Introduction to Machine Learning

PSC 8185: Machine Learning for Social Science

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January 10, 2022

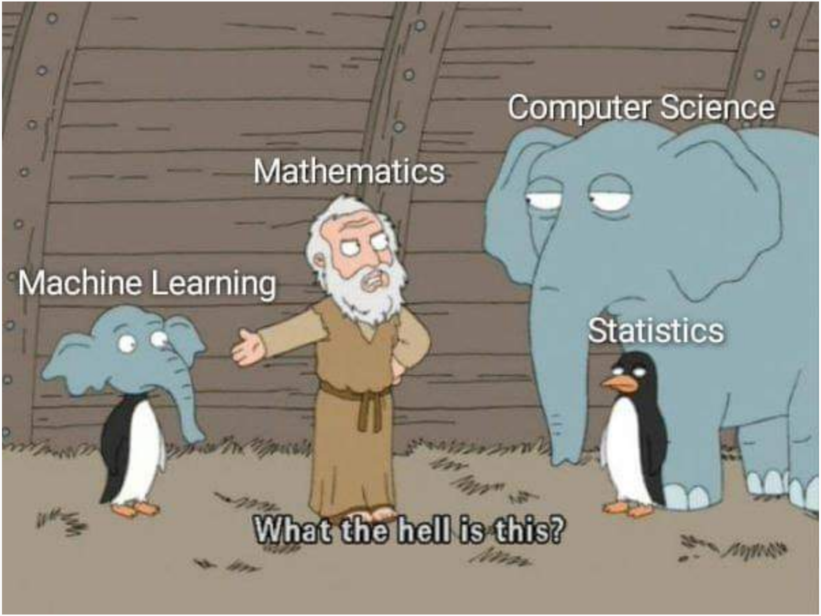
Materials adapted from Sergio Ballacado and Rochelle Terman

Agenda

1. Motivation
2. Course Overview
3. What is Machine Learning?
4. Preview: Model Assessment and Selection

Motivation

Machine Learning (ML) Seems Intimidating...



But it isn't.

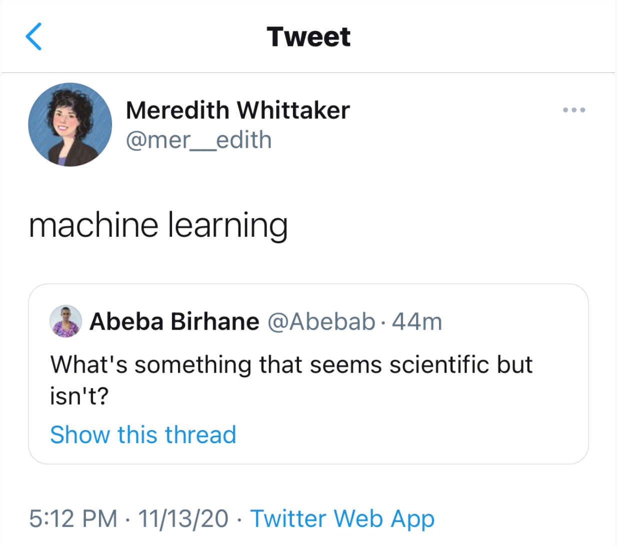


Figure 1: Faculty Director AI Now Institute, Research Prof NYU. Ex-Google.

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- Estimate Apple's stock price in March 2022 based on historical values
- Classify Facebook posts as 'fake' or 'real' news based on words in the title
- Identify future Covid spikes based on Google Trends

Brief History of ML

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- 1990s-2010s: Random Forests, Boosting, Support Vector Machines, Bayesian
- Today:
  - More Computational Power
  - More Data
  - New Algorithms
  - Broader applications, more demand, bigger audience

Image Classification (Tensorflow)

ML Applications

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  - Deliver engaging content to users

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- Social Science
  - Measure polarization in political institutions (Clinton, Jackman, and Rivers 2004)
  - Infer extent and strategy of Chinese censorship (King, Pan, and Roberts 2014)
  - Assess risk of conflict onset and escalation (Malone 2022)

Course Logistics

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1. ML is relevant and useful in a wide range of academic and non-academic fields
2. Growing and diverse audience should be able to understand the models, intuitions, and applications of various approaches
3. Applying ML methods to real-world problems requires quantitative skills + social science reasoning

Course Prerequisites

1. Familiarity with R
2. Basic understanding of statistical regression

Course Outline

1. Supervised Learning

2. Unsupervised Learning

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    1.1 Regression and Classification
    1.2 Cross-Validation
    1.3 Regularization and Feature Selection
    1.4 Random Forests, Boosting, Bagging
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2. Unsupervised Learning
    2.1 Principal Component Analysis
    2.2 Clustering
    2.3 Topic Models (Text Analysis)

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- Cover all ML tools or even most of them
- Teach you to be a professional programmer

Format and Materials

Lecture

- Semi-Flipped Classroom (1/2 Lecture, 1/2 R Coding)
- Recommend R, RStudio, and RMarkdown

Materials

- Lecture Notes, Code, and Data (Blackboard)
- Discussion Board (Blackboard)
- Text: Introduction to Statistical Learning (Free Online)

Evaluation

- Problem Sets (70%):
  - 7 problem sets, approx. every 2 weeks
  - Programming in R should be submitted via R markdown (.Rnw or .Rmd)
  - Collaboration is encouraged, but write up your own
  - First problem set released **Jan 24** $\rightarrow$ due **Feb 7**

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- Final Project (30%)
  - Option 1: Replication Study
  - Option 2: Original Research Design and Prelim Results
  - Let professor know which option by Spring Break

What is Machine Learning?

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- **Non-Technical Take:** ML involves a set of computer algorithms which ‘learn’ patterns in existing data to assist in prediction and inference.
- **Technical Take:** We want to build a model f that optimizes a given loss function in order to maximize model performance

2 Types of Machine Learning

1. Unsupervised Learning
2. Supervised Learning

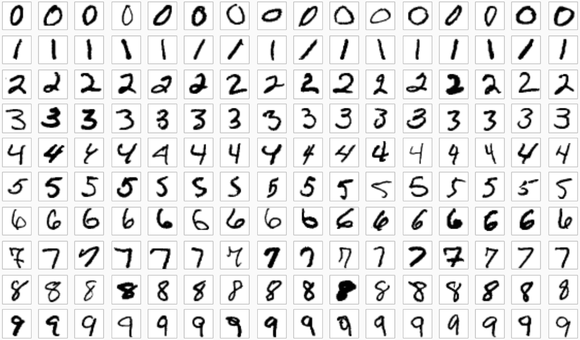
Unsupervised Learning

- Main Idea: Descriptive Data Analysis
- Common Objectives:
    - Identify meaningful groupings of the data $\rightarrow$ **clustering**
    - Simplify high-dimensional data to explain variation in as few dimensions as possible $\rightarrow$ **principal component analysis**

Unsupervised Learning

Real-World Applications:

- Stock Market Anomaly Detection (Insider Trading)
- Hand-Writing Analysis
- Measure Consumer Opinion
- Defining ‘Nationalism’ or ‘State Capacity’



Supervised Learning

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- Real-World Applications: Predict terrorist attacks, predict covid trends, predict election results.

The Economist is analysing polling, economic and demographic data to predict America's elections in 2020

→ **Read more of our election coverage**

harts, maps and analysis of the presidential and congressional races in one place

nate House *Last updated on November 3rd*

Our final pre-election forecast is that **Joe Biden is very likely to beat Donald Trump** in the electoral college.

House	Chance of winning the electoral college	Chance of winning the most votes	Predicted range of electoral college votes (270 to win)
 **Joe Biden** Democrat	**better than 19 in 20** or 97%	**better than 19 in 20** or >99%	**259-415**
 **Donald Trump** Republican	**less than 1 in 20** or 3%	**less than 1 in 20** or <1%	**123-279**

The probability of an electoral-college tie is <1%

Supervised Learning

- Common Objective: Learn relationship between outcome variable (Y) and input variables ($X = (X_1, X_2, \ldots, X_i)$) by estimating f
- Assume relationship between Y and X_i such that...

$$y = f(X) + \epsilon \tag{1}$$

  - f is fixed, but unknown function.
  - f captures information (systematic patterns) about how X affects Y
  - ϵ is “noise” in the model (error term)

Why Learn the Relationship Between X and Y?

1. Inference

2. Prediction

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    1.1 Inputs and outputs readily available
    1.2 Want to understand how Y changes as $X = (X_1, X_2, \ldots, X_i)$ changes
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    1.4 e.g. Which factors *explain* covid cases?
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2. Prediction
   2.1 Inputs are readily available, but Y is not
   2.2 Want to predict $\hat{Y} = \hat{f}(X)$
   2.3 Better model $\rightarrow$ more accurate predictions ($\hat{Y} \approx Y$)
   2.4 e.g. What factors *predict* covid cases?

An Analogy

- Inference: Why is the car running?
- Prediction: Where is the car going?

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How do we estimate f?

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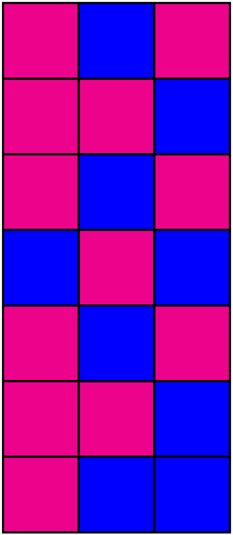
   2.3 Evaluate whether $\hat{f}$ good model by comparing predicted response $\hat{f}(x)$ (aka $\hat{Y}$) with true response Y

Data Set

Data: $(x_1, y_1), (x_2, y_2), \ldots (x_n, y_n)$

Test and Training Set



Partition Data into Test and Training Set

Figure 2: Training Set

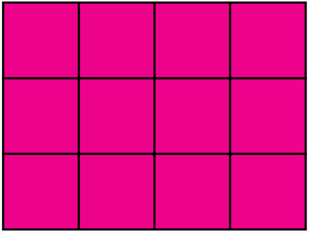
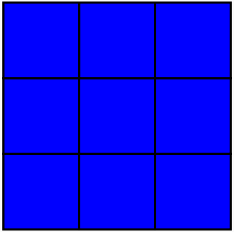
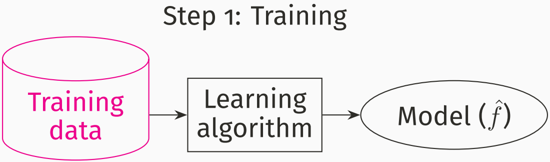


Figure 3: Test Set



Train Model $\hat{f}$ then Test Accuracy of Predictions



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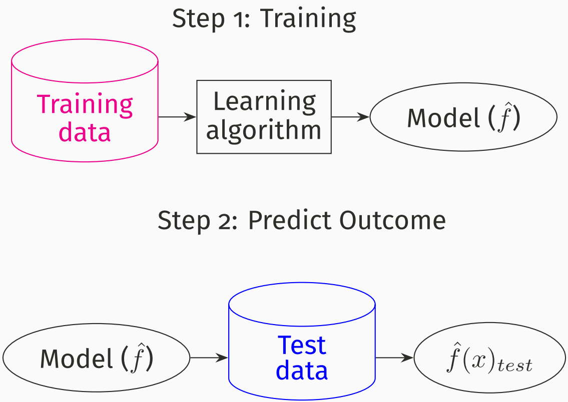

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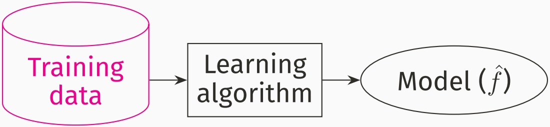
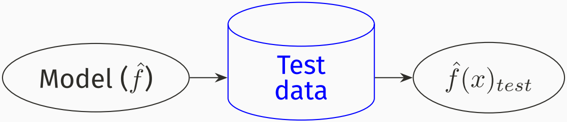
Step 1: Training



Step 2: Predict Outcome



Step 3: Evaluate Test Predictions

$$\boxed{\hat{f}(x)_{test} \approx Y_{test}?}$$

Preview: Model Assessment and Selection

New Terminology So Far

Training Data: $(x_1, y_1), (x_2, y_2), \ldots (x_n, y_n)$
Test Data: $(x'_1, y'_1), (x'_2, y'_2), \ldots (x_m, y_m)$
Loss Function: Optimization Function to Maximize Model Performance
Prediction Function Estimate: $\hat{f}$

Lingering Questions

- How do I evaluate test predictions?
- How do I choose learning algorithm?

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- If (x_m, y_m) is an out-of-sample (not used in training) datapoint, then $\hat{f}(x_m)$ and y_m should be close
- Popular measure of closeness is mean squared error (MSE) $(y_m - \hat{f}(x_m))^2$

Assess Model Using Test Mean Squared Error

Given many test set datapoints $\{(x_i', y_i'); i = 1, \ldots, m\}$, estimate model performance using loss function known as test mean squared error:

$$\frac{1}{m}\sum_{i=1}^{m}(y_i' - f(\hat{x}_i'))^2 \tag{2}$$

Why Not Use Training MSE?

If you don't have extra test data, why not assess model performance using training mean squared error?

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - f(\hat{x}_i))^2 \tag{3}$$

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Answer: Model will always fit training data well, but tells us nothing about if it fits test data well. Small training error does not imply small test error.

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    - Low Bias

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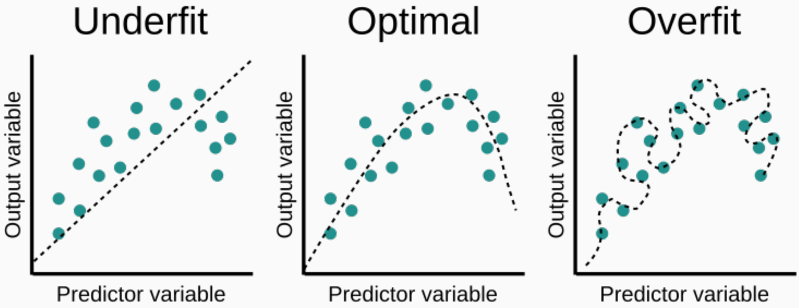
- Best Model will achieve:
    - Low Variance
    - Low Bias
- **Problem:** Easier said than done.

Bias-Variance Trade-Off

- Bias-Variance Trade-Off: Models tend to result in either (1) low variance and high bias (under-fitting) or (2) high variance and low bias (over-fitting).



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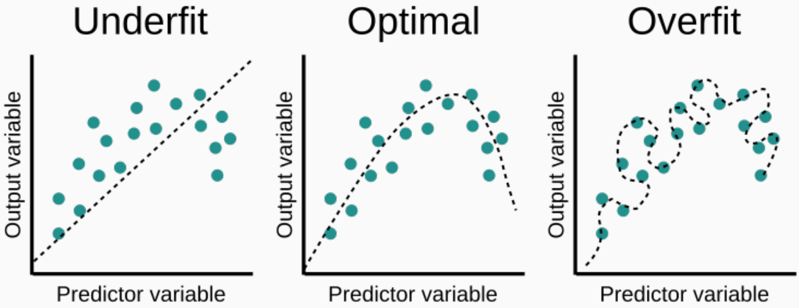

- A central ML challenge is finding a method that minimizes *both* variance and bias.
- Rule of Thumb: More flexible methods will result in higher variance, but lower bias.

Preview: Model Selection

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2. Non-Parametric

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    1.1 More rigid $\rightarrow$ low variance
    1.2 Assumes f has fixed form with fixed number of parameters $(\beta_1, \ldots \beta_p)$
    1.3 Estimating f $\rightarrow$ estimating parameters
    1.4 Ex. Linear Regression Model

$$\hat{f}(X) = X_1\beta_1 + \cdots + X_p\beta_p \tag{5}$$

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2. Non-Parametric
   2.1 More flexible $\rightarrow$ low bias
   2.2 No fixed f to describe data
   2.3 $\hat{f}$ is “black box”

Conclusion

- ML aims to learn patterns and make good predictions about out-of-sample (test) data
- Best ML model minimizes test MSE
- Picking best model means optimizing bias-variance trade-off
- Non-parametric methods reduce bias, but increase variance