LECTURE 01:

INTRODUCTION TO MACHINE LEARNING

SDS 293: Machine Learning

September 11, 2017

Introductions & background

Jordan

(he / him,
computer scientist)

- **2017 on: Asst. Prof. in CS (Smith)**
- 2015 to 2017: Visiting Asst. Prof. in SDS (Smith)
- 2013 – 2015: Research Scientist (MITLL)
- 2010 – 2013: PhD in Visual Analytics (Tufts)
- 2008 – 2010: MSc in Educational Tech. (Tufts)
- 2004 – 2008: BA in CS and Math (Smith)

Office hours: Mondays 10:30 to noon and by appointment

Ford 355 (office) or Ford 343 (Lab)

People

3 Minute Biographies:

- Your name and pronouns
- Your year, school, and major / area of focus
- Technical background
  - Programming language(s) you know/like
  - Stats courses you've taken

3 Questions:

- What brought you to **this course**?
- What's one **big thing** you hope to get out of it?
- What's one **problem / idea / curiosity** that sometimes keeps you up at night?

Outline

- About this course
- What is Machine (a.k.a. Statistical) Learning?
- Example problems
- Data science refresher
- Structure of this course

Resources: course website

cs.smith.edu/~jcrouser/SDS293

Resources: slack channel

sds293.slack.com

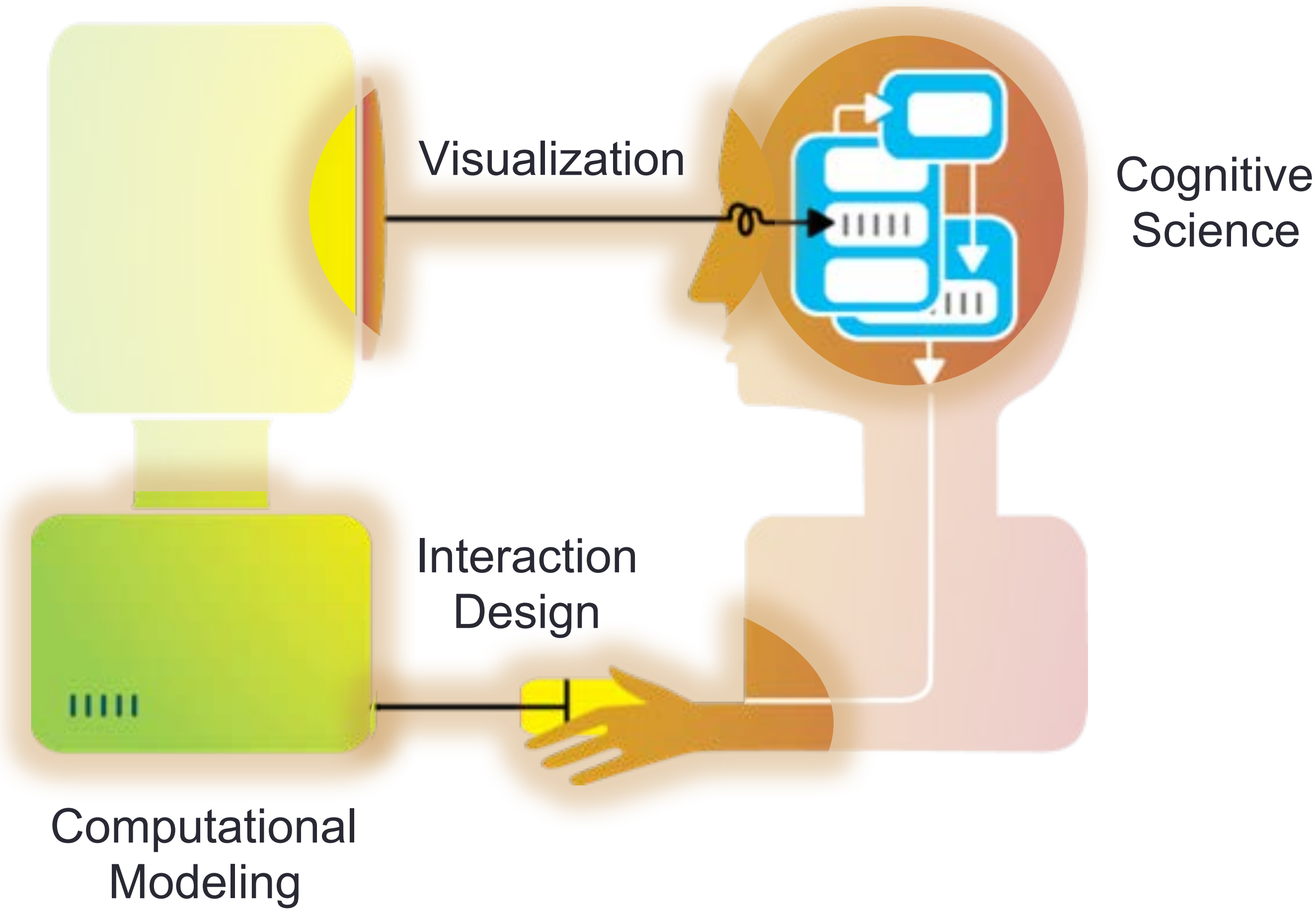
Resources: tutorials, mini-courses, etc.

DataCamp

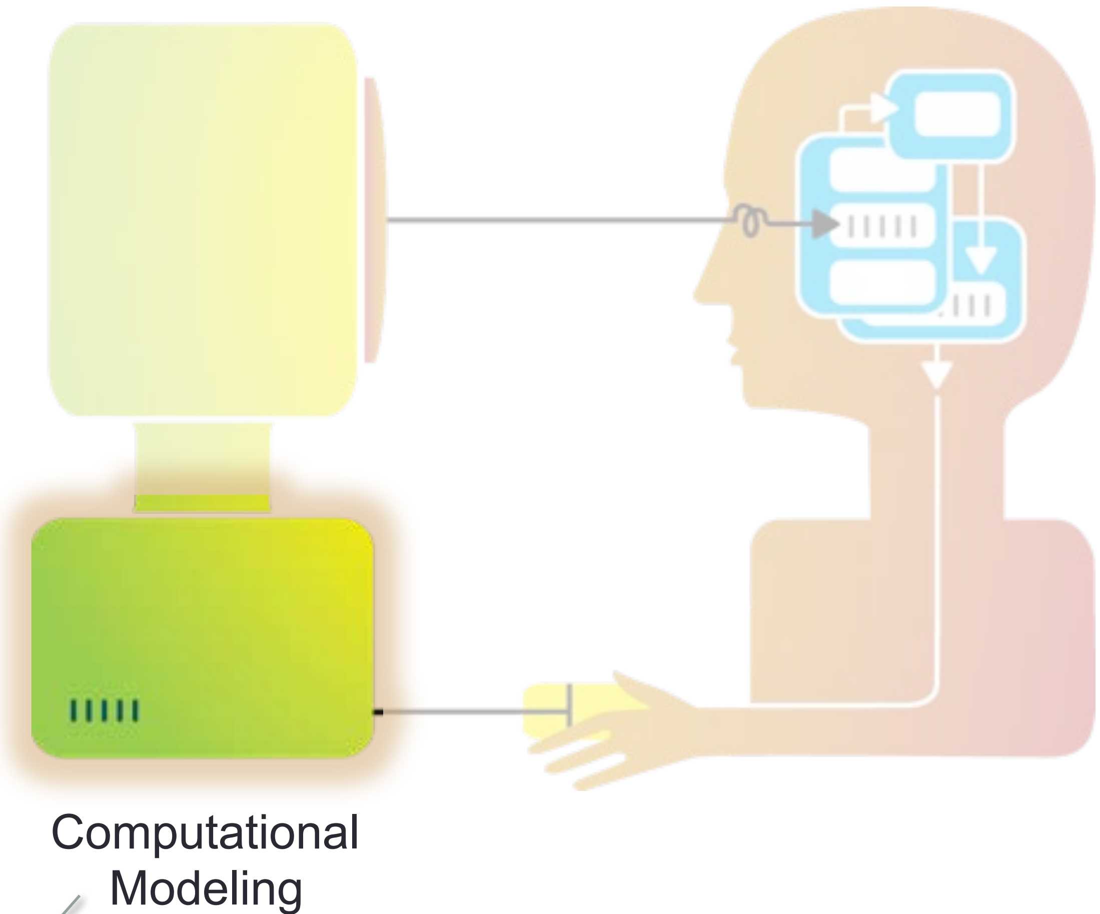
datacamp.com/groups/sds293-machine-learning

Free access to ALL content until March 2018

Some context: my research



About this course



Machine
Learning

What is machine learning?

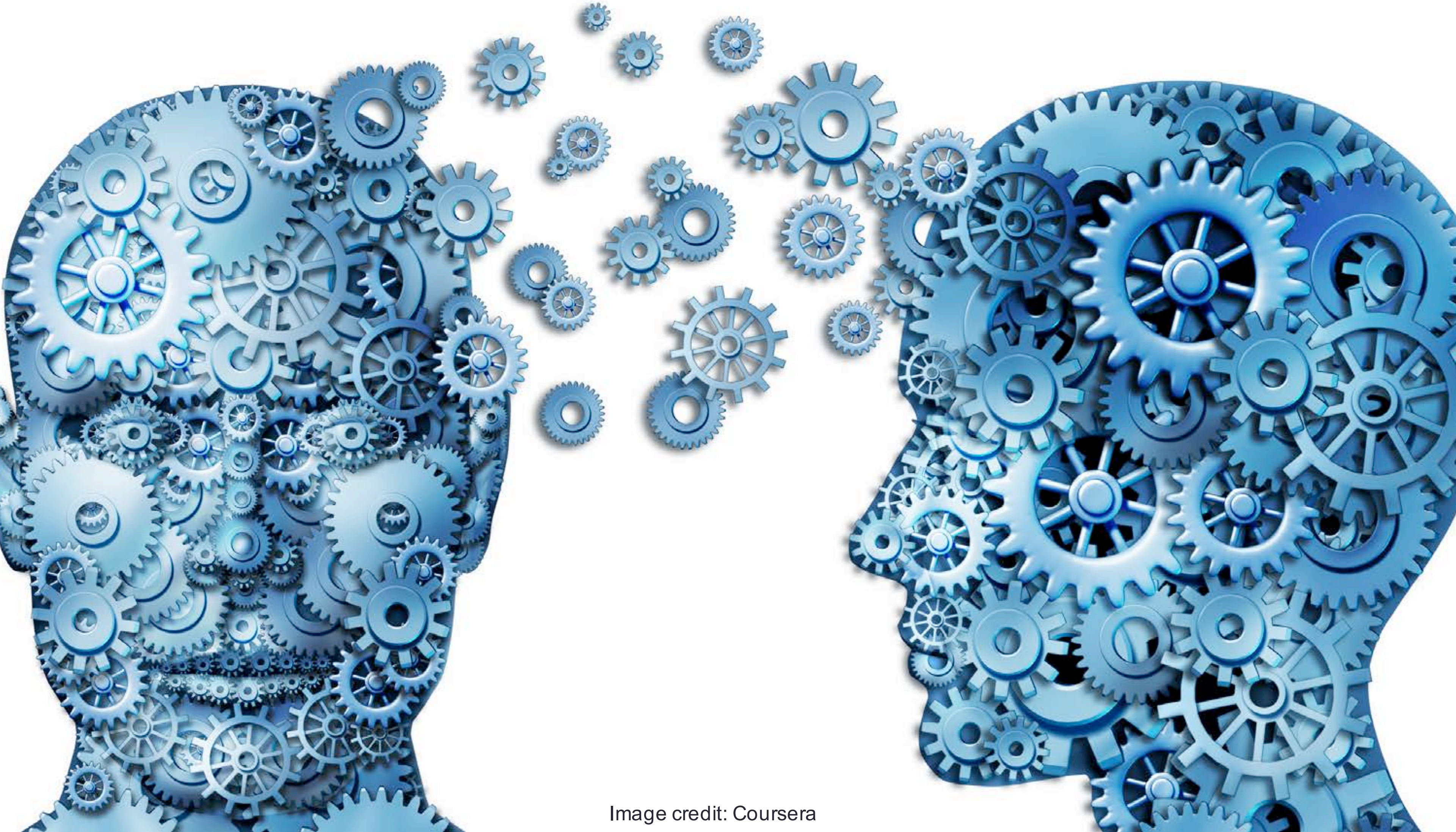


Image credit: Coursera

What is ~~machine~~ learning?

learn·ing

/ˈlərniNG/

noun

the acquisition of knowledge or skills through experience, study, or by being taught.

"these children experienced difficulties in learning"

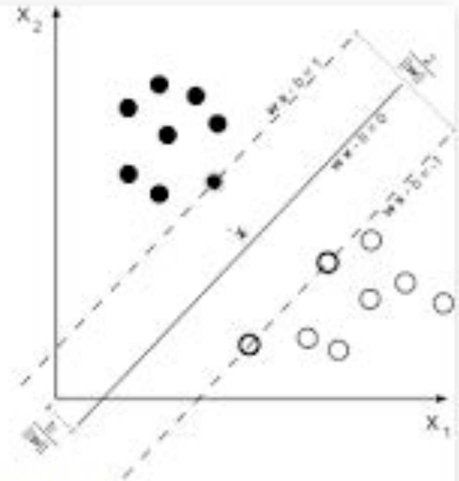
synonyms: study, studying, education, schooling, tuition, teaching, academic work; research

"a center of learning"

Translations, word origin, and more definitions

Machine learning: Wikipedia

Machine learning is a subfield of computer science that evolved from the study of pattern recognition and computational **learning** theory in artificial intelligence. **Machine learning** explores the study and construction of algorithms that can learn from and make predictions on data.

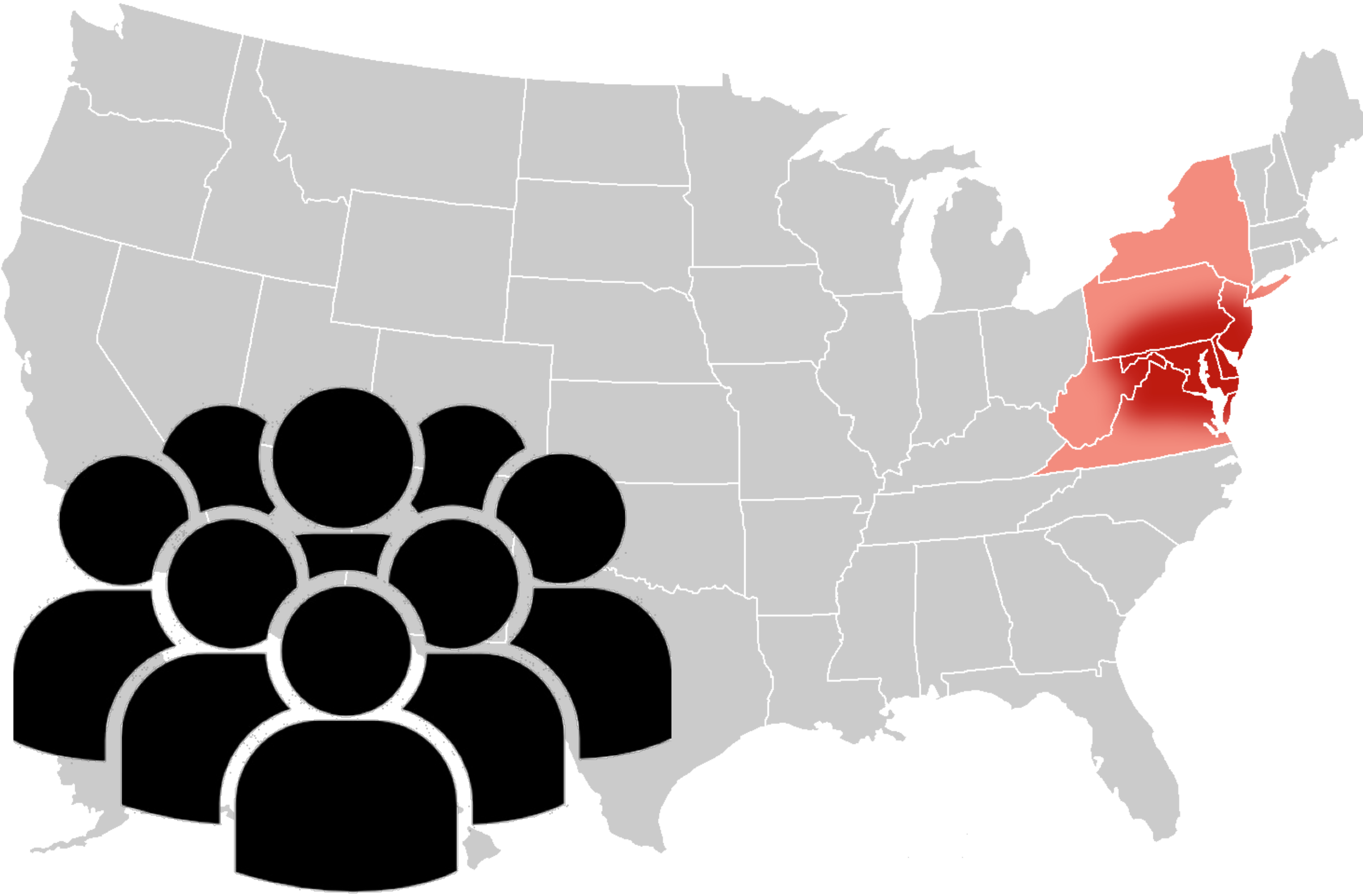


Machine learning - Wikipedia, the free encyclopedia
https://en.wikipedia.org/wiki/**Machine_learning** Wikipedia

Machine learning: a working definition

- Machine learning is a set of **computational tools** for building **statistical models**
- These models can be used to:
  - **Group** similar data points together (*clustering*)
  - **Assign** new data points to the correct group (*classification*)
  - Identify the **relationships** between variables (*regression*)
  - Draw conclusions about the **population** (*density estimation*)
  - Figure out **which variables** are important (*dimension reduction*)

Example: men & money in the mid-Atlantic



Example: men & money in the mid-Atlantic

- `Wage` dataset available in the `ISLR` package
- **Sample**: 3000 male earners from the mid-Atlantic, surveyed between 2003 and 2009
- Dimensions:
  - Year each datapoint was collected
  - Age of respondent
  - Martial status
  - Race
  - Educational attainment
  - Job class
  - Health
  - Whether or not they have health insurance
  - Wage

Example: men & money in the mid-Atlantic

- **Question**: what is the effect of an earner's `age`, `education`, and the `year` on his `wage`?
- Find some friends, then go explore the data at:

  cs.smith.edu/~jcrouser/SDS293/examples/wage.html

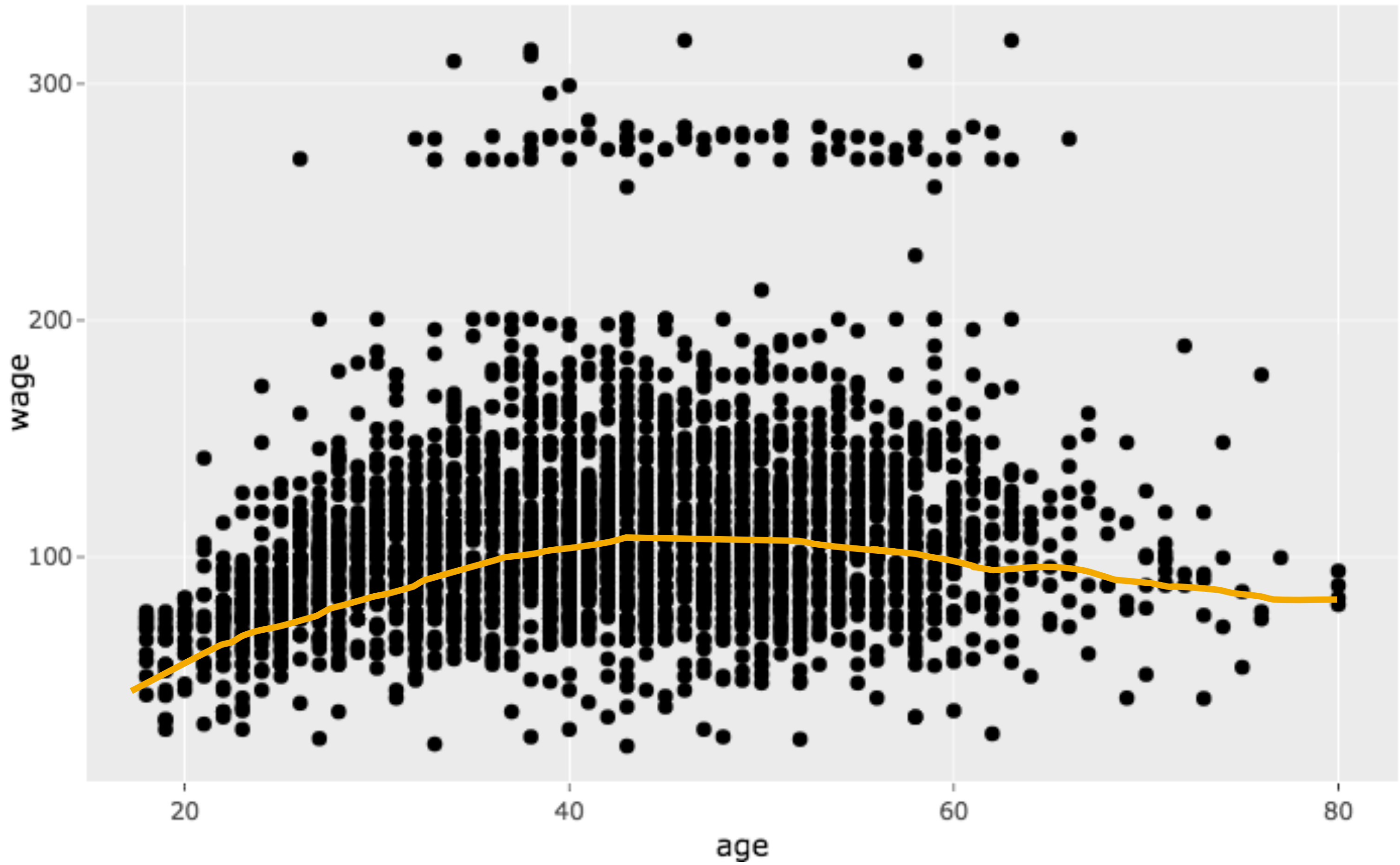
#protip

in classes with Jordan,
This icon means
"your turn to talk"

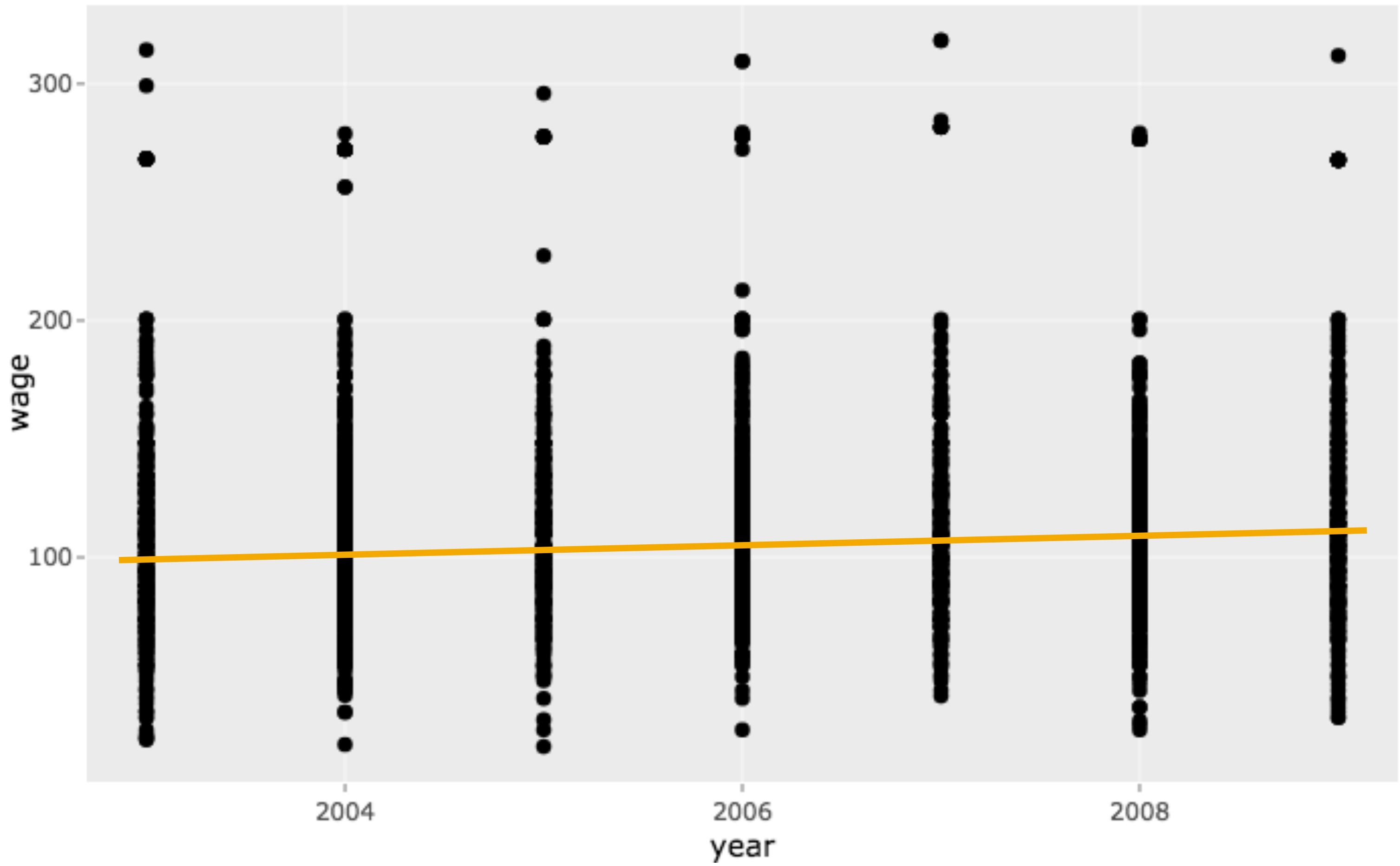
Example: men & money in the mid-Atlantic

cs.smith.edu/~jcrouser/SDS293/examples/wage.html

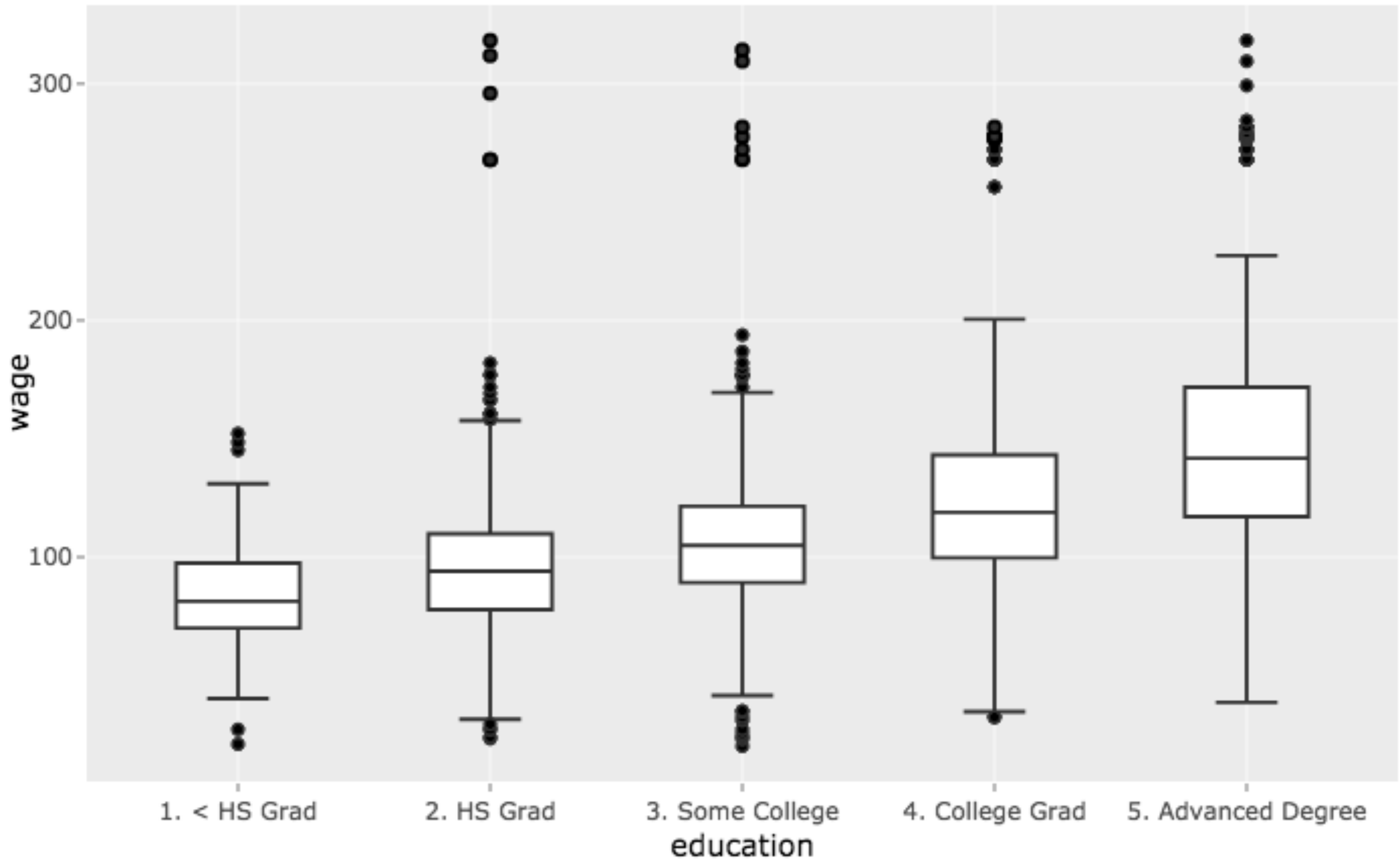
wage vs. age



`wage` vs. `year`

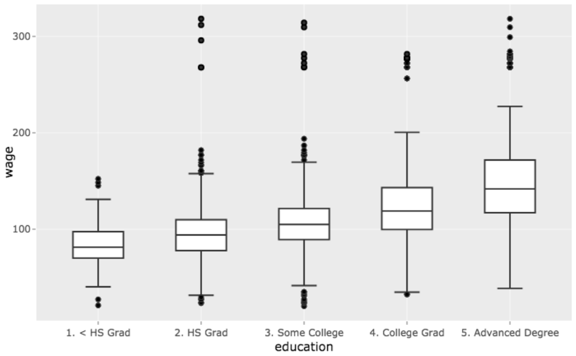


wage vs. education

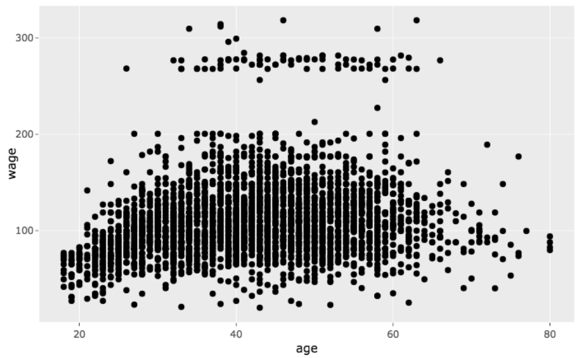


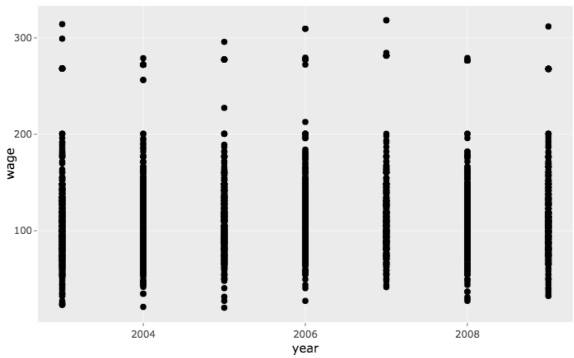
Example: men & money in the mid-Atlantic

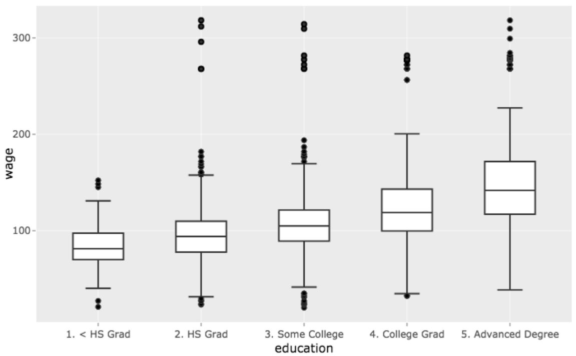
- If we had to pick **just one**, we should probably use `education`



- In reality, the **best predictor** is probably a **combination** of all three







Supervised machine learning

- In this example, we used the value of **input variables** to predict the value of **output variables**

- Another way to think about this:

Supervised machine learning

- **Goal**: explain some observable phenomenon Y as a function of some set of predictors X:

$$Y = f(X) + \epsilon$$

- **Problem**: we don't know what the function actually looks like; we have to *estimate* it
- **Machine learning**: computational tools for estimating f

Unsupervised machine learning

- We sometimes have only **input variables**, but no clearly defined “response”
- Can’t check (“supervise”) our analysis: **unsupervised**
- Can’t fit a regression model (why?)
- What **can** we do?

Example: personalized marketing

amazon

Example: personalized marketing

amazon

Example: personalized marketing

amazon.com

Recommended for You

Amazon.com has new recommendations for you based on items you purchased or told us you own.

LOOK INSIDE!

Google Apps Deciphered: Compute in the Cloud to Streamline Your Desktop

LOOK INSIDE!

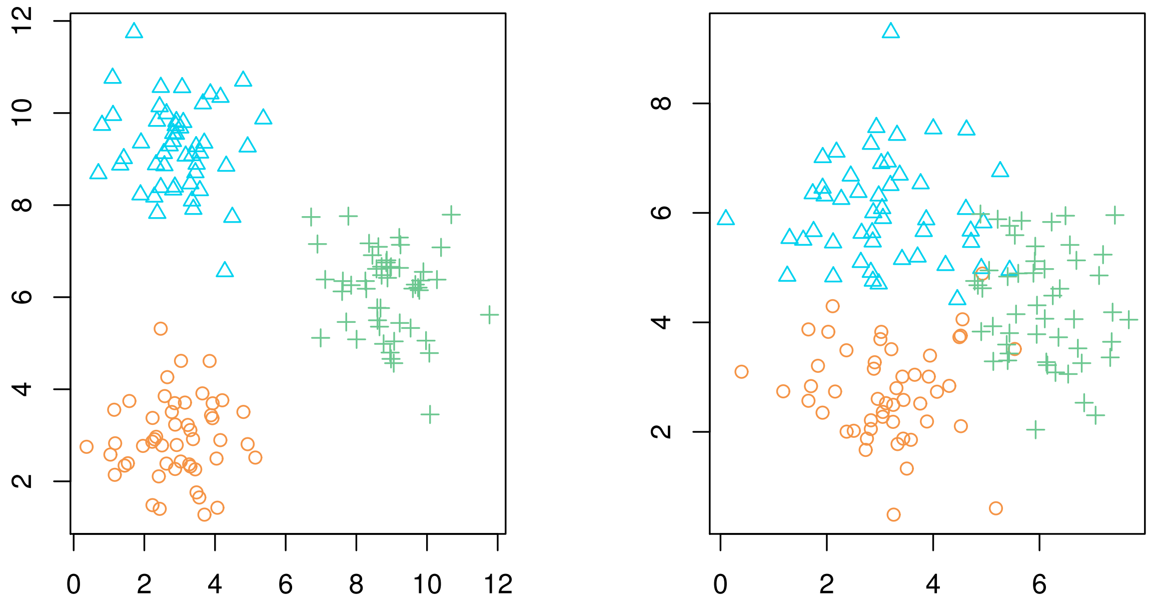
Google Apps Administrator Guide: A Private-Label Web Workspace

LOOK INSIDE!

Googlepedia: The Ultimate Google Resource (3rd Edition)

Unsupervised machine learning

- **Challenge**: identify whether the data separates into (relatively) distinct groups



- This kind of problem is called **cluster analysis** (Ch. 10)

Data science refresher: what is “data”?











Data: a definition

A dataset has some set of *variables* available for making predictions. For example:

Tuition rates, enrollment numbers, public vs. private, etc.

Data: a definition

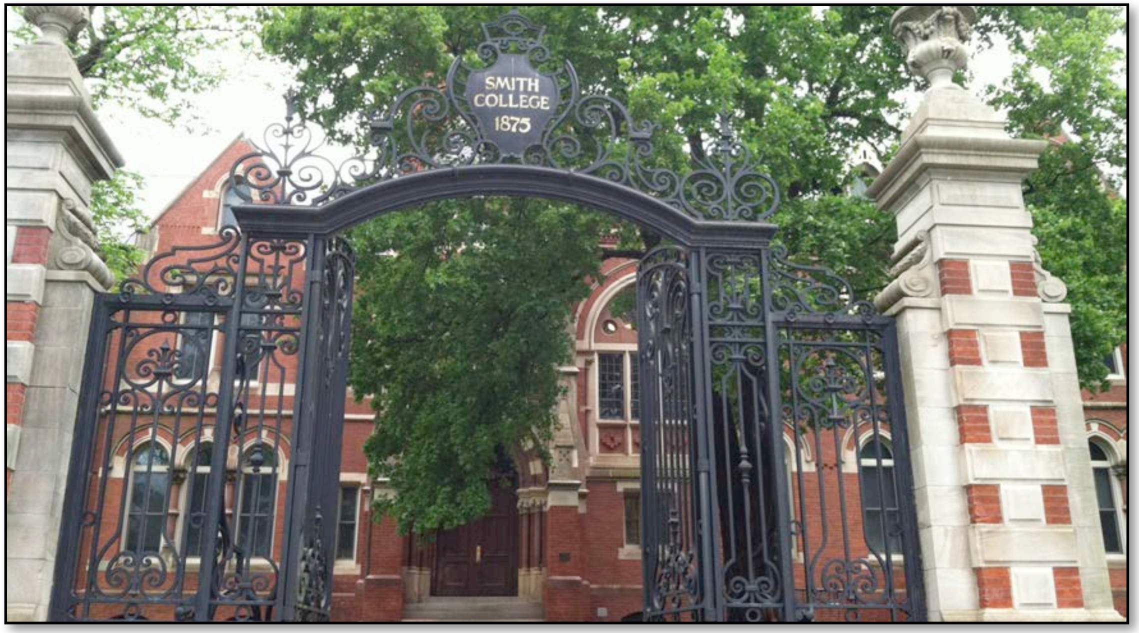
Each variable may be either *independent* or *dependent*:

- An *independent variable (iv)* is not controlled or affected by another variable (e.g., time in a time-series dataset)

- A *dependent variable (dv)* is affected by a variation in one or more associated independent variables (e.g., temperature in a region)

Data: a definition

A dataset also contains a set of **observations** (also called *records)* over these variables. For example:



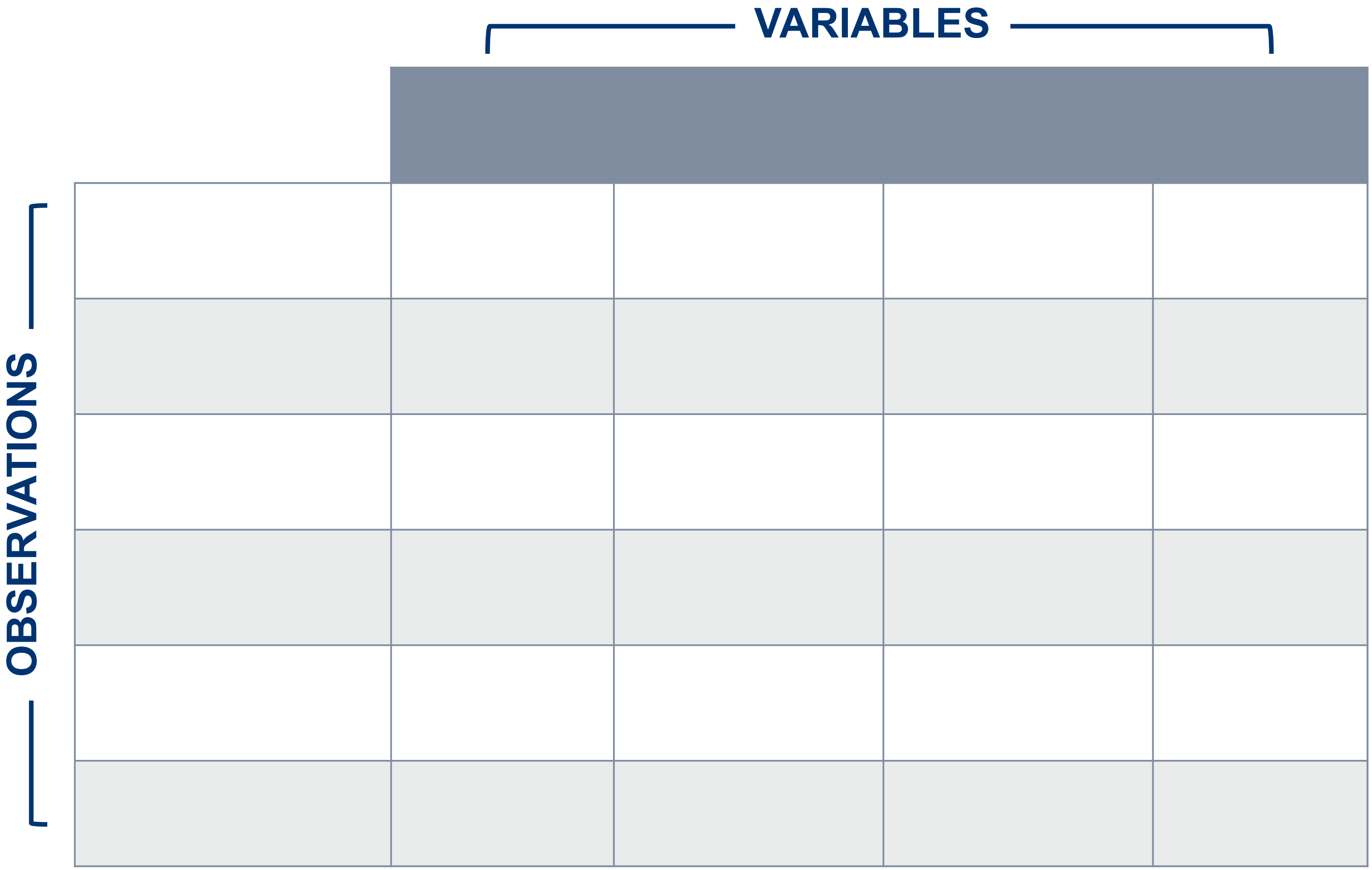
tuition = $46,288, *enrollment* = 2,563,
private, etc.

Data: a definition

A dataset also contains a set of ***observations*** (also called *records)* over these variables. For example:

tuition = $16,115, *enrollment* = 28,635, *public, etc.*

One way to think about this:



Another way to think about this

```
class school_obs:
    def __init__(tuition, enrollment,
                 pub_or_priv):
        self.tuition = tuition
        self.enrollment = enrollment
        self.pub_or_priv = pub_or_priv
```

VARIABLES

OBSERVATIONS

Basic data types

- Nominal
- Ordinal
- Scale / Quantitative
  - Ratio
  - Interval

An **unordered** set {…}

of non-numeric values

For example:

- Categorical (finite) data

  {apple, orange, pear}

  {red, green, blue}

- Arbitrary (infinite) data

  {“12 Main St. Boston MA”, “45 Wall St. New York NY”, …}

  {“John Smith”, “Jane Doe”, …}

Basic data types

- Nominal
- Ordinal
- Scale / Quantitative
  - Ratio
  - Interval

An **ordered set** <…>

(also known as a tuple)

For example:

- Numeric: <2, 4, 6, 8>
- Binary: <0, 1>
- Non-numeric:

  <G, PG, PG-13, R>

Basic data types

- Nominal
- Ordinal
- Scale / Quantitative
  - Ratio
  - Interval

A **numeric range** [...]

Ratios

- Distance from “absolute zero”
- Can be compared mathematically using division
- For example: height, weight

Intervals

- Ordered numeric elements that can be mathematically manipulated, but cannot be compared as ratios
- E.g.: date, current time

Converting between basic data types

- Q → O   [0, 100] → <F, D, C, B, A>
- O → N   <F, D, C, B, A> → {C, B, F, D, A}
- N → O   (??)
  - {John, Mike, Bob} → <Bob, John, Mike>
  - {red, green, blue} → <blue, green, red>
- O → Q   (??)
  - Hashing?
  - Bob + John = ??

Discussion: what do you notice?

Readings in Information Visualization: Using Vision To Think. Card, Mackinglay, Schneiderman, 1999

Basic operations

- Nominal (N)
  - Equality: = and ≠
  - Frequency: how often does *x* appear?
- Ordinal (O)
  - Relation to other points: >, <, ≥, ≤
  - Distribution: inference on relative frequency
- Quantitative (Q)
  - Other mathematical operations: (+, -, *, /, etc.)
  - Descriptive statistics: *average, standard deviation, etc.*

(Hopefully) familiar statistical concepts

- We tend to refer to problems with a **quantitative** response as *regression* problems

- When the response is **qualitative** (i.e. nominal or ordinal), we're usually talking about a *classification* problem

- **Caveat**: the distinction isn't always that crisp. For example:
  - K-nearest neighbors (Ch. 2 and Ch. 4), which works with either
  - Logistic regression (Ch. 4), which estimates the probabilities of a qualitative response

What we'll cover in this class

- Ch. 2: Statistical Learning Overview (next class)
- Ch. 3: Linear Regression
- Ch. 4: Classification
- Ch. 5: Resampling Methods
- Ch. 6: Linear Model Selection
- Ch. 7: Beyond Linearity
- Ch. 8: Tree-Based Methods
- Ch. 9: Support Vector Machines
- Ch. 10: Unsupervised Learning

General information

- Course website:

  cs.smith.edu/~jcrouser/SDS293

- Slack Channel is live:

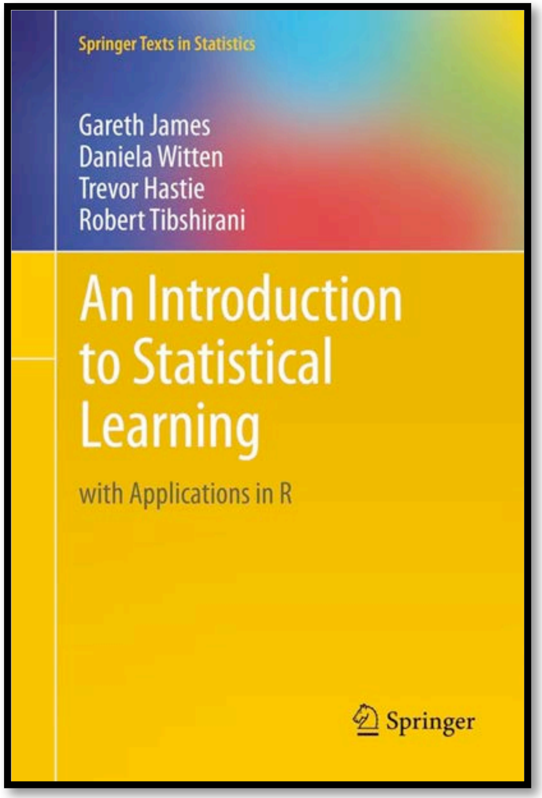
  sds293.slack.com

- Syllabus (with slides before each lecture)
- Textbook
- Assignments
- Grading
- Accommodations

About the textbook

- Digital edition available for free at:
  www.statlearning.com
- Lots of useful R source code (including labs)
- The `ISLR` package includes all the datasets referenced in the book:
  `> install.packages('ISLR')`
- Many excellent GitHub repositories of solution sets available

...wait, what?



Disclaimer

this class is an experiment in
constructionism

(the idea that people learn most effectively

when they're building personally-meaningful things)

- My job as the instructor:

Assignments and grading

- Participation (10%): show up, engage, and you'll be fine
- Labs (30%): run during regular class time, help you get a hands-on look at how various ML techniques work
- 8 (short) assignments (40%): built to help you become comfortable with applying the techniques
- Course project (20%)

Preparing for labs in R

Two options available for using R:

1. You can install R Studio on your own machine: rstudio.com
2. You can use Smith's RStudio Server: rstudio.smith.edu:8787

If you're unfamiliar with R, you might want to take a look at Smith's "Getting Started with R" tutorial:

www.math.smith.edu/tutorial/r.html

Preparing for labs in python

ANACONDA®

- I like the Anaconda distribution from continuum.io, but you're welcome to use whatever you like
- You'll need to know how to **install packages**
- Either 2.7 or 3.6 is fine – we'll run into bugs either way ☺

Course project (20%)

- Topic: ANYTHING YOU WANT
- Goals:
  - Learn how to break big, unwieldy questions down into clear, manageable problems
  - Figure out if/how the techniques we cover in class apply to your specific problems
  - **Use ML to address them**
- Several (graded) milestones along the way
- Demos and discussion on the final day of class
- More on this later…

Course learning objectives

1. Understand what ML is (and isn't)

2. Learn some foundational methods / tools

3. Be able to choose methods that make sense

What I expect from you

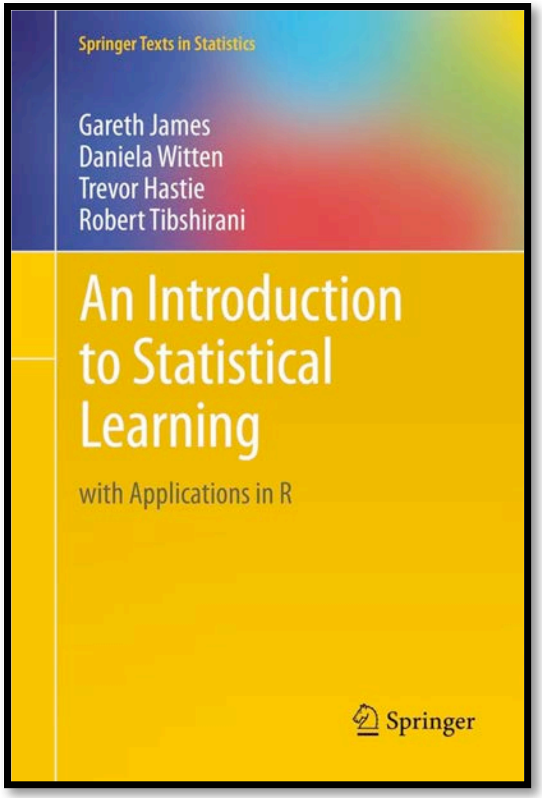
- You like difficult problems and you’re excited about “**figuring stuff out**”
- You have a solid foundation in **introductory statistics**
- You are proficient in **coding and debugging** (or are ready to work to get there)
- You’re comfortable asking **questions**

What you can expect from me

- Your learning **experience and process** is important to me
- I’m **flexible** w.r.t. the topics we cover
- I’m happy to share my **professional connections**
- Somewhat **limited in-person access**

Reading

- In today's class, we covered ISLR: p. 15-28
- Next class, we'll be talking about how to compare various kinds of models (ISLR: p. 29-37)



For Wednesday

Make sure you can access the slack channel

DataCamp

Need a refresher on something? Just ask!

#questions?