Lecture #1: Introduction to CS-S109A

aka STAT121A, AC209A, CSCIE-109A

CS-S109A: Introduction to Data Science

Kevin Rader

HARVARD Summer School

With thanks to Pavlos Protopapas, *et al*.

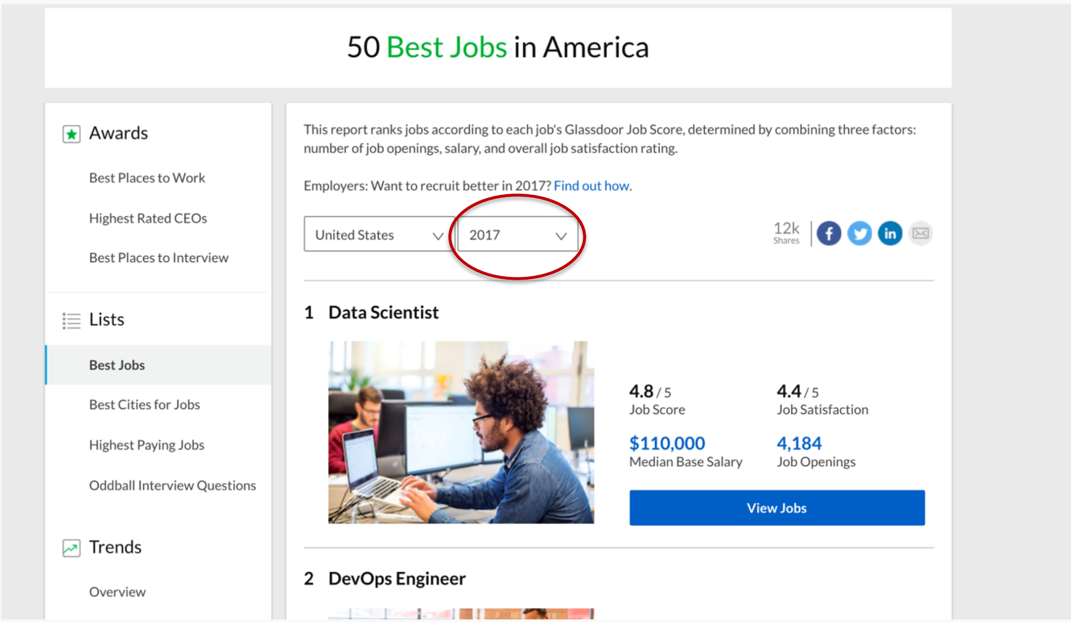
Lecture Outline

- Why data science? Why taking CS109A?
- What is data science?
- What is this class and what it is not?
- The data science process
- What are Data?
- Data Exploration
    - Descriptive Statistics
    - Visualizations
- An Example

Reading: Syllabus & Ch. 1 in *An Introduction to Statistical Learning* (ISLR)

Why?

Jobs!



50 Best Jobs in America
Awards
Best Places to Work
Highest Rated CEOs
Best Places to Interview
Lists
Best Jobs
Best Cities for Jobs
Highest Paying Jobs
Oddball Interview Questions
Trends
Overview
This report ranks jobs according to each job's Glassdoor Job Score, determined by combining three factors: number of job openings, salary, and overall job satisfaction rating.
Employers: Want to recruit better in 2017? Find out how.
United States
2017
12k Shares
1 Data Scientist
4.8 / 5
Job Score
4.4 / 5
Job Satisfaction
$110,000
Median Base Salary
4,184
Job Openings
View Jobs
2 DevOps Engineer

Why?

Jobs!

glassdoor Jobs Company Reviews Salaries Interviews Salary Calculator Sign In Write Review For Employers Post Jobs Fr

Job Title, Keywords, or Company | Jobs | Location | Search

50 Best Jobs in America for 2019

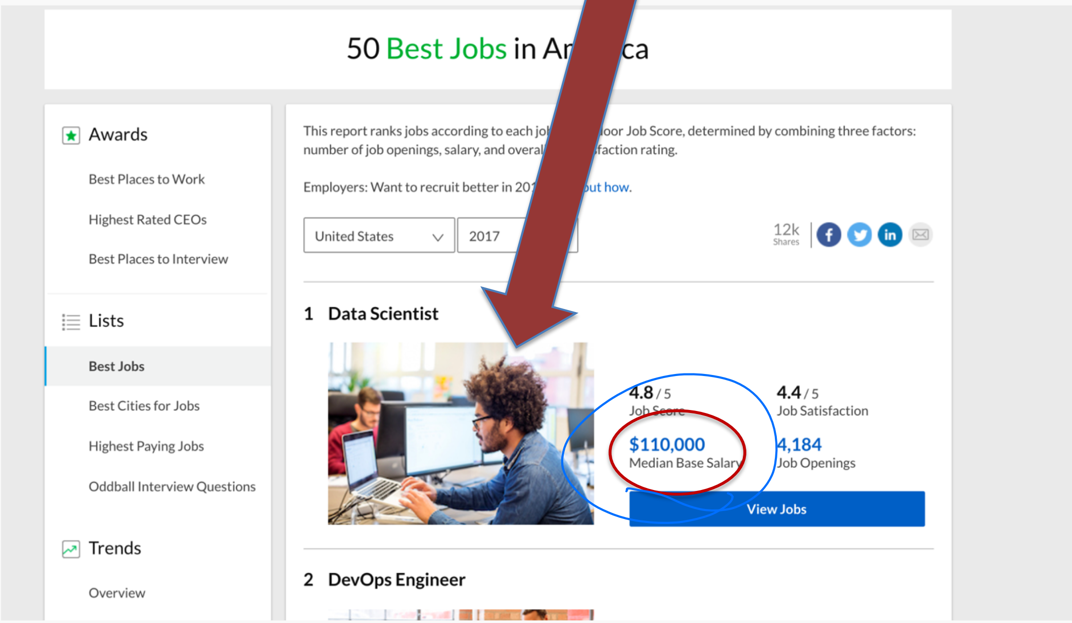
Best Jobs | 2019 | United States

Share

	Job Title	Median Base Salary	Job Satisfaction	Job Openings	
#1	Data Scientist	$108,000	4.3/5	6,510	View Jobs
#2	Nursing Manager	$83,000	4/5	13,931	View Jobs
#3	Marketing Manager	$82,000	4.2/5	7,395	View Jobs
#4	Occupational Therapist	$74,000	4/5	17,701	View Jobs
#5	Product Manager	$115,000	3.8/5	11,884	View Jobs

Why?

Jobs!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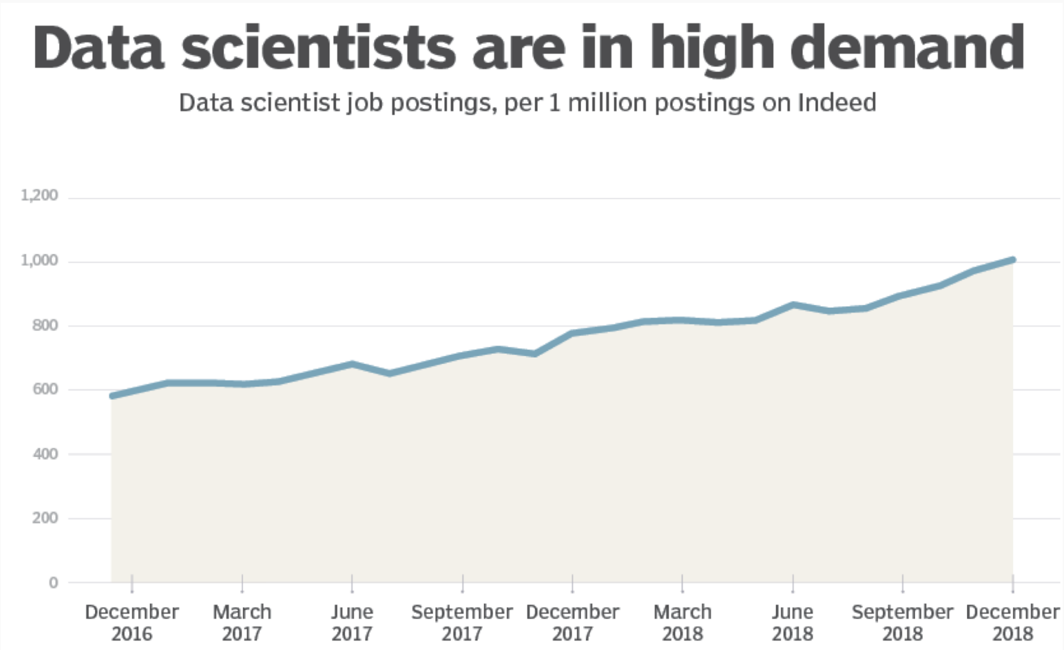
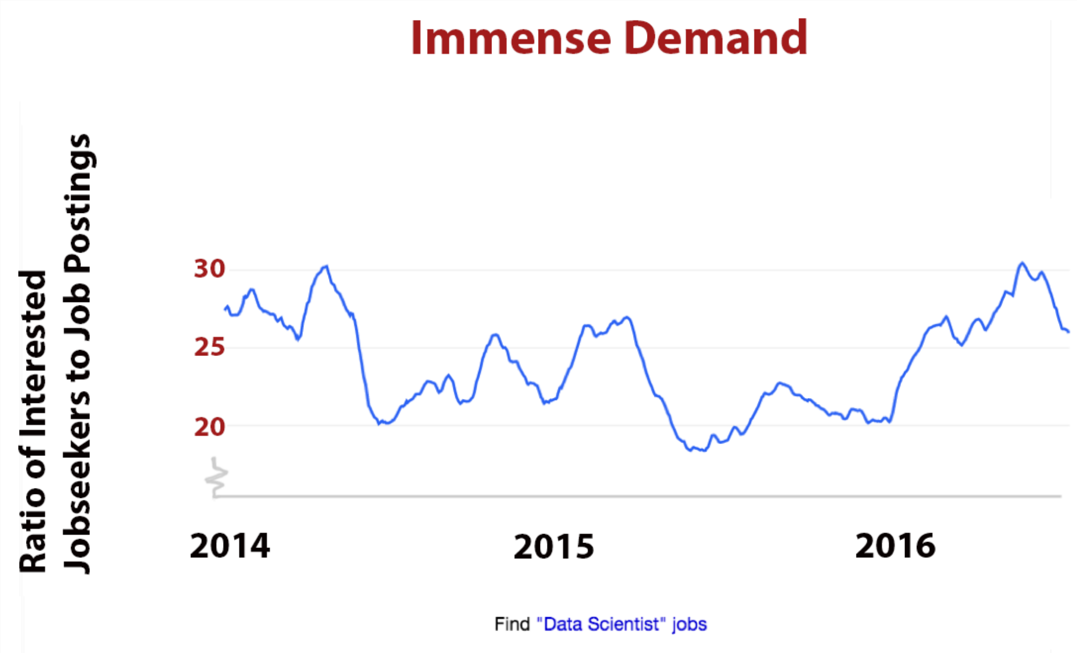
Why?


Data scientists are in high demand
Data scientist job postings, per 1 million postings on Indeed
1,200
1,000
800
600
400
200
0
December 2016
March 2017
June 2017
September 2017
December 2017
March 2018
June 2018
September 2018
December 2018

Why?



Immense Demand
Ratio of Interested Jobseekers to Job Postings
30
25
20
2014
2015
2016
Find "Data Scientist" jobs

Why?

Why do I love data science?

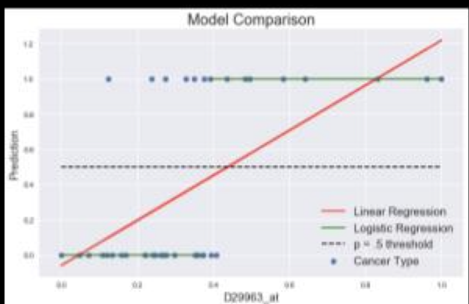
Why are you here?

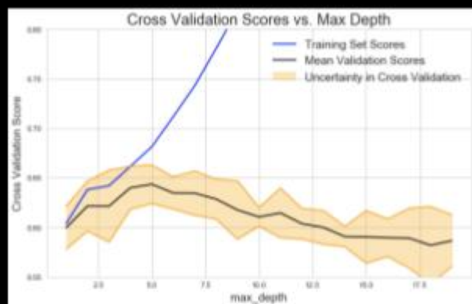
what my friends think I do

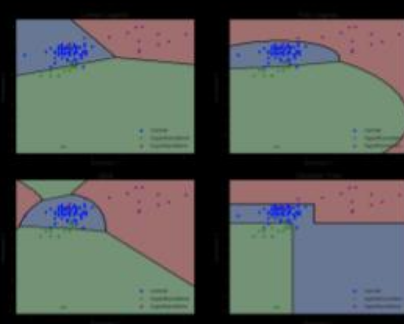
what my family thinks I do

what society thinks I do

what I actually (will) do in Data Science 1







A

Why?

Why are you here?

A little bit of history

data = tabulated numbers

History

Long time ago (thousands of years) science was only empirical and people counted stars

History (cont)

Long time ago (thousands of years) science was only empirical and people counted stars or crops

History (cont)

Long time ago (thousands of years) science was only empirical and people counted stars or crops and used the data to create machines to describe the phenomena

devices to automatically keep track of information

stonehenge: tell time and build calendars in the world of physics: deterministic

History (cont)

Few hundred years: theoretical approaches, try to derive equations to describe general phenomena.

1. $\nabla \cdot \mathbf{D} = \rho_V$
2. $\nabla \cdot \mathbf{B} = 0$
3. $\nabla \times \mathbf{E} = -\frac{\partial \mathbf{B}}{\partial t}$
4. $\nabla \times \mathbf{H} = \frac{\partial \mathbf{D}}{\partial t} + \mathbf{J}$

$$T^2 = \frac{4\pi^2}{GM} a^3$$

can be expressed as simply

$$T^2 = a^3$$

If expressed in the following units:

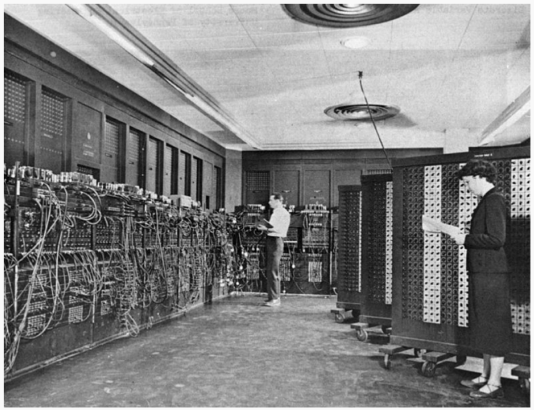
T	Earth years
a	Astronomical units AU (a = 1 AU for Earth)
M	Solar masses $M_\odot$

Then $\frac{4\pi^2}{G} = 1$

$$H(t)|\psi(t)\rangle = i\hbar \frac{\partial}{\partial t} |\psi(t)\rangle$$

History (cont)

About a hundred years ago: computational approaches



History (cont)

And then …. data science

↳ with the abundance of data in modern world, we need to be able to describe and model trends, relationships, and distributions of data

What is data science?

What?

The Data Science Process

- Ask an interesting question
- Get the Data
- Explore the Data
- Model the Data
- Communicate/Visualize the Results

What?

The Data Science Process

- Ask an interesting question
- Get the Data
- Explore the Data
- Model the Data
- Communicate/Visualize the Results

What is the scientific goal?

What would you do if you had **all** of the data?

What do you want to predict or estimate?

What?

The Data Science Process

Ask an interesting question

Get the Data

Explore the Data

Model the Data

Communicate/Visualize the Results

How were the data sampled?

Which data are relevant?

Are there privacy issues?

What?

The Data Science Process

- Ask an interesting question
- Get the Data
- Explore the Data
- Model the Data
- Communicate/Visualize the Results

Plot the data.

Are there anomalies or egregious issues?

Are there patterns?

EDA: exploratory data analysis

What?

The Data Science Process

- Ask an interesting question
- Get the Data
- Explore the Data
- Model the Data
- Communicate/Visualize the Results

Build a model.

Fit the model.

Validate the model.

Interpret the model

What?

The Data Science Process

- Ask an interesting question
- Get the Data
- Explore the Data
- Model the Data
- Communicate/Visualize the Results

What did we learn?

Do the results make sense?

Can we effectively tell a story?

What?

The material of the course will integrate the five key facets of an investigation using data:

1. data collection; data wrangling, cleaning, and sampling to get a suitable data set
2. data management; accessing data quickly and reliably
3. exploratory data analysis; generating hypotheses and building intuition
4. prediction or statistical learning
5. communication; summarizing results through visualization, stories, and interpretable summaries.

What?

Week 1:

Getting ready with python, jupyter notebooks, environments and numpy.

Basic statistics, visualization, pandas and data scraping

What?

Week 2:

Regression, and sklearn:

- knn regression
- Linear and Polynomial Regression
- Multiple Regression
- Inference in Regression (hypothesis tests, confidence intervals , bootstrapping, etc.).

What?

Week 3:

Model Selection, Regularization and Polynomial Regression

Logistic Regression and kNN

What?

Week 4:

PCA, High Dimensionality, and Dealing with Missingness

Decision Trees

What?

Week 5:

Random Forests, Boosting, and Stacking

Neural Nets

What?

Week 6:

Ethics, model visualizations and model interpretations

Experimental Design

Case study

Who? Instructor

Kevin Rader

Senior preceptor in Statistics. Teaches CS 109A & Stat 139 in the fall and Stat 102 and Stat 98 in the spring.

Research interests include complex survey analysis and causal inference. Hobbies include the outdoors, sports

(especially the aquatic variety), and of course, farming.

Who? Head TF

Chris Gumb

Chris is currently working towards a graduate degree in Data Science from Harvard Extension School with a particular focus on NLP. His other interests and hobbies include: music theory & jazz improvisation; and film history.

Who? Teaching Fellows

Nabib Ahmed
Dominique Cantave
Sol Girouard
Tessa Han
Erik Johnsson

Dennis Lin
Arpit Panda
Rylan Schaeffer
Joel Zhang

Lectures, Labs, Sections and Office Hours

During lecture will cover the material which you will need to complete the homework, and to survive the rest of your life in CS109A. *Attending* lectures is not necessarily required, but there will be quizzes at the end of each lecture (drop 50% of them) which will be available for 36 hours after lecture ends.

We will use a mix of notes and examples via notebooks.

1. Lecture notes and associated notebooks will be posted before lecture on GitHub.
2. Lectures will be recorded and posted within approximately 24 hours on web page.

Mondays and Wednesdays 12-3pm @Zoom

Lectures, **Labs**, Sections, and Office Hours

Labs are meant to help you better understand the lecture materials via examples, and will be heavily focused on implementing the coding via Jupyter Notebooks. Very little new conceptual material will be presented.

Labs will be recorded and posted within approximately 24 hours on Canvas.

Fridays 12-2pm @Zoom

Lectures, Labs, **Sections** and Office Hours

For those in different time zones or that work during the day, supplementary sections will be available on Tuesday and Thursday evenings, 9-10:30pm. There is no need to attend section if you attend lecture…it is a repeat of the work.

These sections will go through the Jupyter Notebooks from lecture. They will be led by the TFs.

Homework(s)

There will be 5 homework (not including Homework 0):

- Homework 0 (due Thursday)
- Homework 1: Web scraping, Beautiful Soup
- Homework 2: Regression kNN and Linear Regression
- Homework 3: Logistic Regression, Model selection, and Prediction Accuracy
- Homework 4: Decision Trees, Random Forests, PCA
- Homework 5: Ensemble Methods and Neural Nets

Homework(s)

You are encouraged but not required to submit in pairs on all homework assignments.

We will be using the Groups function in Canvas to do this, details to be announced later.

All homework are **due 11:59pm Tuesday** and homework will be released on Tuesday 5:00pm (a week in advance).

Final Exam

There will be an individual final exam due on Monday, August 3 (11:59pm).

The exam will be cumulative, and will be roughly the same length of a HW assignment.

Open-book and open-notes. Not open friend :(

Help

Help

The process to get help is:

1. Post the question in Ed and hopefully your peers will answer. We monitor the posts and we will respond within 12 hours from the posting time (allows for peer discussion/comments).
2. Go to Office Hours, this is the best way to get help.
3. For private matters send an email to the Helpline: s109a2020@gmail.com. The Helpline is monitored by all the instructors and TFs.
4. For personal matters send an email Kevin.

krader@fas.harvard.edu

rader@stat.

Sundays will be slow days, so please be patient!

Grades

Grades

- Homeworks: 60%
- Quizzes: 15% (50% of quiz grades are dropped)
- Final Exam: 25%
- **Total: 100%**

We do not have predefined cuts for grades. We look for breaks in the cumulative distribution. We will follow the summer school's policy on letter grades:

https://www.summer.harvard.edu/resources-policies/grades

What are Data?

The Data Science Process

Recall the data science process.

- Ask an interesting question
- Get the Data
- Explore the Data
- Model the Data
- Communicate/Visualize the Results

Data-heavy steps

Today we will begin introducing the data collection and data exploration steps.

What are data?

"A datum is a single measurement of something on a scale that is understandable to both the recorder and the reader. Data are multiple such measurements."

Claim: everything is (can be) data!

Where do data come from?

- **Internal sources:** already collected by or is part of the overall data collection of you organization.
  For example: business-centric data that is available in the organization data base to record day to day operations; scientific or experimental data.
- **Existing External Sources:** available in ready to read format from an outside source for free or for a fee.
  For example: public government databases, stock market data, Yelp reviews, [your favorite sport]-reference.
- **External Sources Requiring Collection Efforts**: available from external source but acquisition requires special processing.
  For example: data appearing only in print form, or data on websites.

scraping

Ways to gather online data

How to get data generated, published or hosted online:

- **API (Application Programming Interface):** using a prebuilt set of functions developed by a company to access their services. Often pay to use. For example: Google Map API, Facebook API, Twitter API

we may do this

- **RSS (Rich Site Summary):** summarizes frequently updated online content in standard format. Free to read if the site has one. For example: news-related sites, blogs

we won't do this

- **Web scraping:** using software, scripts or by-hand extracting data from what is displayed on a page or what is contained in the HTML file (often in tables).

we will do this

Web scraping

- **Why do it?** Older government or smaller news sites might not have APIs for accessing data, or publish RSS feeds or have databases for download. Or, you don't want to pay to use the API or the database.
- **How do you do it?** See HW1 (beautifulsoup)
- **Should you do it?**
  - You just want to explore: Are you violating their terms of service? Privacy concerns for website and their clients?
  - You want to publish your analysis or product: Do they have an API or fee that you are bypassing? Are they willing to share this data? Are you violating their terms of service? Are there privacy concerns?

Types of data

What kind of values are in your data (data types)?

Simple or atomic:

- **Numeric:** integers, floats ← quantative
- **Boolean:** binary or true false values ← binary/dummy
- **Strings:** sequence of symbols ← categorical

Data types

What kind of values are in your data (data types)? Compound, composed of a bunch of atomic types:

- **Date and time:** compound value with a specific structure
- **Lists:** a list is a sequence of values

Database

- **Dictionaries:** A dictionary is a collection of key-value pairs, a pair of values *x* : *y* where *x* is usually a string called the key representing the "name" of the entry, and *y* is a value of any type.

Example: Student record: what are *x* and *y*?

- First: Kevin
- Last: Rader
- Classes: [CS-109A, STAT139]

Data storage

"Excel Spreadsheet"
.csv files

How is your data represented and stored (data format)?

- **Tabular Data:** a dataset that is a two-dimensional table, where each row typically represents a single data record, and each column represents one type of measurement (csv, dat, xlsx, etc.).
- **Structured Data:** each data record is presented in a form of a [possibly complex and multi-tiered] dictionary (json, xml, etc.)
- **Semistructured Data:** not all records are represented by the same set of keys or some data records are not represented using the key-value pair structure.

Tabular Data

In tabular data, we expect each record or observation to represent a set of measurements of a single object or event. We've 'seen' this already in Lecture 1:

First Look At The Data

In [27]:
```
hubway_data = pd.read_csv('hubway_trips.csv', low_memory=False)
hubway_data.head()
```

columns are variable

Out[27]:

	seq_id	hubway_id	status	duration	start_date	strt_statn	end_date	end_statn	bike_nr	subsc_type	zip_code	birth_da
0	1	8	Closed	9	7/28/2011 10:12:00	23.0	7/28/2011 10:12:00	23.0	B00468	Registered	'97217	1976.0
1	2	9	Closed	220	7/28/2011 10:21:00	23.0	7/28/2011 10:25:00	23.0	B00554	Registered	'02215	1966.0
2	3	10	Closed	56	7/28/2011 10:33:00	23.0	7/28/2011 10:34:00	23.0	B00456	Registered	'02108	1943.0
3	4	11	Closed	64	7/28/2011 10:35:00	23.0	7/28/2011 10:36:00	23.0	B00554	Registered	'02116	1981.0
4	5	12	Closed	12	7/28/2011 10:37:00	23.0	7/28/2011 10:37:00	23.0	B00554	Registered	'97214	1983.0

rows are observations

python indexing starts at zero

Tabular Data

First Look At The Data

In [27]:
```
hubway_data = pd.read_csv('hubway_trips.csv', low_memory=False)
hubway_data.head()
```

Out[27]:

	seq_id	hubway_id	status	duration	start_date	strt_statn	end_date	end_statn	bike_nr	subsc_type	zip_code	birth_da
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4	5	12	Closed	12	7/28/2011 10:37:00	23.0	7/28/2011 10:37:00	23.0	B00554	Registered	'97214	1983.0

dimensions

p, k

Each type of measurement is called a **variable** or an **attribute** of the data (e.g. `seq_id`, `status` and `duration` are variables or attributes). The number of attributes is called the **dimension**. These are often called **features**.

We expect each table to contain a set of **records** or **observations** of the same kind of object or event (e.g. our table above contains observations of rides/checkouts).

number of observations

sample size (n)

Types of Data

We'll see later that it's important to distinguish between classes of variables or attributes based on the type of values they can take on.

- **Quantitative variable:** is numerical and can be either:
  - **discrete -** a finite number of values are possible in any bounded interval. For example: "Number of siblings" is a discrete variable
  - **continuous -** an infinite number of values are possible in any bounded interval. For example: "Height" is a continuous variable
- **Categorical variable:** no inherent order among the values For example: "What kind of pet you have" is a categorical variable

Common Issues

Common issues with data:

data

- Missing values: how do we fill in?
- Wrong values: how can we detect and correct?
- Messy format
- Not usable: the data cannot answer the question posed

collected for a different ~~purple~~ purpose.

Messy Data

The following is a table accounting for the number of produce deliveries over a weekend.

What are the variables in this dataset? What object or event are we measuring?

	Friday	Saturday	Sunday
Morning	15	158	10
Afternoon	2	90	20
Evening	55	12	45

crosstab, contingency table

What's the issue? How do we fix it?

sample size = ?

n = 9

id	time	day	#deliveries
1	morning	Friday	15
2			
3	morning	Sat	158
⋮	⋮	⋮	⋮
9			

Messy Data

We're measuring individual deliveries; the variables are Time, Day, Number of Produce.

	Friday	Saturday	Sunday
Morning	15	158	10
Afternoon	2	90	20
Evening	55	12	45

Problem: each column header represents a single value rather than a variable. Row headers are "hiding" the Day variable. The values of the variable, "Number of Produce", is not recorded in a single column.

Fixing Messy Data

We need to reorganize the information to make explicit the event we're observing and the variables associated to this event.

ID	Time	Day	Number
1	Morning	Friday	15
2	Morning	Saturday	158
3	Morning	Sunday	10
4	Afternoon	Friday	2
5	Afternoon	Saturday	9
6	Afternoon	Sunday	20
7	Evening	Friday	55
8	Evening	Saturday	12
9	Evening	Sunday	45

Tabular = Happy Kevin ☺

Common causes of messiness are:

- Column headers are values, not variable names
- Variables are stored in both rows and columns
- Multiple variables are stored in one column/entry
- Multiple types of experimental units stored in same table

In general, we want each file to correspond to a dataset, each column to represent a single variable and each row to represent a single observation.

We want to **tabularize** the data. This makes Python happy.

our models and functions expect "tabular" data.

Data Exploration: Descriptive Statistics

Basics of Sampling

all observations we theoretically care about.

Population versus sample:

- A **population** is the entire set of objects or events under study. Population can be hypothetical "all students" or all students in this class.
- A **sample** is a "representative" subset of the objects or events under study. Needed because it's impossible or intractable to obtain or compute with population data.

Biases in samples:

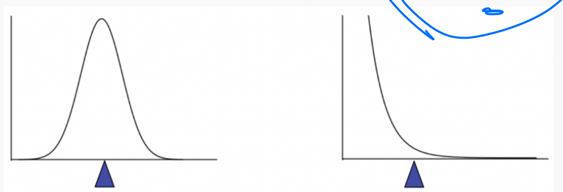
- **Selection bias**: some subjects or records are more likely to be selected
- Volunteer/**nonresponse bias**: subjects or records who are not easily available are not represented

Examples?

Sample mean (Sample average)

The **mean** of a set of *n* observations of a variable is denoted $\bar{x}$ and is defined as:

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} = \frac{1}{n}\sum_{i=1}^{n} x_i$$



The mean describes what a "typical" sample value looks like, or where is the "center" of the distribution of the data.

Key theme: there is always uncertainty involved when calculating a sample mean to estimate a population mean.

Sample median

middle numbered in an ordered list

The **median** of a set of n number of observations in a sample, ordered by value, of a variable is is defined by

$$\text{Median} = \begin{cases} x_{(n+1)/2} & \text{if } n \text{ is odd} \\ \frac{x_{n/2}+x_{(n+1)/2}}{2} & \text{if } n \text{ is even} \end{cases}$$

Example (already in order):

Ages: 17, 19, 21, 22, 23, 23, 23, 38

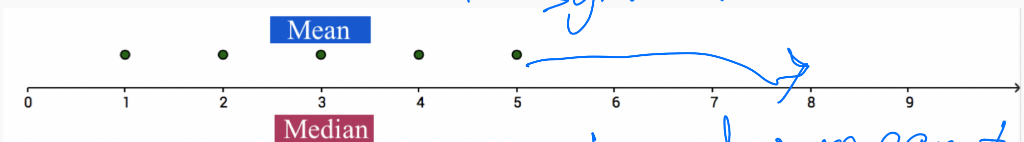
Median = (22+23)/2 = 22.5

The median also describes what a typical observation looks like, or where is the center of the distribution of the sample of observations.

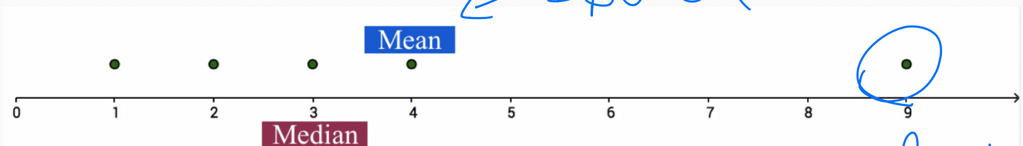
Mean vs. Median

The mean is sensitive to extreme values (**outliers**)

symmetric: mean = median



skewed: mean ≠ median

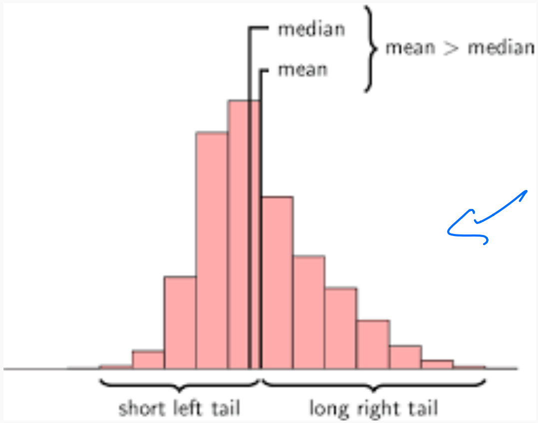


right-skewed

(direction of skew follows the "long" tail of how the mean compares to the median

Mean, median, and skewness

The mean is sensitive to outliers:



classic right-skewed

The above distribution is called **right-skewed** since the mean is greater than the median. Note: **skewness** often "follows the longer tail".

Computational time

How hard (in terms of algorithmic complexity) is it to calculate:

- the mean?

  at most $O(n)$ or $O(n \log n)$?

- the median?

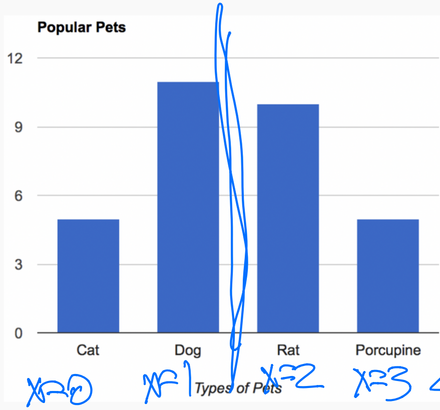
  at most $O(n)$ or $O(n \log n)$?

if you need to sort first

Note: Practicality of implementation should be considered!

Regarding Categorical Variables...

For categorical variables, neither mean or median make sense. Why?



x=0 x=1 x=2 x=3 ← no order of measurement (no "scale")

The mode might be a better way to find the most "representative" value.

↑ most common measurement.

Measures of Spread: Range

The spread of a sample of observations measures how well the mean or median describes the sample.

One way to measure spread of a sample of observations is via the **range**.

Range = Maximum Value - Minimum Value

Measures of Spread: Variance

The (sample) **variance**, denoted s^2, measures how much on average the sample values deviate from the mean:

why n-1? take a stat class

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}|x_i - \bar{x}|^2$$

Note: the term $|x_i - \bar{x}|$ measures the amount by which each x_i deviates from the mean $\bar{x}$. Squaring these deviations means that s^2 is sensitive to extreme values (outliers).

Note: s^2 doesn't have the same units as the x_i :(

What does a variance of 1,008 mean? Or 0.0001?

take the square root of variance? std. deviation.

Measures of Spread: Standard Deviation

The (sample) **standard deviation**, denoted s, is the square root of the variance

$$s = \sqrt{s^2} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} |x_i - \bar{x}|^2}$$

Note: s does have the same units as the x_i. Phew!

* more interpretable: a measure of "average" spread around the sample mean.

Data Exploration: Visualizations

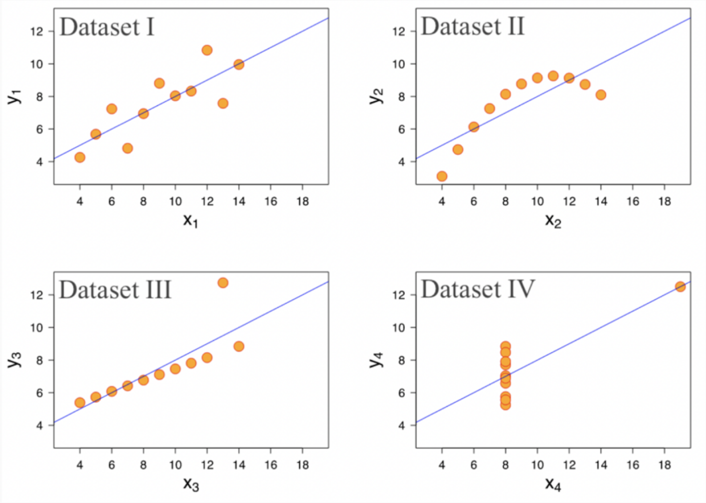
Anscombe's Data

The following four data sets comprise the Anscombe's Quartet; all four sets of data have identical simple summary statistics.

	Dataset I		Dataset II		Dataset III		Dataset IV	
	x	y	x	y	x	y	x	y
	10	8.04	10	9.14	10	7.46	8	6.58
	8	6.95	8	8.14	8	6.77	8	5.76
	13	7.58	13	8.74	13	12.74	8	7.71
	9	8.81	9	8.77	9	7.11	8	8.84
	11	8.33	11	9.26	11	7.81	8	8.47
	14	9.96	14	8.1	14	8.84	8	7.04
	6	7.24	6	6.13	6	6.08	8	5.25
	4	4.26	4	3.1	4	5.39	19	12.5
	12	10.84	12	9.13	12	8.15	8	5.56
	7	4.82	7	7.26	7	6.42	8	7.91
	5	5.68	5	4.74	5	5.73	8	6.89
Sum:	99.00	82.51	99.00	82.51	99.00	82.51	99.00	82.51
Avg:	9.00	7.50	9.00	7.50	9.00	7.50	9.00	7.50
Std:	3.32	2.03	3.32	2.03	3.32	2.03	3.32	2.03

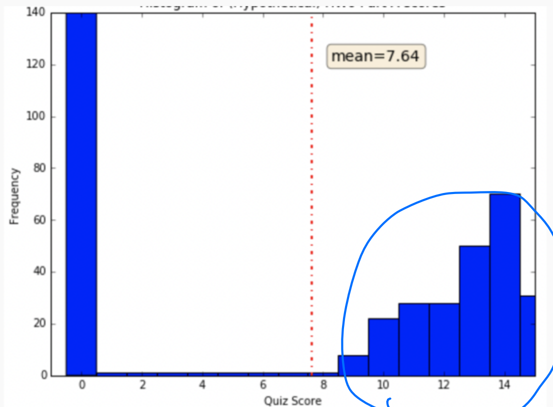
Anscombe's Data (cont.)

Summary statistics clearly don't tell the story of how they differ. But a picture can be worth a thousand words:



More Visualization Motivation

If I tell you that the average score for Homework 0 was: 7.64/15 = $\boxed{50.9\%}$ last year, what does that suggest?



40% of people didn't submit HW0,

different picture

80 – 90% for most people

And what does the graph suggest?

More Visualization Motivation

Visualizations help us to analyze and explore the data. They help to:

- Identify hidden patterns and trends ← that cannot be easily quantified
- Formulate/test hypotheses/models
- Communicate any modeling results
  – Present information and ideas succinctly
  – Provide evidence and support
  – Influence and persuade
- Determine the next step in analysis/modeling

Types of Visualizations

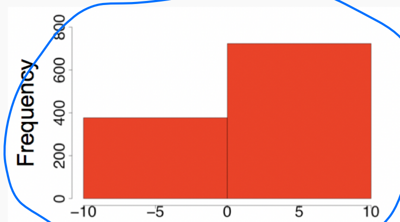
What do you want your visualization to show about your data?

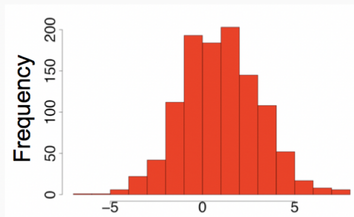
histograms & barplots

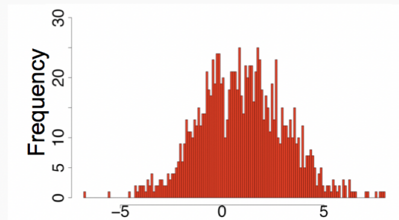
- **Distribution:** how a variable or variables in the dataset distribute over a range of possible values.
- **Relationship:** how the values of multiple variables in the dataset relate . ← side-by-side boxplots, scatterplots, etc...
- **Composition:** how the dataset breaks down into subgroups.
- **Comparison:** how trends in multiple variables or datasets compare.

Histograms to visualize distribution

A **histogram** is a way to visualize how 1-dimensional data is distributed across certain values.







Note: Trends in histograms are sensitive to number of bins.

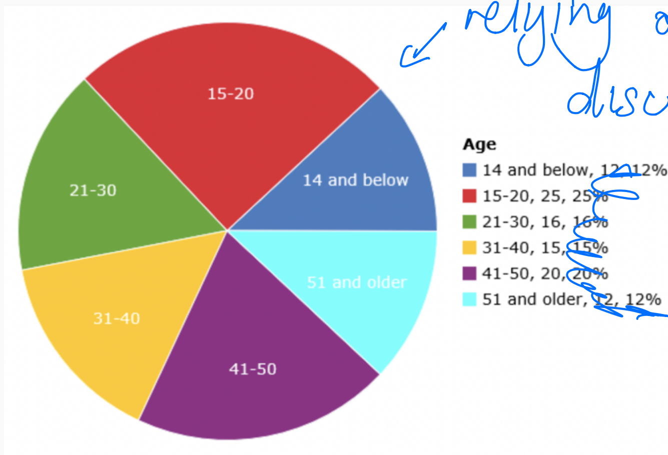
too few bins cannot the main "features"/characteristics

"goldilocks zone"

too many bins can distract the reader

Pie chart for a categorical variable?

A **pie chart** is a way to visualize the static composition (aka, distribution) of a variable (or single group).



relying on angles to discern differences

Pie charts are often frowned upon (and **bar charts** are used instead). Why?

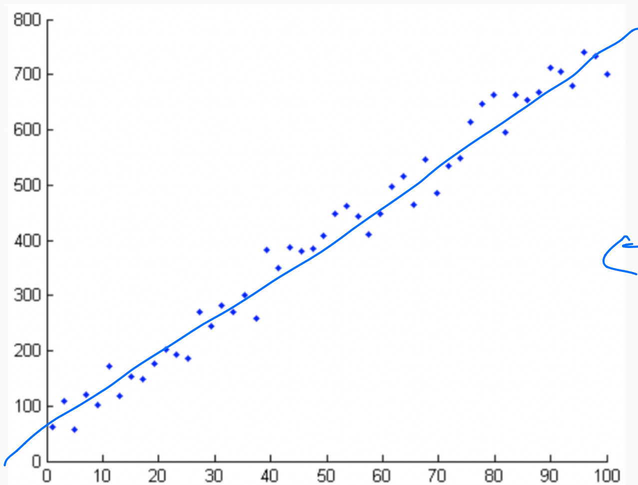
heights to discern differences

Scatter plots to visualize relationships

A **scatter plot** is a way to visualize the relationship between two different attributes of multi-dimensional data.

quantitative

y =



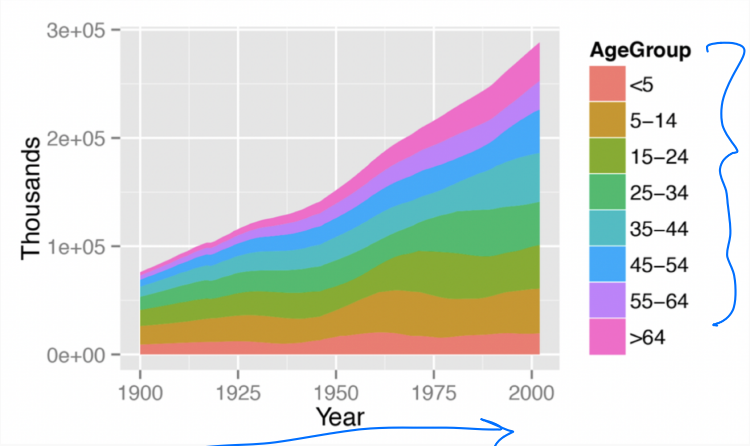
x =

scatterplot

strong positive, linear relationship

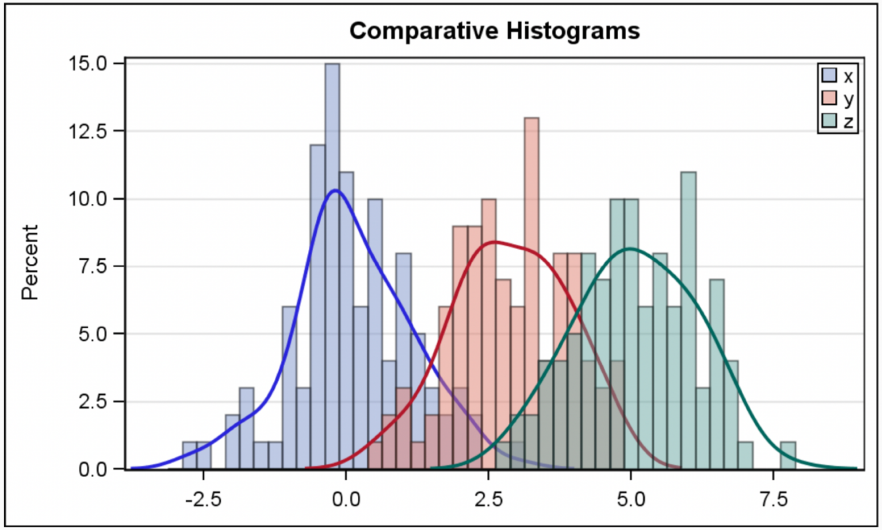
Stacked area graph to show trend over time

A **stacked area graph** is a way to visualize the composition of a group as it changes over time (or some other quantitative variable). This shows the relationship of a categorical variable (AgeGroup) to a quantitative variable (year).



Multiple histograms

Plotting **multiple histograms** (and **kernel density estimates** of the distribution, here) on the same axes is a way to visualize how different variables compare (or how a variable differs over specific groups).

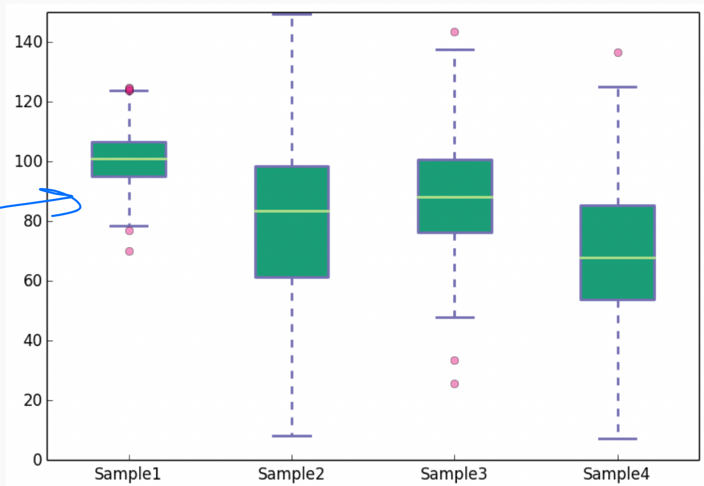


25%
75%
percentiles

Boxplots

A **boxplot** is a simplified visualization to compare a quantitative variable across groups. It highlights the range, quartiles, median and any outliers present in a data set.

less spread, and higher "average" in group 1



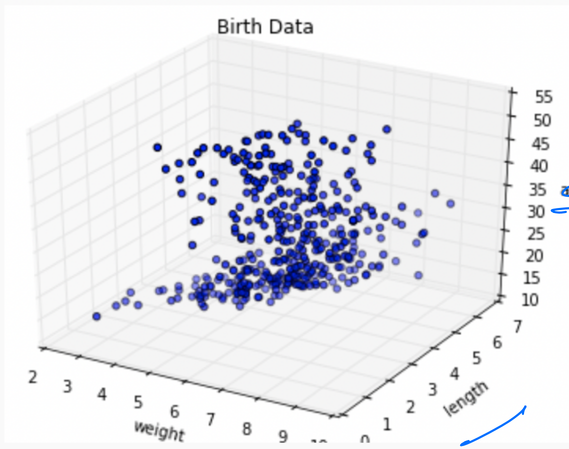
[Not] Anything is possible!

Often your dataset seem too complex to visualize:

- Data is too high dimensional (how do you plot 100 variables on the same set of axes?)
- Some variables are categorical (how do you plot values like Cat or No?)

More dimensions not always better

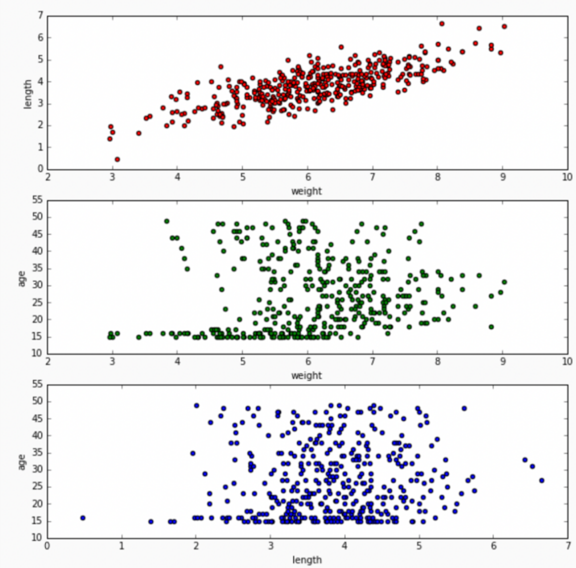
When the data is high dimensional, a scatter plot of all data attributes can be impossible or unhelpful



age (of mother)

Reducing complexity

Relationships may be easier to spot by producing multiple plots of lower dimensionality.

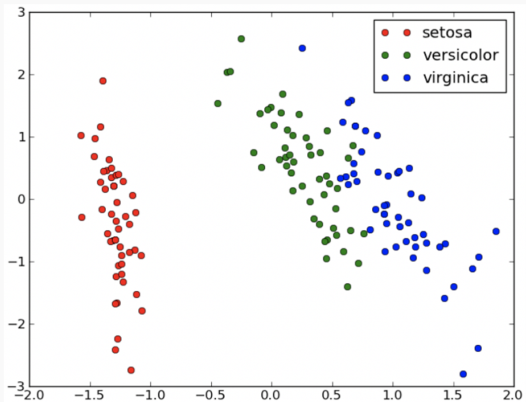


strong, positive

weaker relationships

Reducing complexity

For 3D data, color coding a categorical attribute can be "effective"

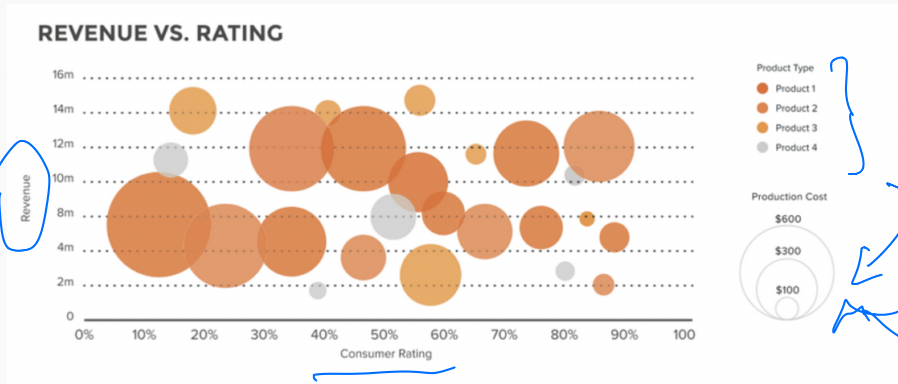


This visualizes a set of Iris measurements. The variables are: petal length, sepal length, Iris type (setosa, versicolor, virginica).

Except when it's not effective.
What could be a better choice?

3D can work

For 3D data, a quantitative attribute can be encoded by size in a bubble chart.



color for a 3rd variable that's categorical

size for a 3rd variable that is quantitative

The above visualizes a set of consumer products. The variables are: revenue, consumer rating, product type and product cost.

An Example: The Data Science Process

What?

The Data Science Process is similar to the scientific process - one of observation, model building, analysis, and conclusion:

Ask an interesting question

Get the Data

Explore the Data

Model the Data

Communicate/Visualize the Results

focus on data collection, wrangling, and exploration

Note: This process is by no means linear!

Analyzing Hubway Data

Introduction: Hubway (now Blue Bikes) was metro-Boston's public bike share program, with more than 1600 bikes at 160+ stations across the Greater Boston area. Hubway is owned by four municipalities in the area.

By 2016, Hubway operated 185 stations and 1750 bicycles, with 5 million ride since launching in 2011.

The Data: In April 2017, Hubway held a Data Visualization Challenge at the Microsoft NERD Center in Cambridge, releasing a few years of trip data.

The Question: What does the data tell us about the ride share program?

The Data Exploration/Question Refinement Cycle

Our original question: **'What does the data tell us about the ride share program?'** is a reasonable slogan to promote a hackathon. It is not good for guiding scientific investigation.

variables

Before we can refine the question, we have to look at the data!

observations

	seq_id	hubway_id	status	duration	start_date	strt_statn	end_date	end_statn	bike_nr	subsc_type	zip_code	birth_date	gender
0	1	8	Closed	9	7/28/2011 10:12:00	23.0	7/28/2011 10:12:00	23.0	B00468	Registered	'97217	1976.0	Male
1	2	9	Closed	220	7/28/2011 10:21:00	23.0	7/28/2011 10:25:00	23.0	B00554	Registered	'02215	1966.0	Male
2	3	10	Closed	56	7/28/2011 10:33:00	23.0	7/28/2011 10:34:00	23.0	B00456	Registered	'02108	1943.0	Male
3	4	11	Closed	64	7/28/2011 10:35:00	23.0	7/28/2011 10:36:00	23.0	B00554	Registered	'02116	1981.0	Female
4	5	12	Closed	12	7/28/2011 10:37:00	23.0	7/28/2011 10:37:00	23.0	B00554	Registered	'97214	1983.0	Female

Based on the data, what kind of questions can we ask?

The Data Exploration/Question Refinement Cycle

Who? Who's using the bikes?

Refine into specific hypotheses:

- More men or more women?
- Older or younger people?
- Subscribers or one time users?

The Data Exploration/Question Refinement Cycle

Where? Where are bikes being checked out?

Refine into specific hypotheses:

- More in Boston than Cambridge?
- More in commercial or residential areas?
- More around tourist attractions?
- More near the 'T' (subway)?

Sometimes the data is given to you in pieces and must be merged!

The Data Exploration/Question Refinement Cycle

When? When are the bikes being checked out?

Refine into specific hypotheses:

- More during the weekend than on the weekdays?
- More during rush hour?
- More during the summer than the fall?

Sometimes the feature you want to explore doesn't exist in the data, and must be engineered!

The Data Exploration/Question Refinement Cycle

Why? For what reasons/activities are people checking out bikes?

Refine into specific hypotheses:

- More bikes are used for recreation than commute?
- More bikes are used for touristic purposes?
- Bikes are use to bypass traffic?

Do we have the data to answer these questions with reasonable certainty?

What data do we need to collect in order to answer these questions?

The Data Exploration/Question Refinement Cycle

How? Questions that combine variables.

- How does user demographics impact the duration the bikes are being used? Or where they are being checked out?
- How does weather or traffic conditions impact bike usage?
- How do the characteristics of the station location affect the number of bikes being checked out?

How questions are about modeling relationships between different variables.

Inspirations for Data Viz/Exploration

So how well did we do in formulating creative hypotheses and manipulating the data for answers?

Check out the winners of the Hubway Challenge:

https://www.bluebikes.com/blog/and-the-2017-hubway-data-challenge-winners-are