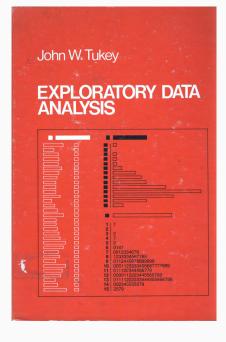
Stat 470/670 Lecture 1

What is Exploratory Data Analysis?



We will be exploring numbers. We need to handle them easily and look at them effectively. Techniques for handling and looking — whether graphical, arithmetic, or intermediate — will be important.

Tukey, Exploratory Data Analysis (1977)

A first example: Heights of the highest points by state

```
## load required packages and data
library(tidyverse)
## -- Attaching packages ------
tidyverse 1.3.0 --
## v tibble 3.0.1 v dplyr 1.0.2
## v tidyr 1.1.0 v stringr 1.4.0
## v readr 1.3.1 v forcats 0.5.0
## v purrr 0.3.4
## -- Conflicts ------
tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
options(tibble.print min = 15)
heights = read_csv("highest-points-by-state.csv")
## Parsed with column specification:
## cols(
## elevation = col double(),
## state = col character()
```

A first try at looking at the data

```
heights
## # A tibble: 50 x 2
##
     elevation state
##
         <dbl> <chr>
##
         733. Alabama
##
       6168. Alaska
##
         3851. Arizona
##
        839. Arkansas
##
        4418. California
##
         4399, Colorado
##
         725. Connecticut
##
         137. Delaware
##
        105. Florida
## 10
         1458. Georgia
## 11
         4205. Hawaii
## 12
         3859. Idaho
## 13
      376. Illinois
## 14
      383. Indiana
## 15
     509. Iowa
## # ... with 35 more rows
```

A second try at looking at the data

```
arrange(heights, elevation)
## # A tibble: 50 \times 2
##
     elevation state
         <dbl> <chr>
##
##
          105. Florida
##
       137. Delaware
##
       163. Louisiana
##
          246. Mississippi
##
          247. Rhode Island
##
          376. Illinois
##
          383. Indiana
## 8
          472. Ohio
## 9
          509. Iowa
## 10
          540. Missouri
## 11
          550. New Jersey
## 12
          595. Wisconsin
## 13
          603. Michigan
## 14
          701. Minnesota
## 15
         725. Connecticut
## # ... with 35 more rows
```

```
arrange(heights, desc(elevation))
## # A tibble: 50 \times 2
##
     elevation state
         <dbl> <chr>
##
##
        6168. Alaska
##
      4418. California
##
      4399, Colorado
##
         4392. Washington
##
         4207. Wyoming
##
      4205. Hawaii
##
      4123. Utah
## 8
         4011. New Mexico
##
      4005. Nevada
## 10
         3901. Montana
## 11
         3859. Idaho
## 12
         3851. Arizona
## 13
         3426. Oregon
## 14 2667. Texas
## 15 2207. South Dakota
## # ... with 35 more rows
```

Stem-and-leaf plots

Goals:

- Write down the set of numbers, keeping as much detail as possible
- Pack the numbers efficiently, so you can see all of them at once

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These are in conflict!

Stem-and-leaf plots

Remedy:

- Notice that parts of the numbers (the beginnings) are repeated.
- The first digit of each number is printed at the beginning of the line, the remainder at the ends.
- The first digit is the "stem", the remainder are the "leaves".

Stem-and-leaf-plot example

Set of numbers:

16, 17, 17, 17, 17, 18

Stem-and-leaf display:

1 | 677778

Stem-and-leaf plot for the elevations in meters:

```
stem(heights$elevation)
##
##
    The decimal point is 3 digit(s) to the right of the |
##
##
    0 | 11222445555667778
    1 | 0011123355566779
##
##
    2 | 0027
    3 | 4999
##
##
    4 | 00122444
##
    5 I
    6 | 2
##
```

The stem-and-leaf plot shows that there are three groups of states:

- Alaska
- The western and Rocky Mountain states (California, Colorado, Washington, Wyoming, Hawaii, Utah, New Mexico, Nevada, Montana, Idaho, Arizona, Oregon)
- All the other states

Note 1

Hoosier Hill: Elevation 1257 feet

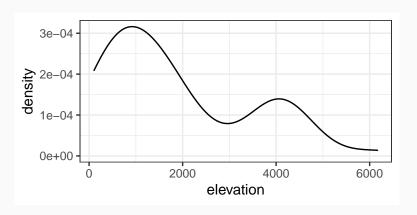


Source: google street view

Note 2

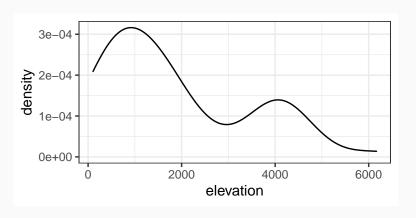
Compare the stem-and-leaf plot with a density estimate

```
ggplot(heights, aes(x = elevation)) + geom_density()
```



Compare the stem-and-leaf plot with a density estimate

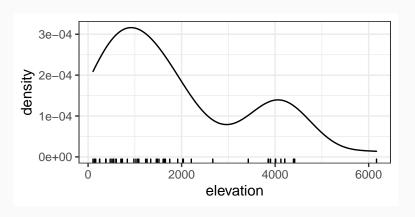
```
ggplot(heights, aes(x = elevation)) + geom_density()
```



Where is Alaska?

Compare the stem-and-leaf plot with a density estimate

```
ggplot(heights, aes(x = elevation)) + geom_density() + geom_rug()
```



Where is Alaska?

We have made an advance in understanding this set of numbers!

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What would traditional statistics have to say about these numbers?

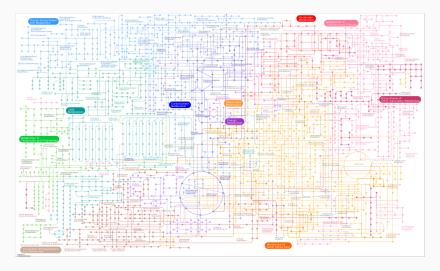
What if we have a many more numbers, e.g. census data?

is her Weste	ally pri e given rn Terri en publi	comp	olete, e	хсер	t for	the N.
DISTICTS		Free aubite Males under fixteen years.	Free white Fe- males, including beads of families.	All other free per- fons.	Slaves.	Total.
Vermont N. Hampsbire Massachusetts Rhode Island Rosel Island New York New Jersey Pennyswania Oelaware Maryland Virginia Kentucky N. Carolina Georgia	22435 36086 24384 95453 16019 60523 83700 45251 110988 11783 55915 110936 15154 69988 35576 13103	34851 24748 87289 15799 54403 78122 41416 106948 51339 116135 17057 77546 37722 14044	70160 46870 190582 32052 117448 152320 83287 206363 22384 101352 215046 28922 140710 66880 25739	630 53 ^k 546 3 3497 2808 46 54 2762 65 37 3899 8043 12866 114 4975 1801 398	948 2764 21324 11423 3737 103036 292627 12430 100572 107094 29264	141885 - 96540 378787 68825 237946 340120, 184139 434373 59094 319728 747610 73677 393751
Fotal number of inhabitants of he United States seclutive of S. Weffern and N. Fersitory.		Free Malen of age.	white	Jons.	Slaves.	1
W. territory	6271	10277	15365	361	3417	35691

Source: US Census Bureau Public Information Office, via the National Geographic Society

Or a large matrix?

Or graph data?



Source: KEGG PATHWAY Database

Exploratory vs. Confirmatory Analyses

Confirmatory analysis

- Probability model for the data specified before analysis takes place
- Given the probability model, test hypotheses or infer parameter values

Exploratory analysis: everything else! In particular:

- Check distributional assumptions
- Check for outliers
- Decide on variable transformations
- Decide on the form of the model: what variables to include

Exploratory analysis: everything else! In particular:

- Check distributional assumptions
- Check for outliers
- Decide on variable transformations
- Decide on the form of the model: what variables to include

BUT: Not limited to the work done before fitting a model! In the highest points example, we had an EDA-based advance that wasn't related to model fitting at all.

What does Tukey say?

Exploratory data analysis is detective work—numerical detective work—or counting detective work—or graphical detective work.

Exploratory data analysis is detective work—numerical detective work—or counting detective work—or graphical detective work.

As all detective stories remind us, many of the circumstances surrounding a crime are accidental or misleading. Equally, many of the indications to be discerned in bodies of data are accidental or misleading. To accept all appearances as conclusive would be destructively foolish, either in crime detection or in data analysis. To fail to collect all appearances because some—or even most—are only accidents would, however, be gross misfeasance deserving (and often receiving) appropriate punishment.

Exploratory data analysis can never be the whole story, but nothing else can serve as the foundation stone—as the first step.

Tukey, Exploratory Data Analysis (1977) pp. 1-3

Exploratory: Collect everything that even seems to be true about the data, detective in character, "magical thinking"

Confirmatory: Given one pre-planned hypothesis, infer parameter values or test hypotheses, judicial in character, set a high bar for what we are willing to believe about the data.

The never ending data analysis cycle:

- 1. Get data.
- 2. Perform exploratory analysis to suggest a model.
- 3. Fit the model.
- 4. Perform exploratory analysis to critique the model and suggest a new model.
- 5. Return to step 3.

The never ending data analysis cycle:

- 1. Get data.
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This workflow is dangerous!

- Using the data more than once
- Assiduous EDA means multiple comparison problems

Tukey's *EDA* also emphasizes tools and best practices for the practice of data analysis, all pen-and-paper based.

Example: Tallying

Standard method:

1 11 111 1111 744

Example: Tallying

Standard method:

1 11 111 1111 +++

Tukey's proposal:

Pen-and-paper methods primarily of historical interest.

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Philosophical descendants are the tidyverse packages in R.

What about this class?

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Two categories of topics: what to do and how to do it.

For what to do, organize by type of data:

- Univariate data
- Bivariate data
- Trivariate/Hypervariate data
- Categorical data
- Distance data
- Graph data
- Other topics according to interest

In addition:

Dangers of EDA and how to avoid them

In the how to do it bin, we will learn to work with

- R
- ggplot2
- tidyverse packages

How is this class different from others?

- Machine learning: We put less emphasis on supervised learning.
- Data mining: More emphasis on visualization.
- Applied statistics: Less emphasis on p-values and inference, more flexibility in the methods used.

Texts:

- Cleveland, Visualizing Data
- Wickham, ggplot2: Elemant Graphics for Data Analysis
- Wickham and Grolemund, R for Data Science
- Other notes posted to the class website and canvas as necessary

Assessment:

- Homeworks (30%).
- Two mini projects (30%).
- Final project (40%).

How to succeed:

- Practice!
- Follow along with the code examples, actually type in the commands instead of copying and pasting.
- Start early on assignments and projects.
- Presentation matters make your documents look nice enough thta you would be happy to show them to potential employers as examples of your work.

We will be exploring numbers. We need to handle them easily and look at them effectively. Techniques for handling and looking — whether graphical, arithmetic, or intermediate — will be important.

Tukey, Exploratory Data Analysis (1977)