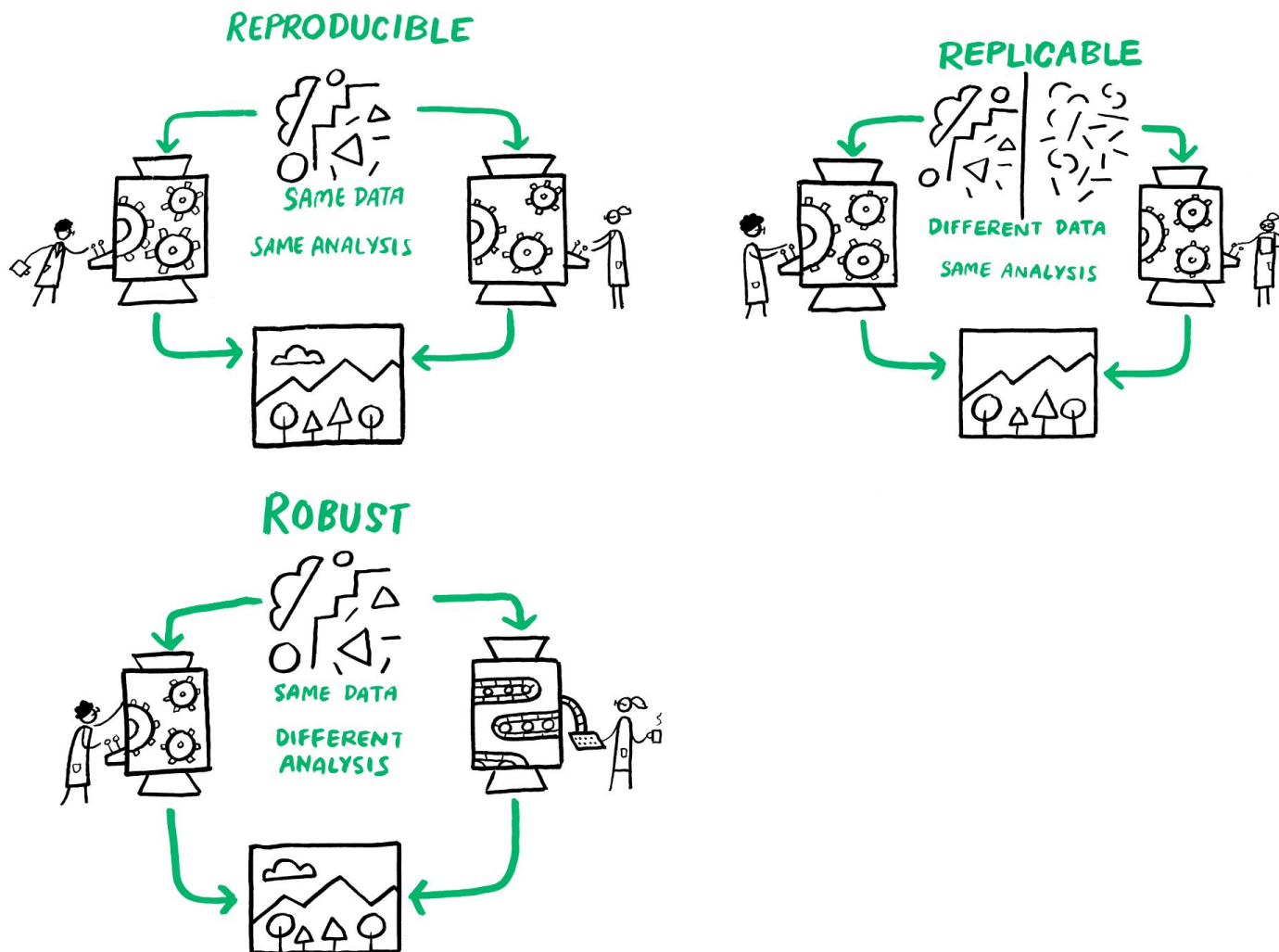
Reproducibility should be the bare minimum



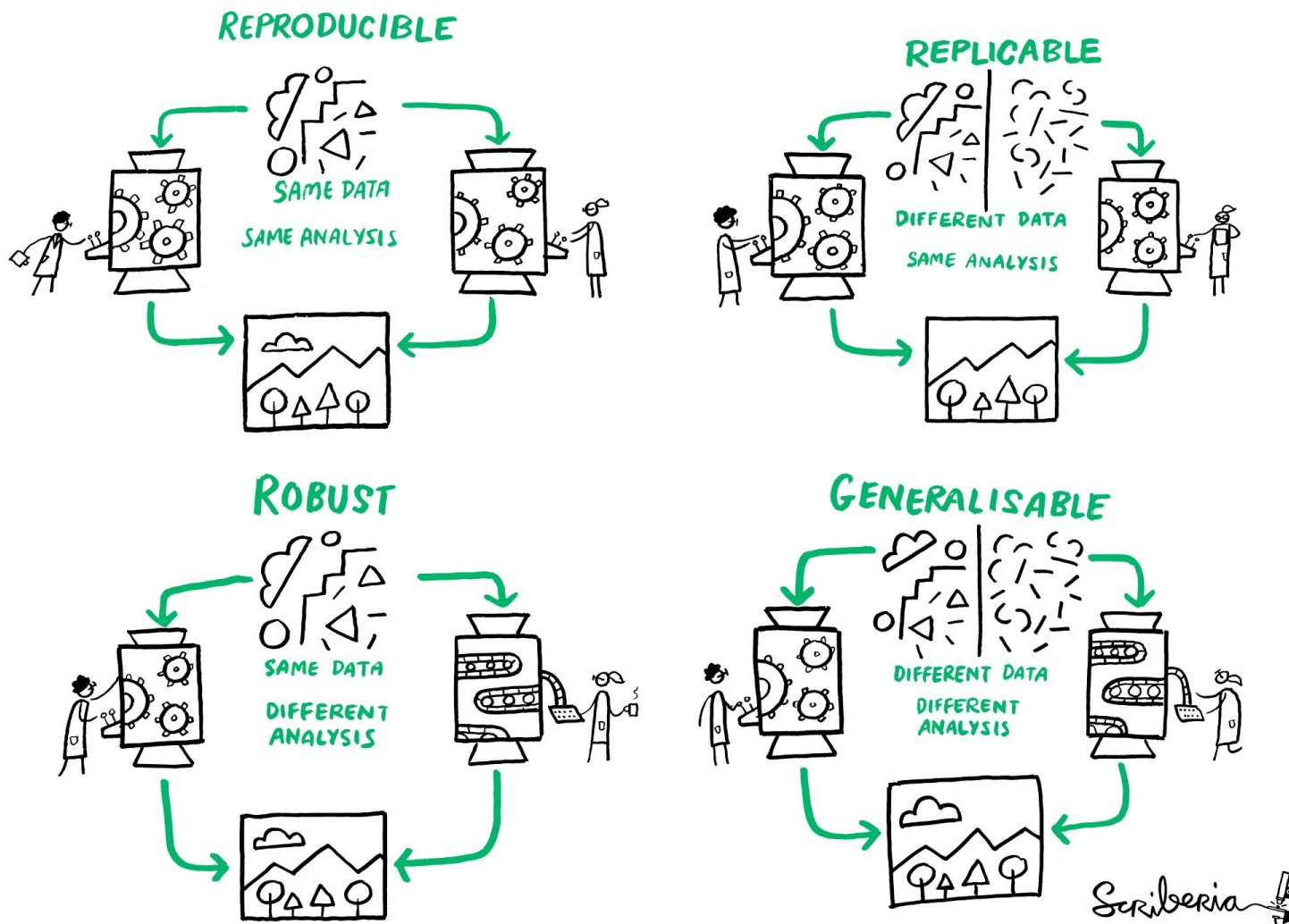
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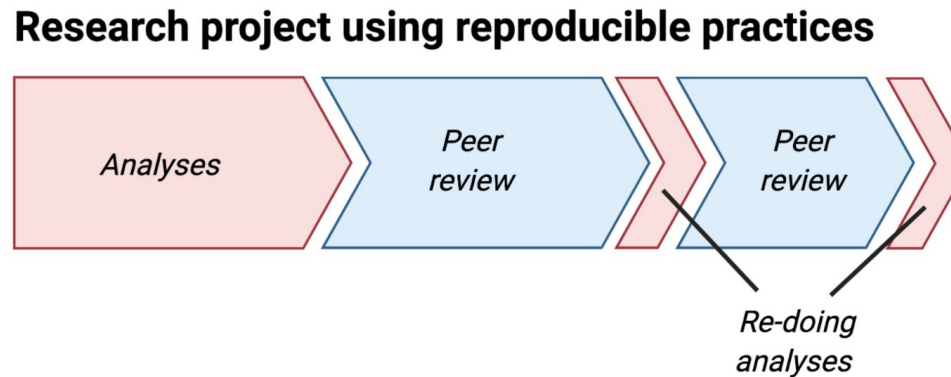
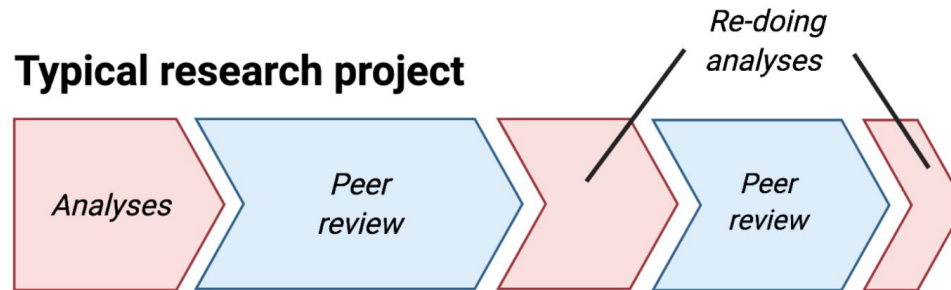
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Reproducibility should be the bare minimum



Makes your own life easier



@dsquintana

oliviergimenez.github.io/reproducible-science-workshop

What do we need to do to have reproducible research?

Reproducibility checklist

- Don't do anything by hand (even “one-off” tasks)

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- Script every interaction with data:
 - Data collection
 - Moving data on your computer
 - Formatting datasets
 - Cleaning data
 - Exploratory data analysis
 - Main analyses
 - Report generation

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 - Main analyses
 - Report generation
- Minimise interactivity/point and click interactions

Reproducibility checklist

- Don't do anything by hand (even “one-off” tasks)
- Script every interaction with data:
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 - Moving data on your computer
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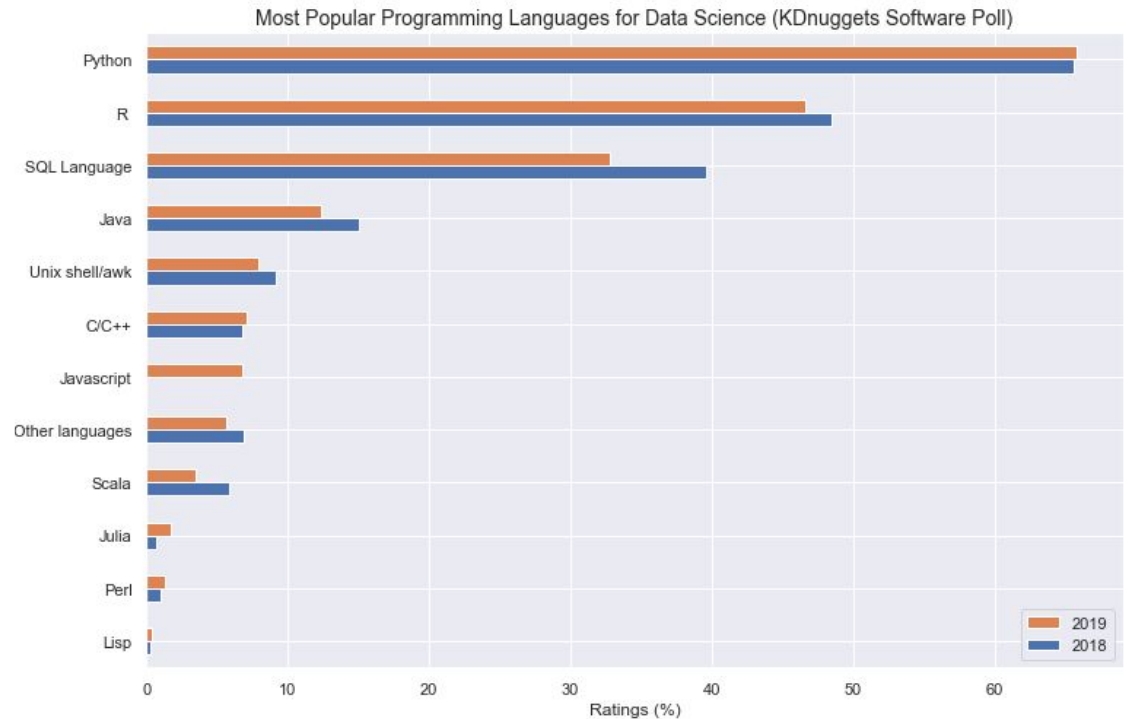
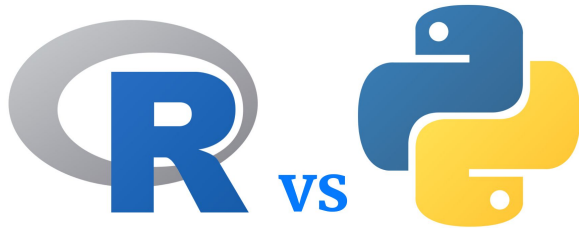
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- Keep track of the exact version of every library/program you use

How do we actually do these things?

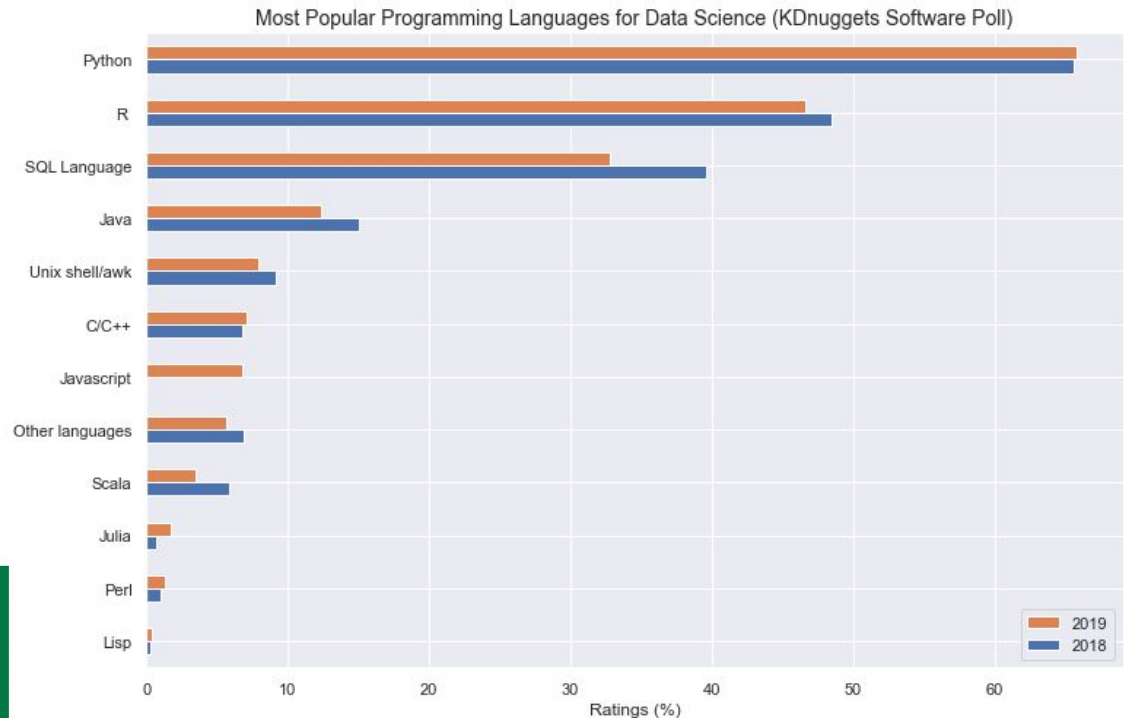
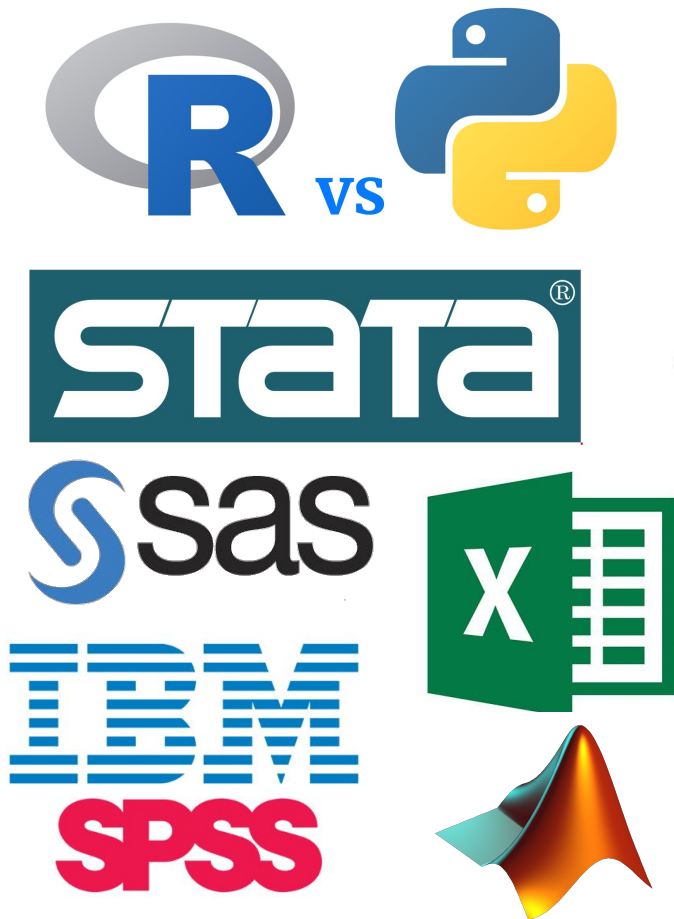
Choose a language that makes it easy to do most/all of your analysis

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<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

RStudio File Edit Code View Plots Session Build Debug Profile Tools Window Help

Flights - RStudio

Go to file/function Addins

flights-example.R x

```
1 library(nycflights13) ## package containing flights dataset
2 library(lubridate)
3 library(dplyr)
4 library(ggplot2)
5
6 head(flights, n = 3)
7 daily <- flights %>%
8   mutate(date = make_date(year, month, day)) %>%
9   count(date) %>%
10  mutate(wday = wday(date, label = TRUE))
11 head(daily, n = 3)
12 ggplot(daily, aes(wday, n)) +
13   geom_boxplot(outlier.colour = "hotpink") +
14   labs(x = "Weekday", y = "Flights",
15        subtitle = "Number of 2013 New York Flights Each Weekday")
16
```

1:1 (Top Level) R Script

Environment History Connections Tutorial

Import Dataset 346 MiB List

R Global Environment

Data

daily 365 obs. of 3 variables

\$ date: Date[1:365], format: "2013-01-01" "2013-01-02" ...

\$ n : int [1:365] 842 943 914 915 720 832 933 899 902...

\$ wday: Ord.factor w/ 7 levels "Sun"<"Mon"<"Tue"<...: 3 ...

Console Terminal Jobs

~/Documents/Flights/

```
# A tibble: 3 x 19
  year month day dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay carrier
<int> <int> <int> <int> <int> <dbl> <int> <int> <dbl> <chr>
1 2013 1 1 517 515 2 830 819 11 UA
2 2013 1 1 533 529 4 850 830 20 UA
3 2013 1 1 542 540 2 923 850 33 AA
# ... with 9 more variables: flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
# distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>
> daily <- flights %>%
+   mutate(date = make_date(year, month, day)) %>%
+   count(date) %>%
+   mutate(wday = wday(date, label = TRUE))
> head(daily, n = 3)
# A tibble: 3 x 3
  date n wday
<date> <int> <ord>
1 2013-01-01 842 Tue
2 2013-01-02 943 Wed
3 2013-01-03 914 Thu
> ggplot(daily, aes(wday, n)) +
+   geom_boxplot(outlier.colour = "hotpink") +
+   labs(x = "Weekday", y = "Flights",
+        subtitle = "Number of 2013 New York Flights Each Weekday")
>
```

Files Plots Packages Help Viewer

Zoom Export

Number of 2013 New York Flights Each Weekday

Weekday

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

Use notebooks to document analyses: Rmarkdown/Quarto

~\Documents\rmarkdown - gh-pages - RStudio

9-notebook.Rmd

```
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
11 [viridis](https://github.com/sjmgarnier/viridis) package. Each
12 plot displays a contour map of the Maunga Whau volcano in
13 Auckland, New Zealand.
14
15 ## Viridis colors
16 ```{r}
17 image(volcano, col = viridis(200))
18 ```
```

3:22 Viridis Notebook R Markdown

Environment History Build Git

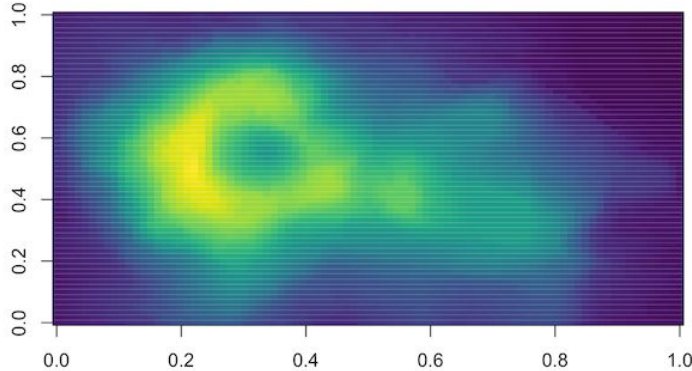
Files Plots Packages Help Viewer

Viridis Notebook

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

Viridis colors

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



Magma colors

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.

BC AB SK MB ON QC NS NB NL

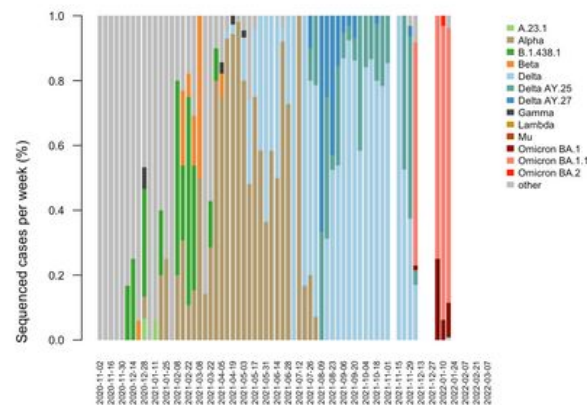
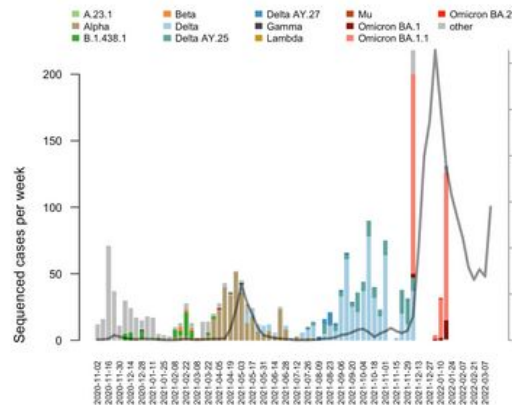
Nova Scotia

Additional up-to-date COVID data for this province can be found here:

<https://experience.arcgis.com/experience/204d6ed723244dfbb763ca3f913c5cad>

Hide

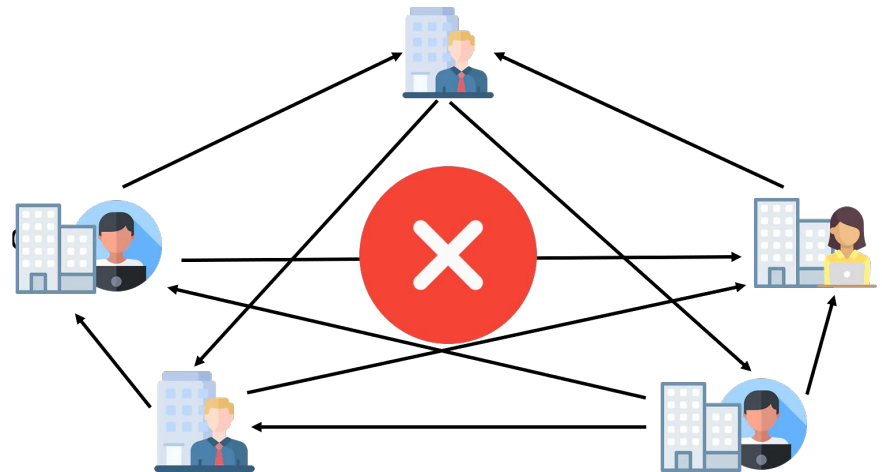
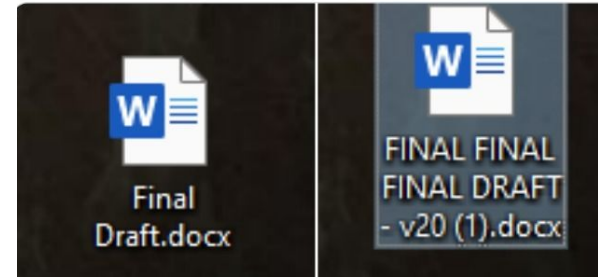
```
plot.variants(region='Nova Scotia')
plot.variants(region='Nova Scotia', scaled=T)
```



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

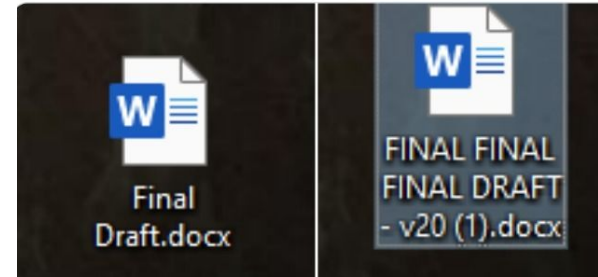
Use standard version control systems

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



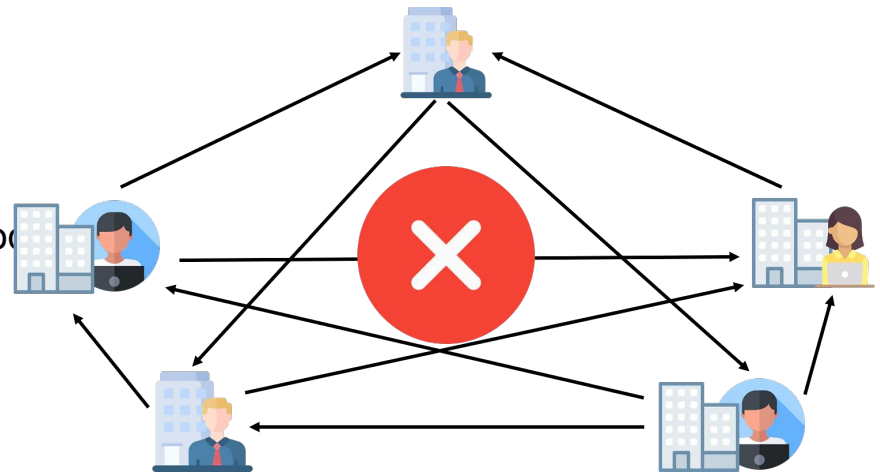
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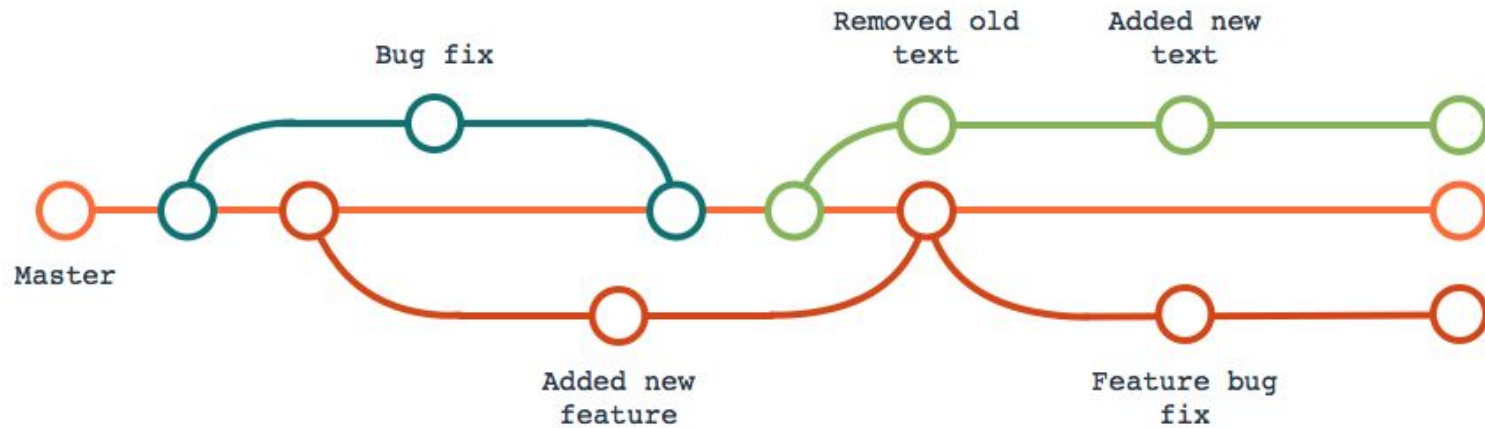


Version control let's you:

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

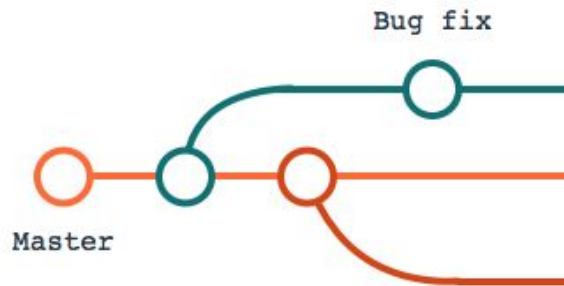


Git Version Control

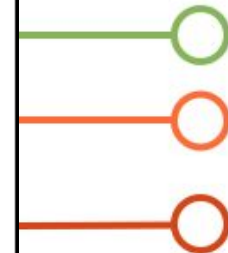


- Most popular
- Decentralised
- Designed for
- GitLab/GitHub Services

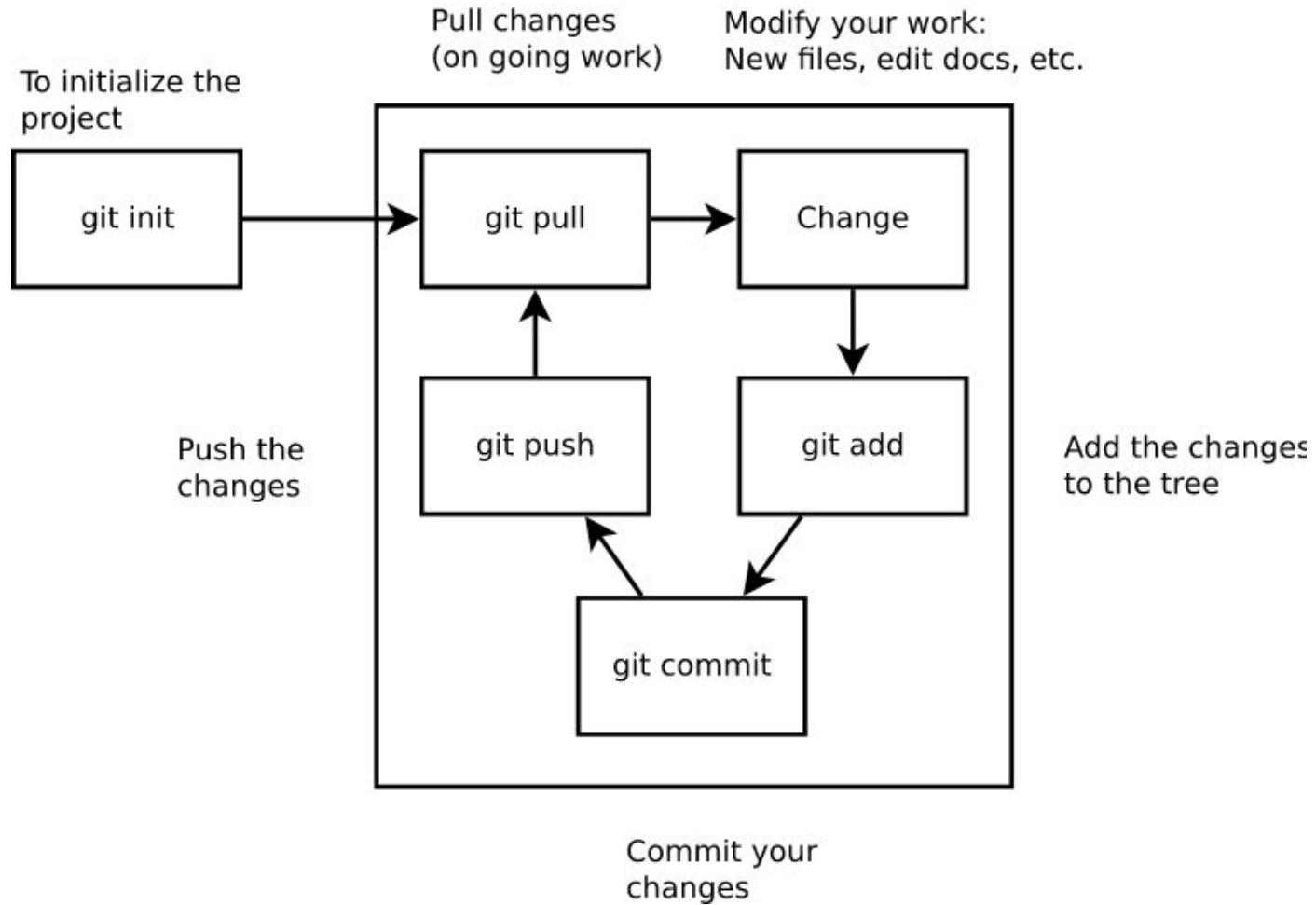
Git Version Control



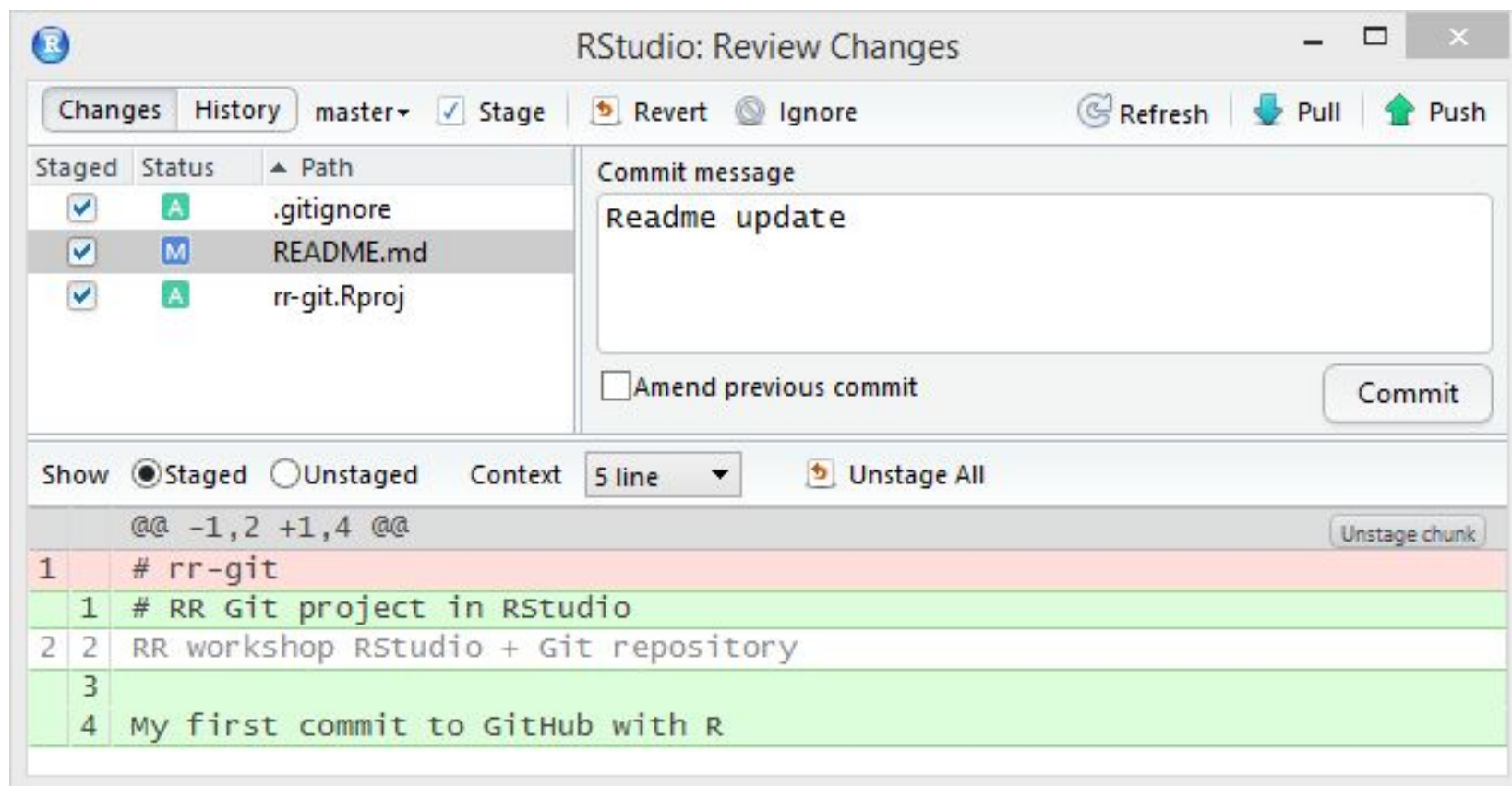
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Git Workflow

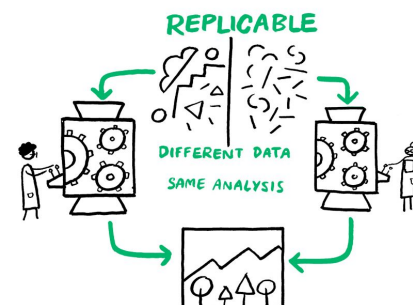
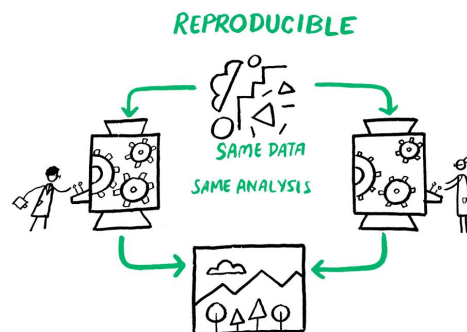


Git is integrated into Rstudio!

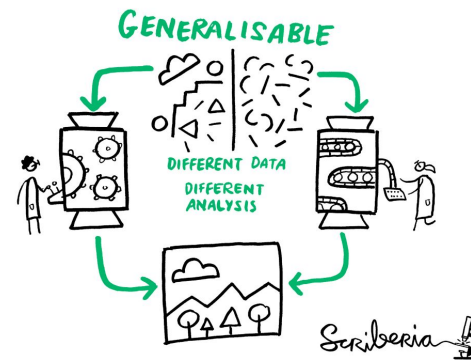
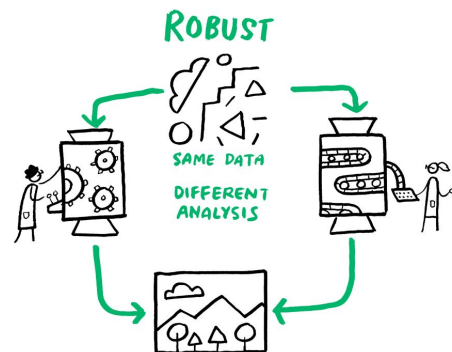


Combine Git+Rmd Notebooks for Reproducibility

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



Scriberia

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](https://doi.org/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>