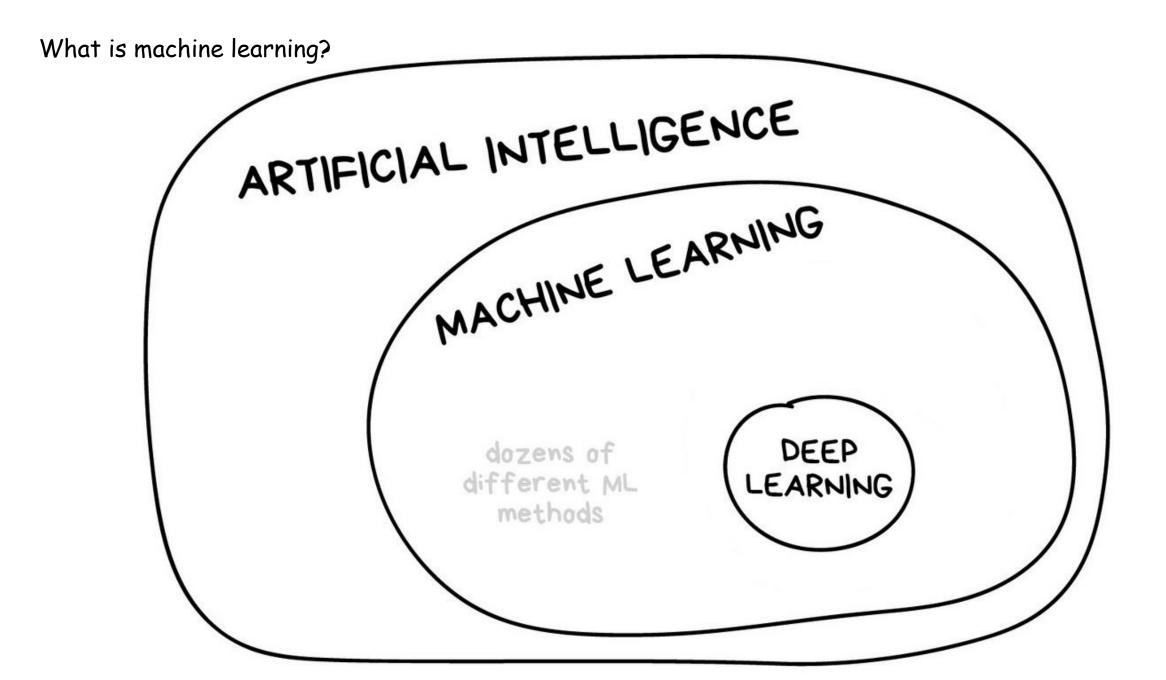
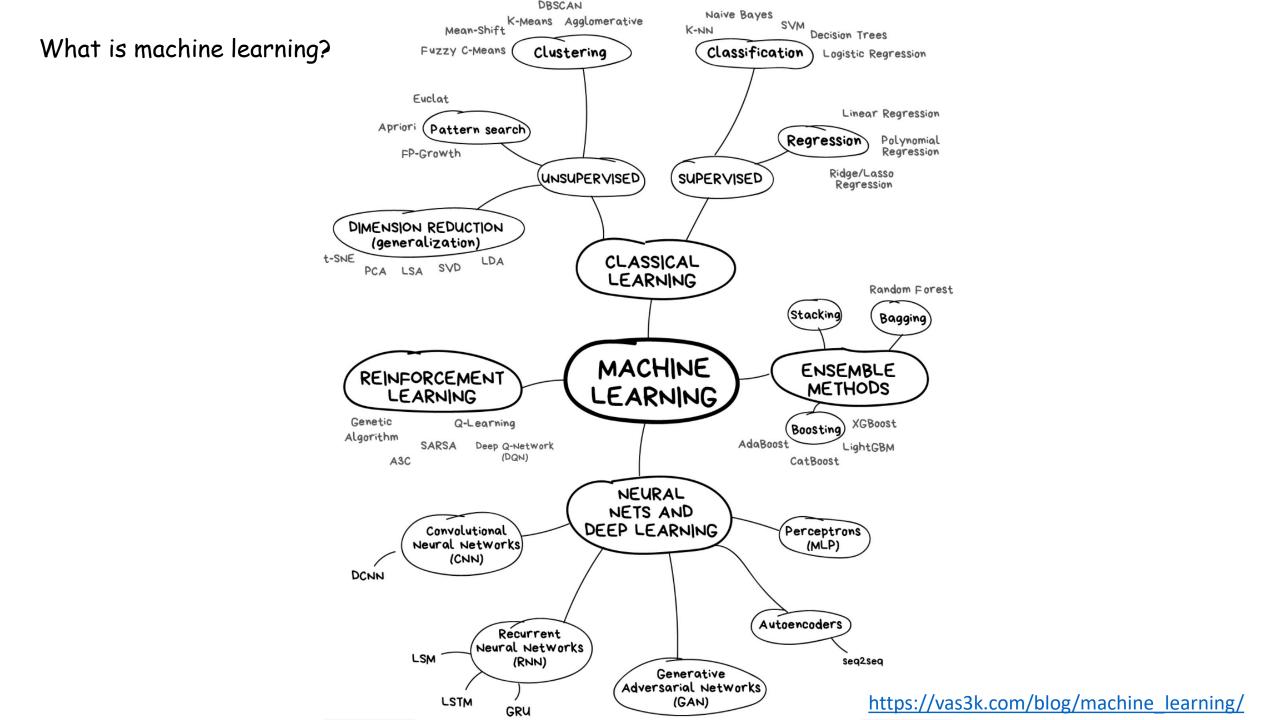


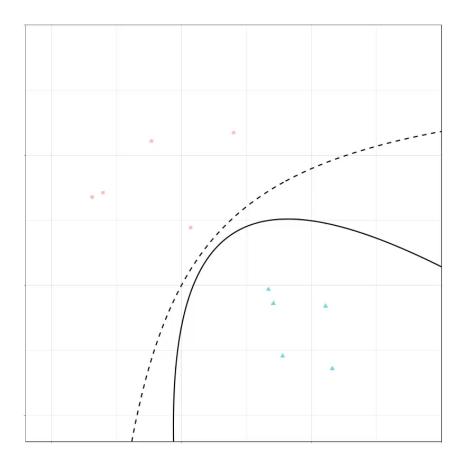
What is machine learning?

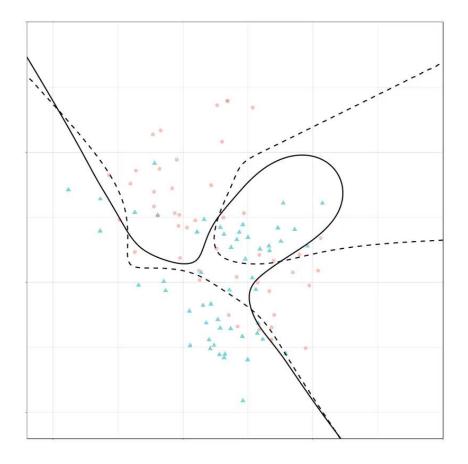






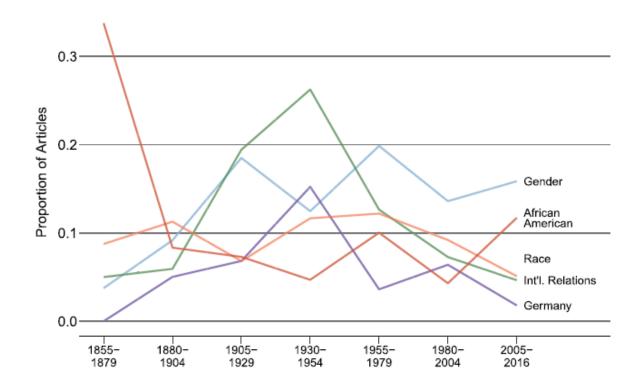
But what is machine learning?



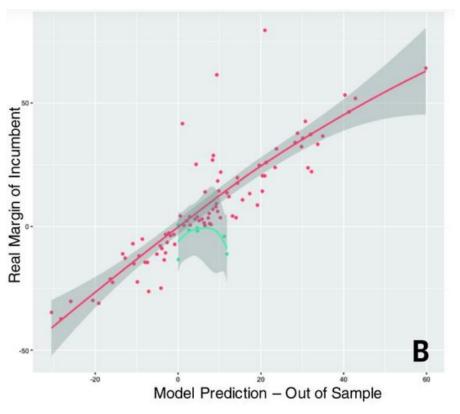


"All the impressive achievements of deep learning [and machine learning] amount to just curve fitting." – Judea Pearl

What can we do with this in social science?

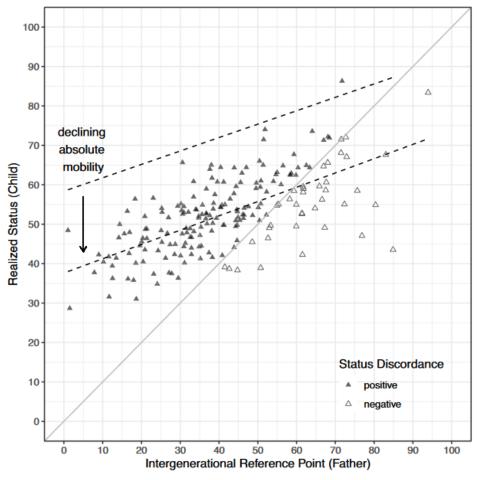


Rodman (2020)



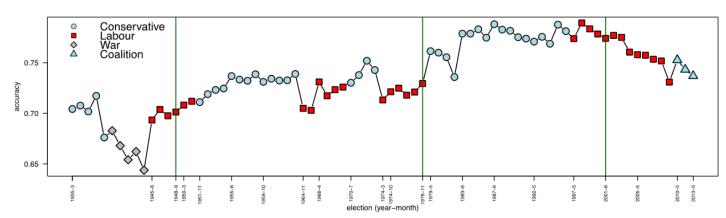
Kennedy et al. (2017)

What can we do with this in social science?



Peterson and Spirling (2018)

Kurer and van Staalduinen (2022)



What to expect

Day One:

What is machine learning?

Machine learning in social science

Basic machine learning vocabulary

The tidymodels package

Day Two:

Supervised machine learning algorithms:

Naive bayes

Support vector machine

Random forest

Day Three:

Neural networks:

Frank Rosenblatt's perceptron
Multi-layer perceptron

Automated text analysis with neural networks:

Word2Vec Word vectors

Bring your own data!

What to expect

Understanding of basic principles and vocabulary of machine learning

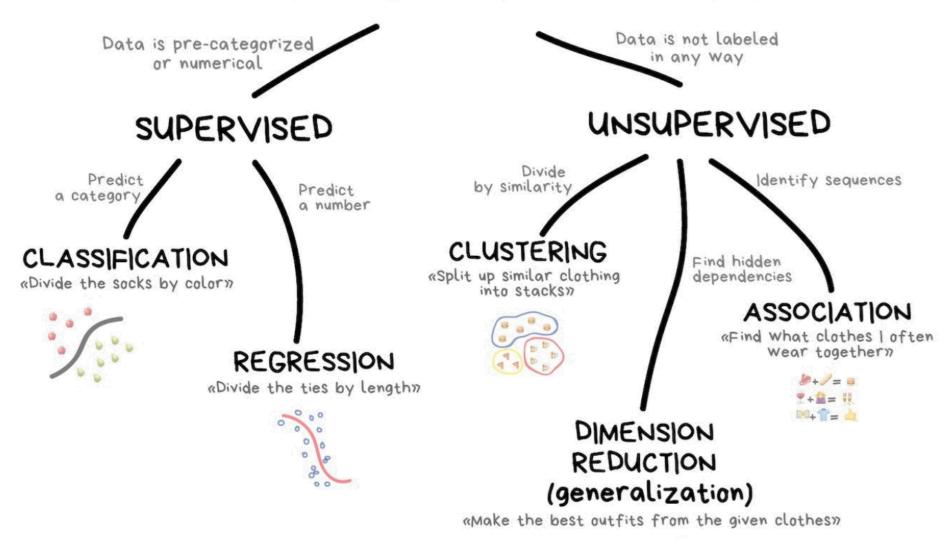
Theoretical idea of most common machine learning algorithms

Basic command of the **tidymodels** package in R

Ability to understand and use tidymodels code

Basic ML principles and vocabulary - supervised and unsupervised machine learning

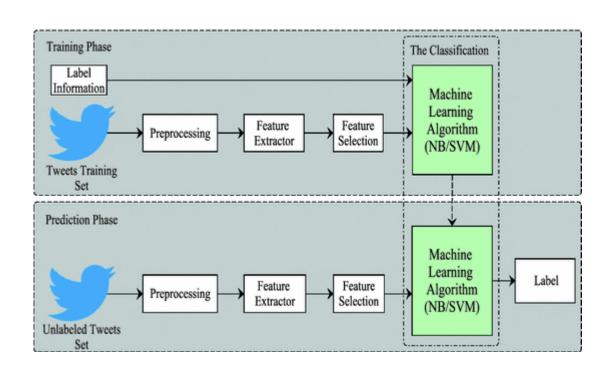
CLASSICAL MACHINE LEARNING

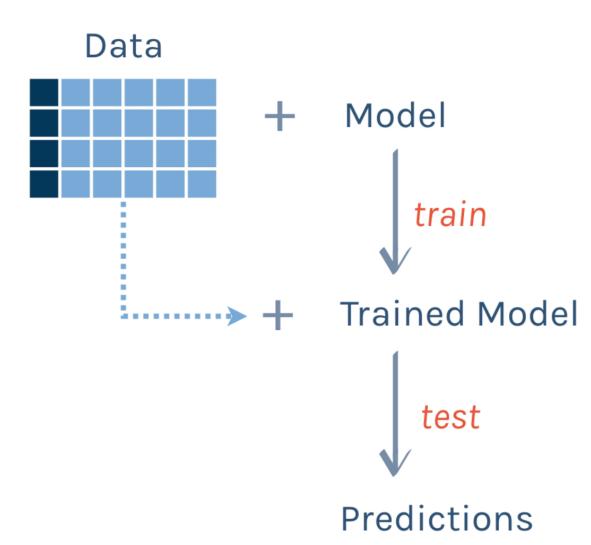




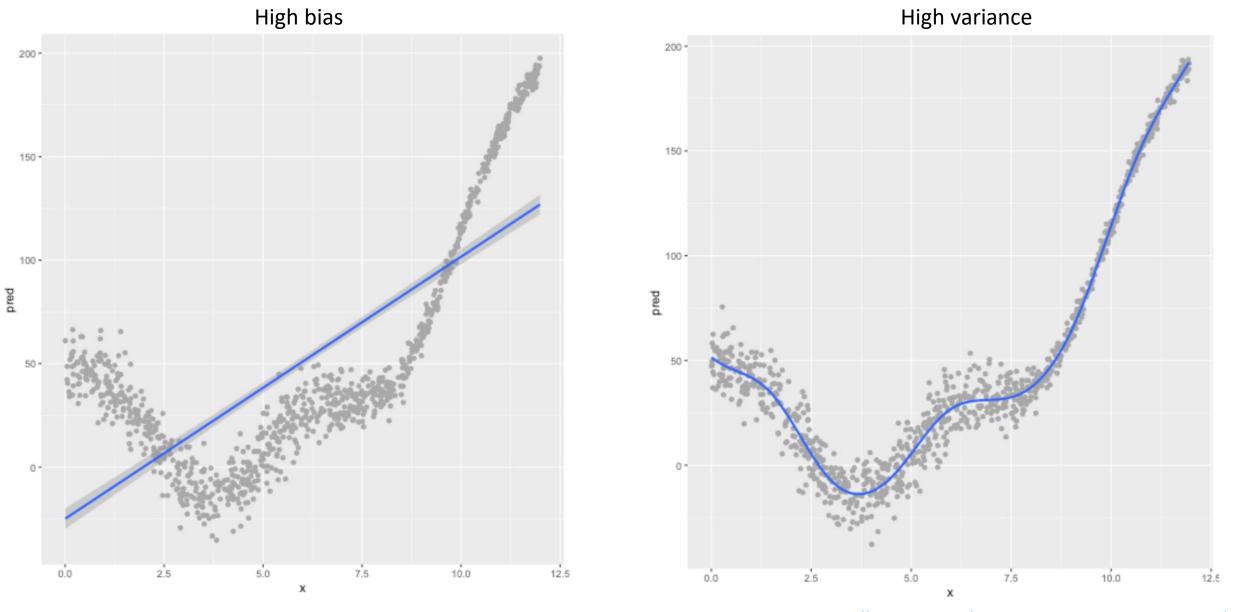
Basic ML principles and vocabulary - training and testing





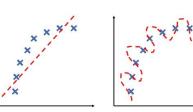


Basic ML principles and vocabulary - the bias-variance trade-off



Basic ML principles and vocabulary - the bias-variance trade-off

Bias



Variance

- How (in-)correct our models' predictions are
- Models with high bias can fail to capture important relationship, they can be under-fitted to the data
- In short, how well our model reflects the patterns in the data

- How sensitive our predictions are to the specific sample on which we trained the model
- Models with high variance can fail to predict different data well, they can be over-fitted to the data
- In short, how stable the predictions of our model are when applied to new data

Regardless of the specific algorithm used, we often wish to balance between bias and variance. This is to balance between under- and over-fitting a model to the data at hand

Basic ML principles and vocabulary - hyperparameters

Hyperparameters might address model design questions such as:

- What degree of polynomial features should I use for my linear model?
- What should be the maximum depth allowed for my decision tree?
- What should be the minimum number of samples required at a leaf node in my decision tree?
- How many trees should I include in my random forest?
- How many neurons should I have in my neural network layer?
- **How many layers** should I have in my neural network?
- What should I set my learning rate to for gradient descent?





tidymodels

tidymodels is a meta-package that installs and load the core packages listed below that you need for modeling and machine learning. Go to package ...



rsample

rsample provides infrastructure for efficient data splitting and resampling. Go to package ...



parsnip

parsnip is a tidy, unified interface to models that can be used to try a range of models without getting bogged down in the syntactical minutiae of the underlying packages. Go to package ...



recipes

recipes is a tidy interface to data pre-processing tools for feature engineering. Go to package ...



yardstick

broom

workflows

workflows bundle your pre-processing, modeling, and post-processing together. Go to package ...

tune

tune helps you optimize the hyperparameters of your model and preprocessing steps. Go to package ...

yardstick

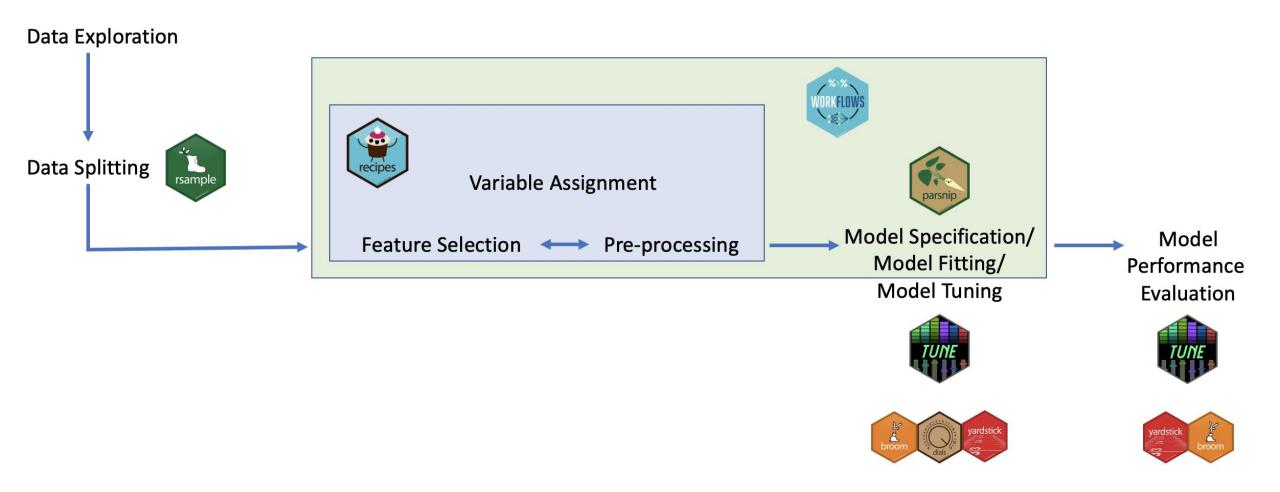
yardstick measures the effectiveness of models using performance metrics. Go to package ...

broom

broom converts the information in common statistical R objects into user-friendly, predictable formats. Go to package ...

dials

dials creates and manages tuning parameters and parameter grids. Go to ${\tt package} \ldots$



Overview of tidymodels Basics		
Package	Step	Functions
rsample	1. Split into testing and training sets	initial_split() training() testing()
recipes	2. Create recipe + assign variable roles	recipe() update_role()
parsnip	3. Specify model, engine, and mode	parsnip function for specifying model (ex. decision_tree()) (https://www.tidymodels.org/find/parsnip/) set_engine() set_mode()
WORK FLOWS	4. Create workflow, add recipe, add model	workflow() add_recipe() add_model()
parsnip	5. Fit workflow	fit()
parsnip	6. Get predictions	predict()
yardstick	7. Use predictions to get performance metrics	rmse() (continuous outcome) accuracy() (categorical outcome) metrics() (either type of outcome)

IDE: https://colab.to/r

Our course folder in Google Drive:

https://drive.google.com/drive/folders/13ZpamWwL10L45q9W6z3JuBlfYs0952Dp?usp=sharing

Website: www.tidymodels.org

Book: www.tmwr.org





View models and

metrics in a tidy way



recipes





and get performance

metrics





Tune hyperparameters