Urban Informatics

Fall 2017

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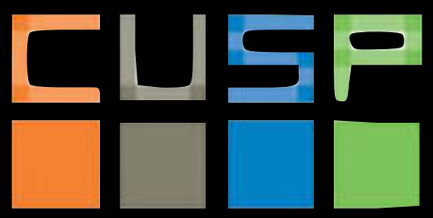
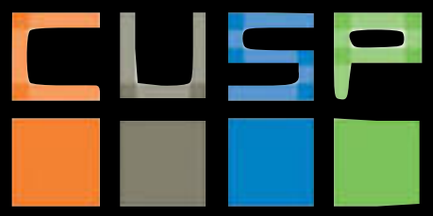
 @fedhere 



Summary:

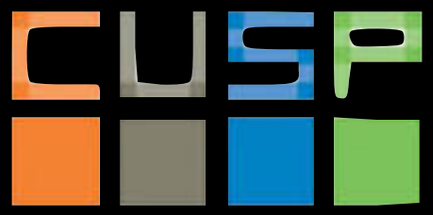
- **Epistemological concepts:**
  falsifiability, law of parsimony,
- **Good scientific practice:**
  reproducibility of research



Summary:

- **Epistemological concepts:**
  falsifiability, law of parsimony,
- **Good scientific practice:**
  reproducibility of research,
- **Gathering and parsing data:**
  data munging or wrangling, data jujitsu.

  - types of data
  - reporting data for reproducibility
  - cleaning and tabulating data
  - reading data from CSV files
  - reading data from JSON files
  - reading data from the CUSP dataHub
  - reading data from APIs



- IDEA
- dataset
  - define ideal data
  - figure out best data available
  - figure out if you can get new data
  - obtain data (including policy issues + technical issues)
- data handling
  - joining databases
  - formatting data
- exploratory data analysis
  - machine learning (clustering? dimensionality reduction?)
- statistics
  - models (regression)
  - prediction
  - validation (simulations)
- interpretation
- presentation
  - visualization
  - write a paper!

- IDEA
- dataset
  - define idea / data
    - figure out best data available
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PROBLEM IDENTIFICATION
FORMULATING HYPOTHESIS

- data handling
  - joining databases
  - formatting data
- exploratory data analysis
  - machine learning (clustering? dimensionality reduction?)
- statistics
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  - visualization
  - write a paper!

DATA PREPARATION

generally takes 70–90% of the life of a data driven investigation

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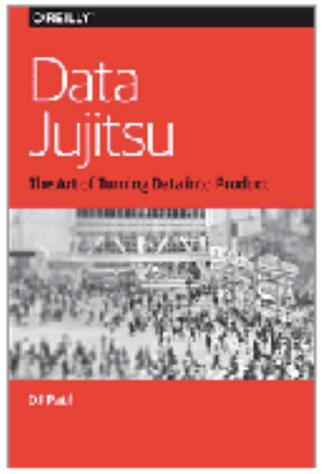


Data Jujitsu: The Art of Turning Data into Product

An O'Reilly Radar Report

By DJ Patil

Publisher: O'Reilly
Pages: 24

5.0

Read 1 Review Write a Review

Description

Acclaimed data scientist DJ Patil details a new approach to solving problems in Data Jujitsu.

Learn how to use a problem's "weight" against itself to:

- Break down seemingly complex data problems into simplified parts
- Use alternative data analysis techniques to examine them
- Use human input, such as Mechanical Turk, and design tricks that enlist the help of your users to take short cuts around tough problems

Learn more about the problems before starting on the solutions—and use the findings to solve them, or determine whether the problems are worth solving at all.

Customer Reviews

5.0 (based on 1 review)

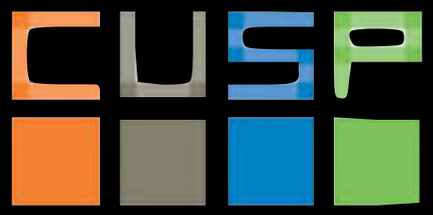
Write a Review

Reviewed by 1 customer

Displaying review 1

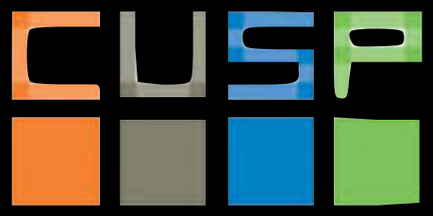
II: Data Wrangling

[…]data products are unique in that they are often extremely difficult, and seemingly intractable for small teams with limited funds. Yet, they get solved every day.
How? Are the people who solve them superhuman data scientists who can come up with better ideas in five minutes than most people can in a lifetime? Are they magicians of applied math who can cobble together millions of lines of code for high-performance machine learning in a few hours? No.
(continue in the next page…)



(…continued)

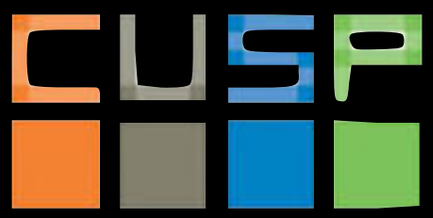
Many of them are incredibly smart, but meeting big problems head-on usually isn't the winning approach. There's a method to solving data problems that avoids the big, heavyweight solution, and instead, concentrates on building something quickly and iterating. Smart data scientists don't just solve big, hard problems; they also have an instinct for making big problems small.



Data are messy

…

(and you have to clean the mess!)



WHAT ARE THEIR BIGGEST CHALLENGES?

Dirty data is the #1 hurdle for data scientists.

66.7%
of data scientists say cleaning and organizing data is their most time-consuming task.

52.3%
of data scientists cite poor quality data as their biggest daily obstacle.

https://www.crowdflower.com/the-data-behind-todays-data-scientists-an-infographic/

2015 survey of data scientists

CUSP

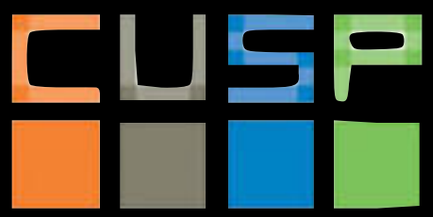
Reproducible research means:

code **raw data**

Raw data formats: API, Json, binary, paper...

Tidy data: tabulated data, binary, csv, tsv, ascii, Excel (ugh!) or (object oriented) Json,…

	var 1	var 2
obs 1	7.4	9.2
obs 2	NaN	13.1



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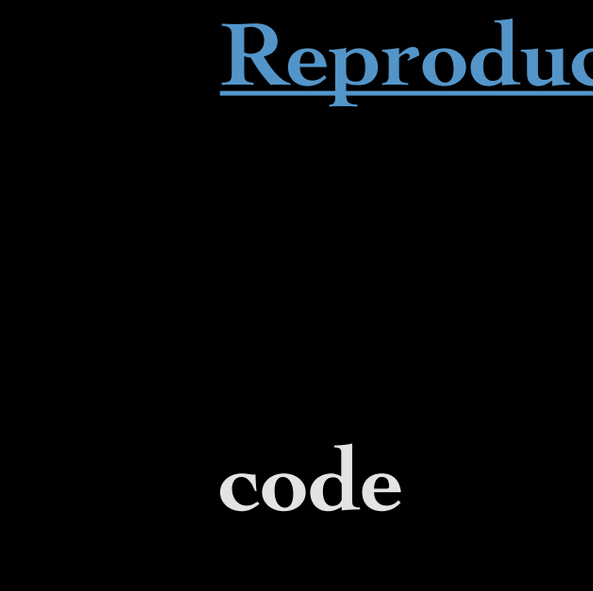
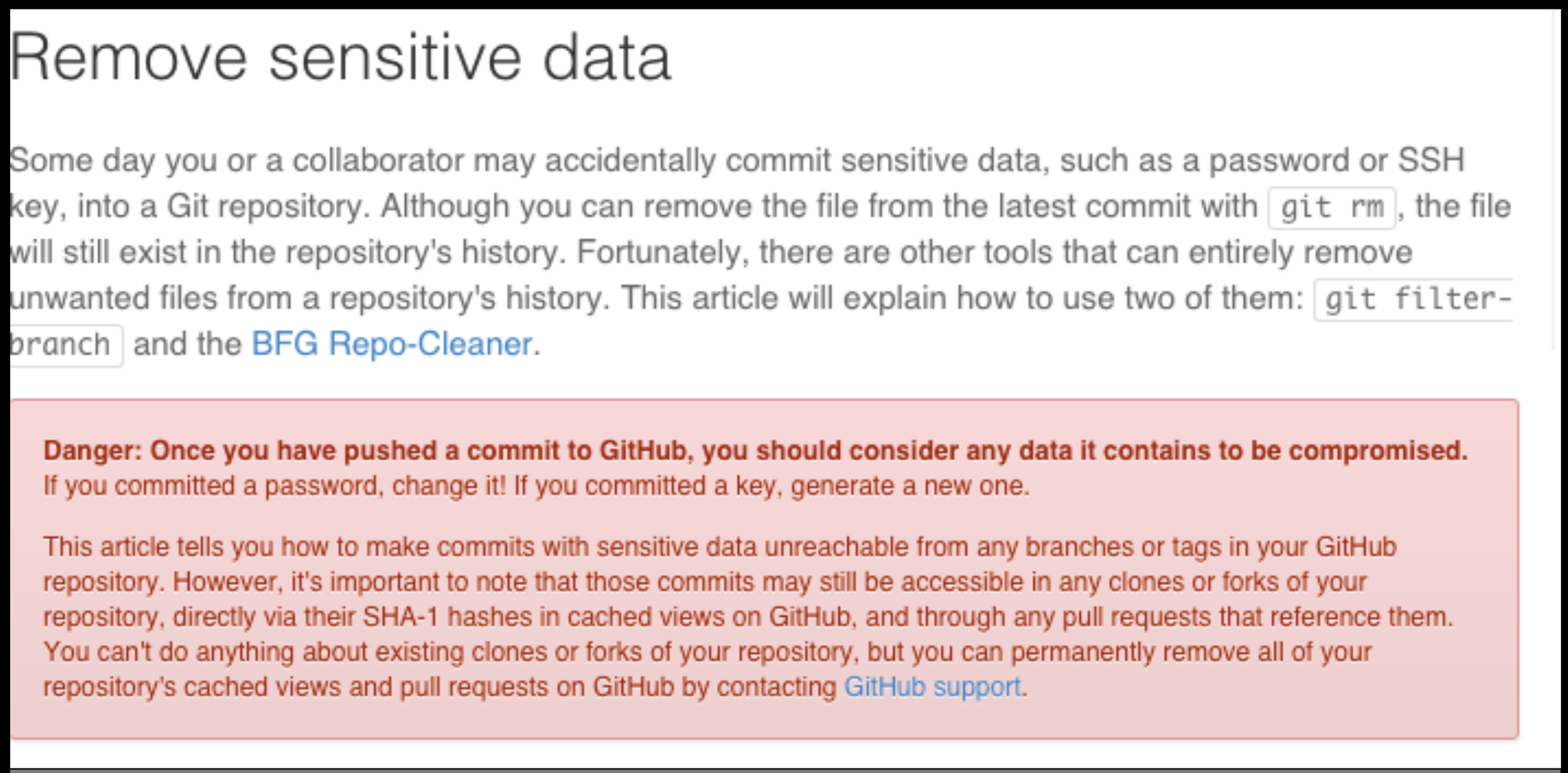




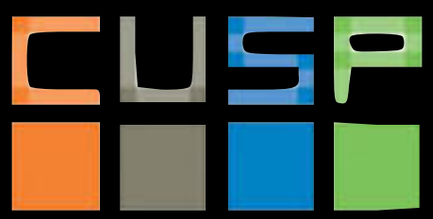
Remove sensitive data

Some day you or a collaborator may accidentally commit sensitive data, such as a password or SSH key, into a Git repository. Although you can remove the file from the latest commit with `git rm`, the file will still exist in the repository's history. Fortunately, there are other tools that can entirely remove unwanted files from a repository's history. This article will explain how to use two of them: `git filter-branch` and the BFG Repo-Cleaner.

Danger: Once you have pushed a commit to GitHub, you should consider any data it contains to be compromised. If you committed a password, change it! If you committed a key, generate a new one.

This article tells you how to make commits with sensitive data unreachable from any branches or tags in your GitHub repository. However, it's important to note that those commits may still be accessible in any clones or forks of your repository, directly via their SHA-1 hashes in cached views on GitHub, and through any pull requests that reference them. You can't do anything about existing clones or forks of your repository, but you can permanently remove all of your repository's cached views and pull requests on GitHub by contacting GitHub support.

https://help.github.com/articles/remove-sensitive-data/



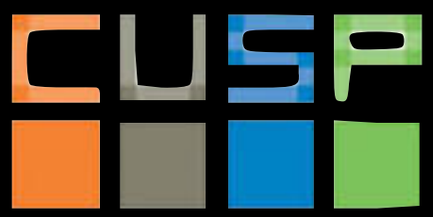
Reproducible research:

How to share your data

- Share/Reference the source of your **raw** data

- Share the "tidy" data

- Share the code used to process the data at each step



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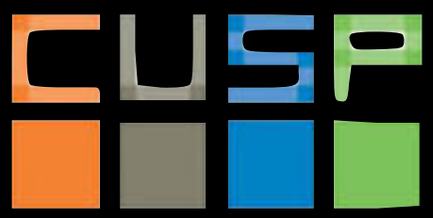
https://github.com/jakevdp/PythonicPerambulations/blob/master/content/downloads/notebooks/ProntoData.ipynb



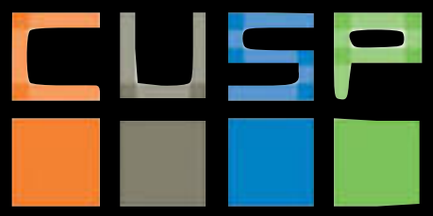
Reproducible research:

How to share your data

let's agree on a single location for PUI data. That way the graders home dirs do not fill up with copies of the same dataset.

PUI RULE: place all your data in PUIdata

where PUIdata is pointed to by an env variable PUIDATA



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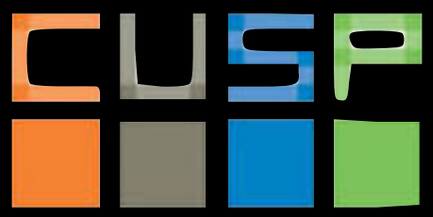
```
#downloading data
!curl -O https://s3.amazonaws.com/pronto-data/open_data_year_one.zip
#unpacking into $PUIDATA
!unzip open_data_year_one.zip -d $PUIDATA
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100 70.8M  100 70.8M    0     0  8587k       0  0:00:08  0:00:08 --:--:-- 9783k
Archive:  open_data_year_one.zip
  inflating: /Users/fbianco/science/Dropbox/UI/PUIdata/2015_station_data.csv
  inflating: /Users/fbianco/science/Dropbox/UI/PUIdata/2015_status_data.csv
  inflating: /Users/fbianco/science/Dropbox/UI/PUIdata/2015_trip_data.csv
  inflating: /Users/fbianco/science/Dropbox/UI/PUIdata/2015_weather_data.csv
  inflating: /Users/fbianco/science/Dropbox/UI/PUIdata/README.txt
```

```
!ls $PUIDATA
```

```
2015_station_data.csv nybb_16d.zip          zbp06totals.zip
2015_status_data.csv  nycb2010_16d          zbp07totals.zip
2015_trip_data.csv    rows.csv              zbp08totals.zip
2015_weather_data.csv t_sf1_dp_cd.xlsx      zbp09totals.zip
ACS_10_SF4_DP03       t_sf1_dp_nyc.xlsx     zbp10totals.txt
```



export PUIDATA="$HOME/PUIdata"

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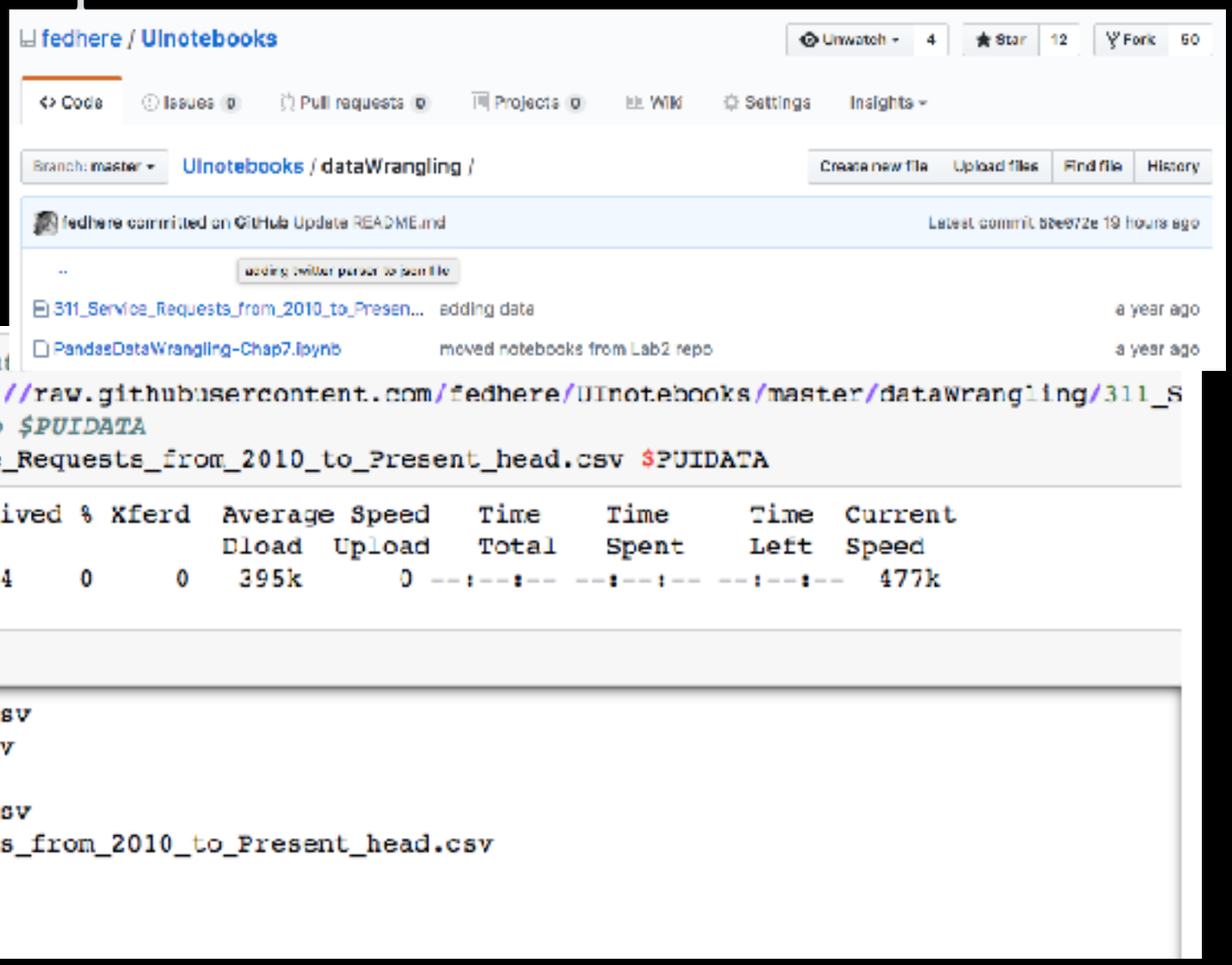


https://github.com/fedhere/UInotebooks/tree/master/dataWrangling

Reproducible research:

How to share your data

if you are working on compute or jupiterhub at CUPS and you are working with data available in the CUSP Data Facility (DF) you can directly read the data

```
from __future__ import print_function
__author__ = '__fbb__'

import os
import pandas as pd
%pylab inline

DFDATA = os.getenv("DFDATA")
DFDATA
```

```
Populating the interactive namespace from numpy and matplotlib
```

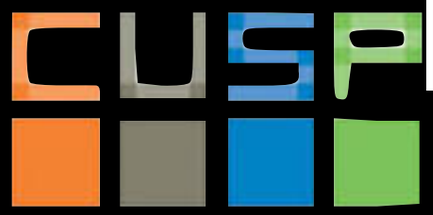
```
'/gws/open/NYCOpenData/nycopendata/data'
```

```
DFDATA = "/gws/open/NYCOpenData/nycopendata/data/"
```

Reads in CSV files from the CUSP Data Facility and plots numberical values and time series NOTE: must have the DFDATA environmental variable pointing to "/gws/open/NYCOpenData/nycopendata/data/" Part 1 uses the Natural Gas Consumption data https://datahub.cusp.nyu.edu/dataset/uedp-fegm Part 2 uses the Social Media metions of NYC agencies data https://datahub.cusp.nyu.edu/dataset/5b3a-rs48

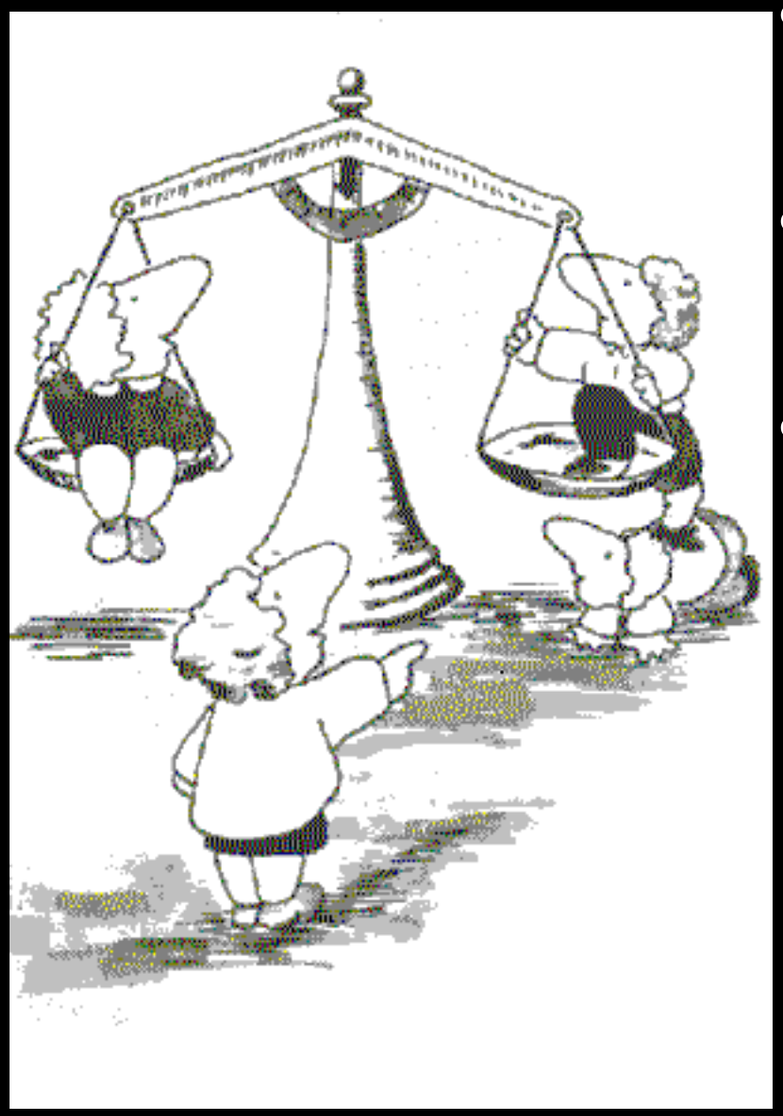
Part 1. Gas Data

```
# read in gas data
df_gas = pd.read_csv(DFDATA + "/uedp-fegm/1414245967/uedp-fegm")
```



Reproducible research means:

Data are noisy

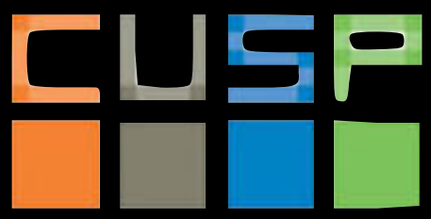


- Data entry errors
- Measurement errors
- Extraction errors

Make sure you do not make them noisier…

Typical data wrangling issues

Licensing issues/Privacy (some data unavailable)
Missing required field
Primary key violation (two people with the same social security number)
Parsing text into fields (separator issues)
Naming conventions: NYC vs New York
Different representations (2 vs Two)
Fields corrupted (too long get truncated)
Formatting issues – especially dates
Redundant Records (exact match or other)



Reproducible research means:

code **raw data**

data munging

Tabulated data

Reproducible research means:

code **raw data** formats: API, Json, binary, paper...

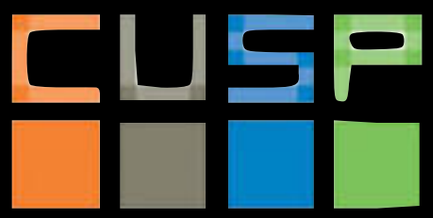
tabulated data: binary, csv, tsv, ascii, Excel (ugh!) or (object oriented) Json,…

Reproducible research means:

code **raw data**

Proper data table orientations:
columns -> variables
rows -> observations

	var 1	var 2
obs 1	7.4	9.2
obs 2	NaN	13.1



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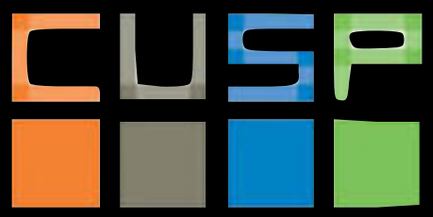
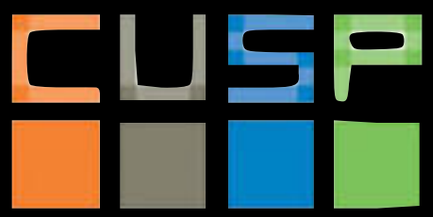


Reproducible research means:

code **raw data**

provide detailed observation info if possible

	var 1	var 2	link
obs 1	7.4	9.2	URL 1
obs 2	NaN	13.1	URL 1



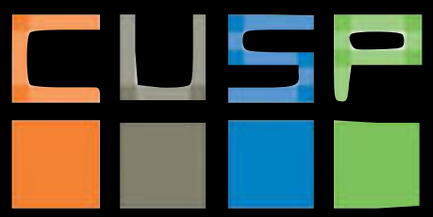
Reproducible research means:

code **raw data**

impute missing data correctly and unambiguously

	var 1	var 2	link
obs 1	7.4	9.2	URL 1
obs 2	NaN	13.1	URL 1

never use fake values for missing data!



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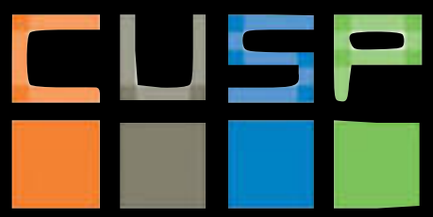
Raw data formats: API, Json, binary, paper…

Tidy data: tabulated data, binary, csv, tsv, ascii, Excel (ugh!) or (object oriented) Json,…

Report separately :

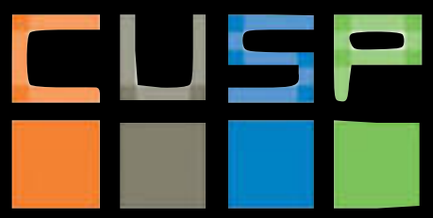
- **Details about variables**: e.g. date: "date when test was performed"
- **Units**: remember the Mars Rover that was lost at sea cause scientists got Metric and Imperial units mixed up?!?!



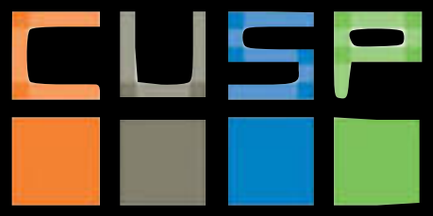
Reproducible research means:

code raw data

	speed (m/s)	distance (m)	link	accessed date
obs 1	7.4	9.2	URL 1	09/16/17
obs 2	NaN	13.1	URL 1	09/23/16



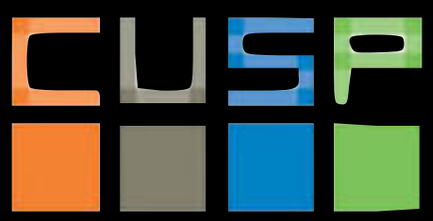
data ingestion



Types of Data Files:

- **CSV** comma separated values (also TSV - tab)
- **JSON: corresponds to a Python data dictionary**
- XML: similar to HTML

support nested structures

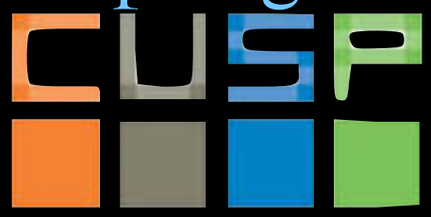


loading data on a computer

https://github.com/fedhere/UInotebooks/blob/master/dataWrangling/readingData.ipynb

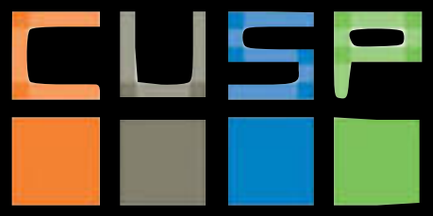
Python for Data Analysis (Pandas manual) Chapter 7

https://github.com/fedhere/UInotebooks/blob/master/dataWrangling/PandasDataWrangling-Chap7.ipynb



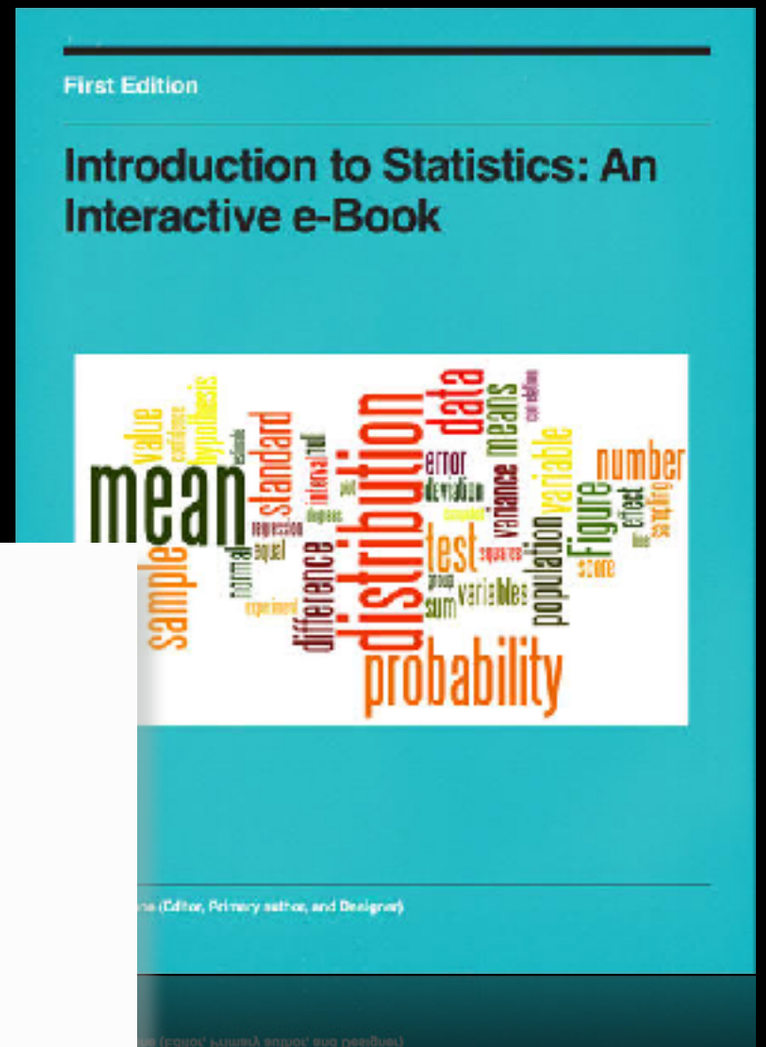
II: Data Wrangling

data types



Online Statistics Education

Introduction to Statistics
Online Edition
Primary author and editor:
David M. Lane1



Introduction to Statistics

Online Edition

Primary author and editor:
David M. Lane[1]

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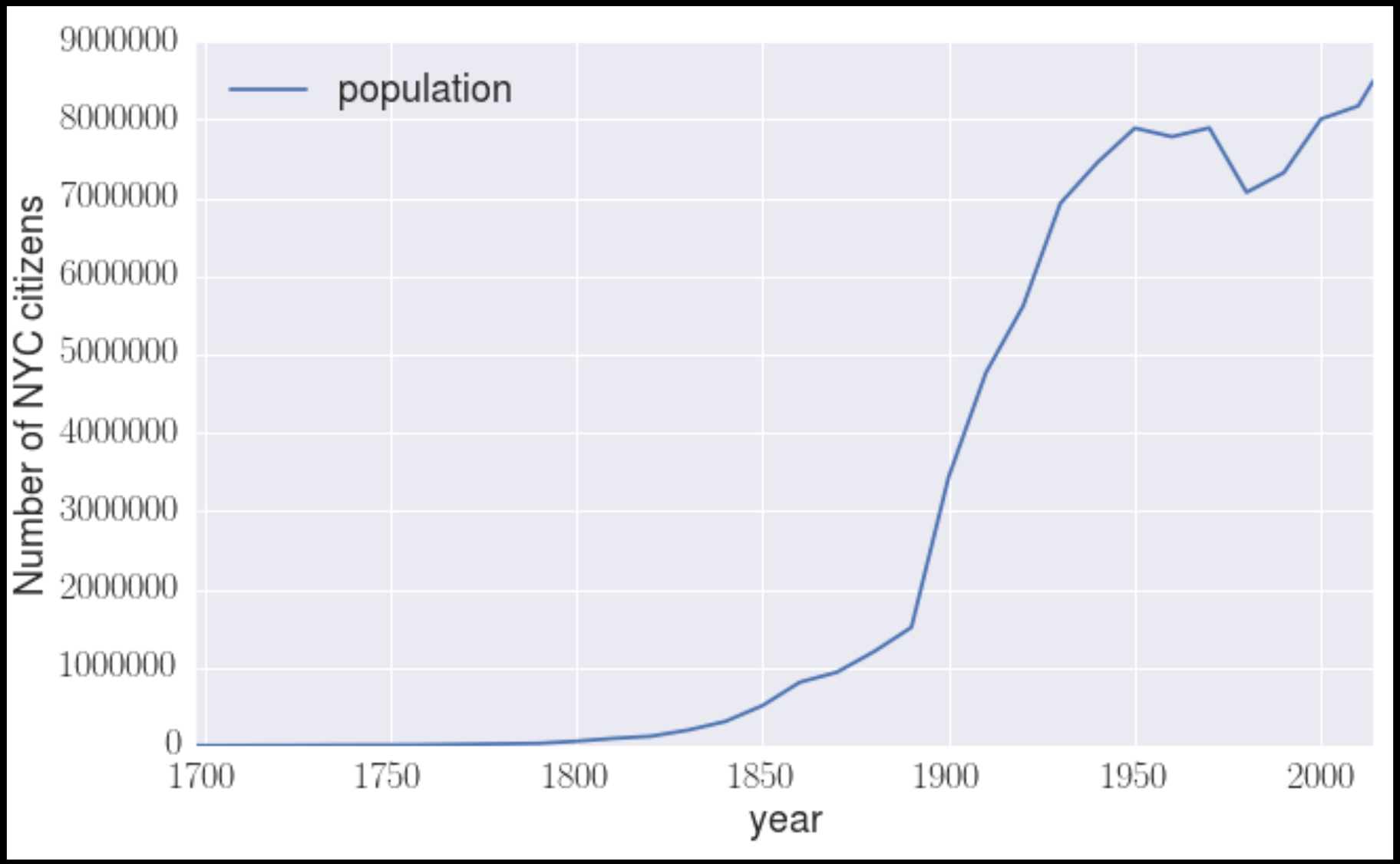
David Scott[1], Mikki Hebl[1], Rudy Guerra[1], Dan Osherson[1], and Heidi Zimmer[2]

[1]Rice University; [2]University of Houston, Downtown Campus

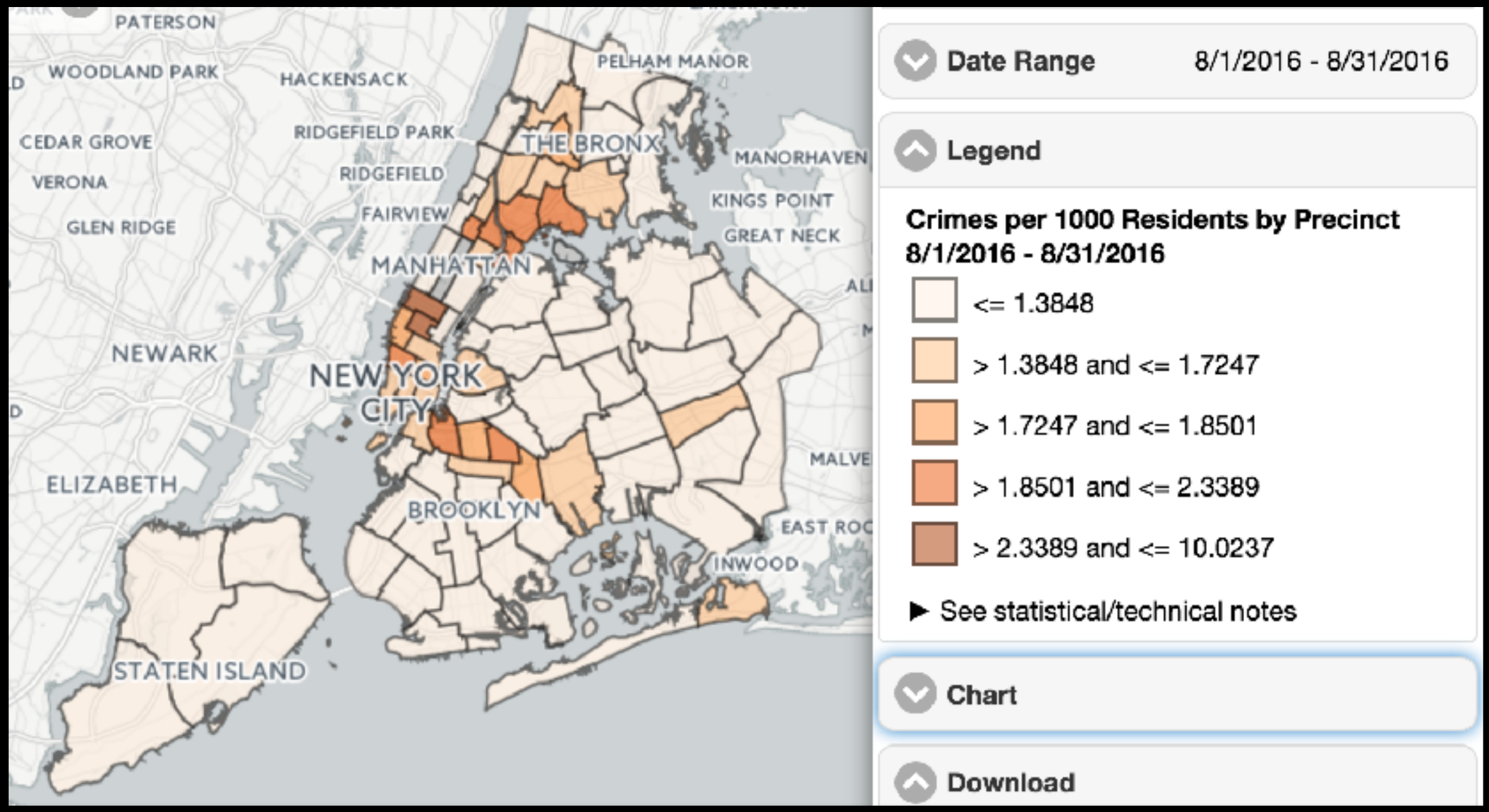
II: Data Wrangling

Dependent vs Independent Variable



http://flowingdata.com/2016/09/12/watch-bacteria-evolve-resistance-to-antibiotic/

Dependent vs Independent Variable



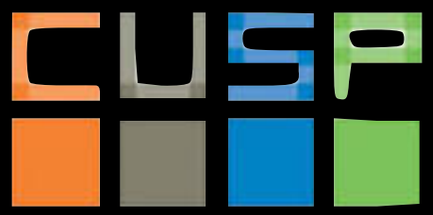
https://maps.nyc.gov/crime/

Dependent vs Independent Variable

http://flowingdata.com/2016/09/12/watch-bacteria-evolve-resistance-to-antibiotic/

Dependent vs Independent Variable

Levels of an independent variable:
the number of experimental conditions.
e.g.: control test and experiment are 2 levels



Types of Data: *Qualitative* variables

- **No ordering**

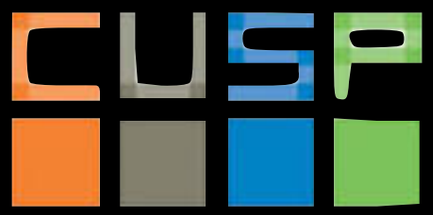
  UrbanScience e.g. precinct, state, gender

  Also called *Nominal, Categorical*

Types of Data: *Quantitative* variables

- **Ordering is meaningful**

  Time, Distance, Age, Length, Intensity, Satisfaction



Types of Data: *Quantitative* variables

- **Continuous:** 
- **Discrete:**

Types of Data: *Quantitative* variables

- **Continuous:** distance to the closest park
- **Discrete:** *any* countable, e.g. number of crimes

Discrete data may be:

- **Counts:** number of bacteria at time t in section A
- **Ordinal:** survey response Good/Fair/Poor

Continuous data may be:

- **Continuous Ordinal:** Earthquakes (notlinear scale)
- **Interval:** F temperature - interval size preserved
- **Ratio:** Car speed - 0 is naturally defined

Data may also be:

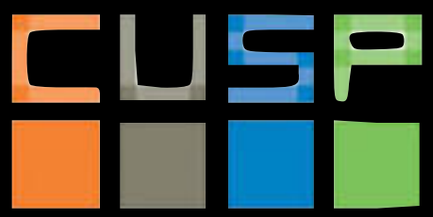
- **Censored:** age>90
- **Missing:** "Prefer not to answer" (NA / NaN)

Data Definitions

- **Data:** observations that have been collected
- **Population:** the complete body of subjects we want to infer about
- **Sample:** the subset of the population we actually studied

- **Census:** collection of data from the entire population

- **Parameter:** numerical value describing an attribute of the *population*
- **Statistics:** numerical value describing an attribute of the *sample*



Data Definitions

The analysis of our ____
showed that for our 10 _____ the mean height is 6.4 ft.
The standard deviation of the _____ means is 0.5 ft.
From this _____ we infer for the _____ a mean
height _____ 6.4 +/- 5 ft

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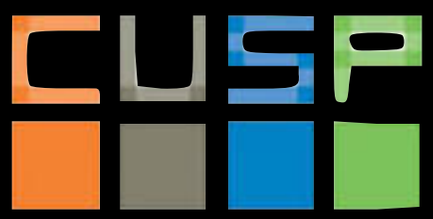
sample parameter data population statistics



Data Definitions

The analysis of our **data**
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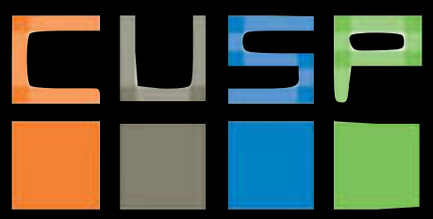
From this **statistic** we infer for the **population** a mean height **parameter** 6.4 +/- 5 ft



basic data inputation and manipulation Lab: FormattingTables.ipynb

CUSP

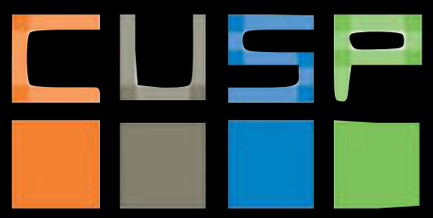
II: Data Wrangling

How to acquire data

- **Downladable files**

- API *Application Program Interface*

- **Databases (MySQL, MongoDB…**
  Prof. Huy Vo guest lecture)



How to acquire data

- **Downladable files**

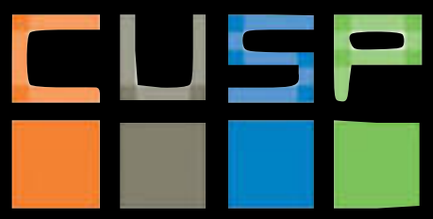
PROS: easy to do
reproducibilty: you can provide the data
CONS: store the data locally (bad if large)

- API *Application Program Interface*

PROS: works directly with the source
CONS: store the data locally
reproducibility: relies on data source to be permanent & API stable and accessible

- **Databases (MySQL, MongoDB… Prof. Huy Vo guest lecture)**

PROS: fast and flexible
can query only data of interest
reproducibilty : can host remotely & provide access
CONS: must build a database

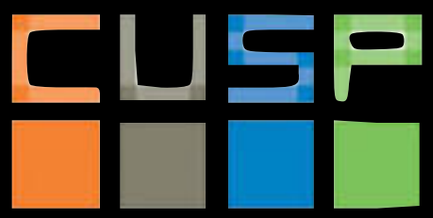


Downloading files directly in your notebook

https://github.com/fedhere/UInotebooks/blob/master/dataWrangling/acquiringData.ipynb

Types of Data Files:

- **CSV** comma separated values (also TSV - tab)
- **JSON: corresponds to a Python data dictionary**
- XML: similar to HTML



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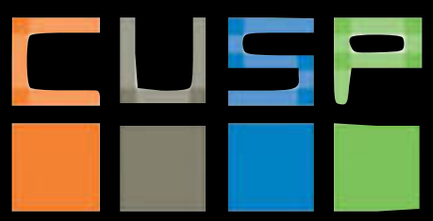

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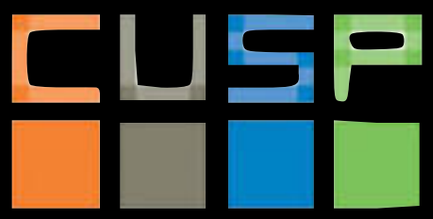

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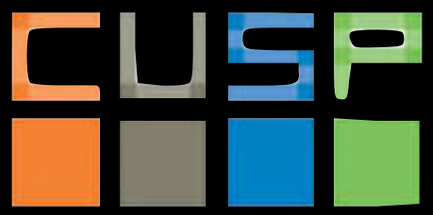
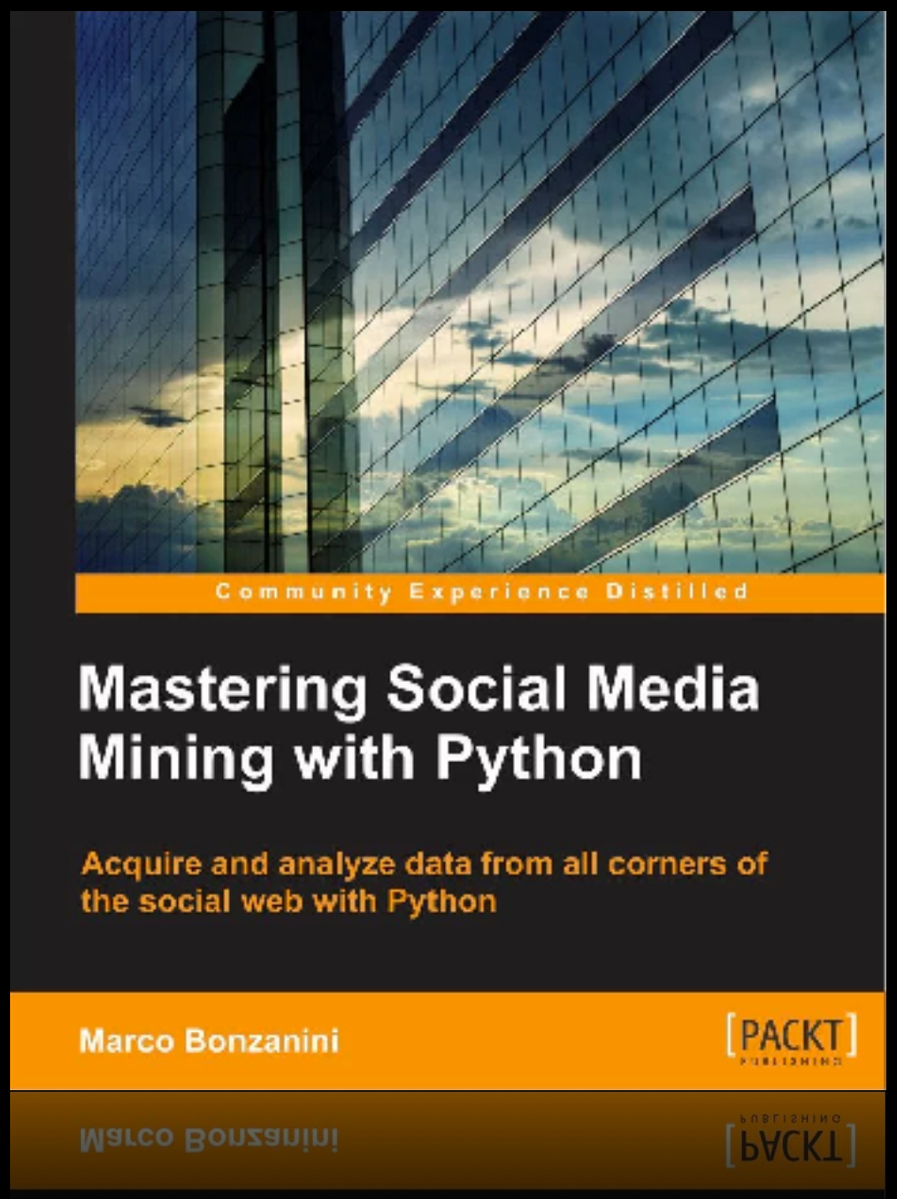
https://dev.twitter.com/rest/tools/console



https://github.com/fedhere/PUI2016_fb55/blob/master/Lab2_fb55/twitterJson.py

http://json.parser.online.fr/

download an online, nested JSON file



https://marcobonzanini.com/2015/03/02/mining-twitter-data-with-python-part-1/

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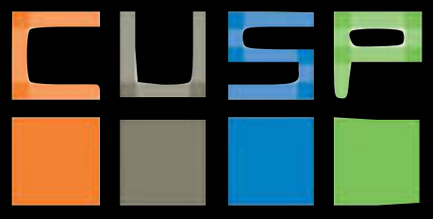
Access data through API

http://openweathermap.org/api



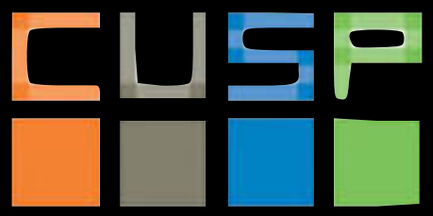
API scraping and JSON manipulation lab

II: Data Wrangling

Key Concepts:

- importance of reproducibility
- data ethics and data curation
- types of variables
- CSV, JSON file formats properties

- DATA Facility data access
- API data access
- JSON data manipulation
- working with Pandas Dataframes



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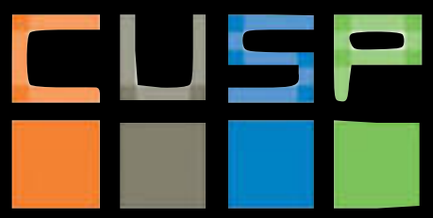

Resources:

D.Lane 2014
Introduction to Statistics Chapters 1.6-1.8 & 6.1-6.3
http://onlinestatbook.com/

Mohit Sharma 2016
CUSP UCSL tutorials Python Dictionaries
https://sharmamohit.com/tutorials/ucsl/Python-Dictionaries/

Allen B. Downey 2012
Thinking Python (free online) Appendix A ASSIGNED READING
http://greenteapress.com/thinkpython/html/thinkpython021.html

Wes McKinney 2013
Pandas for Data Analysis Chapter 7
http://tinyurl.com/hydko7p

https://github.com/fedhere/UInotebooks/blob/master/dataWrangling