

THE DATA'S JOURNEY

Hypothesis



Validation



Cleaning & Normalization



Data Exploration



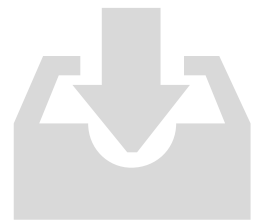
Data Collection



Analysis



FINAL PART OF OUR JOURNEY



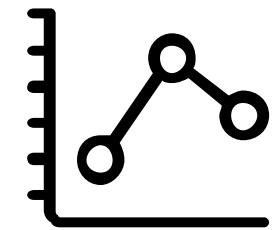
DATA COLLECTION



EXPLORATORY
DATA ANALYSIS



DATA ANALYSIS

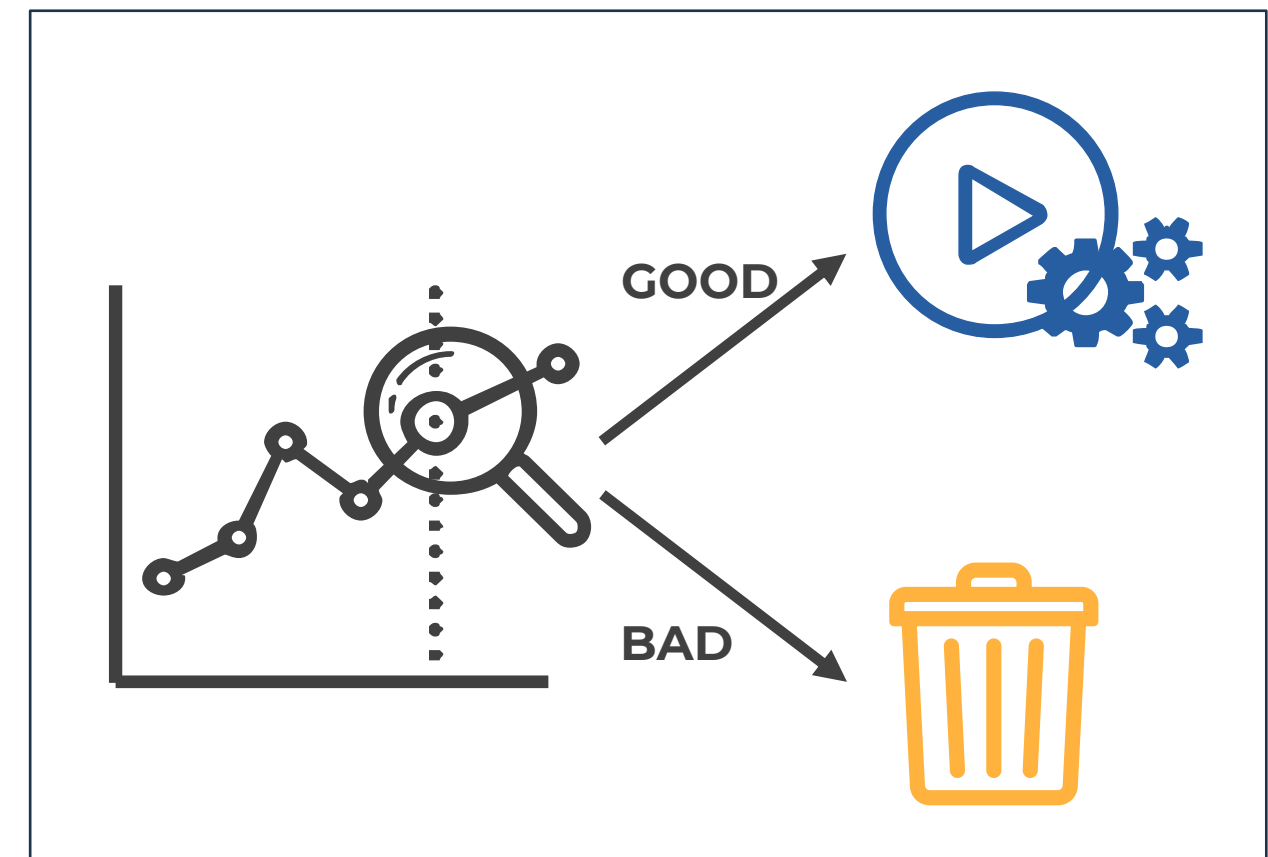


MODEL EVALUATION



MODEL EVALUATION

- How do we measure the performance of a model?
- How much/far can we trust the results we have obtained?
- How do we interpret the results of the evaluation?

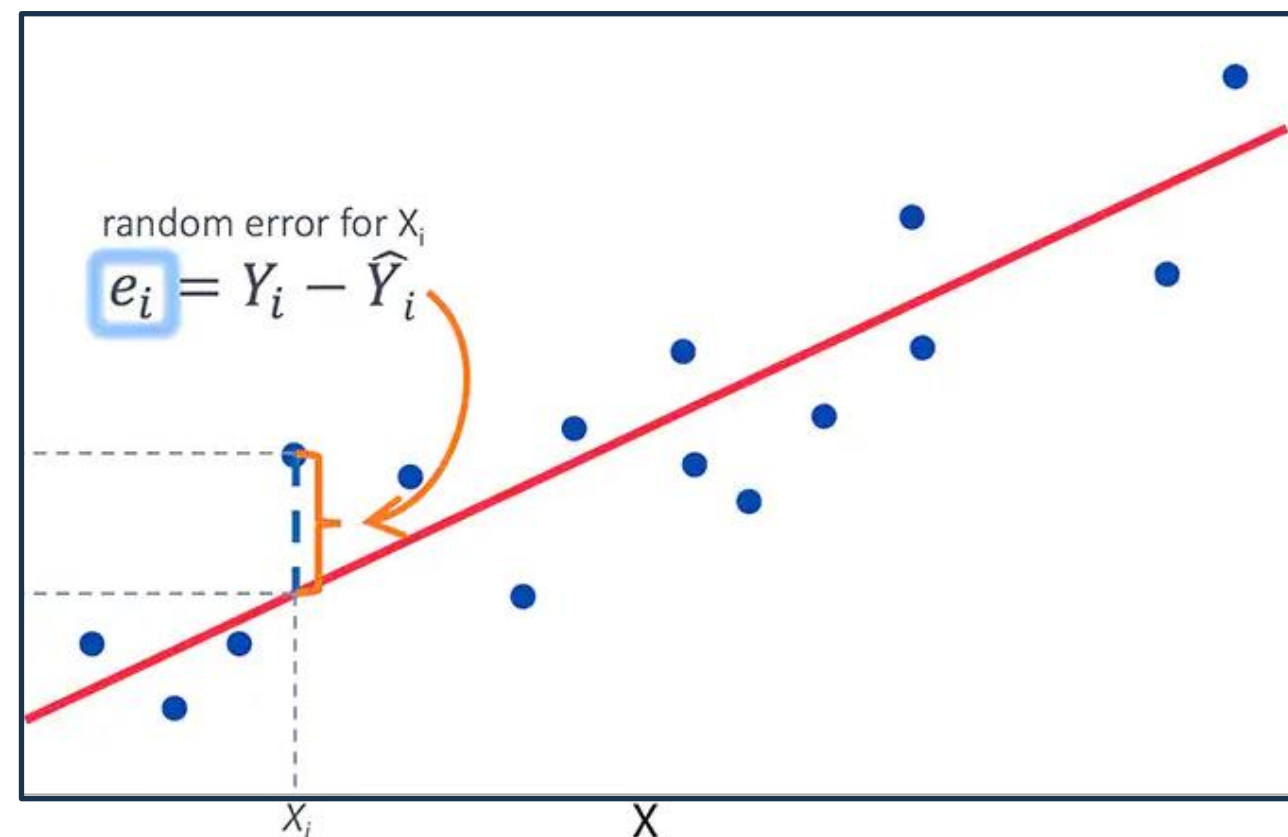


Pick evaluation metric based on research question, data and model.

MODEL PERFORMANCE

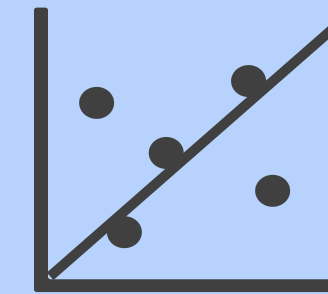
How well does the model fit the data?

- Criteria depend on model type
- Good models capture the underlying trends and characteristics



PERFORMANCE METRICS:

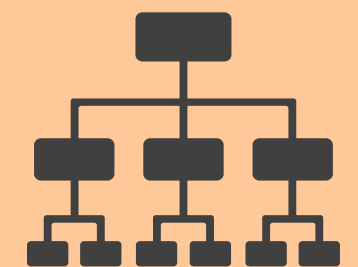
- R-squared
- MSE
- RMSE
- RMSLE



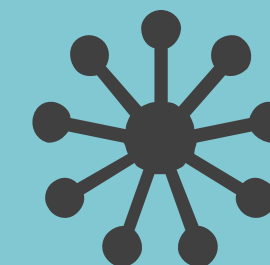
REGRESSION

CLASSIFICATION

- Accuracy
- Precision
- Recall
- ROC/AUC



- Silhouette
- Adj. Rand Indx.
- Gap statistic
- Davies-Bouldin

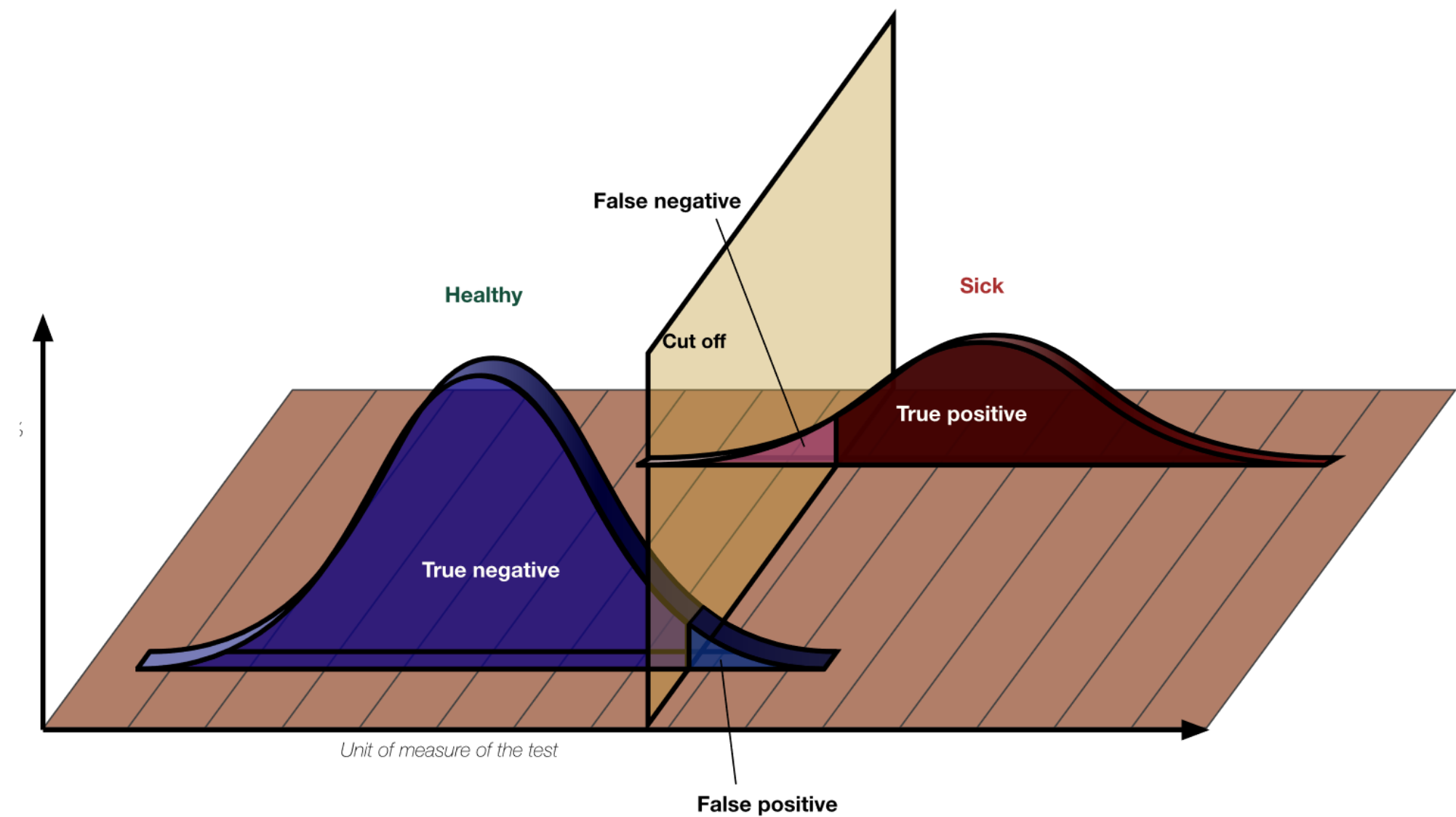


CLUSTERING

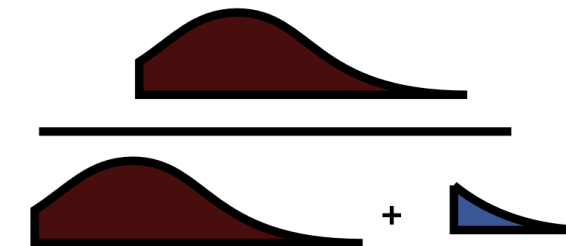
CLASSIFIER PERFORMANCE

Performance measures of classifiers depend on the chosen cutoff.

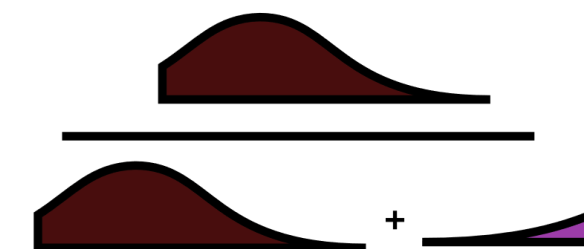
One can easily optimize on the number of false positives or false negatives, but not both at the same time.



Precision :

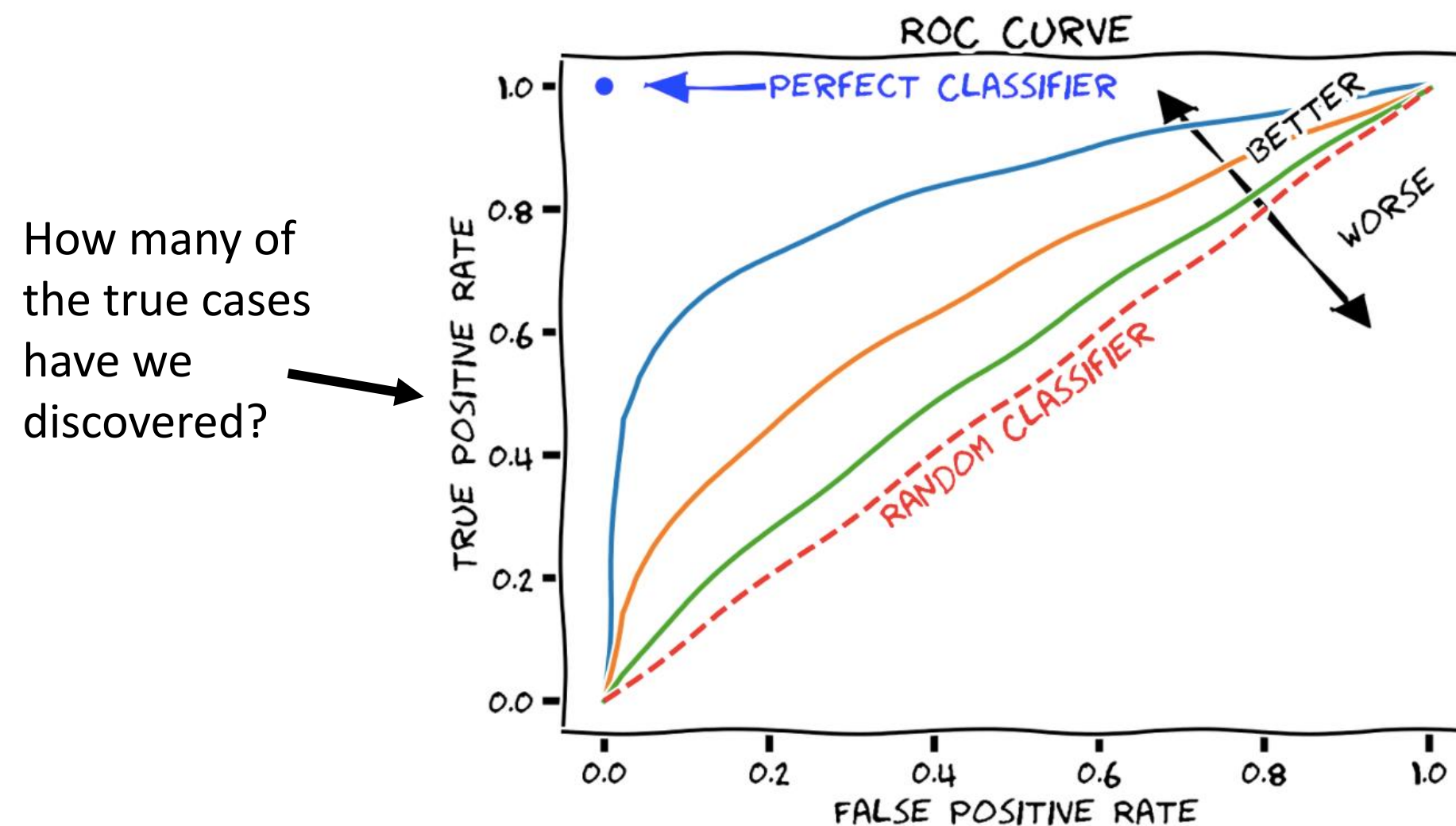


Recall/
True positive rate



AREA UNDER THE CURVE (AUC)

This is why we use the AUC to report on the goodness of the classification.



- Receiver Operator Curve (ROC)
- Plotted by using every possible cutoff.
- Each True Positive Rate has an associated False Positive rate.

GROUP DISCUSSION 4.1

For a medical screening procedure to detect a disease, what does each of these terms correspond to:

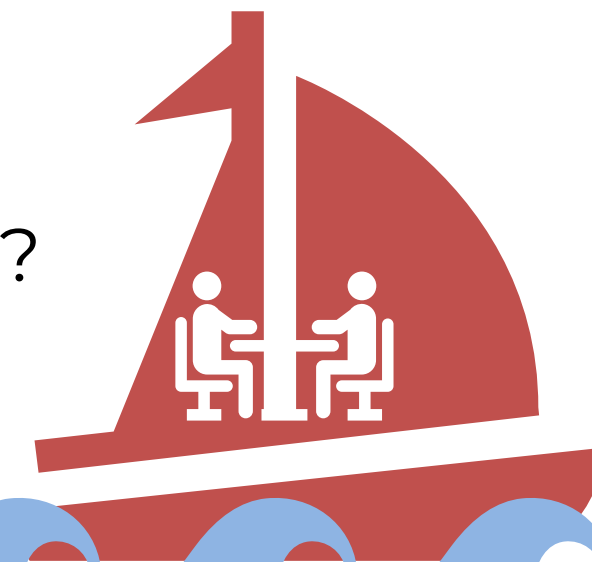
- True positive
- False positive
- True negative
- False negative

$$\text{Precision} = \frac{tp}{tp + fp}$$

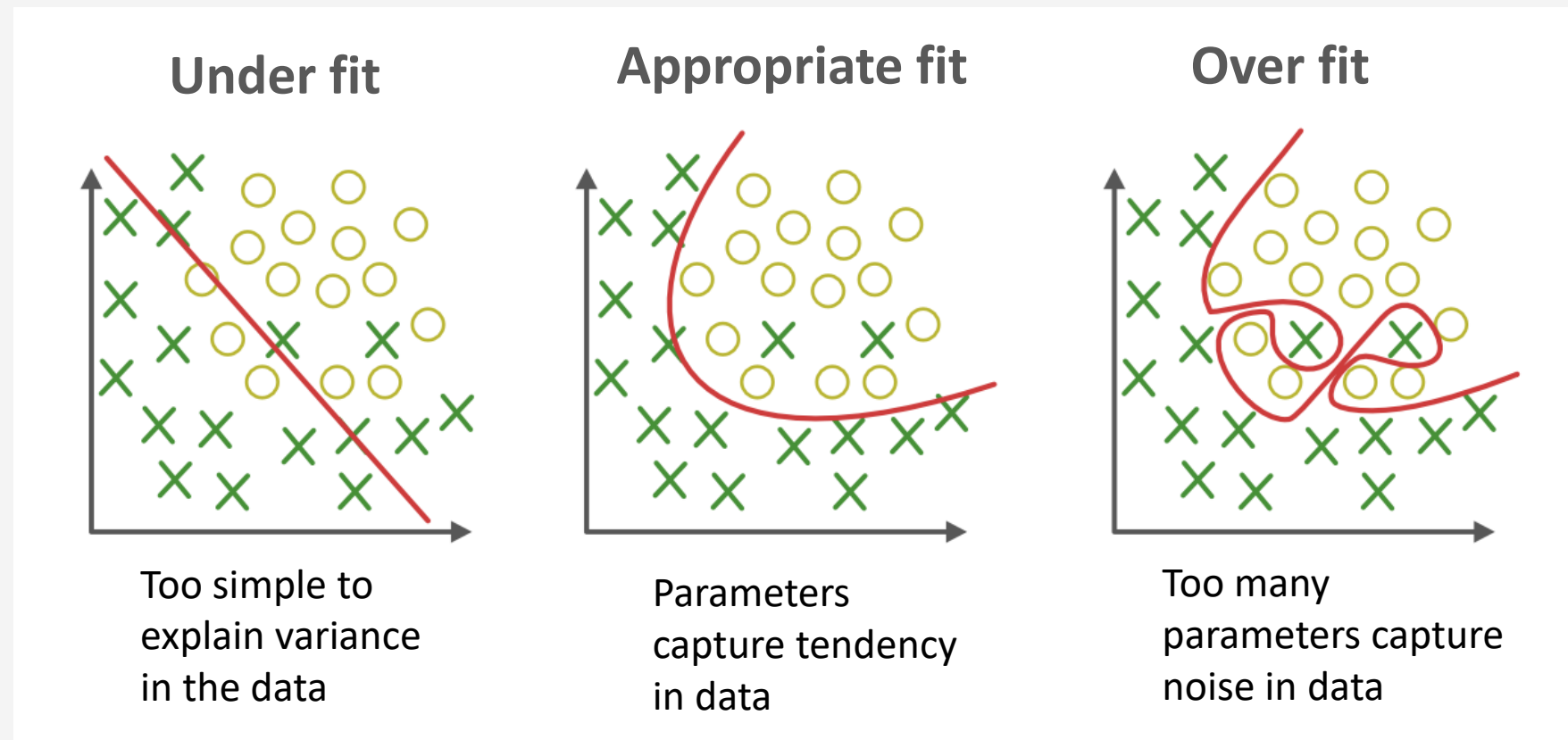
$$\text{Recall} = \frac{tp}{tp + fn}$$

On the right you have the formulas for precision and recall.

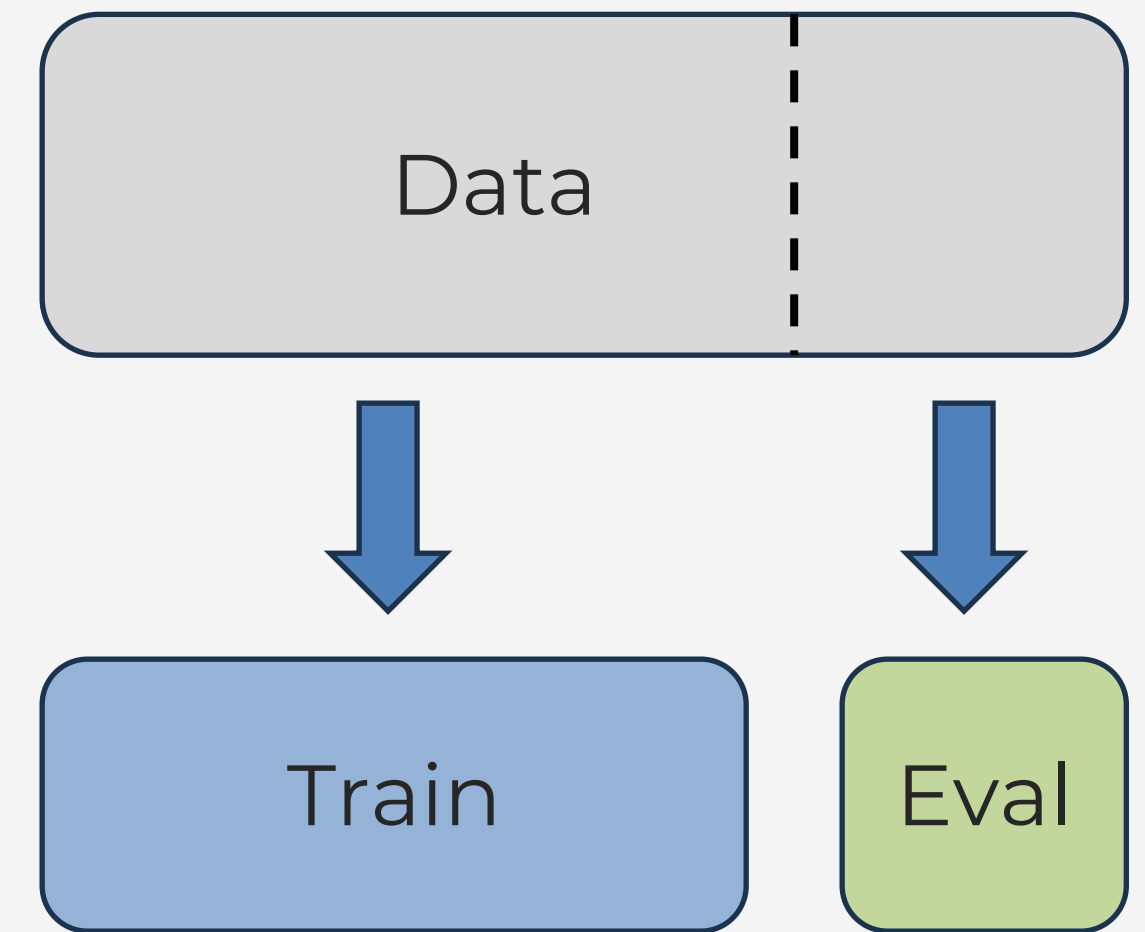
Discuss what are the benefits and drawbacks of optimizing one over the other in relation to a disease screening program?



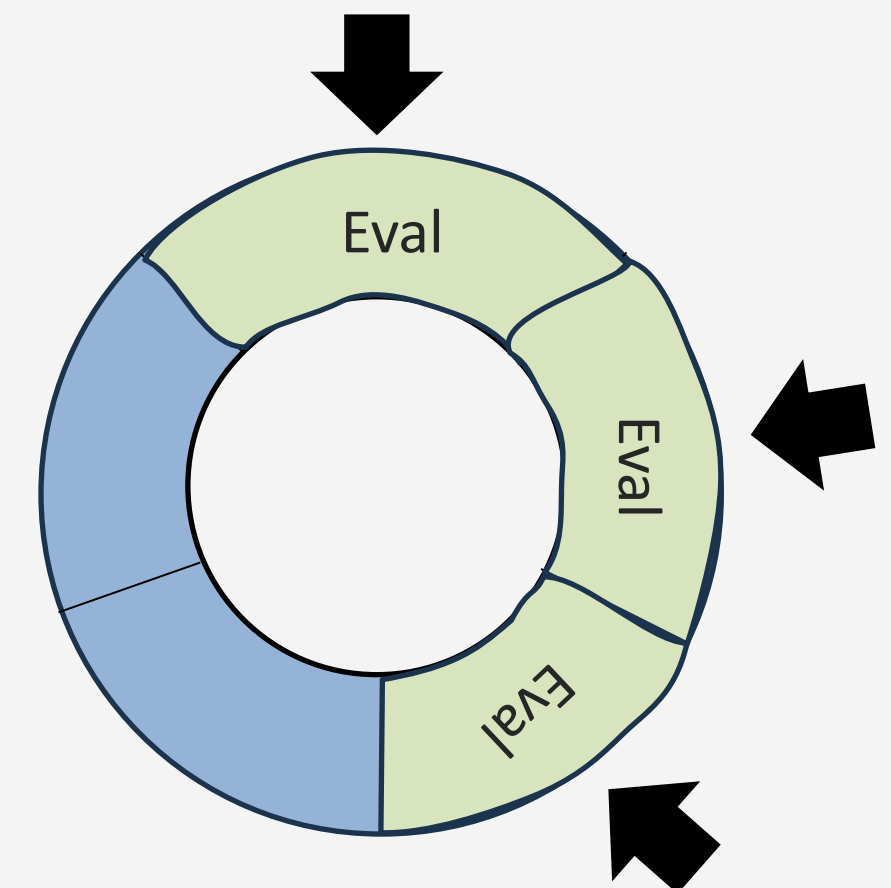
OVERFITTING

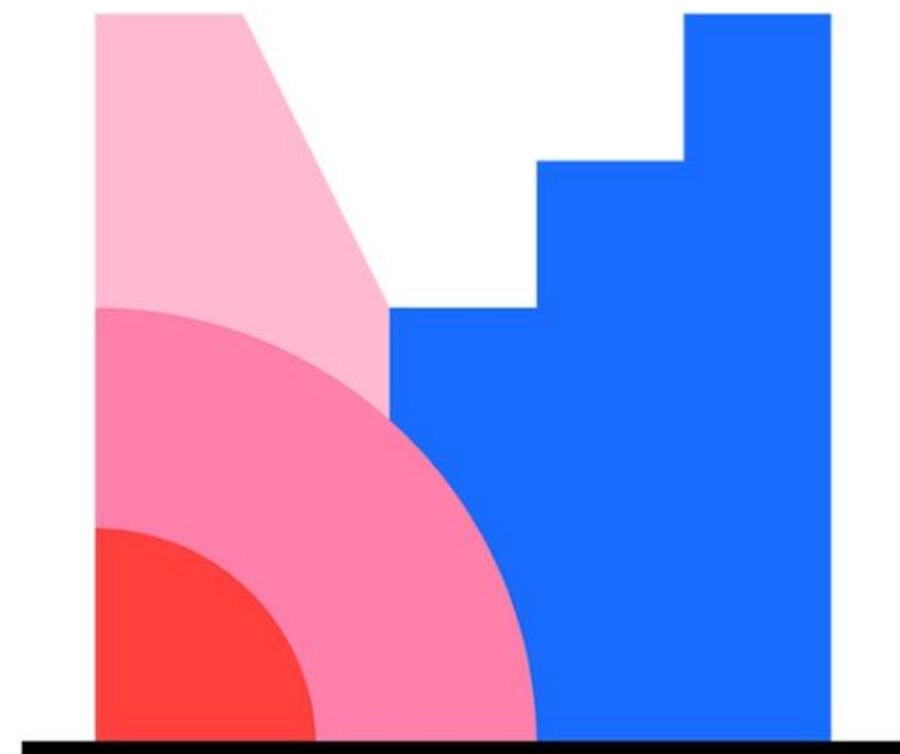


- When a model follows the data too closely we get an effect known as overfitting.
- We avoid this by splitting the data into training and evaluation sets and controlling the number of free parameters.



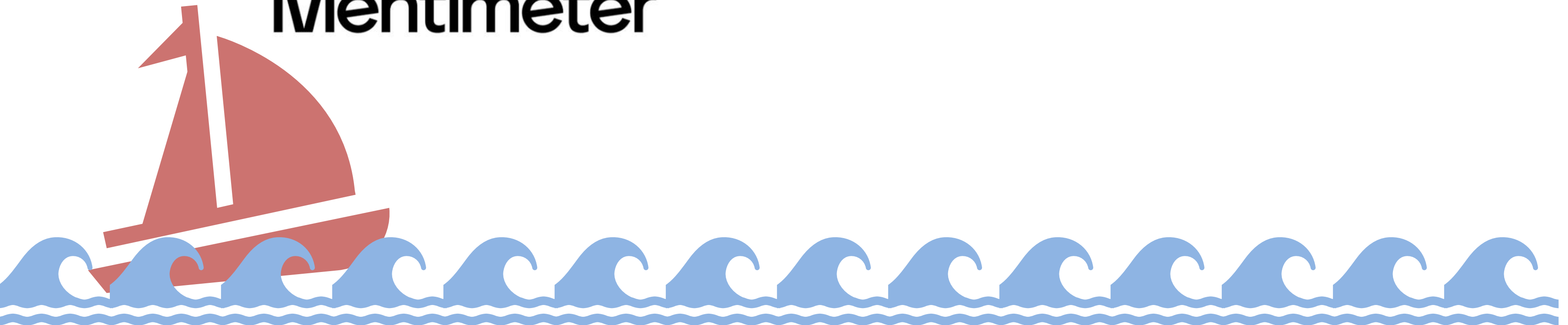
Cross
Validation





2 questions

Mentimeter

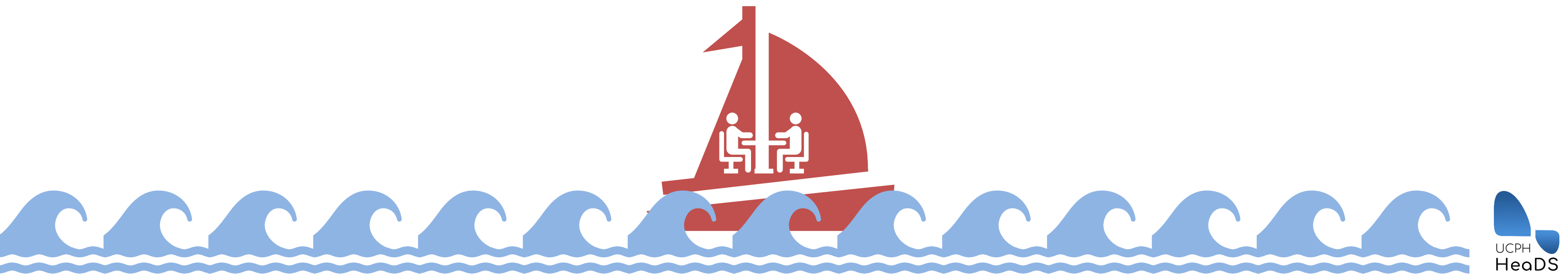


GROUP DISCUSSION 4.2

On your table you have a print-out in which the same data has been fitted with three different models (the red lines).

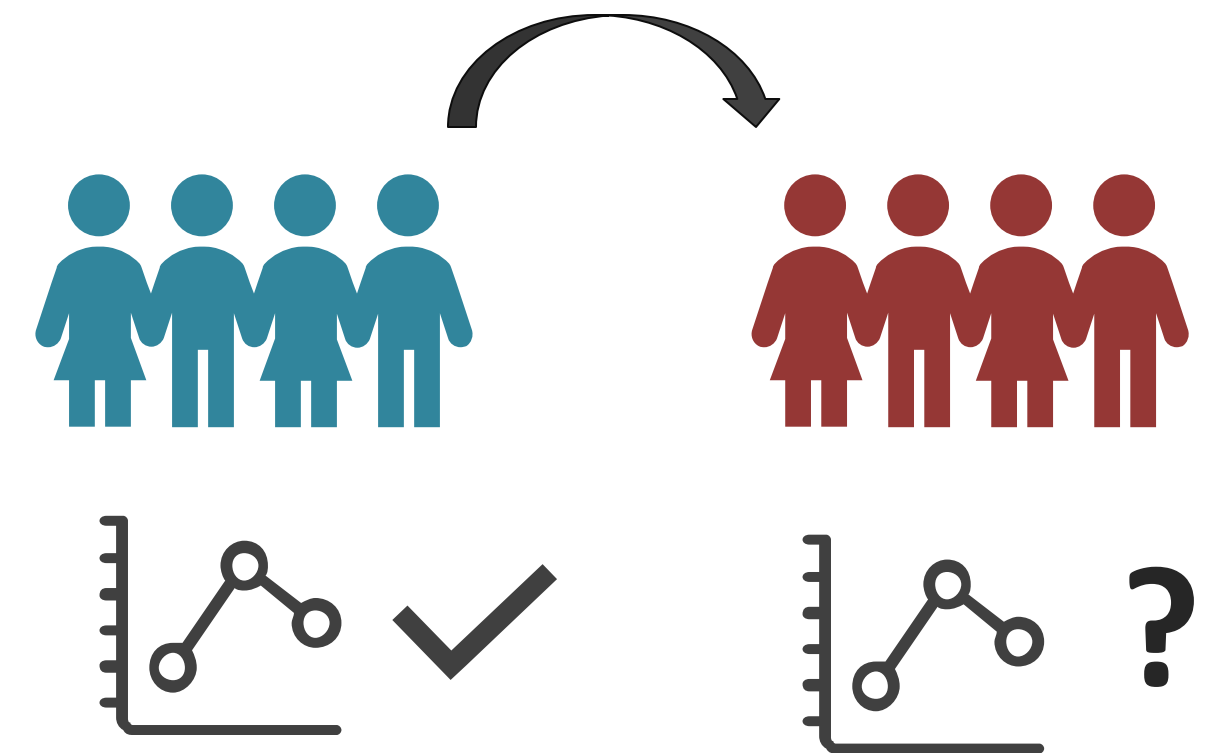
In your group, discuss which of these you think is the **most suitable** and **why**.

In general, what is the problem with high-dimensional model with many parameters?



BIASES

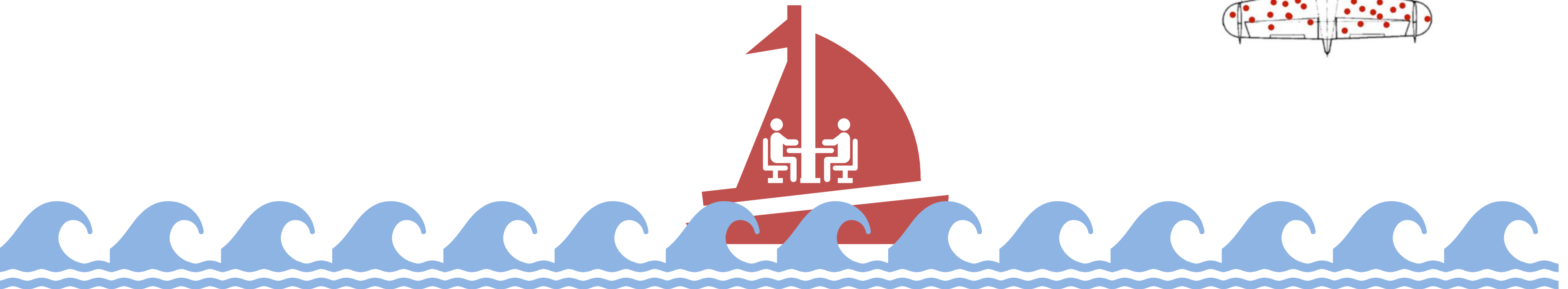
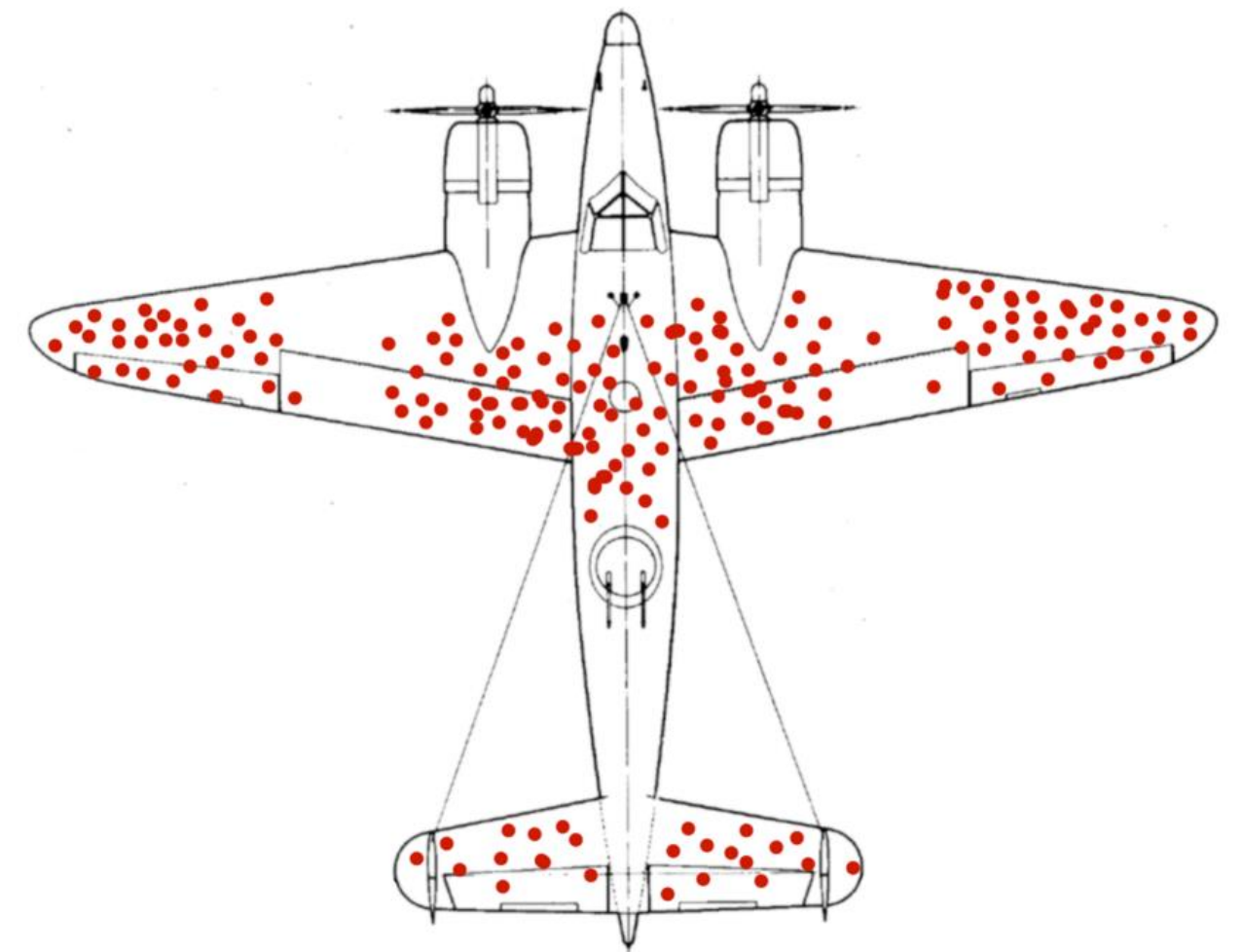
- What biases could have influenced the results?
- Bias arises primarily from how the data was gathered and processed.
- Bias can reduce model validity, i.e. a model trained in one population may not work in another.



GROUP DISCUSSION 4.3

Consider the following schematic of bullet holes on returning WW2 planes.
It shows with red circles where each plane was struck.

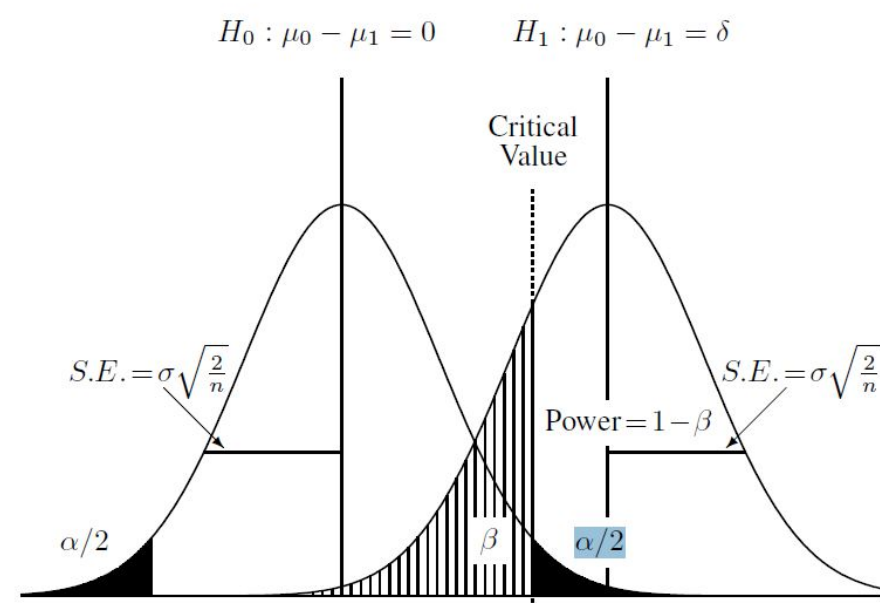
Based on this data, which part of the plane do you think should be reinforced to better protect the plane from being damaged?



WHAT DO THE RESULTS MEAN?

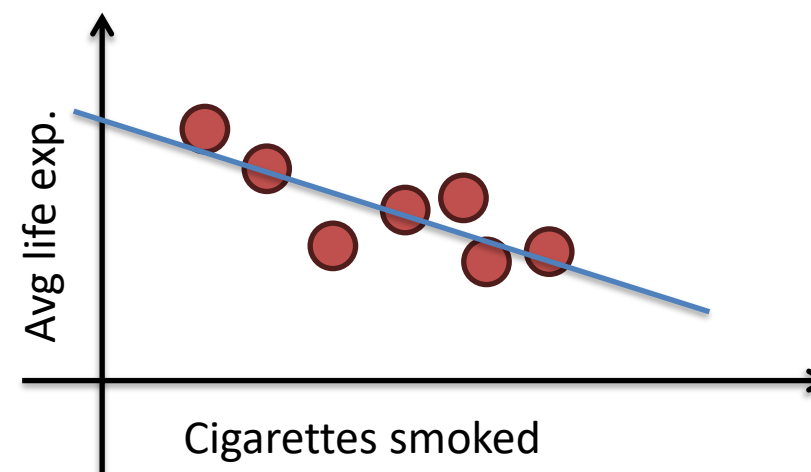
Hypothesis testing

A significant p-value supports the rejection of the null hypothesis.



Classification / Prediction

- Poor model performance, the model does not capture the data pattern.
- Interpretable parameters?
- Coefficients/Feature importance tell which predictor variables have a large influence in outcome



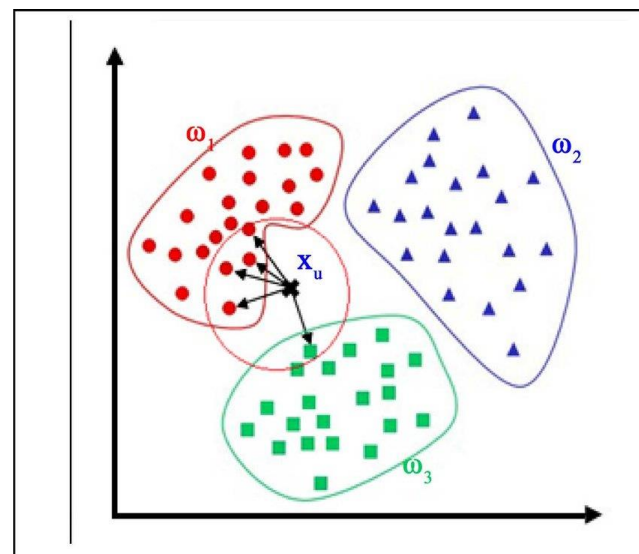
Regression model:

birth weight ~
mother's weight +
smoking +
mother's age

WHAT DO THE RESULTS MEAN?

Unsupervised Learning/Clustering

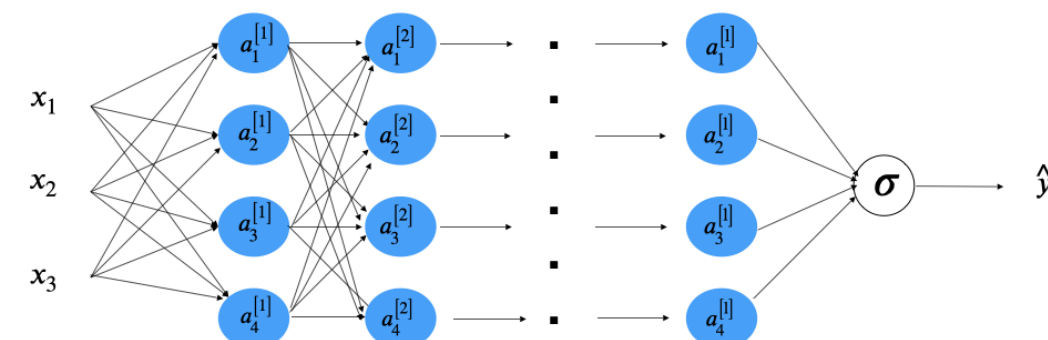
- Insights about the structure of the data, esp. number of clusters
- Further analyse properties of discovered clusters (**biological meaning**)
- Predict cluster membership of new data points



Black Box models

- Highly non-linear models with many parameters are difficult to interpret
- We mostly use the performance instead of trying to gain insights

1 - Layer Neural Network

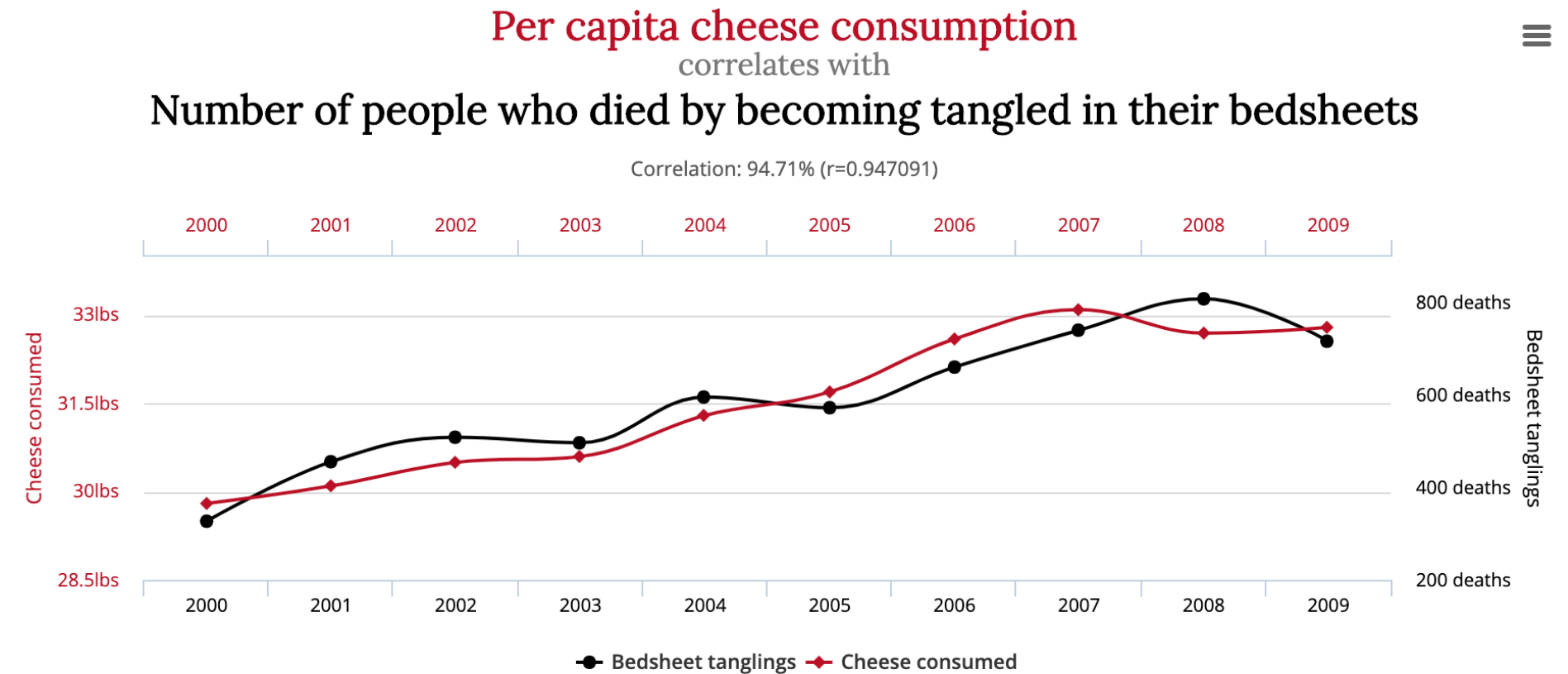


CORRELATION \neq CAUSATION

One goal of modelling is to discover relationships between predictor and outcome variable.

However, modelling is **not primarily concerned with causality**.

If our model shows that a relationship exists, that does not mean the relationship is causal.



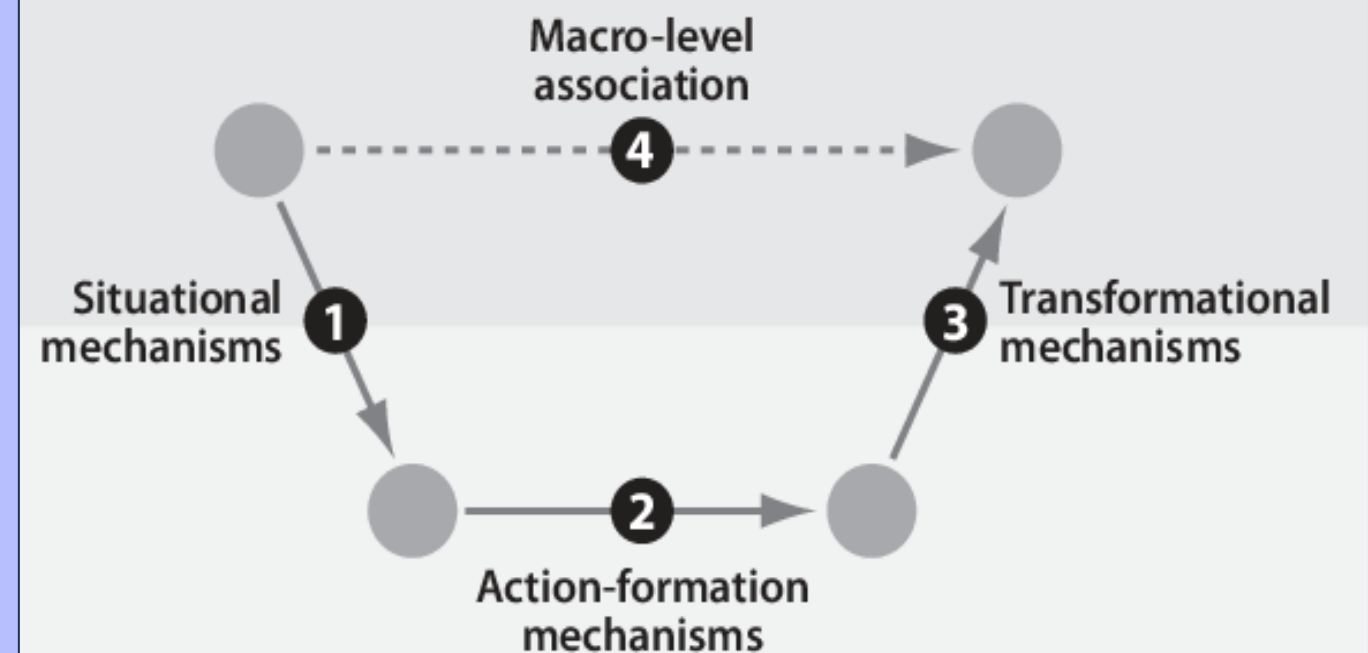
Data sources: U.S. Department of Agriculture and Centers for Disease Control & Prevention

tylervigen.com

THE QUESTION OF CAUSALITY

Where does this leave us?

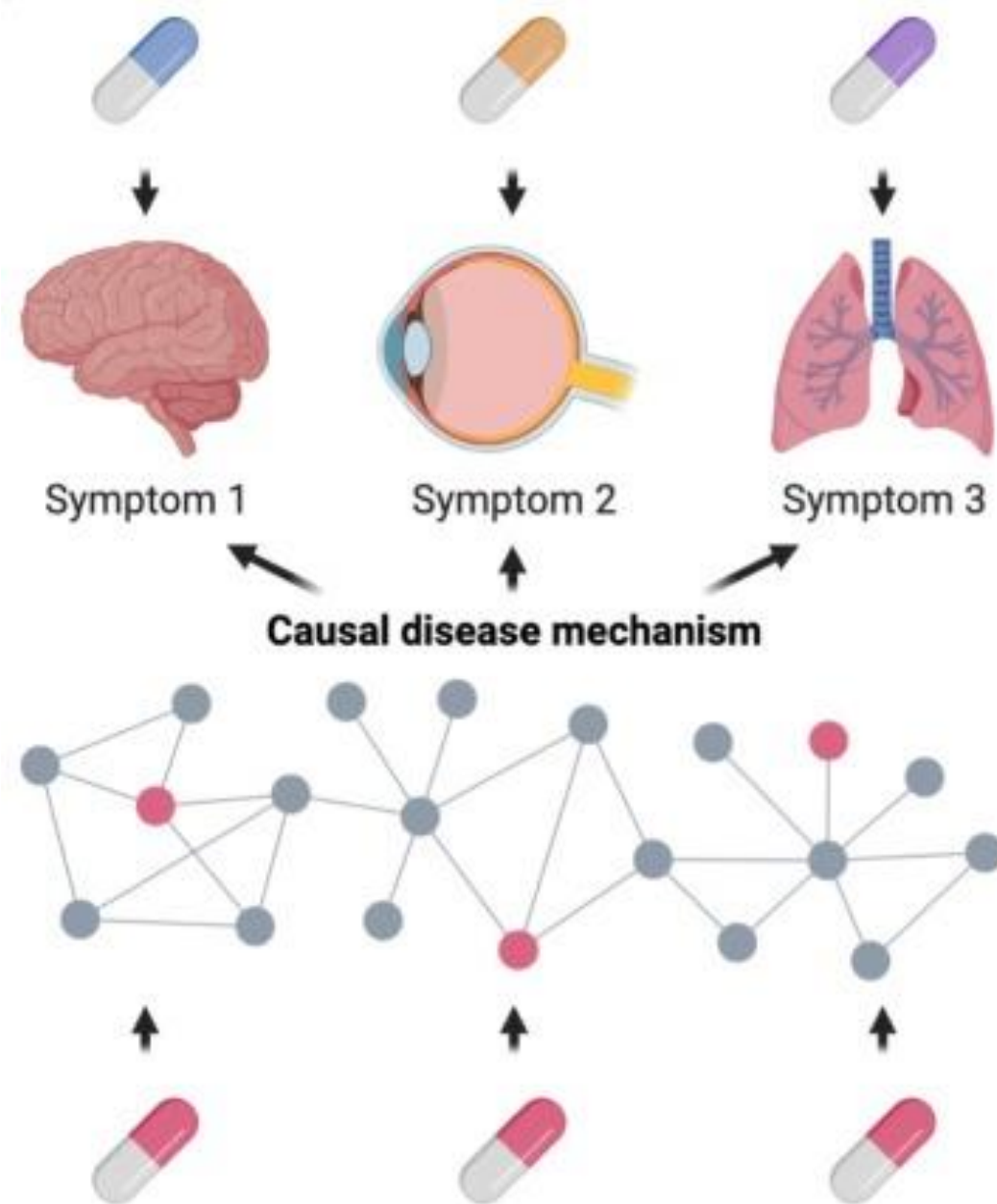
- Causality can only be surmised in the statistical framework of causal inference.
- **Mode of action** is vital.
- If A causes B, how so?
- Does that make sense in the framework of existing domain knowledge?



Hedström, P. and Petri Y. " *Annual review of sociology* 36 (2010): 49-67.

- Causality can be shown by gathering convergent evidence from different lines of inquiry and direct cause-effect experiments (animal/cell studies).

THE QUESTION OF CAUSALITY



Is causality always central in (Health) Data Science Analysis?

The answer is that it depends on what we are trying to achieve:

A question of causality:

- **YES:** Underlying biological mechanism -> true treatment of disease
- **NO:** Diagnosis of disease (causality is nice but not necessary)

GROUP DISCUSSION 4.4

1. In a cross-sectional study, researchers observed that the number of vaccinations a population received was positively associated with the prevalence of certain diseases.
2. In a cohort study, researchers found an inverse (negative) relationship between exercise and prevalence of arthritis in a group of individuals, i.e. less exercise more likely to be diagnosed with arthritis.

Discuss the two studies above and their conclusion, does vaccination *cause* an increase in disease development and does lack of exercise *cause* the development of arthritis? Think about confounders...



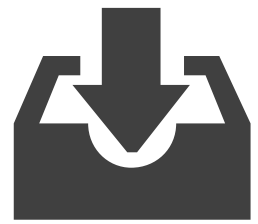
GROUP DISCUSSION 4.5

1. In a recent population study on alcohol consumption and cancer development, analysis revealed that people who often drink wine, have an increased risk of developing lung cancer compared to people who do not.

Does drinking wine cause lung cancer? Can you think of any confounding factors which could explain this correlation, i.e. life style choices, socioeconomic group, etc.?



OVERVIEW OF OUR JOURNEY



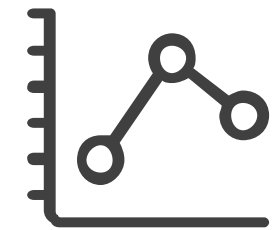
DATA COLLECTION



**EXPLORATORY
DATA ANALYSIS**



DATA ANALYSIS



MODEL EVALUATION



HEALTH DATA SCIENCE – YOUR NEXT STEP

COURSES



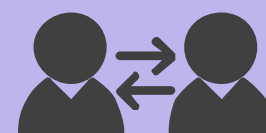
HeaDS:

- *Programming (Python, R)*
- *High performance compute*
- *Applied health DS analysis*



Biostatistics
NNF Centers (ReNew, CPR)
SUND faculty

DATA SCIENCE COLLABORATION



- Conferences & seminars on DS
- Matchmaking events
- Contact relevant department, group, support - and core facility

ONLINE RESOURCES



- <https://www.coursera.org/>
- <https://www.codecademy.com>
- <https://www.datacamp.com/>
- <https://towardsdatascience.com/>
- Stack Overflow & Reddit
- **Books:**
"R for Data Science"
"Python Data Science Handbook",
"Statistics for Health Data Science"

BACK TO THE FUTURE

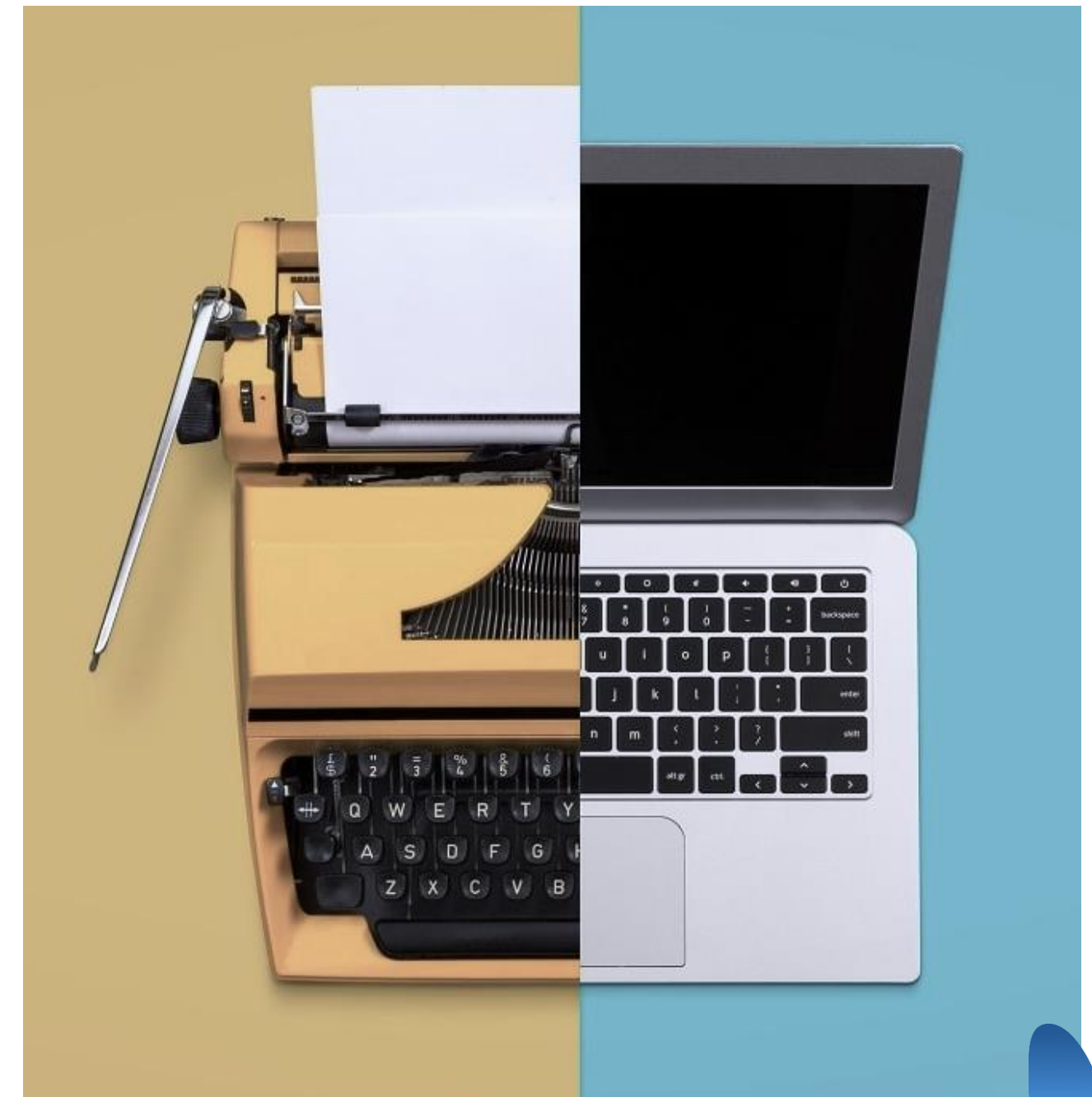
The Digital Core Curriculum (**DCC**) initiative:

- KU educations to include digital literacy and data science competences
- DS in Medical Research is the future!
- As a domain expert, so what is your role?
 - Form a collaboration with a data scientist
 - Encourage your staff to take DS courses
 - Know where to get help with DS analysis



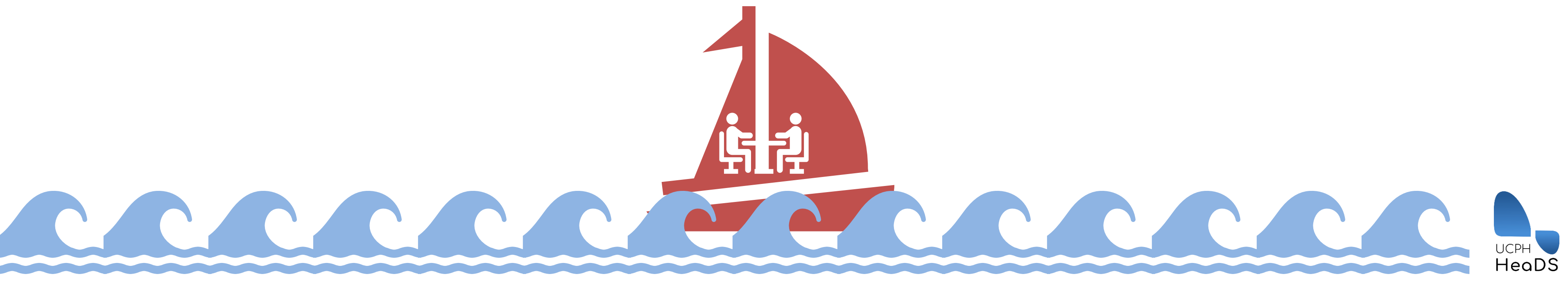
DATA SCIENCE IN YOUR TEACHING

- **Could you incorporate more data science in your teaching?**
 - Take courses and learn yourself
 - Get inspired by colleagues
 - Collaborate with colleagues in DS on course materials
- **Start a little at a time:**
 - Move from Excel → R or Python
 - Think about old analysis and RQs in a new 'DS light'
 - Encourage your students to explore DS tools (Github, Programming, HPC)
 - Get familiar with ChatGPT

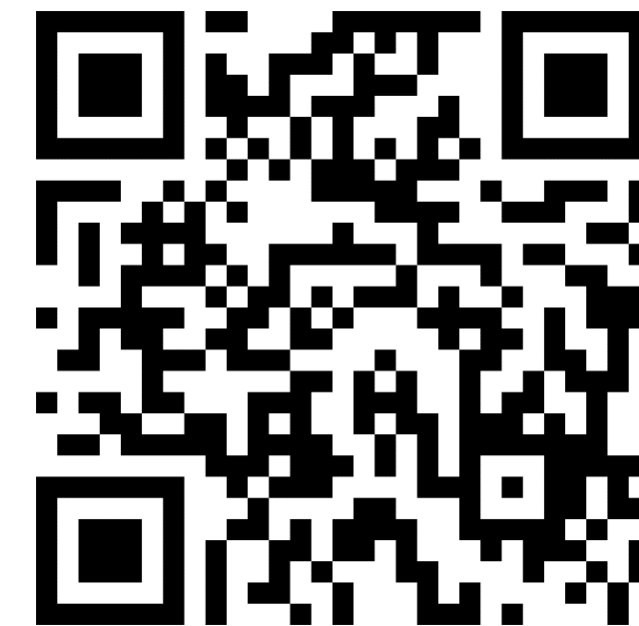
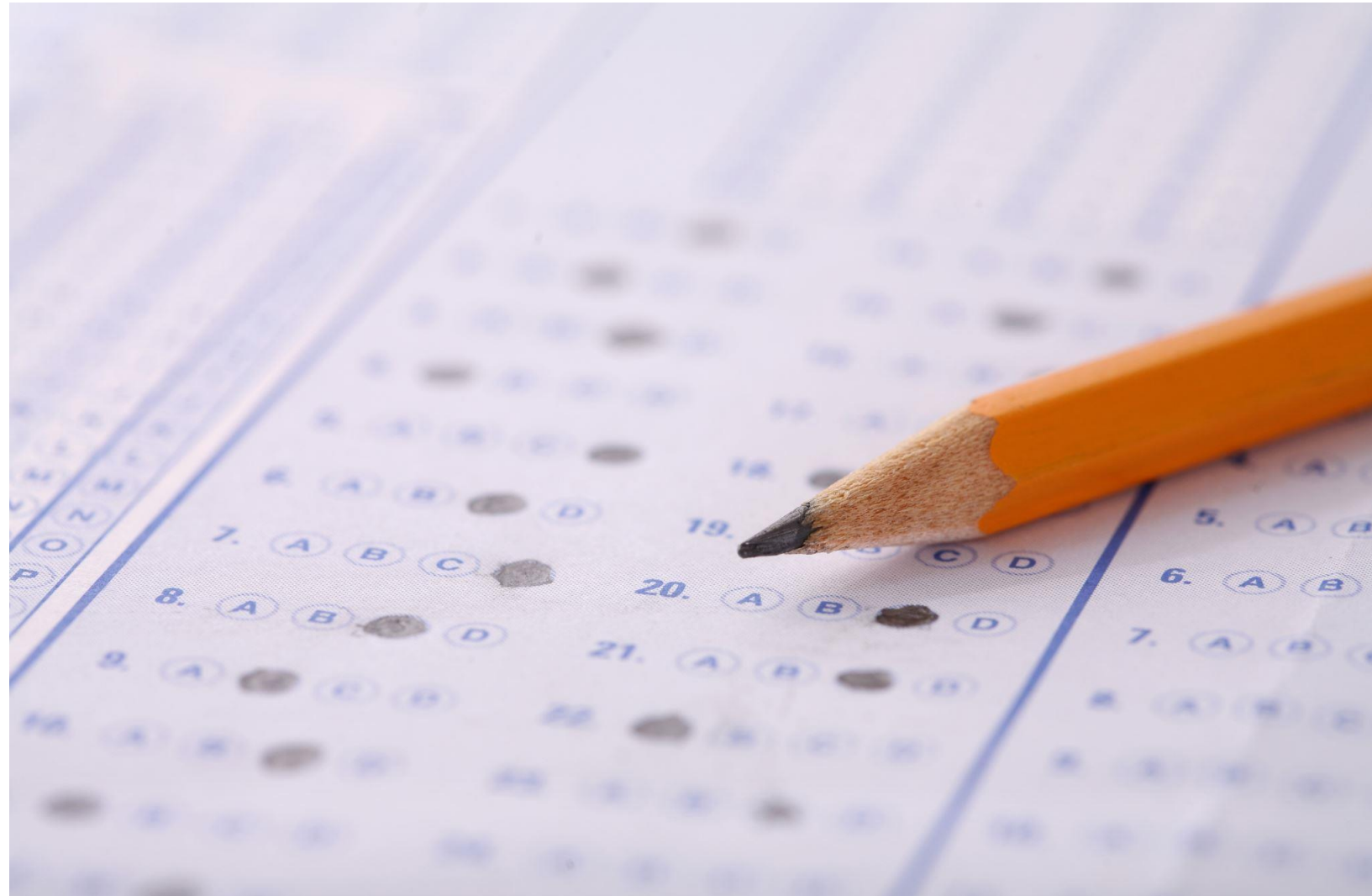


GROUP DISCUSSION 4.6

- What is your main take away from today?
- Has what you have learned today changed your perspective on Data Science?
- How do you think your future relationship to Data Science will be?
- In what ways can you incorporate Data Science thinking into your teaching?



COURSE EVALUATION



<https://forms.office.com/e/Ffc2csjk7R>

THANK YOU

