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DATA 202

Fall 2020

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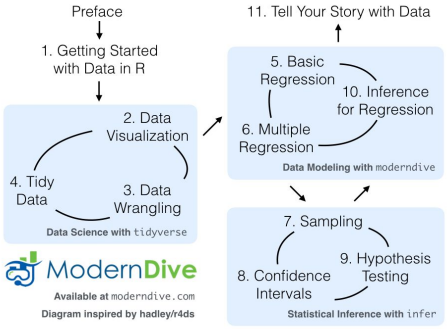
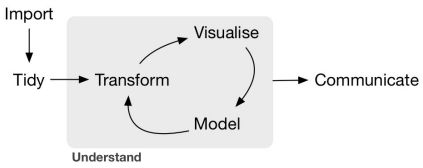
Visualization 1

ModernDive Preface and Chapter 1

PREFACE



- Data/Science Pipeline:



- Reproducible Research:
    - **computational reproducibility**. This refers to being able to pass all of one's data analysis, datasets, and conclusions to someone else and have them get exactly the same results on their machine.

CHAPTER 1: Getting Started w/ Data in R

- *Vectors*: a series of values. These are created using the `c()` function, where `c()` stands for "combine" or "concatenate." For example, `c(6, 11, 13, 31, 90, 92)` creates a six element series of positive integer values.
- Logical operators: `&` representing "and" as well as `|` representing "or."

Errors, warnings, & messages

- **Error:** something legitimately went wrong; prefaced with "Error in…" & will try to explain what went wrong. Generally, code will not run.
    - Something is wrong; figure out what's causing it.
- **Warnings**: code will generally still work, but with caveats.

    - Everything is working fine; but watch out / pay attention.
- **Messages:** just a friendly message. Helpful diagnostic messages.
    - Everything is working fine; keep going.

Packages:

- Always load them first. library(packagename)

Functions for viewing data:

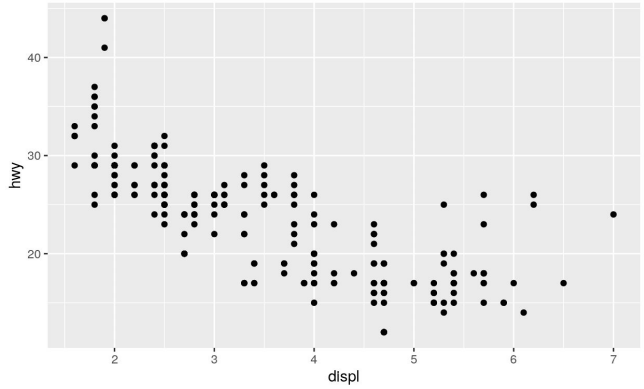
- kable(dataframename): used to display data in a print-friendly format.
- $ operator: extracts only specified variable, and returns a vector of length (row)

Variable Types:

- **Identification variable**: uniquely identifies each observational unit (like airport name, GRR, LAX, SNA, MDW, or Gerald R Ford International Airport, Los Angeles International, John Wayne Airport, Chicago Midway International Airport, etc)
    - Good practice = ID variable on left side of dataframe
- **Measurement/Characteristic Variable**: describe the properties of each observational variable (like latitude, longitude, altitude, etc)

Data Viz Basics Tutorial

```
ggplot(data = mpg) +
   geom_point(mapping = aes(x= displ, y = hwy)
```



Mapping argument: defines which variables are mapped to which axes in the graph.

- Mapping is always paired w/ aes()

Graphing workflow: common for making graphs w/ ggplot2

1. Start graph w/ ggplot()
2. Add elements to graph w/ geom_[] function
3. Select variables with the mapping = aes() argument

```
ggplot(data = <DATA>) +
   <GEOM_FUNCTION>(mapping = aes(<MAPPINGS>))
```

Helpful hints:
"**+**" must be at the *end* of a line, not the start.

Aesthetics: an aesthetic is a visual property of the objects in your plot. Aesthetics include things like the size, the shape, or the color of your points.

- x, y, colour, size…
- Do this inside of mapping = aes (HERE)
- MAPPING tells us which variables to map *to which visual properties*
- The same variable can be mapped to multiple aesthetics.

If you want all your data to have the same color/size/anything, do this *outside* of the aes() function, like:
geom_point(mapping = aes(x=,y=), color = "blue") [need quotes for color names]

Setting vs. Mapping
Setting: set the aesthetic to a ***value*** in the visual space, set it outside of aes()
Mapping: map the aesthetic to a ***variable*** in the data space, map it inside of aes

To ____	the aesthetic to a ____	in the ____ space,	do so ___ of aes().
SET	value	visual	Outside
MAP	variable	data	Inside

* if you need a *legend* to understand the color/shape/etc., then put it *inside* of aes().
* if there's no meaning, do it outside of aes()

Geometric Objects

- Geoms: the geometrical object that a plot uses to represent observations
- (like bar, line, boxplot, point, smooth [fitted line])
- See ggplot2 cheatsheet
- See any geom's help page (?geom_smooth)

Exercise 1:
What geom would you use to draw a:
Line chart: geom_line()
Boxplot: geom_boxplot()
Histogram: geom_histogram()
Area chart: geom_area()

Exercise 2:
`se` argument to geom_smooth(): add/remove a standard error ribbon around the smooth line

This is the ***G***rammar of ***G***raphics… or, ***gg***plot

Lecture, Day 1: Intro to Data Science

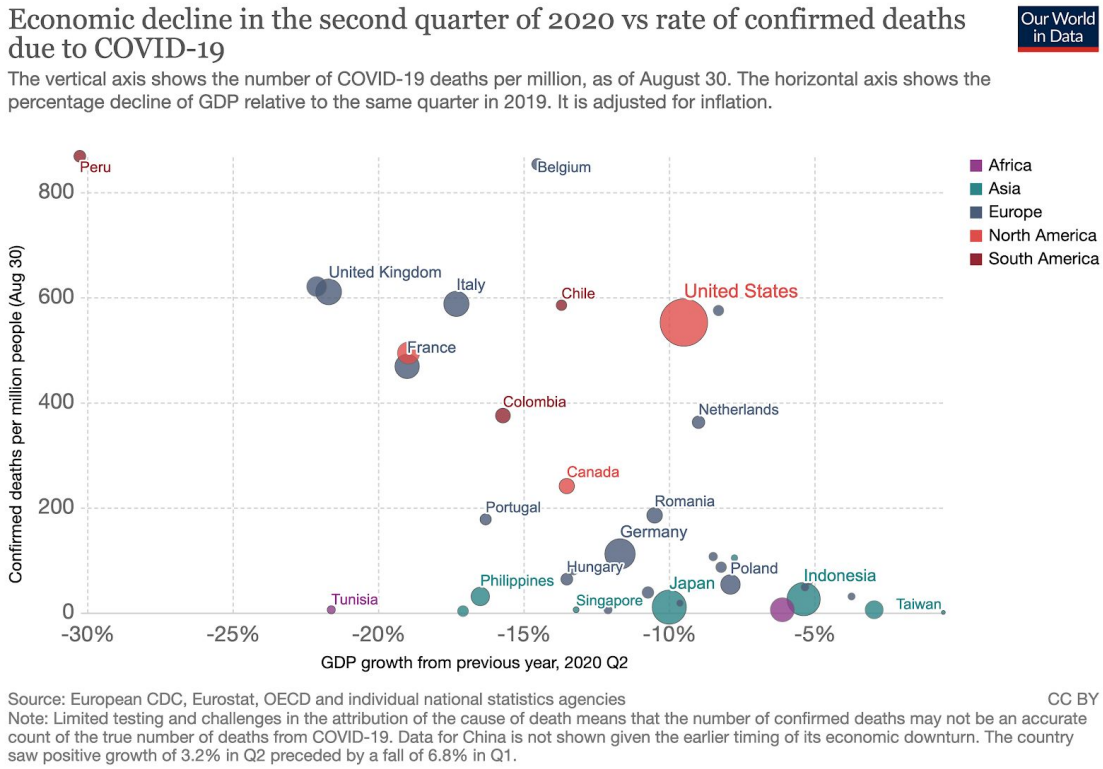
What *is* Data Science??

- People —> computers —> people
- Collecting, analyzing, sharing/communicating, visualizing.
- “Systematic collection & study of data”
- A tool that helps us see

What does data science help you *see*??

Viz, Inference, Prediction.

- See patterns on a large scale
- Show inequalities: every individual decision may seem fair, but *aggregated*, there’s inequalities that appear. (trade off depth for breath)
- How countries are *doing* w/ COVID: able to use specific metrics, can geet overall trends.
    - U.S.: investing economically? Or, investing in health.
    - **VISUALIZATION:**
        - Econ:
        - Health: case/population, death/case,
        - Is there a correlation between econ & health?

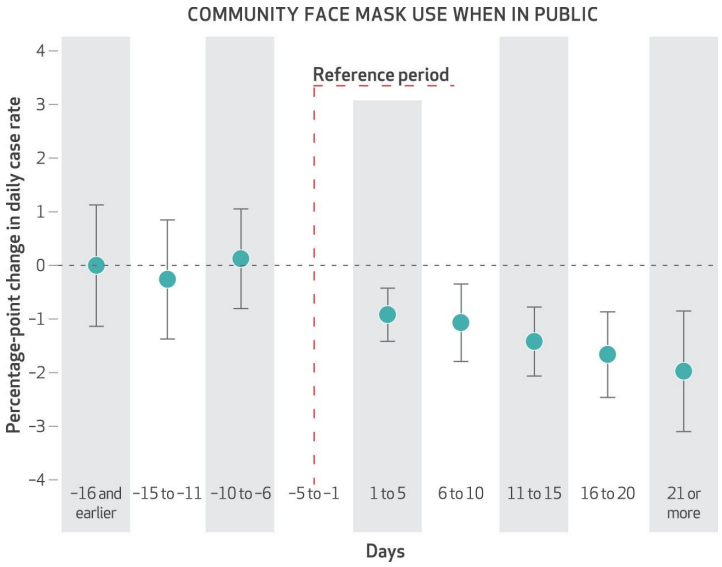


-

- Opposite of what you might expect… it doesn't just “trade off”
- Countries w/ better health = w/ better economy
    - Just hit not as hard?
        - In the visualization with the relationship between COVID death rates and economic decline, I wondered if the relationship was due to how hard the countries were hit by COVID. For example, a county with a low death rate might simply be indicative of a low number of COVID cases, not necessarily of large health interventions put into place. This seemed to differ from the explanation you had provided in class, so my question (probably outside the scope of this class) would be what is really causing this relationship between death rate and GDP decline. Obviously, I would have to read the article to get more information on this, but I thought that was interesting.

- INFERENCE

- Community face mask use when in public
- https://www.healthaffairs.org/doi/10.1377/hlthaff.2020.00818



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- PREDICTION

- Focus of this class… *predictive analytics*
- Used minivan price estimates
    - Based on past sales of used cars
    - The #s comse from data
- Good model: Number tells you @ what price it’ll be
- Why is this useful? -- ultimately, the prediction from a model is used for the benefit of people.

This class…

- Covers:
    - wrangling
    - predictive modeling and validation
    - visualization and communication
- but touches on all of the DS lifecycle.
- Uses:
    - **R** (tidyverse, tidymodels, ggplot/plotly) the *first* time we see something
    - **Python** (Pandas, sklearn) the *second* time we see something
    - occasionally: SQL, other tools according to student interest -- there's some flexibility towards the end of the course
- Goals:
    - *Skill*: how to do these things
    - *Knowledge*: understanding the underlying concepts
    - *Character*: wisdom in practicing these skills
      - humility (cite sources for data & processes, acknowledge limitations, transparent processes, validation of results) [RMarkdown -- the whole process is that code!]
      - integrity (resisting the temptation to manipulate data to get the answer you want) (evaluation claims, articulate analysis decisions and rationale, using exploratory analytics to validate data against assumptions)
      - hospitality (choose our tools to clarify, not obscuring) (good visualizations = hard to misunderstand, making your processes clear to others)
      - compassion & justice (don't cause harm; reveal it)
    - Bring up issues in Random channel, or email him.

Day 2: Lab — Dino Data

Why R? -- it gives **names to concepts**

- Python: using syntax to do something
- R: use a named function to do that same thing)

Why git?

- reproducibility, hospitality, everybody uses it!

Dino Data Lab -- Helpful Notes & Tips

pipe operator: %>%, takes what comes before it and sends it as the first argument to what comes after it. We can pronounce it "then".

Insert chunk: *CMD+OPT+i*

Day 2.5: HW —

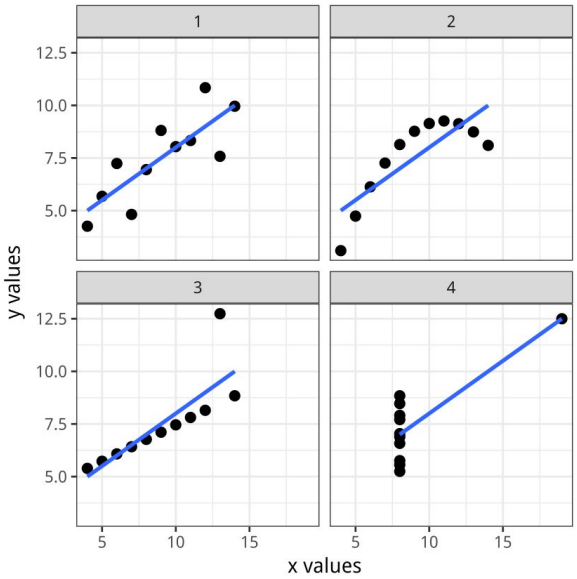
Getting started:
Open RStudio –> File –> New Proj –> Version Control –> Git –> Repository URL –> Tab –> Create!

Visualization 2

WHY: Healy "Look at Data" (from Data Visualization)

Look @ Data: *Look at the examples: can you explain to someone else what those examples show?*
Anscombe's Quartet: shows that standard measures of the association (correlation coeff, mean, med, mode, etc) aren't enough to tell you about data. This is why viz is important.

- summary statistics alone are not sufficient for data exploration



Types of problems with figures:

- Aesthetic -- ugly, inconsistent design choices
- Substantive -- due to data being presented
- Perceptual -- confusing/misleading because of how people perceive it

Tips to make things better:

- maximize the "data-to-ink" ratio
    - Delete backgrounds, gridlinees, superfluous axis marks, legends
    - YET: it's not memorable if it doesn't have all that extra stuff

Continue looking @ other plots on this website for good and bad plots. You know most of this intuitively or from DATA 101, though.

HOW: ModernDive "Data Visualization"

Data Visualization: *Try to actually answer the "Learning Check" questions for yourself. Yes this takes longer than just skimming right past them. But they may show up on a quiz…*

5 Named Graphs:

1. scatterplots
2. linegraphs
3. histograms
4. boxplots
5. barplots

Application: You did some visualization in Lab 1. How did that exercise relate to the "why" reading?

Class, Week 2, Day 1: Meet the Toolkit

Reproducible Data Analysis

- Someone can replicate your work & get the same results
- Share the steps (how) & the reasoning (why)
- "Near term goals:"
    - Can you ***re-make*** all tables and figures easily?
    - Does the code ***actually do*** what you think it does?
    - Is it clear ***why*** decisions were made? (e.g., how were parameter settings chosen?)
        - Rmarkdown lets you seamlessly embed a discussion about your code!
- "Long-term goals:"
    - Can the code be used for ***other data***?
        - Not great for excel, if you have references to rows 1:17… if you add a row 18, you have to change everything
    - Can you extend the code to ***do other things***?
- Ideally: document, explain, share everything (the code, data, & report)

Toolkit

What we're using:

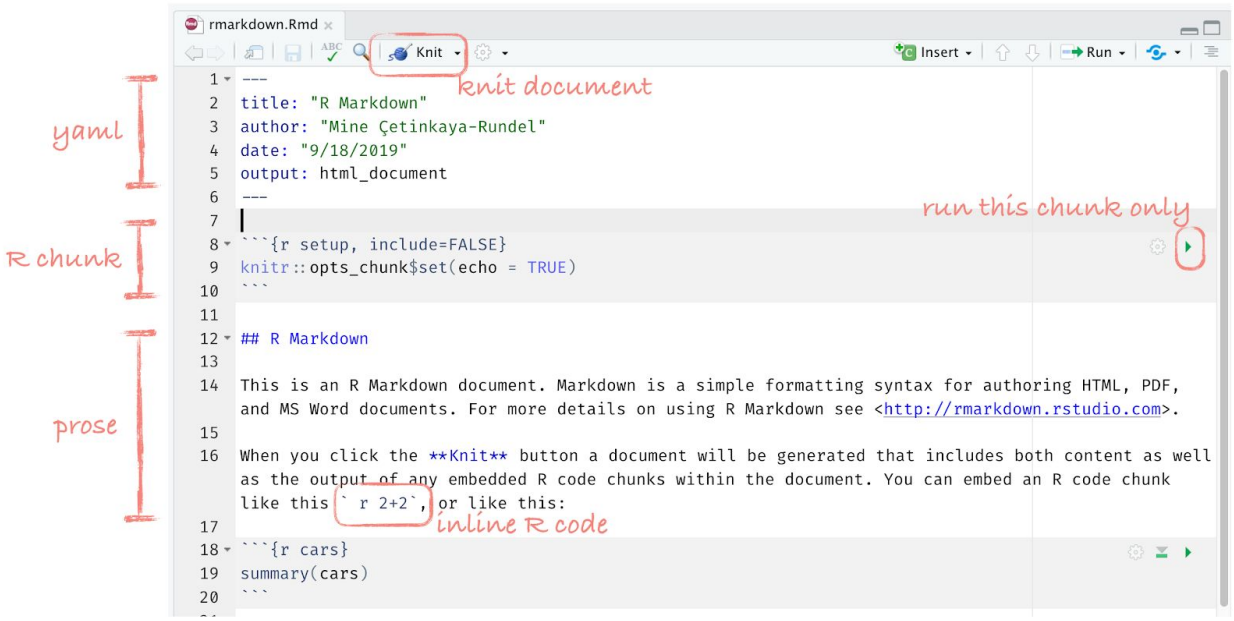
- Scriptability: R
- Literate programming (all in one place): R Markdown
- Version control: Git / GitHub

R

- Most common data type = "data frame"
        - Rows = same structure
        - Columns = same structure
    - Example: nursing: people, and their pulse, blood pressure, & other vitals
    - Example: `mtcars` in R
- The $ operator to access a variable w/in a data frame
- Functions = verbs (glimpse, view, make_plot)
    - You can arrange these into a pipeline
    - Something %>% another thing %>% etc.
- Package = basic unit shareable code
    - Tidyverse, ggplot2, dplyr…
    - Over 16k packages on CRAN (comprehensive R Archive Network)
        - Contain nice functions! Prepackaged for you! No need to program yourself!

    - How do you combine the pieces that exist to do what we want?
- Using packages:
    - install.packages("x")
    - library(x) (or `require` if it's in a function…)
    - ?x (or, click their name in the page list in RStudio)

RMarkdown



- *This is a yaml file?!?!?!* (metadata)
- R chunk
    - He names them?
    - Benefit of naming chunk
- Markdown
    - **bold**
    - *italics*
    - `in line r code`
- TIPS
    - Environment
        - 2 environments... R Markdown document env, vs. Console env
    - Always run a chunk after editing it

GUAC

CNTL+SHIFT+ALT: allows for clipboard functionality within guacamole
Vignettes = helpful text walkthrough

TODAY'S QUESTIONS to ask Prof. Arnold:

Saving workspace?

- Always clear it, go into settings to set this as the default

Naming chunks?

- Shows up on bottom & displays during knitting progress -- helpful for identifying time consuming chunks

Logging out of guac?

- Log out as if you're a user logging out

Env

- Saverds

Class, Week 2, Day 2: Fundamentals of Data Viz

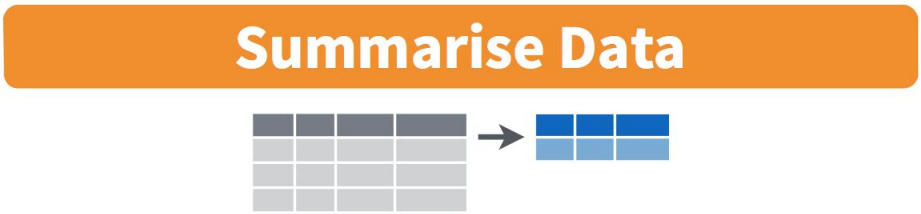
Misc. Q & A:

- Assignment operators? <- and =

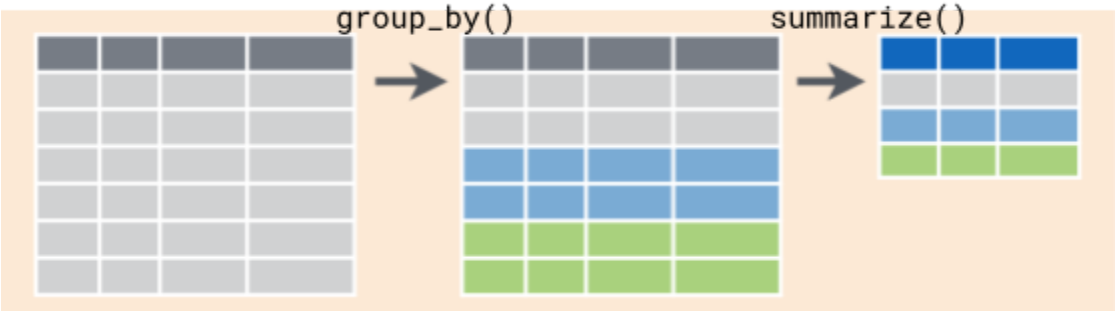
<-	assigns variables in current environment	data <- read_csv()
=	labels arguments to functions	ggplot(data = dino_data)

- .Rmd vs. .md
  - html doesn't show up nicely in github, so if we make an md that works.
  - Knit (CMD+SHIFT+K)
- STEPS:
  1. Knit
  2. Commit (everything)
  3. Push
     !!!!!
- %>% takes the thing on the left and uses it as an argument for what's on the right.
  - glimpse(data)
  - data %>% glimpse()
- HOW TO ASK Qs:
  - Always include your code and the error
  - Create a minimum working example (we'll keep working on this throughout the semester)
  - Use code formatting

GAPMINDER: see 0909healthandwealth.Rmd

```
```{r}
library(tidyverse)
library(ggplot2)
library(dplyr)
gapminder <- read.csv('https://sldr.netlify.app/data/gapminder_clean.csv')
```
```

```
ggplot(data = gapminder) +
  geom_point(mapping = aes(x = income, y = life_expectancy, colour = four_regions,
                           size = population, alpha = .1))
```

Wrangling 1

Prep: ModernDive Ch3 & “Working w/ Data” Tutorial

ModernDive Ch3

- filter(): subset observations
- summarize():
- group_by(): assign different rows to be part of the same group.
- mutate(): mutate its existing columns/vars to create new ones
- arrange(): sort in ascending or descending order (use desc())
- join(): merge two data frames together using a “key” variable.

3.3 `summarize` variables



- Returns a data frame w/ only one row with summary statistics
- ```
  summary_temp <- weather %>%
      summarize(mean = mean(temp, na.rm = T),
                std_dev = sd(temp, na.rm = T))
  ```
- `na.rm`: remove NAs.

- *Functions that take many values & returns one. SUCH AS:*
- `mean()`: the average
- `sd()`: the standard deviation, which is a measure of spread
- `min()` and `max()`: the minimum and maximum values, respectively
- `IQR()`: interquartile range
- `sum()`: the total amount when adding multiple numbers
- `n()`: a count of the number of rows in each group. This particular summary function will make more sense when `group_by()` is covered in Section 3.4.
  ```

3.4 `group_by` rows



Uses:

- Computing 12 mean temperatures, one for each month separately
  - "Group" temp observations by the values of another variable (by month)
  - Use group_by —> summarise

> *It is important to note that the `group_by()` function doesn't change data frames by itself. Rather it changes the meta-data, or data about the data, specifically the grouping structure. It is only after we apply the `summarize()` function that the data frame changes.*

To remove this grouping structure meta-data, pipe the resulting data frame into the `ungroup()` function

`sum()` VS. `n()`

- while `sum()` returns the sum of a numerical variable, `n()` returns a count of the number of rows/observations.

Working w. Data

Animated Plots?: Plotly, frame = date

Class, Week 3, Day 1: Grammar of Data Transformation

ggplot2: concepts worn on their sleeve, obvious what is doing what
dplyr: similar…. But for data transformation instead of viz

- Functions = verbs
- Concepts show up again in Python w/ Pandas & SQL

Grammar of Data Wrangling:

- `select`: pick columns by name

- `arrange`: reorder rows
- `slice`: pick rows by index(es)
- `slice_sample`: randomly sample rows
- `filter`: pick rows matching criteria
- `distinct`: filter for unique rows
- `mutate`: add new variables -- maybe better renamed as derive
- `summarize`: reduce variables to values

- Rules for dplyr functions:
  - Don't modify in place, it makes a new data frame
  - 1st argument: data frame
  - Subsequent args: what to do w/ that df
  - Returns: a data frame

Looking @ Bike Crashes in NC 2007-2014 -- selecting only a few columns, and sorting by the values in a column

Select:

```
ncbikecrash %>%
  select(county, bike_age)
```

```
## # A tibble: 7,467 x 2
##    county      bike_age
##    <chr>       <chr>
##  1 Wayne       52
##  2 Vance       66
##  3 Lincoln     33
##  4 Columbus    52
##  5 New Hanover 22
##  6 Robeson     15
##  7 Richmond    41
##  8 Wake        14
##  9 Columbus    16
## 10 Craven      54
## # … with 7,457 more rows
```

Select, then arrange:

```
ncbikecrash %>%
  select(county, bike_age) %>%
  arrange(bike_age)
```

```
## # A tibble: 7,467 x 2
##    county      bike_age
##    <chr>       <chr>
##  1 New Hanover 0
##  2 Carteret    1
##  3 Guilford    1
##  4 Pitt        10
##  5 Cumberland  10
##  6 Carteret    10
##  7 Hoke        10
##  8 Martin      10
##  9 New Hanover 10
## 10 Onslow      10
## # … with 7,457 more rows
```

** be aware of ***data types***… if you try sorting bike_age in order, and if it's of character type, it's going to be 0, 1, 10, 2, etc… weird.

`%>%`: a pipe

- Normally: nested functions
  - `arrange(select(ncbikecrash, county, bike_age), bike_age)`
- w/ Pipes: you "pipe" the output of the previous line of code as the first input of the next line of code

```
- ncbikecrash %>%
    select(county, bike_age) %>%
    arrange(bike_age)
```

Looking @ Hotel bookings

Class, Week 3, Day 2: Practice with Data Transformation

- How to: sort in descending order
    - desc() around a variable w/ arrange()

- Class Structure Changes:
    - *enrichment activities*: Do one or two optional activities throughout the semester, report back to the class
        - ICPSR Data Fair next week, "Philosophy of Data Science" podcast, propose others!
    - *Data Science in the News:* share current events related to DS
        - Articles that use data science to tell a story
        - Articles about data science

Wrangling 2

Class, Week 4, Day 1: Tidying

To plot the number of covid cases over time, what should the table look like?
Each row is a case.

DAY	STATE	COUNTY
09/20/2020	MI	Kent

Or, what if each row is a state-day?

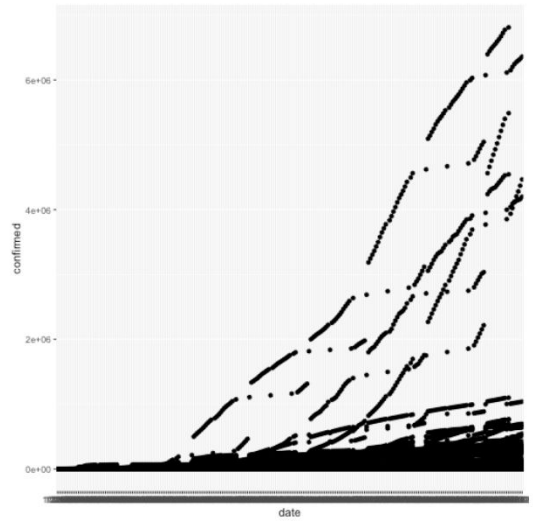
Tidying Step 1: `pivot_longer`

```
confirmed_global %>%
  pivot_longer(
    -(1:4) # the first 4 columns are not part of the pivot
  )
```

```
## # A tibble: 64,638 x 6
##    province_or_state country_or_region   Lat  Long name    value
##    <chr>             <chr>             <dbl> <dbl> <chr>   <dbl>
##  1 <NA>              Afghanistan        33.9  67.7 1/22/20     0
##  2 <NA>              Afghanistan        33.9  67.7 1/23/20     0
##  3 <NA>              Afghanistan        33.9  67.7 1/24/20     0
##  4 <NA>              Afghanistan        33.9  67.7 1/25/20     0
##  5 <NA>              Afghanistan        33.9  67.7 1/26/20     0
##  6 <NA>              Afghanistan        33.9  67.7 1/27/20     0
##  7 <NA>              Afghanistan        33.9  67.7 1/28/20     0
##  8 <NA>              Afghanistan        33.9  67.7 1/29/20     0
##  9 <NA>              Afghanistan        33.9  67.7 1/30/20     0
## 10 <NA>              Afghanistan        33.9  67.7 1/31/20     0
## # … with 64,628 more rows
```

```
confirmed_global_long <-
 confirmed_global %>%
 pivot_longer(
   -(1:4),
   names_to = "date",
   values_to = "confirmed"
 )
```

```
confirmed_global_long %>%
  ggplot(aes(x = date, y = confirmed)) +
  geom_point()
```

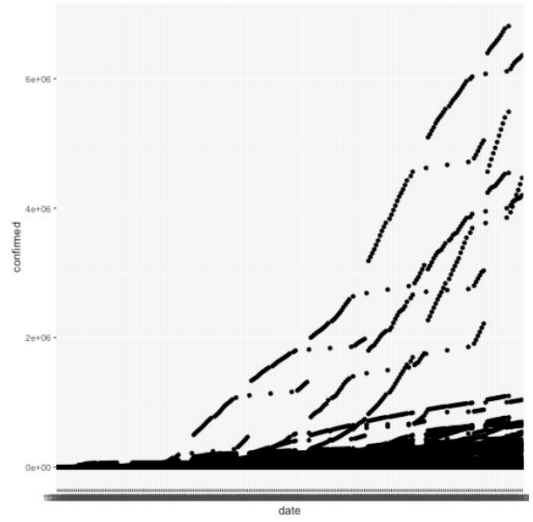


What is so terribly wrong with this graph?
Geom line would be even worse….?

Class, Week 4, Day 2: Tidying & Joining Data

https://github.com/Calvin-DS202-FA20/lab04-E2

```
confirmed_global_long %>%
  ggplot(aes(x = date, y = confirmed)) +
  geom_point()
```



Date is kinda weird….

- Is it writing every single date value on top of each other?
- How is it sorting? (factor?)

Select! == heym I want this data

- select(-Lat, -Long)
    - Take out Lat & Long

Homework 4: Python & Plotly

Plot.ly and Seaborn.

```
%>% Code here!
```

Wrangling 3

Class, Week 5, Day 1: Joining Data from Multiple Sources

Discussion 3: Collect example visualizations; post a critique;

- A visual you RESPECT, but DISAGREE with.
- Different POV, and reason WHY you disagree w/ it.
- From a different point on the spectrum

`mutate()`

- Actually, poorly named.
- Should be: add computed column

`count()` vs. `group_by %>% summarize()`

- Group by & summarize is better
- count() is mostly just shorthand for group_by(s) %>% summarize(n = n())

`select` vs. `filter`

- Select: select_columns
- Filter: select_rows
- Filter IN rows. Keep these.

`~ approach ~`

- Think about what you WANT
- And THEN write the code.
- Draw out in detail what you want the result to look like.
- If you don't know how to do the code from there, show your sketch to everyone else & ask on Q&A.

`tests & assessments`

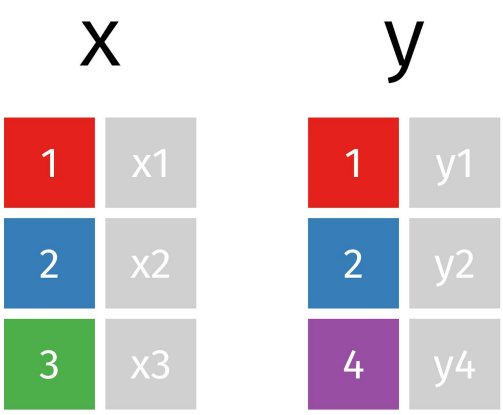
- Open-everything (except for people)
- Goal: be able to get conceptual foundation that can be used & applied in various other scenarios
- Not know how to do things very specifically from memory

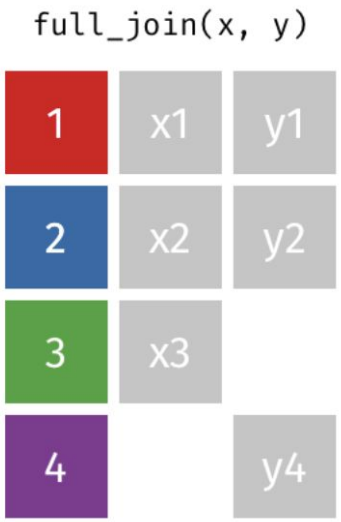
`joins!!!`

Data frame, x (COVID cases)

Extra information about the things in x, y (population of countries)

Needs a `key`: what has to match -- must match EXACTLY.





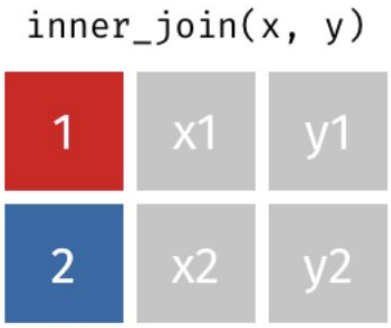
Types of Joins

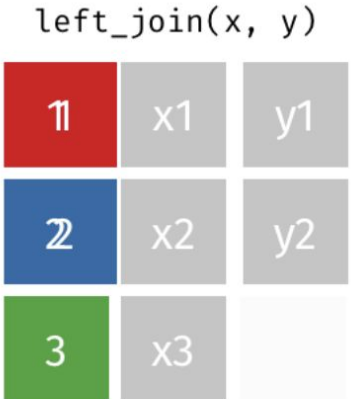
"What you do when things don't exactly line up."

`FULL / OUTER`: leaves blanks (NA) for matches

`INNER`: drops rows w/ *any* mis-matchees

`LEFT / RIGHT`: drops rows where *one* of the sides has a mismatch

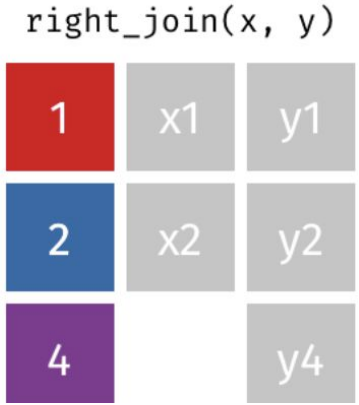




Going through Lab4:

How do you rename a column?

```
left_join(
    Confirmed_global_long %>%
        rename(country = country of region),
    Population,
    By = "country"
)
```



If you do `group_by` & `summarize`, you'll only ever get those columns you specified. So…

1. group_by(ADD IN YOUR EXTRA COLNAME!)

2. Add something to summarize??
3. Do join the opposite way?????

```
mutate(
    Country = case_when(
        TRUE ~ country_or_region  #default case! Reads:
                        #if true, use country_or_region
as metric
        ??
```

```
confirmed_global_long %>%
mutate(country = case_when(
  country_or_region == "Russia" ~ "Russian Federation",
  country_or_region == "US" ~ "United States",
  country_or_region == "Korea, South" ~ "Korea, Rep.",
  TRUE ~ country_or_region
))
```

Class, Week 5, Day 2: Problem Solving

- Know your goal… have a very specific picture in mind of what you want

- **Understand your data**: at the input and at each step in a pipeline.
    - Read the first row out loud. What does it say?
    - How many rows are there? What does each row represent? Express what that row is telling you.
- **Think about your goal**
    - What should the first row of my output be?
    - If I had to work out each value in that row by hand, what parts of the input would I need?
- **Take small steps**
    - Look at the results after each step
    - Work out your computation for one datum first, then go to all of them.

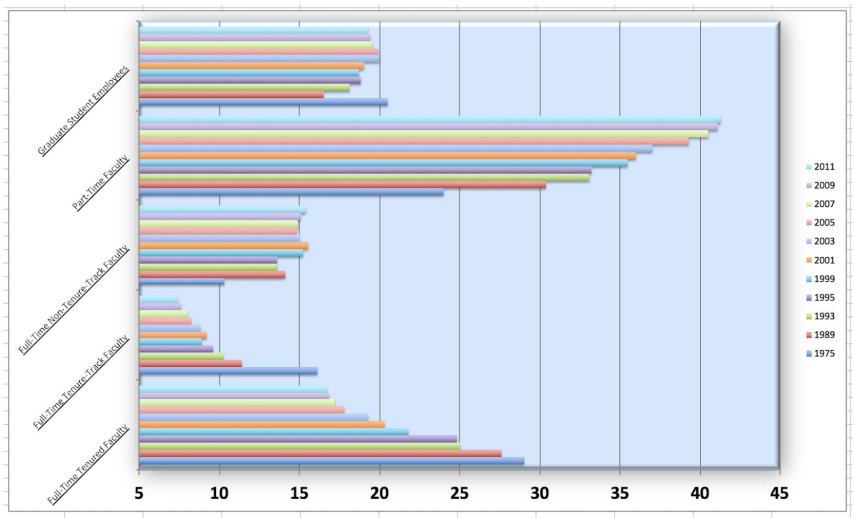
- Data science is **not magic**. Deliberate application of concepts and strategies will (eventually) bear fruit, no matter what language / library.

Class, Week 5, Day 3: Data tidying and reshaping

`tidyr`

Data we're looking at:

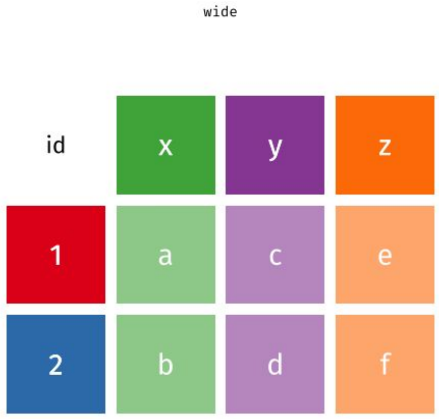
- Trends in instructional staff employment
- Ugly graph :(-- it doesn't obviously show what it could so clearly & obviously show!



-

Faculty type	Year	Percentage of hires
Full time tenured	1975	29
Full time tenure track	1975	16.1
Full time non tenured	1975	10.3
Part time faculty	1975	24
Grad student	1975	20.5
[same]	1989	etc.

We want: 5*11 = 55 total rows
Tidy dataframes are *longer.*



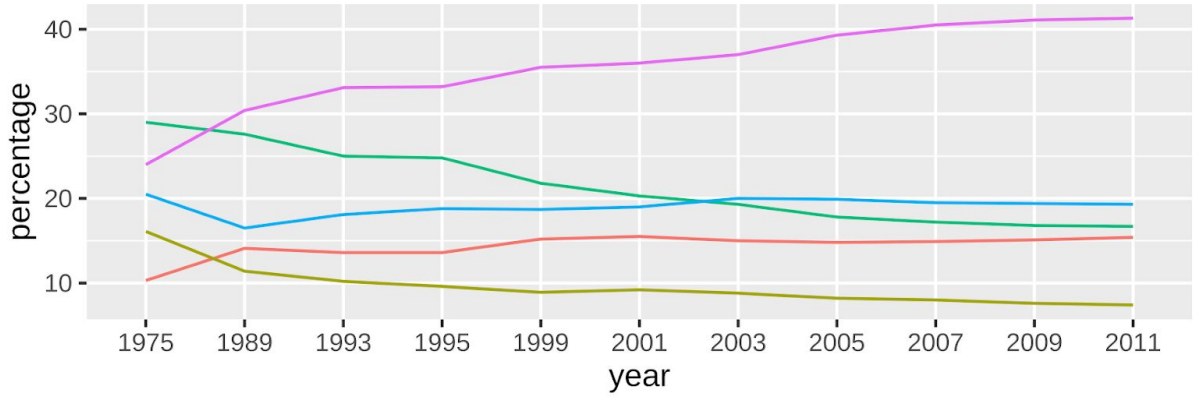
`pivot_longer(data, cols, names_to = "name", values_to = "value")`

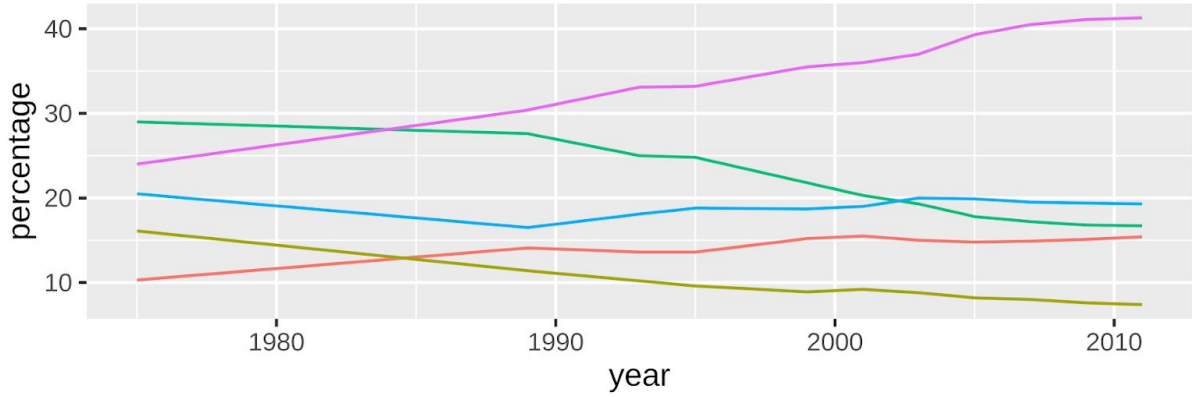
`cols` = which columns to pivot into longer format. Which do you want to change?
In our case, it's everything except for faculty_type.

`names_to = "name"` = name of the column we want it to put the column names ("year")

`values_to = "value"` = the name of the column to put the values ("percentage"

```
staff_long <- staff %>%
 pivot_longer(
   cols = -faculty_type,
   names_to = "year",
   values_to = "percentage"
   )
```





- Spacing of first one uses factor, or character
  - Doesn't maintain the distances, because it doesn't know what they MEAN...
- Second one uses the actually *date… this is a NUMBER*
  - `mutate(year = as.numeric(year))`

Voice Threads
Case_when
… it's like an if / elif / else in python.

```
case_when(
    age < 0  ~ "invalid",
    age < 18 ~ "child",
    TRUE     ~ "adult"
)
```

- First to True wins! (in both python and R)

- `TRUE` corresponds to else (the default)

Case_when can be used on vectors! Nice!!!
So, if…
Age <- c(-1, 0, 17, 18)
Case_when will be applied to *every element of the vector.*

Case_when vs. if_else

Which is preferable?

```
if_else(
      age < 0, “invalid”,
            if_else(age < 18, “child”, “other”))
```

That’s gross -- case_when is just a lot more readable and understandable.

- Can be used within mutate!

Country == “United STates” ~ “USA”,
Iso3c == “GBR” ~ “UK”,
TRUE ~ country

NICEEEE

Modeling

Class, Week 6, Day 1: Predictive Modeling Intro

Predictive Modeling: powerful tool to turn data into action

- Works because the universe is predictable (the world has actionable structure)
    - So, if we learn how to perceive that structure & act within it,
    - We can have better actions, be less surprised by what we see (predicting our perceptions)
- Need for wisdom -- great good & great harm....
- Harm due to...
    - Lack of Fairness: facial recognition, sentencing, lending, job applicant scoring
    - Lack of Transparency: how “Big Data” systems make conclusions
    - Lack of Privacy: as data is increasingly collected & aggregated
    - Amplification of extreme positions in social media, YouTube, etc.
    - Oversimplification of human experience
    - Hidden human labour
    - Illusion of objectivity

Stating and refining the question

- *This is what data science tasks often start with!*
- 6 TYPES of questions
- Six types of questions
    - ***Descriptive***: summarize a characteristic of a set of data
        - severity of viral illnesses in a set of data collected from a group of individuals
    - ***Exploratory***: analyze to see if there are patterns, trends, or relationships between variables (hypothesis generating)
        - examine *relationships* between a range of dietary factors and viral illnesses
    - ***Inferential***: analyze patterns, trends, or relationships in representative data from a population
        - examine whether *any relationship* between dietary factors and viral illnesses found in the sample *hold for the population at large*
    - ***Predictive***: make predictions for individuals or groups of individuals
        - given a person's demographics and diet, *predict the severity* of illness
    - ***Causal***: whether changing one factor will change another factor, on average, in a population

        - whether people who were *randomly assigned* to eat a diet high in fresh fruits and vegetables or one that was low in fresh fruits and vegetables contract more severe viral illnesses
    - ***Mechanistic***: explore "how" as opposed to whether
        - *how* a diet high in fresh fruits and vegetables leads to a reduction in the severity of viral illnesses
- & of these, our focus: prediction….

Prediction

What we'll do:

- Predict something unknown from something known. Specifically: complete-the-table model

How we'll do it:

- methods that consider similar examples (Nearest Neighbors)
- methods that look at overall trends (linear/logistic regression)
- more advanced methods, time permitting

Example: Home Sale Prices

From Ames, Iowa home sales, 2006-2010. (De Cock, 2011)

Lot_Area	Total_Bsmt_SF	Gr_Liv_Area	Garage_Cars	Sale_Price
31770	1080	1656	2	215000
11622	882	896	1	105000
14267	1329	1329	1	172000
11160	2110	2110	2	244000
13830	928	1629	2	189900

(2930 total rows)

- *Y*: *response* variable (aka *outcome*, *dependent variable*): `Sale_Price`
- *X*: *features* (aka *predictors*, *covariates*, etc.): everything else

Note: X is much easier to measure than Y

-

Class, Week 6, Day 2: What makes a good prediction?

Types of Tasks

Regression: predict a *number* ("continuous") -- number should be "close" to the correct number
Classification: predict a *category* -- 2 groups? 500000 groups? How likely is it to be in group *i*?

Regression	**Classification**
How much rain in GR next year?	Inside / outside of a restaurant?
How much will this home sell for?	Is this person having a seizure?
How much time will this person spend watching this video?	Which word did this person mean to type?

How big a fruit will this plant produce?	Will this person “like” this post?

Examples for Today:
CLASSIFICATION: The embrace2 -- a wrist-worn wearable that detects seizures. (seizure classication)
REGRESSION: Ames, IA home prices

~~ What makes a good prediction?: Regression ~~

Measuring a good prediction… how do you know if it’s a *good* prediction vs. a *bad* prediction?
For one data point:
Residual: actual – predicted (200 - 250 = –50k)
absolute error: |200-250 = –50k| = +50k
squared error: (50k)^2 = 2500k -- because being off my 50k might be more than twice as bad as 25k

Across the entire dataset:
average error: tend to predict too high? Too low?
Max absolute error
Mean absolute error
Mean squared error (MSE)
Normalized Squared Error: MSE / Variance

- & the confusingly named “R2” (R^2) = (1 – normalized squared error)

~~ What makes a good prediction?: Classification ~~

Make a 2x2 matrix!

	Seizure Happened	No Seizure Happened
Seizure Predicted	True +	*False* + (type 1 error)
No seizure predicted	*False* – (type 2 error)	True –

Accuracy (% correct) **=** (TP + TN) / (**#** episodes)
False negative (“miss”) **rate =** FN / (**#** actual seizures)
False positive (“false alarm”) **rate =** FP / (**#** true non-seizures)

Trade Offs: for a seizure alert system, do you want sensitivity & specificity to be high or low?

- Ideally, you want both sensitivity and specificity to be high -- this will give you the most True Positives and True Negatives. For the seizure alert system specifically, it’s probably better to have higher sensitivity (err on the side of too many false positives), because you could follow up and check if a seizure is actually occuring or not.

- If you prioritize sensitivity: a lot of false positives -- “boy who cried wolf” scenario
    - If it’s important to catch every single event, you’ll choose this.
    - If there’s even a *slight* possibility that the event is occurring, prioritize sensitivity.
- If you prioritize specitivity: a lot of false negatives --

Week 6, Day 3: Modeling interactive experience

Mean Absolute Error:

- When we set incept to MEDIAN, we get lowest M.A.E.
- (Lowest M.S.E. when we set intercept to mean)

Training vs. Testing Dataset

- On test set, M.A.E. is higher (bad) :(
- Training (26.17)
- Testing (56.16)

ADDING Slope:

- Int: 121
- Slope: .0046 (lot area)
- MAE: 22.12
- MSE: 984.23
- OR…
- Int: 113
- Slope: .0046 (lot area)
- MAE: 23.59
- MSE: 932.41
- OR…
- Int = 141?
- Slope = .0002? Lot_Area
- 906.39?

Qs:

- When adding slope, i needed to adjust the intercept -- because
- Better error was achieved using slope & intercept, beecause more parameters = better fit.

Validation:

- You *must* validate your model on *unseen* data.
- No overfitting -- failure to generalize

Class, Week 7, Day 2: Predictive Models

RECAP: regression error measures
MAE: mean absolute error ($)
MSE: mean squared error ($^2)
RMSE: sqrt/(MSE) $!! :)

If we're looking @ sale price in $s...

Abbreviation	Error measure	Units
MAE	Mean *absolute* error	$
MSE	mean *squared* error	$^2
RMSE	sqrt(MSE)	$

- Make sure to report it in units of understandable things.

When to use what? (MSE, MAE…?)

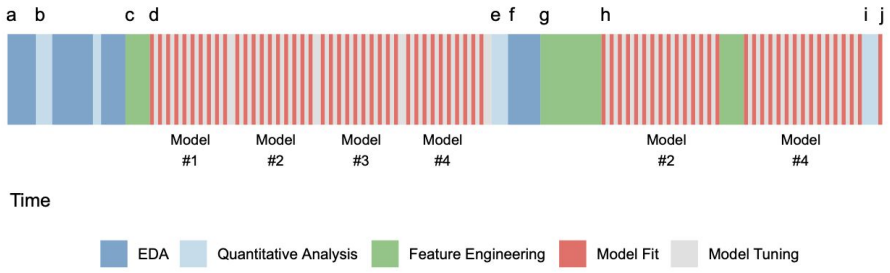
Think: use Mean or Median to summarize errors? (Mean: sensitive to outliers)

- (*) If the model is mostly good but makes a few large errors, is that *bad* (use MSE), or does it mean we should probably ignore those points as outliers (use MAE)
- Median minimizes MAE. Mean minimizes MSE.
  - What choice would minimize *max absolute* error?

Instead of finding coeffs by guessing, is there a better way?

- Practically: ML / stats. Just throw @ computer at it.
- Mathematically: Gradient descent
  - From your data, randomly pick a batch of a few observations.
  - Put those X's through your model, tracing the computations on the way.
  - Compute error (e.g., MSE) on that batch.
  - Compute what small change to each coefficient would have reduced error?
  - Make all of those small changes, repeat.

EDA: exploratory data analysis.



Predictive Modeling Workflow

1. ***Define the problem***: predict *what*, based on *what*? What *metrics* will indicate success? (Measure success in multiple ways!)
2. ***Explore*** your data (EDA): understand its structure, make lots of plots

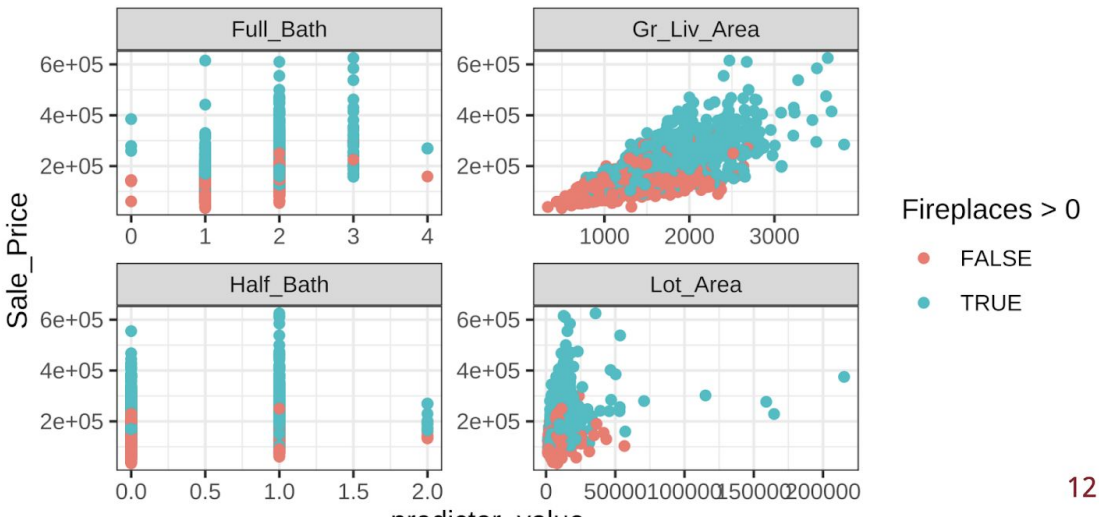
3. ***Pick a model***: Which type(s) of models are appropriate for task and data?
4. ***Transform the data*** as needed by the model ("feature engineering", preprocessing", "recipe")
5. ***Split the data*** to allow for validation.
6. ***Fit and evaluate the model***
7. ***Tune***: adjust model hyperparameters
8. ***Analyze model errors*** and refine all earlier steps

How we'll do this…

```
library(tidymodels)
```

- `parsnip`: ***Specify*** and ***train*** the model you want
- `recipes`: ***Prepare*** the data
- `rsample`: ***Split*** data into training and validation
- `yardstick`: Compute ***metrics*** for performance
- `tune`: Helps you set the dials.

```
ames %>% select(Sale_Price, Gr_Liv_Area, Lot_Area, Full_Bath, Half_Bath, Fireplaces) %>%
  pivot_longer(-c(Sale_Price, Fireplaces), names_to = "predictor", values_to = "predictor_value") %>
  ggplot(aes(x = predictor_value, y = Sale_Price, color = Fireplaces > 0)) + geom_point() +
  facet_wrap(vars(predictor), scales = "free") + theme_bw()
```



Validation

Hold out some data to use for validation:

```
set.seed(10)
ames_split <- initial_split(ames, prop = 3/4)
ames_train <- training(ames_split)
ames_test <- testing(ames_split)
glue("Using {nrow(ames_train)} sales to train, {nrow(ames_test)} to test")
```

```
## Using 1809 sales to train, 603 to test
```

Specify the model to use.
Train the model on the training set

```
my_trained_model <- my_model_spec %>%
  fit(Sale_Price ~ Lot_Area + Gr_Liv_Area + Full_Bath, data = ames_train)
```

Make predictions on training set:

```
train_predictions <-
  my_trained_model %>%
    predict(ames_train)
train_predictions
```

```
## # A tibble: 1,809 x 1
##     .pred
##     <dbl>
## 1 115287.
## 2 156986.
## 3 200732.
## 4 194610.
## 5 210156.
## 6 199231.
## # … with 1,803 more rows
```

```
train_predictions %>%
  bind_cols(ames_train) %>% # Put back the ori
  yardstick::metrics(truth = Sale_Price, estim
```

```
## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard   47334.
## 2 rsq     standard       0.557
## 3 mae     standard   31936.
```


Evaluate on test set:

```
my_trained_model %>%
  predict(ames_test) %>%
  bind_cols(ames_test) %>%
  metrics(truth = Sale_Price, estimate = .pred)
```

```
## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard   44606.
## 2 rsq     standard       0.548
## 3 mae     standard   32442.
```

Class, Week 7, Day 3: Predictive Modeling

Formula interface

`y ~ x`

`y ~ x1 + x2 + x3`

* note: this doesn't include coefficients, right? Yeah. So it'd actually look more like:
y = c1*x1 + c2*x2 + c3*x3 + c4, yeah.

Class, Week 8, Day 3: Feature Engineering

Project:

1. Data: source & assumptions
2. Vis design: retinal variables chosen for which data variables & why?

Midterm Quiz: Quiz 8 open for a week… similar structure to Quiz 7

RECIPES:

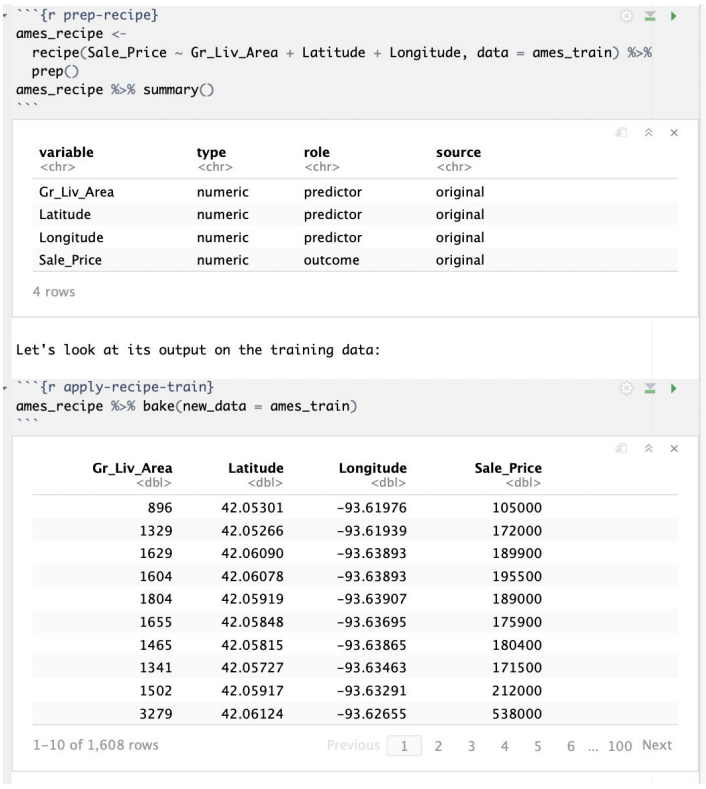
- A recipe is a data processing pipeline (like %>%) where the steps can be "smart".

Why Recipes:

- Add expressive power (like conditional logic) to simple modeels
- Make the model more (/less) understandable

```
ames_recipe <-
  recipe(Sale_Price ~ Gr_Liv_Area + Latitude + Longitude, data = ames_train) %>%
  prep()
ames_recipe %>% summary()
```

Get the structure in place….



```{r prep-recipe}
ames_recipe <-
  recipe(Sale_Price ~ Gr_Liv_Area + Latitude + Longitude, data = ames_train) %>%
  prep()
ames_recipe %>% summary()
```

variable <chr>	type <chr>	role <chr>	source <chr>
Gr_Liv_Area	numeric	predictor	original
Latitude	numeric	predictor	original
Longitude	numeric	predictor	original
Sale_Price	numeric	outcome	original

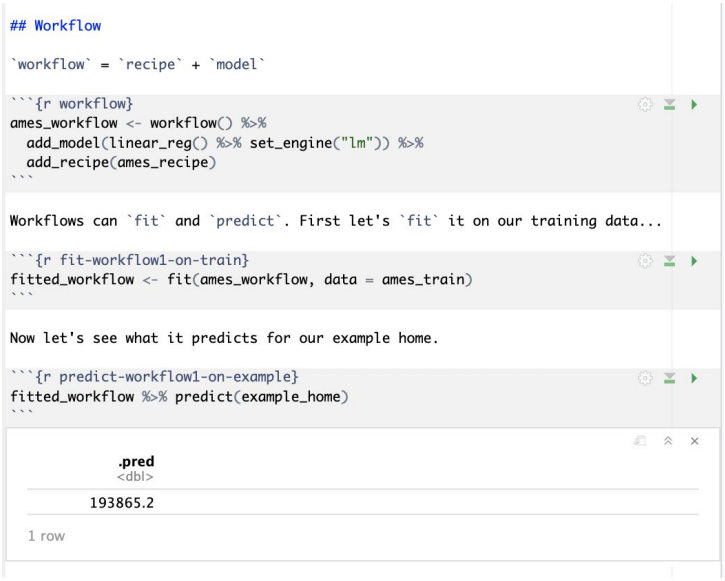
4 rows

Let's look at its output on the training data:

```{r apply-recipe-train}
ames_recipe %>% bake(new_data = ames_train)
```

Gr_Liv_Area <dbl>	Latitude <dbl>	Longitude <dbl>	Sale_Price <dbl>
896	42.05301	-93.61976	105000
1329	42.05266	-93.61939	172000
1629	42.06090	-93.63893	189900
1604	42.06078	-93.63893	195500
1804	42.05919	-93.63907	189000
1655	42.05848	-93.63695	175900
1465	42.05815	-93.63865	180400
1341	42.05727	-93.63463	171500
1502	42.05917	-93.63291	212000
3279	42.06124	-93.62655	538000

1–10 of 1,608 rows Previous 1 2 3 4 5 6 … 100 Next



Workflow

`workflow` = `recipe` + `model`

```{r workflow}
ames_workflow <- workflow() %>%
  add_model(linear_reg() %>% set_engine("lm")) %>%
  add_recipe(ames_recipe)
```

Workflows can `fit` and `predict`. First let's `fit` it on our training data...

```{r fit-workflow1-on-train}
fitted_workflow <- fit(ames_workflow, data = ames_train)
```

Now let's see what it predicts for our example home.

```{r predict-workflow1-on-example}
fitted_workflow %>% predict(example_home)
```

.pred
<dbl>
193865.2

1 row

```{r unscaled-fitlong}
fitted_workflow %>%
  tidy() %>%
  filter(term != "(Intercept)") %>%
  ggplot(aes(x = estimate, y = term)) + geom_col()
```

term	estimate	std.error
<chr>	<dbl>	<dbl>
(Intercept)	-7.030236e+07	5.103450e+06
Gr_Liv_Area	1.005362e+02	2.400789e+00
Latitude	5.802497e+05	6.461711e+04
Longitude	-4.905791e+05	4.400979e+04

4 rows

We get huge coefficients...

Because these features are on such totally different scales, if we want a similar effect, we need a huge coefficient.

```{r}
ames_train %>% select(Gr_Liv_Area, Latitude, Longitude) %>% summary()
```

```
  Gr_Liv_Area      Latitude       Longitude
 Min.   : 334   Min.   :41.99   Min.   :-93.69
 1st Qu.:1103   1st Qu.:42.02   1st Qu.:-93.66
 Median :1432   Median :42.03   Median :-93.64
 Mean   :1483   Mean   :42.03   Mean   :-93.64
 3rd Qu.:1734   3rd Qu.:42.05   3rd Qu.:-93.62
 Max.   :3820   Max.   :42.06   Max.   :-93.58
```

Because these features are on such totally different scalees, if we want a similar effect, we need a huge coefficient.

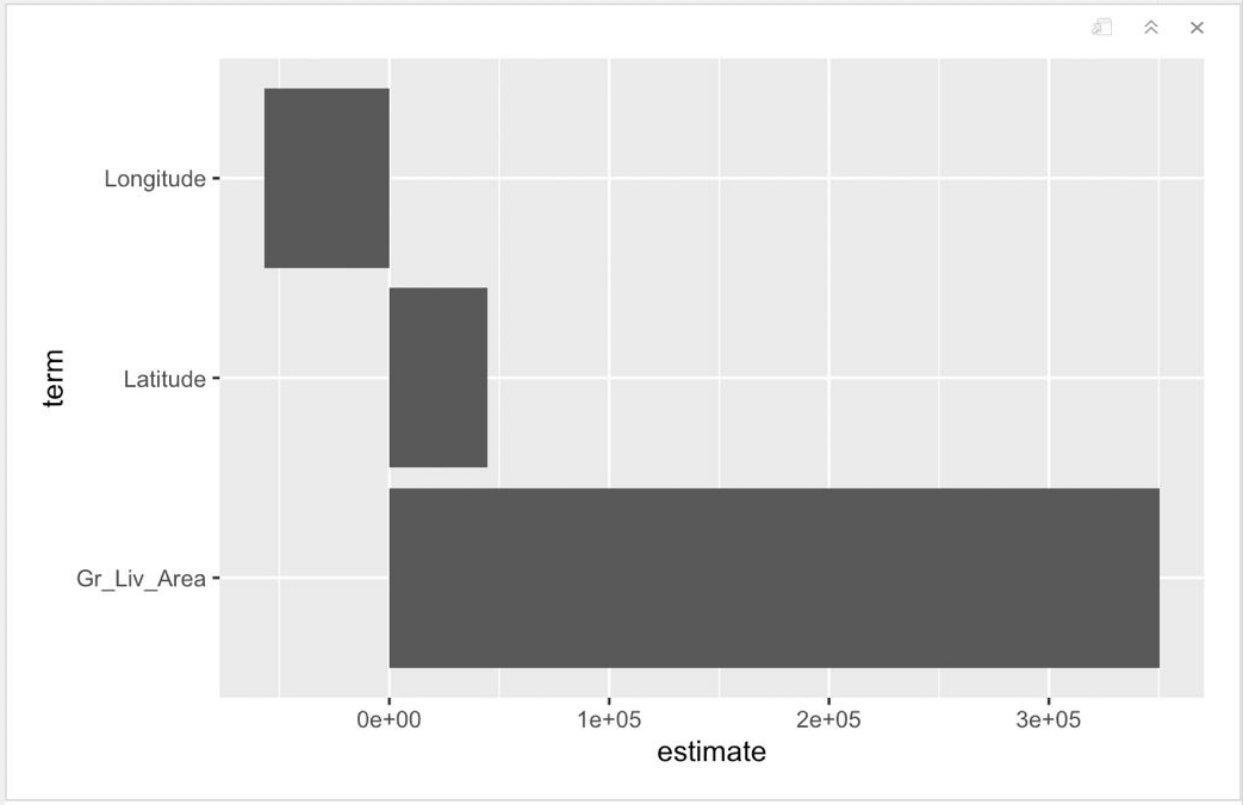
SO, ADD:

```
ames_recipe <-
  recipe(Sale_Price ~ Gr_Liv_Area + Latitude + Longitude, data = ames_train) %>%
  #make the scale the SAME for all of these!!!!
  step_range(Gr_Liv_Area, Latitude, Longitude, min = 0, max = 1) %>%
  prep()
ames_recipe %>% summary()
```

```{r prep-recipe}
ames_recipe <-
  recipe(Sale_Price ~ Gr_Liv_Area + Latitude + Longitude, data = ames_train) %>%
  #make the scale the SAME for all of these!!!!
  step_range(Gr_Liv_Area, Latitude, Longitude, min = 0, max = 1) %>%
  prep()
ames_recipe %>% summary()
```

- Our units aren't helpful anymore… but it tells us about the relative weights of each one more easily.

```{r unscaled-latlong}
fitted_workflow %>%
  tidy() %>%
  filter(term != "(Intercept)") %>%
  ggplot(aes(x = estimate, y = term)) + geom_col()
```



Class, Week 9, Day 1: Feature Engineering & Review

Q&A

Recipes vs. Data Wrangling Pipelines

- Recipe = a data wrangling pipeline
    - … that can be easily applied to new data (e.g., a test set)
    - … that can have learnable state (like ranges of data values)
    - (kinda like a… function??)
- Linear regression is linear, doesn't care what units the data is in… so the specific range didn't matter (0 to1), (-1 to 1), only the coeffs change

REVIEW

- Go over summarize(), group_by(), count()

```
rides %>%
      muate(weekendweekday = case_when(
                  day_of_week == “Sat” ~ “weekend”,
                  day_of_week == “Sun” ~ “weekend”,
                  TRUE ~ “weekday”

Avg duration of ride by d.o.w.
Rides %>%
      group_by(day_of_week) %>%
      summarize()
```

Class, Week 9, Day 2: Conditional Logic

Good Questions

> Final project?

- No final exam, just final project.
- Should demonstrate modeling and validation
- Can optionally be an extension of your midterm project
- Can optionally be groups
- Proposals and matchmaking Moodle forum next week!

> Was there a homework or lab this week?

No, to allow time to work on midterm project & exam. But yes next week.

> Can we review data wrangling stuff like joins and factors?

Review session during my office hours today (3-4pm). NH 295.

Today:

- Apply dummy encoding to add simple conditional logic to linear regression models
    - Explain how many columns get added in dummy encoding, and why
- Compare and contrast how linear regression and decision tree regression make predictions

Notes in ~/lab08-template

What computations can a linear model do?

- Add terms
- Multiple each term by a constant
- (that's it…)

He reviews papers -- interesting, i wonder which journal it's for…!

Aside: the *sum-as-count* pattern

```
ames_2 %>%
  group_by(remodeled) %>%
  summarize(n = n()) %>%
  mutate(proportion = n / sum(n))
```

```
## # A tibble: 2 x 3
##   remodeled     n proportion
##   <lgl>     <int>      <dbl>
## 1 FALSE      1303      0.540
## 2 TRUE       1109      0.460
```

```
ames_train_2 %>% summarize(
  num_remodeled = sum(remodeled == "yes"),
  prop_remodeled = mean(remodeled == "yes")
)
```

```
## # A tibble: 1 x 2
##   num_remodeled prop_remodeled
##           <int>          <dbl>
## 1           742          0.461
```

Why does this work?

```
as.numeric(remodeled[1:10] == "yes")
```

```
##  [1] 0 0 1 0 0 1 0 0 0 0
```

Its *sum* is the number of 1's (rows where the condition is true). Its *mean* is the sum divided by the total number, i.e., the *proportion*.

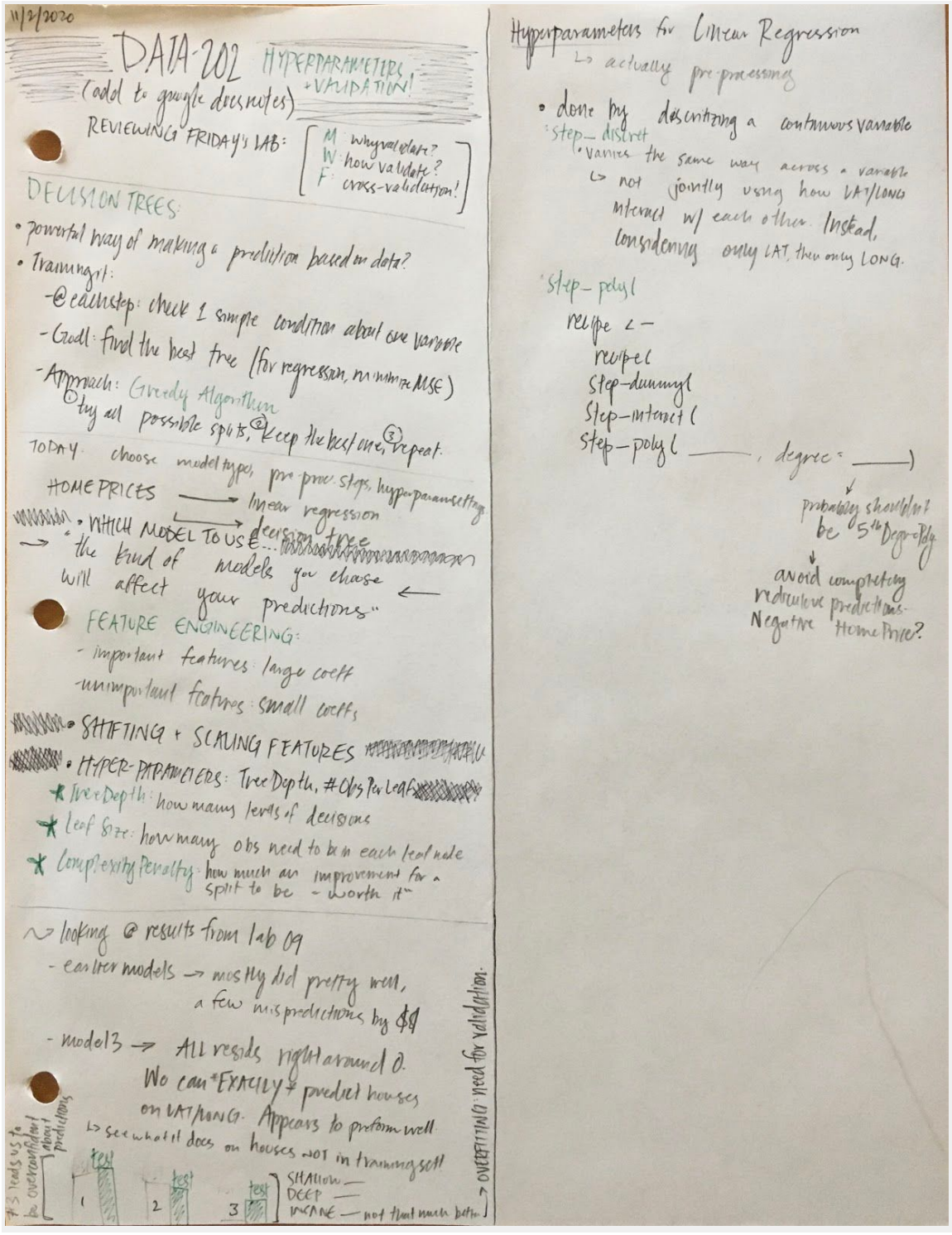
7 / 1

```
Ames_2 %>%
  group_by (remodeled) %>%
  summarize(n = n() %>%
  mutate(proportion = n / sum(n))
```

~ 46% remodelled

```
Sum of a boolean, counting the truths
Ames_2 %>%
  summarize(num_remodelled = sum(remodelled == “yes”),
            Prop_remodelled = mean(remodelled == “yes”))
```

Class, Week 10, Day 1: Hyperparameters and Validation



<--INSERT MONDAY'S NOTES HERE!!--> [my laptop wasn't turning on…]

Class, Week 10, Day 2: Cross-Validation

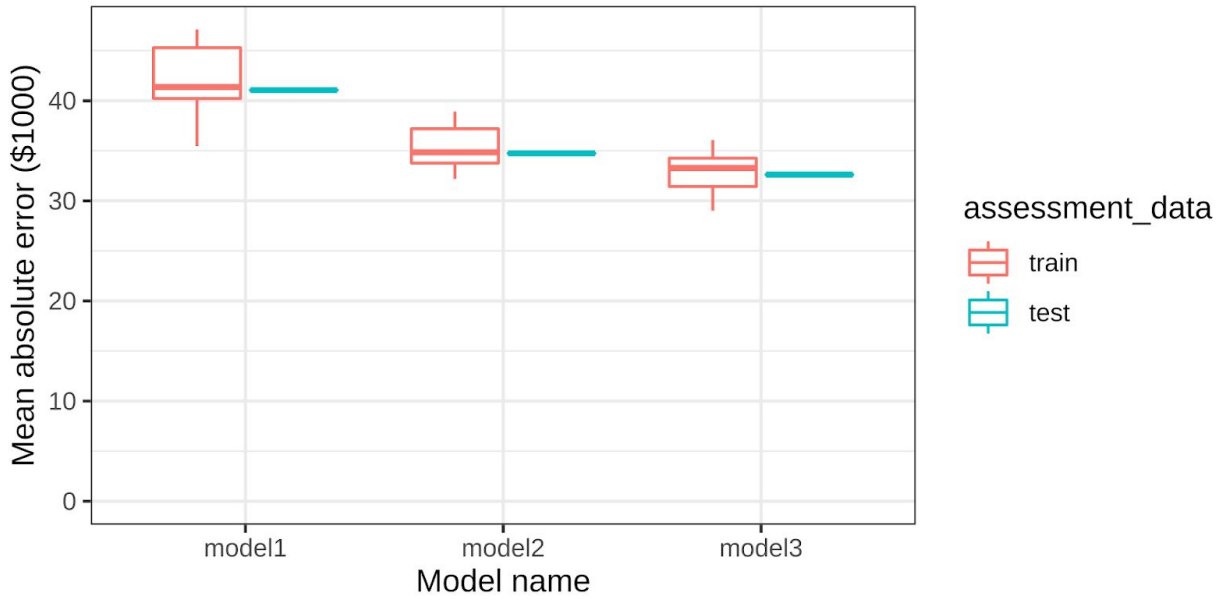
Q&A on decision trees:

- Decision tree vs. lin regression?
    - Decision tree: crisp regions are easy, smooth variation is hard
    - Linear regression: smooth variation is easy; crisp regions are hard
- Linear regression can use different types of basis functions -- splines, sinusoids, rectifiers
    - Like more cyclic data (yearly), you don't want lin.reg., you want something that'll smooth the boundaries
- Limit to num of decisions?
    - Skldfj
- Can greedy algorithms be worse?
    - Yep… short-term gain gives long-term regret.
        - >> it's a nice analogy too lol
    - Do outliers mess it up? Or why is this bad? -- not sure, not answered.

Cross-Validation

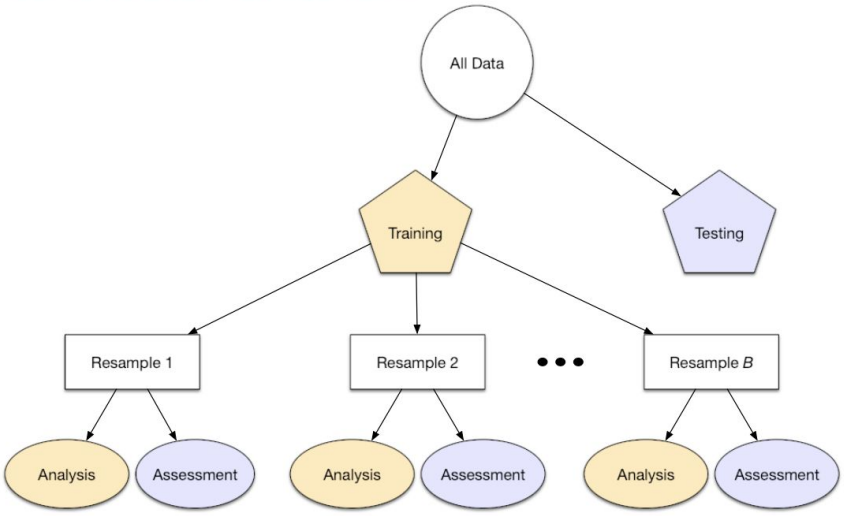
Why?: measure accuracy on unseen data *without peek @ test set!!*

Lab 9: gives a much better assessment compared to

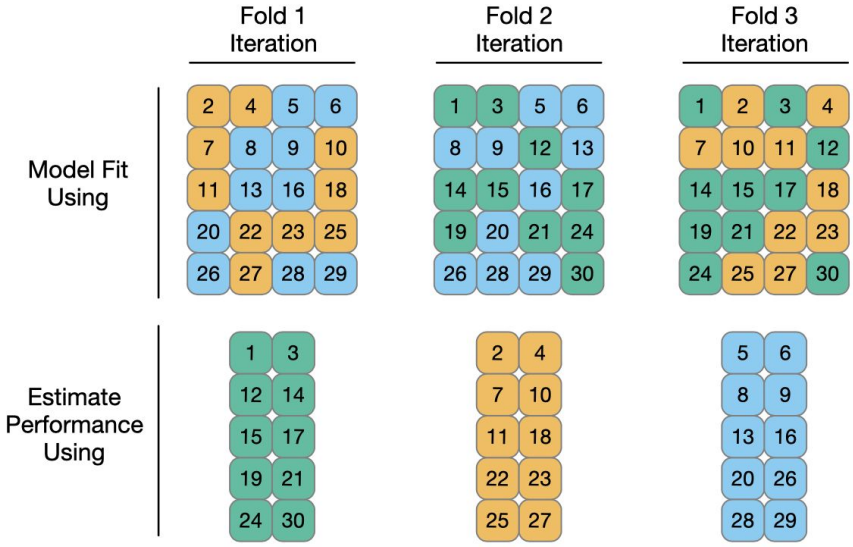


Estimates of model performance….

What is it doing?



- Resampling!
    - Draw with replacement?
    - Resample 1 MAY CONTAIN some of the same data points as Resample 2



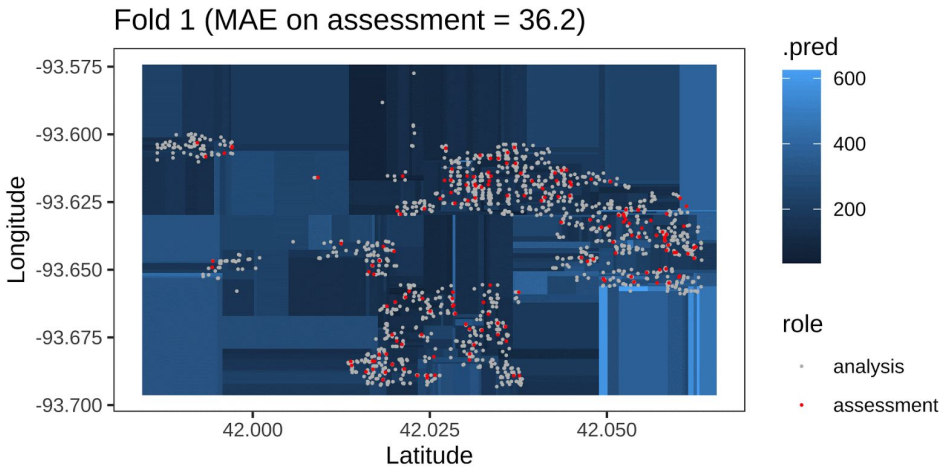
-
    - Estimates are still somewhat related (not independent assessments) because they have some fitting overlap
    - Testing has no overlap
    - Good for moderate —> large datasets.
        - Nested cross-validation: reassign the folds multiple times

How to do Cross-Validation?

0. Ideally, have more data to (test/train) on???
1. Declare splitting strategy

a. rsample::vfold_cv(v = 10)
b. `Ames_resamples <- ames_train %>% vfold_cv(v = 10)`

2. Fit on each resample, evaluate using a set of metrics…
   a. Houses in the analysis set (grey, not red) tell us about the patterns the decision tree picks up on



   b. FIT RESAMPLES!!

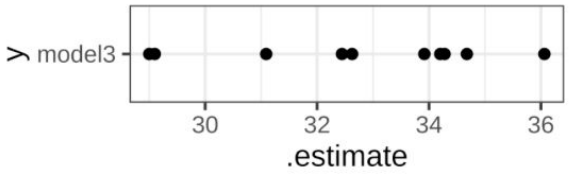
```
model3_samples <- model3_spec %>%
 fit_resamples(
   Sale_Price ~ Latitude + Longitude,
   resamples = ames_resamples,
   metrics = metric_set(mae))
model3_samples %>% collect_metrics(summarize = FALSE)
```

```
## # A tibble: 10 x 4
##    id     .metric .estimator .estimate
##    <chr>  <chr>   <chr>          <dbl>
## 1 Fold01 mae     standard        34.2
## 2 Fold02 mae     standard        31.1
## 3 Fold03 mae     standard        29.0
## 4 Fold04 mae     standard        33.9
## 5 Fold05 mae     standard        29.1
## 6 Fold06 mae     standard        36.1
## # … with 4 more rows
```

3. Plot and/or summarize the metrics
   a. PLOT:

```
model3_samples %>%
 collect_metrics(summarize = FALSE) %>%
 ggplot(aes(x = .estimate, y = "model3")) +
```

```
 geom_point()
```



b. SUMMARIZE:

```
model3_samples %>%
 collect_metrics(summarize = TRUE)
```

```
## # A tibble: 1 x 5
##   .metric .estimator  mean     n std_err
##   <chr>   <chr>      <dbl> <int>   <dbl>
## 1 mae     standard    32.7    10   0.751
```

TIDY WAY TO COMPARE MODELS:

1. Data frame of model specs

```
all_models <- tribble(
 ~model_name, ~spec,
 "model1",    decision_tree(mode = "regression", tree_depth
= 2),
 "model2",    decision_tree(mode = "regression", tree_depth
= 30),
 "model3",    decision_tree(mode = "regression",
cost_complexity = 1e-6, min_n = 2)
)
```

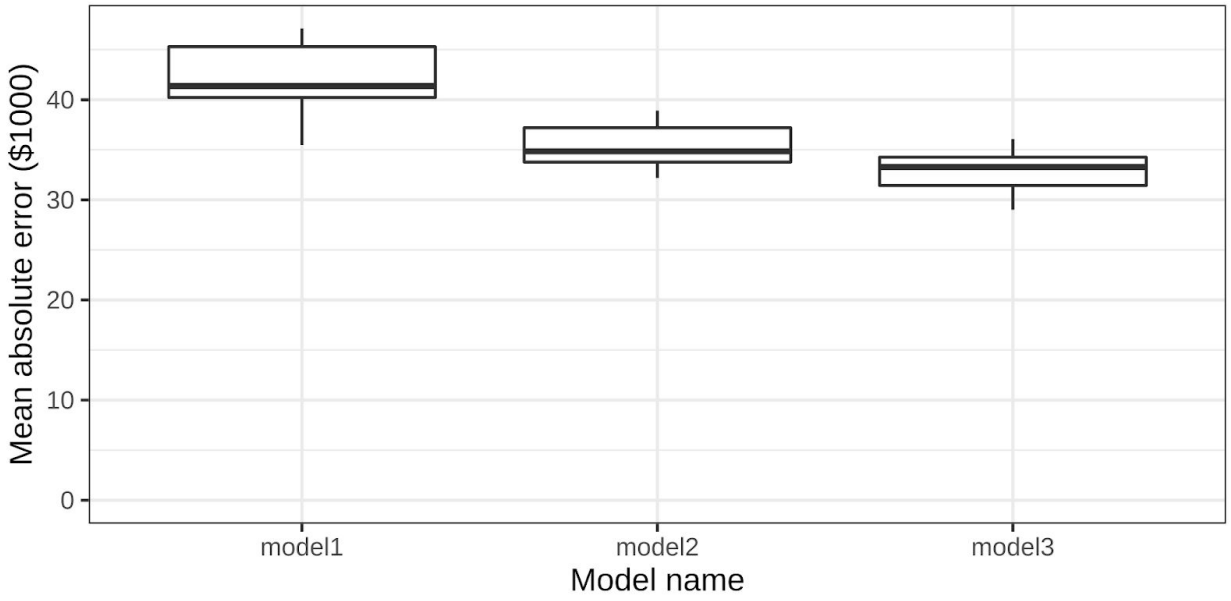
2. Sample each model (using dplyr::rowwise) -- essentially making a group for each row… a for loop?

```
models_with_samples <- all_models %>%
 rowwise() %>%
 mutate(samples = list(
   spec %>% fit_resamples(
     Sale_Price ~ Latitude + Longitude,
     resamples = ames_resamples,
     metrics = metric_set(mae))))
```

```
models_with_samples
```

```
## # A tibble: 3 x 3
## # Rowwise:
##   model_name spec      samples
##   <chr>      <list>    <list>
## 1 model1     <spec[+]> <tibble [10 × 4]>
## 2 model2     <spec[+]> <tibble [10 × 4]>
## 3 model3     <spec[+]> <tibble [10 × 4]>
```

```
models_with_samples %>%
 rowwise(model_name) %>%
 summarize(collect_metrics(samples, summarize = FALSE)) %>%
 ggplot(aes(x = model_name, y = .estimate)) +
   geom_boxplot() + labs(x = "Model name", y = "Mean
absolute error ($1000)") + coord_cartesian(ylim = c(0, NA))
```



Week 11 Day 1: Cross-Validation

Why?

- Puzzle:
  - We want to pick the model that works best on unseen data.... but as soon as we try one model, we've peeked at the data!
- Solution:
  - Divide training data into V piles (e.g., 10)
  - Hide one pile from yourself.
    - train on ("analyze") the rest,
    - evaluate ("assess") on the one you held out.
  - Repeat for each of the V piles.
  -

```
cross_val_scores <- function(complete_model_spec, training_data, v, metrics = metric_set(mae)) {
  # Split the data into V folds.
  set.seed(0)
  resamples <- vfold_cv(training_data, v = v)

  # For each of the V folds, assess the result of analyzing on the rest.
  raw_cv_results <- complete_model_spec %>%
    fit_resamples(resamples = resamples, metrics = metrics)

  # Return the collected metrics.
  collect_metrics(raw_cv_results, summarize = FALSE)
}
```

A model spec?

- A workflow: recipe e+ model_spec
- A model spec is like a class, and a model is like a specific instance of a class.

Workflow = recipe + modelSspec.

```
spec <- workflow() %>%
  add_recipe(recipe) %>%
  add_model(model)
```

e.g.,

```
spec <- workflow() %>%
  add_recipe(
    recipe(Sale_Price ~ Latitude + Longitude, data = ames_train)
  ) %>%
  add_model(
    linear_reg()
  )
```

-

Week 11, Day 2: Classification

~ Classification: Which of several categories? ~

- Problem intro: EDA, Data wrangling in R
- Classification workflow:
    - Models: decision tree, logistic regression
    - Model outputs: scores and decisions
    - Model metrics: accuracy, sensitivity, specificity
    - Validation

Logistics notes:

- Project should be:
- ***Interesting:*** should be interesting in *some* aspect… really thorny data wrangling, or really interesting modeling, or bringing it together with another dataset, (gene annotations / systems), or asking really interesting questions of it. >> *think: which parts are the interesting parts*
- ***Your own:*** ask a different question of the same data; here's two ways to do this, and here's what I think is better

Week 11, Day 3 : Python Data Wrangling & Classification

- Logistic regression: essentially classifying (categorization) with linear regression.
- Cross validation!!!!! Only seeing training data! Neither the initial train/test, nor cross-validation

Week 12, Day 1: Data Scraping

Data Scraping Examples
Used to be different tidyverse (readr) vs. utils
Defaults changed though, so its similar
Dotted version: tries to fix column names
Replaces columns with X1 and like X2…. helpful fix… really actually unhelpful.

Week 12, Day 2: Inference

What's the goal?

Predict unseen labels

How much will this house sell for?

Does this child have autism?

Is this a positive or negative movie review?

Infer relationships between features and labels

How much does home size affect price?

Is DNA methylation a marker of autism?

Does "sick" indicate a positive or negative review?

Understand the **causal** effect of interventions

How much will building an addition increase the price of my home?

Will antioxidants prevent autism?

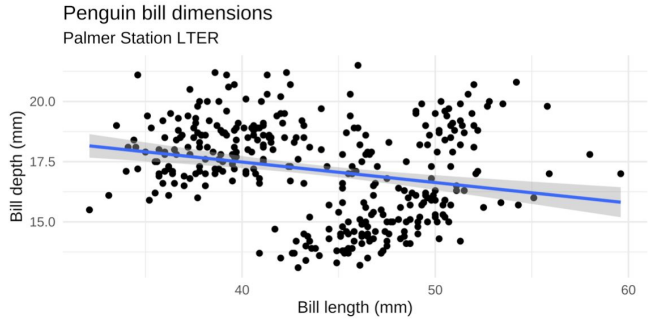
Gold standard: randomized clinical trial

Will cutting this scene make my movie get better reviews?

Techniques for Inference…

- Statists: 2-sample t tests, chi squared tests, ANOVA
- Inference about model parameters (coefficient standard errors)
- Variable importance plots
- Benefit of adding each feature

How does bill length relate to bill depth?



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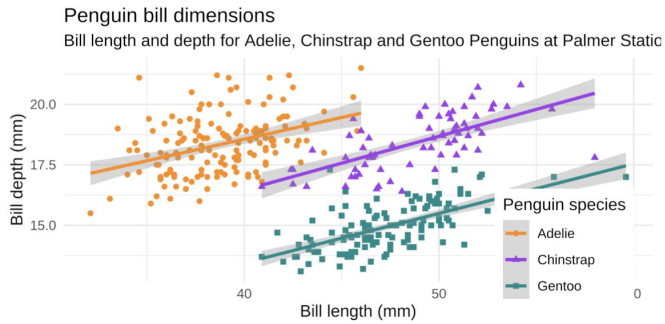
- It looks like a negative relationship...

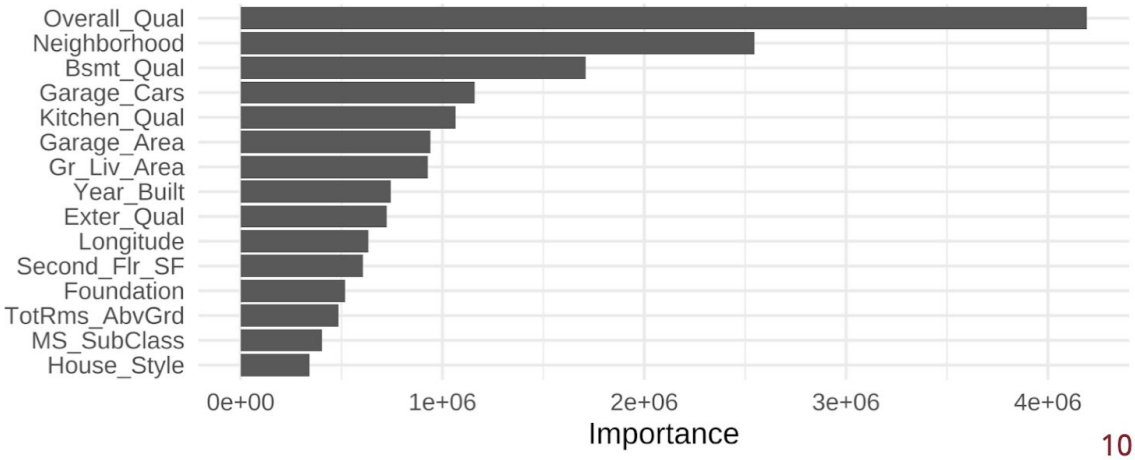
How does bill length relate to bill depth?



- But it's really a positive relationship! (*Simpson's Paradox*)
- Taking into account the species can drastically change our interpretation of other features
    - It rarely makes sense to think about one feature in isolation

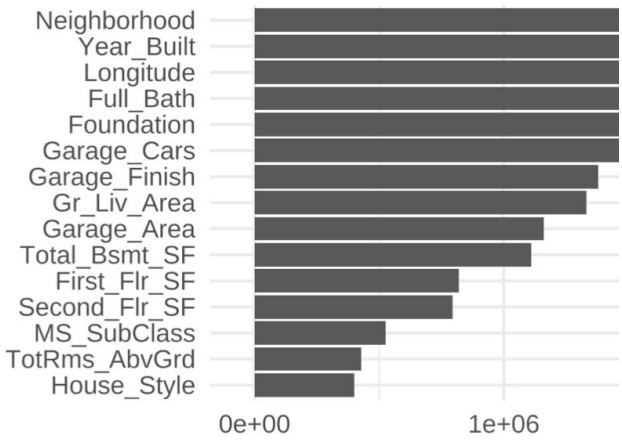
Variable Importance Plots

```
regresion_workflow <- workflow() %>%  add_model(decision_tree(mode = "regression") %>% set_engine('rpart'))

model <- regresion_workflow %>%
  add_recipe(recipe(Sale_Price ~ ., data = ames_train)) %>%
  fit(data = ames_train)

model %>% pull_workflow_fit() %>% vip::vip(num_features = 15L)
```



Yet...when we take out the overall_quality, we see other features get prioritized?!?!

- Year built, longitude, full_bath go way up



-
- (Because it's built into it???)

How much does it help to have a feature in?

- Take it out and see what happens.
- See appendix.

Week 12 Day 3: Clustering

Midterm Average: 85%
Inference for Projects:

Try dropping out predictors, try VIP plots.
Keep in mind: you might be capturing the information in one variable in another variable. They could be correlated.
Interactions: see plot strategy in Lab 10 (plotting marginal effects of each predictor)
Difference in MAE (or RMSE, specificity, eetc) to be meaningful? —> look @ confidence intervals.

Project:

By thanksgiving, have some initial EDA
Use packages: tidyverse, glue, knitr

Clustering

Supervised Learning:

We have a *target* we're trying to predict

"How much will these homes *sell* for?"
"How long will this person spend watching this video?"

Unsupervised Learning

We don't have an *exact target* to predict, or we want to explore relationships in the data

"What general *types of homes* are

Are there distinct types of COVID symptoms?

Clustering

GOAL: put observations into groups…

Same group = similar to each other

Different groups = different from each other

QUESTIONS:

How many groups? Broad buckets, or fine grained?

How do we define "similar" / "different"

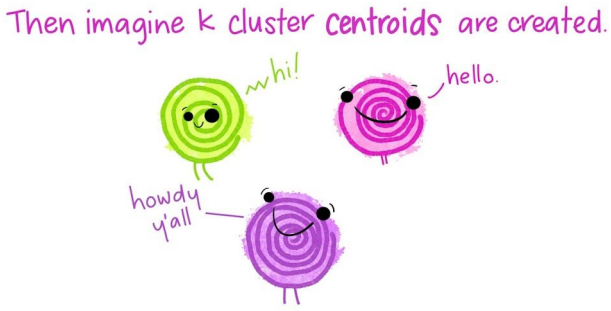
Is it based on geographical location? Neighbors are "similar"? Or what if your house is a cottage and the neigboring house isa mansion?

K-means clustering…!

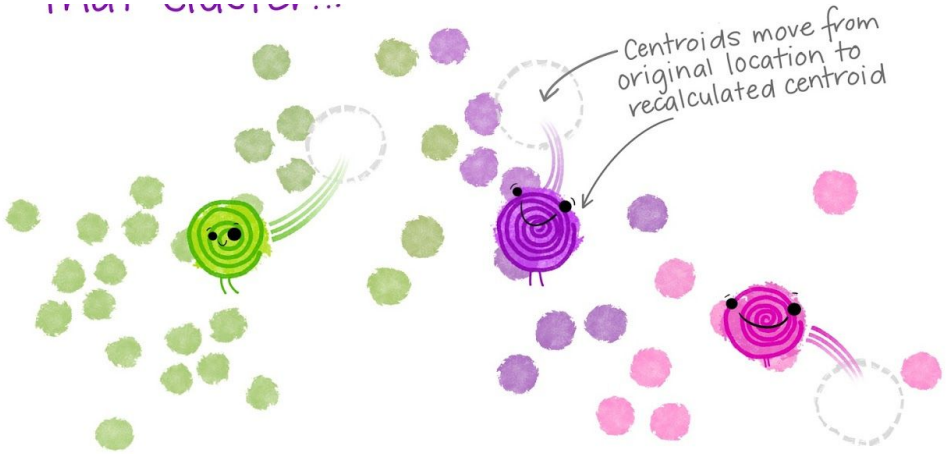
K-means clustering:

Assign each observation to one of *k* clusters based on the nearest cluster centroid.

1. Specify # of clusters (e.g., k = 3)



2. Place the k centroids at random in your space
3. Each observation gets temporarily "assigned" to its closest (by Euclidean distance) centroid
4. Then the centroid of each cluster is calculated based on all the observations assigned to that cluster.



OH: now that the cluster centroids have moved, some of the observations are now closer to a *different* centroid!...

5. So, **observations get reassigned** to a different cluster based on the recalculated centroid.
6. Now that observations have been reassigned, the centroids need to move again! **Recalculate centroids from updated clusters.**
7. (repeat steps 5 & 6)
8. Once centroids no longer move / once observations are no longer reassigned, then iteration is done & each observation is assigned to its final cluster.

Week 13 Day 1: Ethics

Q&A Review:

- A bigger step_range makes the feature “more important” because of the euclidean distance between 2 things.

A Series of Mini discussions… See cohort channel!

Week 14 Day 1: Databases & Data Formats

Q&A:
Social media censoring:

- Who makes the choices? Moderators on subreddits, or a committee on Twitter?
- Control @ the source (Twitter) vs. recommendations/ads (Facebook)
- Should we even *have* algorithms recommending / ranking content? “Is it worth the cost?”
- Individual responsibility vs. corporate responsibility.

Data Formats

Tabular, delimited (csv/tsv), or fixed-width
Tabular, structured (excel, SPSS/Stata/SAS)
Hierarchical -- more flexibility, can have tables within tables (JSON, XML, HTML)
Database: SQLite (most apps), PostgreSQL/MyQSL/Oracles (in cloud), Google Big Query

Spreadsheets vs Databases

Spreadsheets	**Databases**
Often exchange by email	Centralized, highly available servers
Hope the format doesn’t change	Documented schema
Capacity Limited (article/article)	Large capacity
Slow to query	Fast queries
Decentralized (resilient?) -- if it goes down, you don’t all go down?	

APIs

- Querying an external provider for the data you want
- examples:
    - Spotify
    - Google maps
    - Twitter
    - Disgenet, NCBI

Local Data	**API**

Any query you want	Only queries the API exposees
As much as you want	Often rate-limited
Full dataset must fit on your computer	Contain practically unlimited data… But you can only see a small part of it
Must be complete dataset	Can stream in new data

Example API: Bike Share Feeds

RETRIEVE DATA

station_info_response <-
httr::GET("https://gbfs.capitalbikeshare.com/gbfs/en/station_information.json")
station_info_response

PARSE THE RESULTS

```
station_info <- jsonlite::fromJSON(station_info_text,
simplifyDataFrame = TRUE)
stations <- station_info$data$stations
stations %>% glimpse()
```

PROFIT

```
capacity_palette <- leaflet::colorNumeric("GnBu", domain = stations$capacity)
lp <- stations %>%
 leaflet() %>%
 addProviderTiles(providers$CartoDB.Positron) %>%
 addCircleMarkers(~ lon, ~ lat, color = ~capacity_palette(capacity), radius = 2, stroke = FALSE,
fillOpacity = 1) %>%
 addLegend("bottomright", pal = capacity_palette, values = ~capacity)
lp$height <- 300
lp
```

SQL

Grammar of Data

dplyr (`data %>%`)	Pandas	SQL
`select(col1, col2)`	`data[['col1', 'col2']]`	`SELECT col1, col2 FROM data`
`filter(col1 > 5)`	`data.query('col1 > 5')`	`SELECT * FROM data WHERE col1 > 5`
`left_join(data2, by = "col2")`	`pd.merge(data, data2, by="col2", type="left")`	`SELECT * FROM data LEFT JOIN data2 ON data.col2 == data2.col2`
`group_by(col2) %>% summarize(m = max(col1))`	`data.group_by('col2')['col1'].max()`	`SELECT max(col1) AS m FROM data GROUP BY col2`
`pivot_longer()`	`data.melt()` or `data.pivot()`	**No standard approach**

BigQuery

To use BigQuery, you need to create a project in Google Cloud Platform to use for billing.

```
billing_project <- "calvindsdev"
#you have to make your own, unless you sweet talk Prof. Arnold into joining his, haha
```

Then you can use `bigrquery` to get set up to make BigQuery API calls.

```
library(bigrquery)
bigrquery::bq_auth(email = TRUE)

bq_connection <- DBI::dbConnect(
 bigrquery::bigquery(),
 project = "bigquery-public-data",
 billing = billing_project
)
```

COVID Example

Tbl… it's actually a database, but you can do similar things to dataframes. (glimpse, etc)
-- shows the same thing from dplyr in SQL!

Week 14 Day 2: Text Classification & Bias

Why should ee do ths? Why is it important?

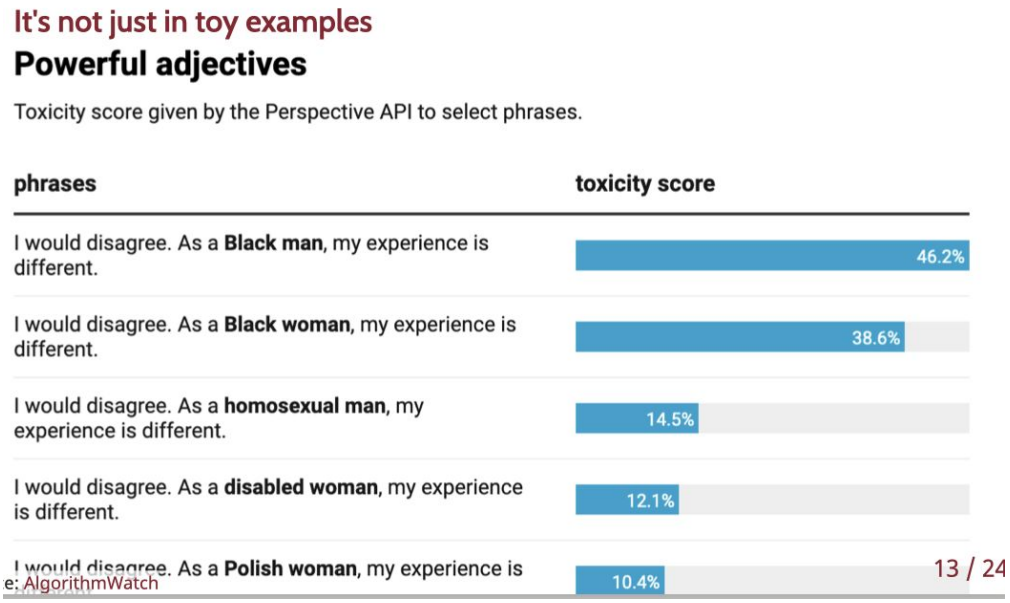
- Lots of data is *only* in text form…
- Text gives more *depth* to existing data
- Text enables new interactions with data

What can we do with text data?

- A lot.

- Net neutrality fake comments
    - Each were different, but followed the same format

"In the matter of restoring Internet freedom. I'd like to recommend the commission to undo The Obama/Wheeler power grab to control Internet access. Americans, as opposed to Washington bureaucrats, deserve to enjoy the services they desire. The Obama/Wheeler power grab to control Internet access is a distortion of the open Internet. It ended a hands-off policy that worked exceptionally successfully for many years with bipartisan support.",
"Chairman Pai: With respect to Title 2 and net neutrality. I want to encourage the FCC to rescind Barack Obama's scheme to take over Internet access. Individual citizens, as opposed to Washington bureaucrats, should be able to select whichever services they desire. Barack Obama's scheme to take over Internet access is a corruption of net neutrality. It ended a free-market approach that performed remarkably smoothly for many years with bipartisan consensus.",
"FCC: My comments re: net neutrality regulations. I want to suggest the commission to overturn Obama's plan to take over the Internet. People like me, as opposed to so-called experts, should be free to buy whatever products they choose. Obama's plan to take over the Internet is a corruption of net neutrality. It broke a pro-consumer system that performed fabulously successfully for two decades with Republican and Democrat support.",
"Mr Pai: I'm very worried about restoring Internet freedom. I'd like to ask the FCC to overturn The Obama/Wheeler policy to regulate the Internet. Citizens, rather than the FCC, deserve to use whichever services we prefer. The Obama/Wheeler policy to regulate the Internet is a perversion of the open Internet. It disrupted a market-based approach that functioned very, very smoothly for decades with Republican and Democrat consensus.",
"FCC: In reference to net neutrality. I would like to suggest Chairman Pai to reverse Obama's scheme to control the web. Citizens, as opposed to Washington bureaucrats, should be empowered to buy whatever products they prefer. Obama's scheme to control the web is a betrayal of the open Internet. It undid a hands-off approach that functioned very, very successfully for decades with broad



This algorithm should not have been doing this…
Look @ training data it's using

Week 14 Day 3: Modeling and Forecasting

It will change everything! Deep learning in protein structures from sequences

Random Forests
Modeling

- Capture complex patterns while minimizing over-fittings

Advanced Modeling in tidymodels

Shortcut: usemodels package (devtools::install_github("tidymodels/usemodels"))

```
data(ames, package = 'modeldata')
usemodels::use_xgboost(Sale_Price ~ ., ames)
```

Also… read about:

- tune package, for helping find good settings for hyperparameters
- finetune package (announcement blog post) for doing that efficiently

Check out this Rstudio blog about classifying images with torch, to tell apart bird species! Has code and steps nicely outlined.

Additionally: 3 things you need to know about Convolutional Neural Networks . From the article:

> A convolutional neural network (CNN or ConvNet), is a network architecture for deep learning which learns directly from data, eliminating the need for manual feature extraction.
> CNNs are particularly useful for finding patterns in images to recognize objects, faces, and scenes. They can also be quite effective for classifying non-image data such as audio, time series, and signal data.

Week 15, Day 1: Wrap-up: Communication and Justice

Last day of class!

Communication: Making a Data Driven Argument
Have a main point & say *how* they're connected, how it supports your main point.
Tell a story: chart 1, therefore chart 2, but chart 3.
Anchor conclusions in data…

- Thee units are probably seconds because ____
- The fit looks good -- because the mean error of $15 is leeds than 0.1% of the price
- This was surprising because I expected _____

Use appropriate language

- Plan language: for the overview, conclusion, and visuals
    - Labels: real names, not `code_names`
    - Don't assume the reader knows the structure of the data
- Technical language: when describing methods (data acquisitions, wrangling, modeling, etc.)
    - What data representation choices (recoding?) did you make? *Why?*
    - What modeling choices (once feature over another?)? *Why?*
    - Recognize when you're making decisions, cite them, say *why,* state your conclusions precisely.

Colors!

Polish is not our primary goal, clarity is.

Sharing

Rs connect!

Publish document

Finalized or source code.

Publish from account. Title.

A Biblical Critique of Secular Justice and Critical Theory

Keller's bullet-point summary of biblical justice:

- Community above individual (voluntarily)
- Equity: equal treatment, dignity
- Collective responsibility
- Individual responsibility
- Advocacy for poor and marginalized

> What does biblical justice require, in the area of data science?

Post your thoughts in your Cohort channel.

Responsibility: being thoughtful and clear about the significance & shortcomings of your findings
Community/Advocacy: making sure that what you're doing is *helping* your community, not hurting it

Classmates' ideas:

- Care for people together with care for environment
- Care for individual people affected, not just general economic impacts

- Cherishing and celebrating what God has made (people, natural resources) instead of exploiting
- Need safeguards to protect from the effects of sin
- Isaiah 56:1, Psalm 82:3

Community:

- Privacy
    - Valuing other people's autonomy and information. The *people* behind the data.
- Integrity in data collection, analysis, reporting, communication.

Equity:

- *Direct* impact
    - Fair risk assessment (loans discussion)
    - Fair resource allocation (who needs what)
    - Fair surveillance (don't hyper-surveil the poor, etc)
- *Indirect* impact
    - ads for criminal background checks more often for Black names
    - don't tolerate higher speech reco error rates for minorities
    - show a representative diversity of age/gender/race/... in image searches

Corporate responsibility:

- Even if I intend no prejudice, my algorithm could be prejudiced because of training data.
- Even if my work is honest, I could be supporting a company that exploits other workers directly or rely on conflict minerals and child labor
- Environmental responsibility is both individual and collective

Individual responsibility:

- I must do what's right, whether or not my company's policies require it.
- When something isn't right, I need to say something even if it risks my job.
    - Be strategic about when, who, and how to say it

Advocacy:

- By *listening to* and *amplifying,* not *speaking for.*
- beware of doing "parachute research" or de-contextualized "Data for Good"
    - Jumping in to solve a problem / have an impact, then leave.

Further Reading

- The Oxford Handbook of Ethics of AI
    - e.g., chapter of Race and Gender was written by Timnit Gebru
- Coded Bias documentary
- Fast.AI Data Ethics course
- Ethics and Data Science by Mike Loukides, Hilary Mason, DJ Patil

- Weapons of Math Destruction: *How Big Data Increases Inequality and Threatens Democracy*, by Cathy O'Neil
- How Charts Lie: *Getting Smarter about Visual Information*, by Alberto Cairo
- How Deceptive are Deceptive Visualizations? Pandey et al., CHI 2015

Who/What He's Reading / Following: Data Ethics

- AI Now Institute
- Data and Society
- AlgorithmWatch
- Harvard BKC
- Data Feminism
- ACM Conference on Fairness, Accountability, and Transparency (FAccT)

People:

- Timnit Gebru
- Rediet Abebe
- J. Nathan Matias
- Joy Buolamwini

Who/What He's Reading / Following: Tech

- RStudio AI blog
- tidyverse blog
- RWeekly
- distill.pub
- Harvard Data Science Review
- TWiML Podcast
- Cassie Kozyrkov (@quaesita)

"What can I do?"

- Choose jobs carefully (How to Interview a Tech Company)
    - You *can* make a difference inside even a "bad" company--but recruit a support network like a missionary.
- Listen a lot. To diverse opinions.
- Keep in touch.