

Logistics

- Pre course survey for EC, due Oct 9
- #FinAid survey on Canvas, due Oct 11
- You should have installed on your machine by next week
 - Git
 - Python
 - Or decide you are using Datahub and nothing else
- Discussion Lab:
 - Week 1: Optional (no turn in) Python review
 - D1 will be posted EOD Fri Week 1, due Fri Week 2 (Oct 11)
- Assignments
 - Practice Assignment, next Wed Oct 9
 - A1 will be posted next Wed Oct 9, due Wed Oct 16

Data tidiness & intuition

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Data Structures Review

Structured data

- can be stored in database
SQL
- tables with rows and columns
- requires a relational key
- 5-10% of all data

Semi-structured data

- doesn't reside in a relational database
- has organizational properties (easier to analyze)
- CSV, XML, JSON

Unstructured

- non-tabular data
- 80% of the world's data
- images, text, audio, videos

Structured Data

Databases!

What is a DB?? An organized collection of structured information

Manage huge datasets

Control access to data

Allow users to find a subset of data with a query

Run an analysis on data inside the DB and return a report

Structured Data

Examples of relational DB

- *SQLite*
- *MySQL*
- *Postgres*

*Relational DB work using tables
of data with “relationships”
established between tables*

Examples of non-relational DB

- *Hadoop*
- *Hive*
- *Apache CouchBase*

*NoSQL DB work with key-value
pairs to lookup data, and that’s
exactly like JSON slides coming
up.*

(Semi-)Structured Data

Data that is stored in such a way that it is easy to search and work with. These data are stored in a particular format that adheres to organization principles imposed by the file format. These are the data structures data scientists work with most often.

CSVs

Each column separated
by a comma

Example CSV - Sheet1 — Notatnik

Plik Edycja Format Widok Pomoc

Email,First Name,Last Name,Company,Snippet 1

example1@domain.com,John,Smith,Company 1,Snippet Sentence1

example2@gmail.com,Mary,Blake,Company 2,Snippet Sentence 2

example3@outlook.com,James,Joyce,Company 3,Snippet Sentence 3

Has the extension “.csv”

Each row
is
separated
by a new
line



Example CSV



File Edit View Insert Format Data Tools Add-ons Help All changes saved in Drive

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fx

	A	B	C	D	E	F
1	Email	First Name	Last Name	Company	Snippet 1	
2	example1@domain.com	John	Smith	Company 1	Snippet Sentence1	
3	example2@gmail.com	Mary	Blake	Company 2	Snippet Sentence 2	
4	example3@outlook.com	James	Joyce	Company 3	Snippet Sentence 3	
5						
6	CSV file					
7						
8						

Example CSV - Sheet1 — Notatnik

Plik Edycja Format Widok Pomoc

Email,First Name,Last Name,Company,Snippet 1

example1@domain.com,John,Smith,Company 1,Snippet Sentence1

example2@gmail.com,Mary,Blake,Company 2,Snippet Sentence 2

example3@outlook.com,James,Joyce,Company 3,Snippet Sentence 3

JSON: key-value pairs

nested/hierarchical data

{"Name": "Isabela"}

The diagram illustrates a JSON object consisting of a single key-value pair. The key is labeled 'Name' and the value is 'Isabela'. Two pink arrows point from the words 'key' and 'value' to their respective components in the JSON string. The word 'key' points to the colon character ':', and the word 'value' points to the double quotes around 'Isabela'.

JSON

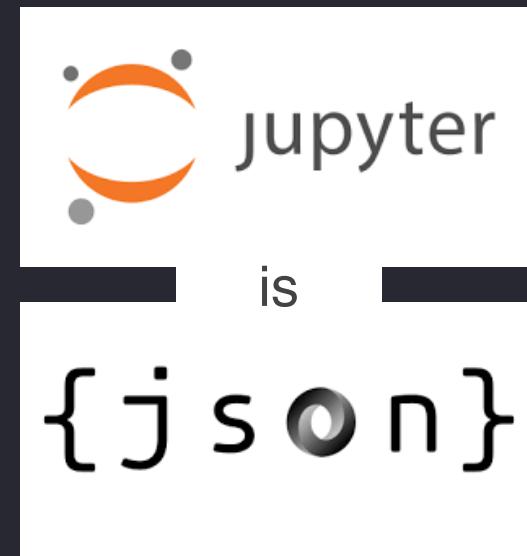
These are all
nested within
attributes

```
"attributes": {  
    "Take-out": true,  
    "Wi-Fi": "free",  
    "Drive-Thru": true,  
    "Good For": {  
        "dessert": false,  
        "latenight": false,  
        "lunch": false,  
        "dinner": false,  
        "breakfast": false,  
        "brunch": false  
    },  
},
```

These are all
nested within
"Good For"

JSON

```
{  
  "cells": [  
    {  
      "cell_type": "markdown",  
      "metadata": {},  
      "source": [  
        "This example represents the output the t-SNE dimensionality reduction algorithm on embeddings computed from Unicode emojis using Keras  
      ]  
    },  
    {  
      "cell_type": "code",  
      "execution_count": null,  
      "metadata": {},  
      "outputs": [],  
      "source": [  
        "import pandas as pd\n",  
        "import holoviews as hv\n",  
        "hv.extension('bokeh')"  
      ]  
    },  
    {  
      "cell_type": "markdown",  
      "metadata": {},  
      "source": [  
        "## Declaring data"  
      ]  
    },  
    {  
      "cell_type": "code",  
      "execution_count": null,  
      "metadata": {},  
      "outputs": [  
        {"text": "jupyter is json"}  
      ],  
      "source": [  
        "jupyter_nbformat: 3",  
        "jupyter_nbformat_minor: 0",  
        "jupyter_version": "1.0",  
        "nbformat": 4, "nbformat_minor": 2,  
        "cells": [  
          {"cell_type": "code", "execution_count": null, "metadata": {}, "outputs": [{"text": "jupyter is json"}], "source": ["jupyter_nbformat: 3", "jupyter_nbformat_minor: 0", "jupyter_version": "1.0", "nbformat": 4, "nbformat_minor": 2]}  
      ]  
    }  
  ]  
}
```



Jupyter notebooks suck to version control

<https://nextjournal.com/schmudde/how-to-version-control-jupyter>

```
{  
    "cell_type": "code",  
    "execution_count": null,  
    "metadata": {},  
    "outputs": [],  
    "source": [  
        "import pandas as pd\n",  
        "import holoviews as hv\n",  
        "hv.extension('bokeh')"  
    ]  
},
```

A large orange arrow pointing to the right, set against a black background. The word "DETOUR" is written in bold, black, sans-serif capital letters across the center of the arrow.

DETOUR

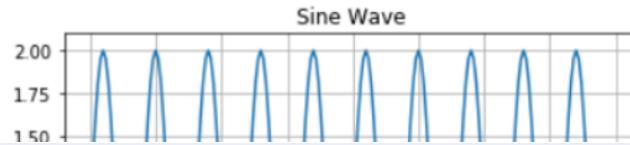
```
In [10]: import numpy as np
import matplotlib.pyplot as plt

# Data for plotting
t = np.arange(0.0, 2.0, 0.01)
s = 1 + np.sin((5 * 2)* np.pi * t)

# Note that using plt.subplots below is equivalent to using
# fig = plt.figure() and then ax = fig.add_subplot(111)
fig, ax = plt.subplots()
ax.plot(t, s)

ax.set(xlabel='time (s)', ylabel='voltage (mV)', title='Sine Wave')
ax.grid()
```

Out[10]:



```
"outputs": [
{
  "data": {
    "image/png": "iVBORw0KGgoAAAANSUhEUgAAAYwAAAECAYAAAB1xKBvAAAABHNCSVQICAgIfAhkiAAAAAlwSFzAAALEgAACxIB0t1+/AAAADl0RVh0U29mdHdhcmUAbWF0cGxvdGxpYiB2ZXJzaW9uIDIuMi4yLCBodHRwOi8vbWF0cGxvdGxpYi5vcmcvhp/UCwAAIABJREFUeJzsXmcHNd13/s9vc4+2EgABHeQEkVSXGGRFLembFNSPn7Wyy45i5UXh5ZjvcSy4xcr78WK5bwkzvKSeI1l0qaVxZKc0JLN+FHc0dxJEVxAAGQBAiCIdbDP0tPT+80fVdXdmOnl1q17ezBm/T6f+QDdXVXnVtU996z3HFFKESNGjBgxYvRDYrkHECNGjBgxVgZigREjRowYMBQQC4wYMWLEiKGFWGDEiBEjRgwtxAIjRowYMWJoIRYYMWLEiBFDC7HAiBEDEJG/JiKPL/c4YsQ4nxELjBgfGojIXSLyoojMiMg"
```

Jupyter notebooks suck to version control

<https://nextjournal.com/schmudde/how-to-version-control-jupyter>

Clear Output Manually

The simplest solution is to always clear the output before committing. **Cell → All Output → Clear → Save**. This removes any binary blobs that have been generated by the notebook. There are three main drawbacks:

- It is a manual process.
- Collaborators on other machines will need to rerun the notebook to see the output, requiring additional time and setup.

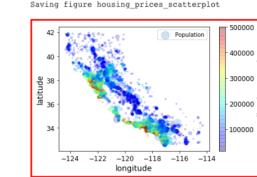
Jupyter notebooks suck to version control

<https://nextjournal.com/schmudde/how-to-version-control-jupyter>

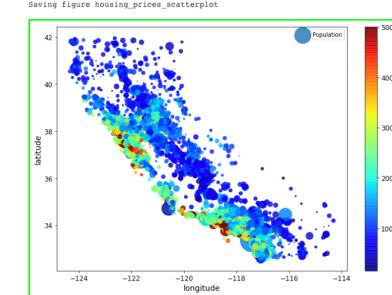
ReviewNB

[ReviewNB](#) is a GitHub app that also offers visual diffing with an interface that looks similar to the traditional Jupyter IDE. Because the outputs are visualized, problems associated with committing binary blobs disappear.

```
1 housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.2,
2   s=housing["population"]*10, label="Population", figsize=(10,7),
3   c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True,
4   sharex=False)
5 plt.legend()
6 save_fig("housing_prices_scatterplot")
```



```
1 housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.2,
2   s=housing["population"]*10, label="Population", figsize=(10,7),
3   c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True,
4   sharex=False)
5 plt.legend()
6 save_fig("housing_prices_scatterplot")
```

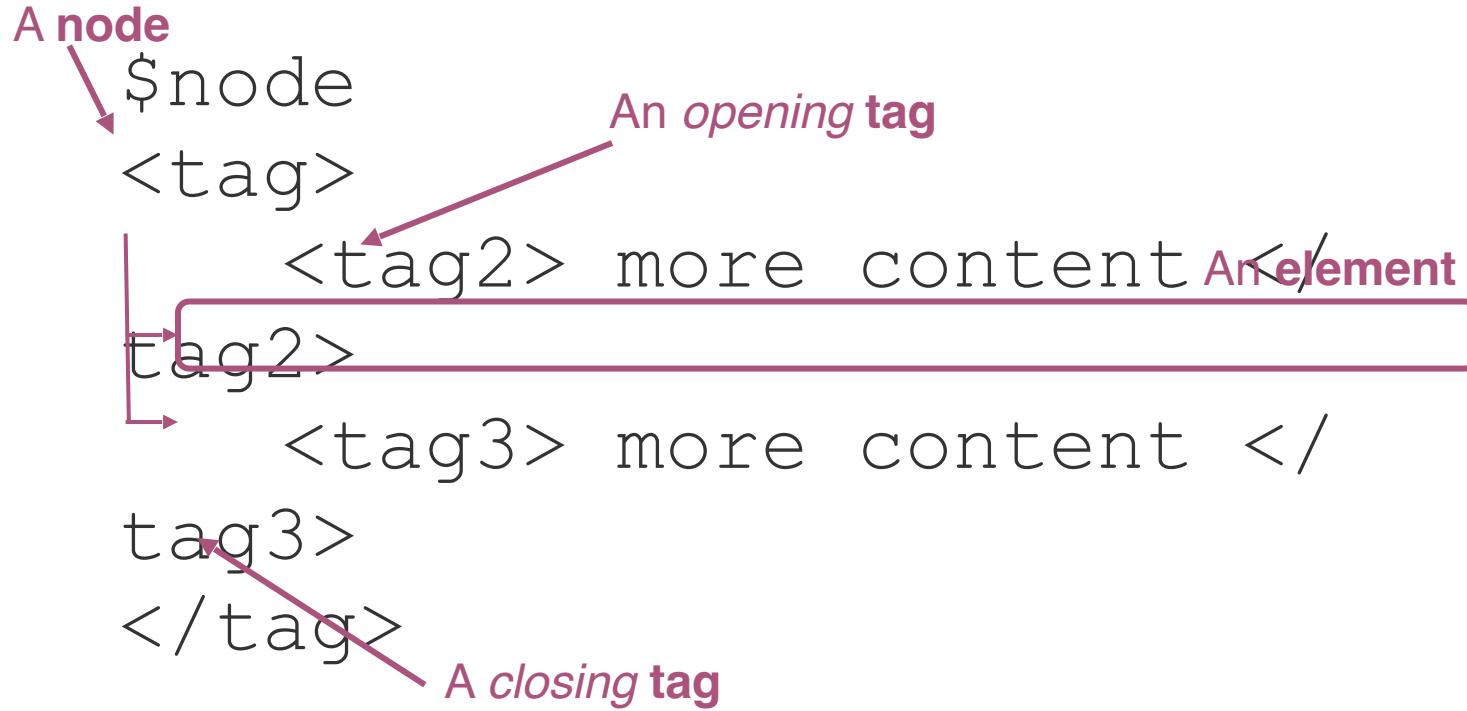


ReviewNB example courtesy of the [ReviewNB website](#)

Back to data formats...

Extensible Markup Language (XML): nodes, tags, and elements

nested/hierarchical data



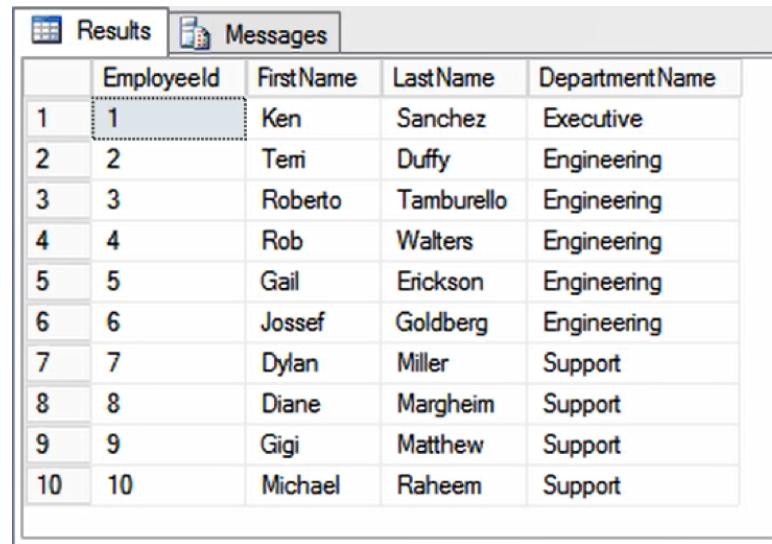
XML

```
<?xml version="1.0" encoding="UTF-8"?>
<customers>
    <customer>
        <customer_id>1</customer_id>
        <first_name>John</first_name>
        <last_name>Doe</last_name>
        <email>john.doe@example.com</email>
    </customer>
    <customer>
        <customer_id>2</customer_id>
        <first_name>Sam</first_name>
        <last_name>Smith</last_name>
        <email>sam.smith@example.com</email>
    </customer>
    <customer>
        <customer_id>3</customer_id>
        <first_name>Jane</first_name>
        <last_name>Doe</last_name>
        <email>jane.doe@example.com</email>
    </customer>
</customers>
```

XML

Relational Databases: A set of interdependent tables

1. Efficient Data Storage
2. Avoid Ambiguity
3. Increase Data Privacy



	EmployeeId	FirstName	LastName	DepartmentName
1	1	Ken	Sanchez	Executive
2	2	Temi	Duffy	Engineering
3	3	Roberto	Tamburello	Engineering
4	4	Rob	Walters	Engineering
5	5	Gail	Erickson	Engineering
6	6	Jossef	Goldberg	Engineering
7	7	Dylan	Miller	Support
8	8	Diane	Margheim	Support
9	9	Gigi	Matthew	Support
10	10	Michael	Raheem	Support

relational database

Information is stored across tables

unique_identifier
AH13JK
JJ29JJ
CI21AA

unique_identifier
AH13JK
JJ29JJ
JJ29JJ
XJ11AS
CI21AA

unique_identifier
AH13JK
SE92FE
CI21AA

entries are *related* to one another by their unique identifier

relational database

restaurant

name	id	address	type
Taco Stand	AH13JK	1 Main St.	Mexican
Pho Place	JJ29JJ	192 Street Rd.	Vietnamese
Taco Stand	XJ11AS	18 W. East St.	Fusion
Pizza Heaven	CI21AA	711 K Ave.	Italian

health inspections

id	inspection_date	inspector	score
AH13JK	2018-08-21	Sheila	97
JJ29JJ	2018-03-12	D'eonte	98
JJ29JJ	2018-01-02	Monica	66
XJ11AS	2018-12-16	Mark	43
CI21AA	2018-08-21	Anh	99

rating

id	stars
AH13JK	4.9
JJ29JJ	4.8
XJ11AS	4.2
CI21AA	4.7

relational database

restaurant

name	id	address	type
Taco Stand	AH13JK	1 Main St.	Mexican
Pho Place	JJ29JJ	192 Street Rd.	Vietnamese
Taco Stand	XJ11AS	18 W. East St.	Fusion
Pizza Heaven	CI21AA	711 K Ave.	Italian

Two different restaurants with
the same name will have
different unique identifiers

health inspections

id	inspection_date	inspector	score
AH13JK	2018-08-21	Sheila	97
JJ29JJ	2018-03-12	D'eonte	98
JJ29JJ	2018-01-02	Monica	66
XJ11AS	2018-12-16	Mark	43
CI21AA	2018-08-21	Anh	99

rating

id	stars
AH13JK	4.9
JJ29JJ	4.8
XJ11AS	4.2
CI21AA	4.7

relational database

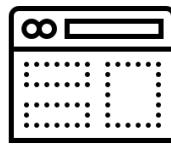
Unstructured Data

Some datasets record information about the state of the world, but in a more heterogeneous way. Perhaps it is a large text corpus with images and links like Wikipedia, or the complicated mix of notes and test results appearing in personal medical records.

Unstructured Data Types



Text files
and
documents



Websites
and
applications



Sensor
data



Image
files



Audio
files



Video
files



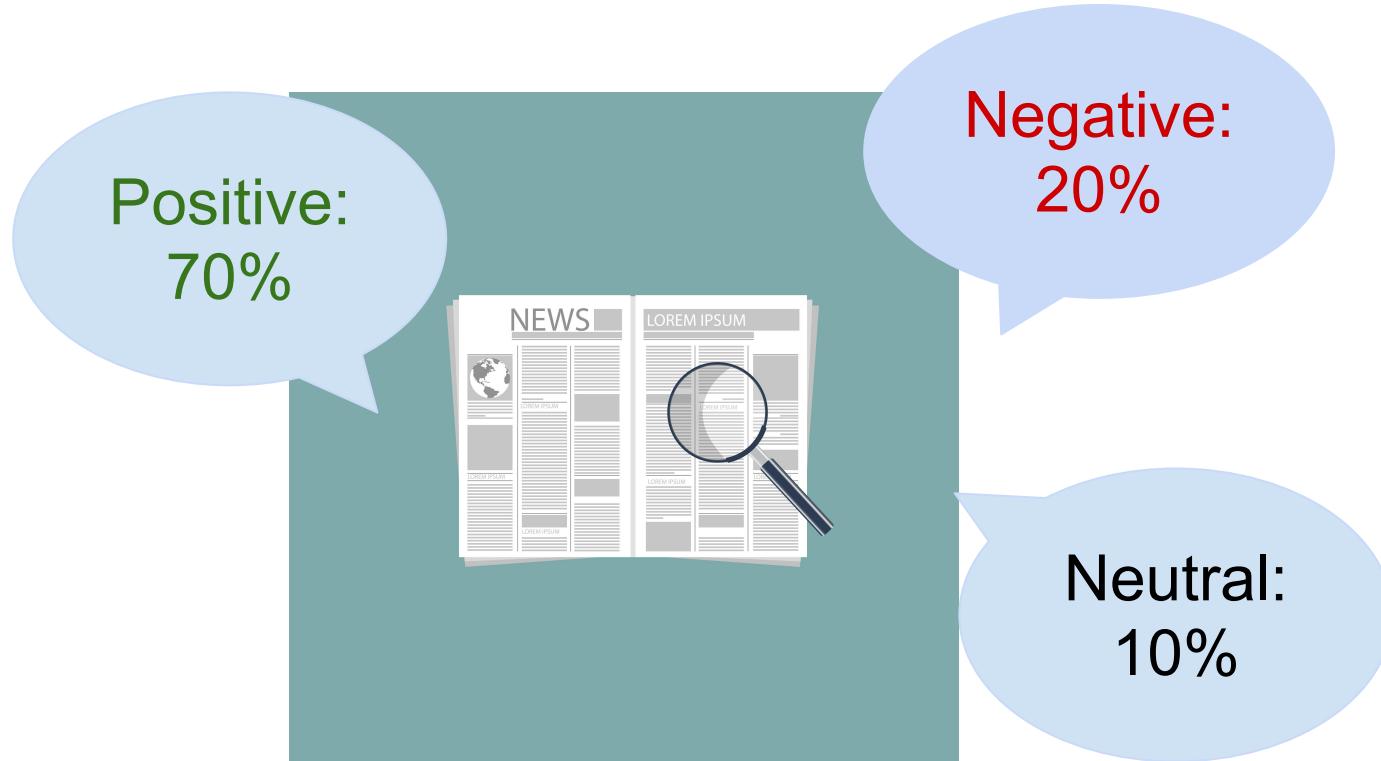
Email
data

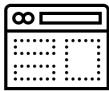


Social
media
data



Text: Sentiment Analysis





PYTHON

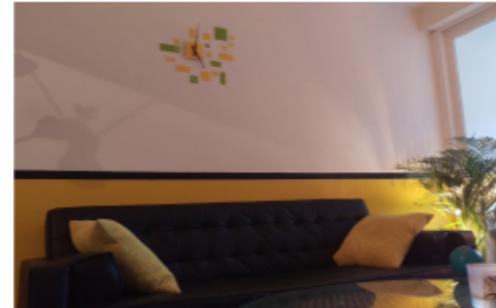
BEAUTIFULSOUP

WEB SCRAPING





Bedroom Or Not?



"The left two photos were correctly predicted as bedrooms; The right two photos were correctly predicted NOT as bedrooms."

Tidy Data

"Good data scientists understand, in a deep way, that the heavy lifting of cleanup and preparation isn't something that gets in the way of solving the problem: it is the problem."

- DJ Patil



Australian Bureau of Statistics

1800.0 Australian Marriage Law Postal Survey, 2017

Released on 15 November 2017

Table 5 Participation by Federal Electoral Division(a), Males and Age Gender apartheid

Table junk

Yeah NA		18-19 years	20-24 years	25-29 years	30-34 years	35-39 years	40-44 years	45-49 years	50-54 years	55-59 years	60-64 years
i22 Lingiari (c)	Total participants	292	1,058	1,465	1,653	1,515	1,516	1,710	1,730	1,753	1,574
i23 Lingiari (c)	Eligible participants	572	2,910	3,789	3,996	3,607	3,506	3,645	3,331	2,960	2,456
i24 Lingiari (c)	Participation rate (%)	51.0	36.4	38.7	41.4	42.0	43.2	46.9	51.9	59.2	64.1
Primary keynotes		Communion									
Merged cells		Total participants	442	1,461	2,066	2,357	2,188	2,057	2,224	2,108	2,134
Solomon		Eligible participants	750	2,991	3,994	4,155	3,634	3,398	3,427	3,066	2,931
Solomon		Participation rate (%)	58.9	48.8	51.7	56.7	60.2	60.5	64.9	68.8	72.8
Northern Territory (Total)		Total participants	734	2,519	3,531	4,010	3,703	3,573	3,934	3,838	3,887
Northern Territory (Total)		Eligible participants	1,322	5,901	7,783	8,151	7,241	6,904	7,072	6,397	5,891
Northern Territory (Total)		Participation rate (%)	55.5	42.7	45.4	49.2	51.1	51.8	55.6	60.0	69.5
Australian Capital Territory Divisions		Covariate as Subheading									
Canberra(d)		Summary of data inside data									
Canberra(d)		Total participants	1,764	4,789	4,817	4,973	4,626	4,453	5,074	4,826	5,169
Canberra(d)		Eligible participants	2,260	6,471	6,448	6,509	5,983	5,805	6,302	5,902	6,044
Canberra(d)		Participation rate (%)	78.1	74.0	74.7	76.4	77.3	76.7	80.5	81.8	85.5
Fenner(e)		Total participants	1,477	4,687	5,178	5,786	6,025	5,463	5,191	4,208	3,948
Fenner(e)		Eligible participants	1,904	6,354	7,121	7,822	7,960	7,155	6,480	5,206	4,692
Fenner(e)		Participation rate (%)	77.6	73.8	72.7	74.0	75.7	76.4	80.1	80.8	84.1
Australia		NA Yeah									
Australia		Total participants	5,241	9,476	9,993	10,739	10,051	9,310	10,205	9,034	9,117
Australia		Eligible participants	4,164	12,825	13,569	14,331	13,943	12,960	12,782	11,108	10,736
Australia		Participation rate (%)	77.8	73.9	73.7	75.1	76.4	76.5	80.3	81.3	84.9
Total		Total participants	151,297	438,166	441,658	460,548	462,206	479,360	524,620	517,693	543,449
Total		Eligible participants	201,439	635,909	646,916	665,250	656,446	660,841	693,850	659,150	664,720
Total		Participation rate (%)	75.1	68.9	68.3	69.2	70.4	72.5	75.6	78.5	81.8

(a) The Federal Electoral Divisions are current as at 24 August 2017

(b) Includes those whose age is unknown

(c) Includes Christmas Island and the Cocos (Keeling) Islands

(d) Includes Norfolk Island

(e) Includes Jervis Bay

Return of the table junk

untidy data

Australian Bureau of Statistics												
1800.0 Australian Marriage Law Postal Survey, 2017												
Released 15 November 2017												
Table 5 Participation by Federal Electoral Division(a) Males and Age												Table junk
Primary keynotes												
Yeah NA												
		18-19 years	20-24 years	25-29 years	30-34 years	35-39 years	40-44 years	45-49 years	50-54 years	55-59 years	60-64 years	
Lingard(c)	Total participants	292	1,058	1,460	1,653	1,515	1,516	1,710	1,730	1,753	1,574	
	Eligible participants	292	2,910	3,049	3,096	3,607	3,506	3,645	3,331	2,960	2,456	
	Participation rate (%)	51.0	36.4	38.7	41.4	42.0	43.2	46.8	51.9	58.2	64.1	
Merged cells												
Solomon	Total participants	442	1,461	2,068	2,357	2,188	2,057	2,224	2,108	2,134	1,772	
	Eligible participants	750	2,991	3,994	4,155	3,634	3,398	3,427	3,066	2,931	2,355	
	Participation rate (%)	56.9	48.8	51.7	56.7	60.2	60.5	64.9	68.8	72.8	75.2	
Northern Territory	Total participants	734	2,519	3,531	4,010	3,703	3,573	3,934	3,838	3,887	3,346	
(Total)	Eligible participants	1,322	5,901	7,783	8,151	7,241	6,904	7,072	6,397	5,891	4,811	
	Participation rate (%)	55.5	42.7	45.4	49.2	51.1	51.8	55.6	60.0	66.0	69.5	
Australian Capital Territory Divisions	Covariate as Subheading											
Canberra(d)	Summary of data inside data											
	Total participants	1,764	4,789	4,817	4,973	4,626	4,453	5,074	4,826	5,169	4,394	
	Eligible participants	2,260	6,471	6,448	6,509	5,983	5,805	6,302	5,902	6,044	5,057	
	Participation rate (%)	78.1	74.0	74.7	76.4	77.3	76.7	80.5	81.8	85.5	86.9	
Fenner(e)	Total participants	1,477	4,687	5,178	5,786	6,025	5,463	5,191	4,208	3,948	3,465	
	Eligible participants	1,904	6,354	7,121	7,822	7,960	7,155	6,480	5,206	4,692	3,945	
	Participation rate (%)	77.6	73.8	72.7	74.0	75.7	76.4	80.1	80.8	84.1	87.8	
	NA Yeah											
Australian Capital Territory (Total)	Total participants	5,542	9,416	9,895	10,155	10,054	9,219	10,205	9,034	9,141	7,659	
	Eligible participants	4,164	12,825	13,569	14,331	13,943	12,960	12,782	11,108	10,736	9,002	
	Participation rate (%)	77.8	73.9	73.7	75.1	76.4	76.5	80.3	81.3	84.9	87.3	
Australia	Total participants	151,297	438,166	441,658	460,548	462,206	479,360	524,620	517,693	543,449	506,799	
	Eligible participants	201,439	635,909	646,916	665,250	656,446	660,841	693,850	659,150	664,720	597,386	
	Participation rate (%)	75.1	68.9	68.3	69.2	70.4	72.5	75.6	78.5	81.8	84.8	
a)	The Federal Electoral Divisions are current as at 24 August 2017											
b)	Includes those whose age is unknown											
c)	Includes Christmas Island and the Cocos (Keeling) Islands											
d)	Includes Norfolk Island											
e)	Includes Jervis Bay											
	Return of the table junk											
	MS Excel or Die											

data → wrangling

tidy data

area	gender	age	State	Area (sq km)	Eligible participants	Participation rate (%)	Total participants	Total Participants
Adelaide	Female	18-19 years	SA	76	1341	83.5	1120	1120
Adelaide	Female	20-24 years	SA	76	4620	81.2	3750	3750
Adelaide	Female	25-29 years	SA	76	4897	81.8	4004	4004
Adelaide	Female	30-34 years	SA	76	4784	79.8	3820	3820
Adelaide	Female	35-39 years	SA	76	4319	79	3411	3411
Adelaide	Female	40-44 years	SA	76	4310	80.6	3472	3472
Adelaide	Female	45-49 years	SA	76	4579	81.4	3728	3728
Adelaide	Female	50-54 years	SA	76	4475	84.7	3791	3791
Adelaide	Female	55-59 years	SA	76	4622	87.3	4033	4033
Adelaide	Female	60-64 years	SA	76	4342	89.3	3879	3879
Adelaide	Female	65-69 years	SA	76	3970	90.7	3602	3602
Adelaide	Female	70-74 years	SA	76	3009	90.3	2716	2716
Adelaide	Female	75-79 years	SA	76	2156	88.5	1908	1908
Adelaide	Female	80-84 years	SA	76	1673	85.1	1423	1423

1	area	gender	age	State	Area (sq km)	Eligible participants	Participation rate (%)	Total participants	Total Participants		
2	Adelaide	Female	18-19 years	SA	76	1341	83.5	1120	1120		
3	Adelaide	Female	20-24 years	SA	76	4620	81.2	3750	3750		
4	Adelaide	Female	25-29 years	SA	76	4897	81.8	4004	4004		
5	Adelaide	Female	30-34 years	SA	76	4784	79.8	3820	3820		
6	Adelaide	Female	35-39 years	SA	76	4319	79	3411	3411		
7	Adelaide	Female	40-44 years	SA	76	4310	80.6	3472	3472		
8	Adelaide	Female	45-49 years	SA	76	4579	81.4	3728	3728		
9	Adelaide	Female	50-54 years	SA	76	4475	84.7	3791	3791		
10	Adelaide	Female	55-59 years	SA	76	4622	87.3	4033	4033		
A	B	C	D	E	F	G	H	I	J		
Australian Bureau of Statistics	Table junk										
1800.0 Australian Marriage Law Postal Survey, 2017											
Released on 31 November 2017											
Table 5 Participation by Federal Electoral Division (a) Males and Age Gender apartheid											
Yeah NA	18-19 years	20-24 years	25-29 years	30-34 years	35-39 years	40-44 years	45-49 years	50-54 years	55-59 years	60-64 years	
Total participants	292	1,059	1,460	1,063	1,515	1,516	1,710	1,720	1,753	1,574	
Eligible participants	292	1,059	1,460	1,063	1,507	1,508	1,701	1,711	1,742	1,565	
Participation rate (%)	51.0	36.4	37.9	45.4	42.0	42.2	46.9	51.9	59.2	44.1	
Primary keyparties											
Merged cells											
Solomon	Eligible participants	443	1,461	2,065	2,367	2,188	2,087	2,234	2,108	2,334	1,771
Participation rate (%)	56.9	48.8	51.7	56.7	60.2	60.5	64.9	68.8	72.8	75.2	
Northern Territory (Total)	Eligible participants	734	2,539	3,551	4,010	3,703	3,573	3,934	3,883	3,887	3,346
Participation rate (%)	59.5	42.7	45.4	49.2	51.1	51.8	55.6	60.0	68.0	69.5	
Australian Capital Territory Divisions	Coverage as Subheading	Summary of territory inside data									
Yeah NA	18-19 years	20-24 years	25-29 years	30-34 years	35-39 years	40-44 years	45-49 years	50-54 years	55-59 years	60-64 years	
Total participants	7,745	4,793	4,817	4,973	4,626	4,453	5,074	4,826	5,369	4,294	
Eligible participants	7,260	4,471	4,648	5,659	5,983	5,805	6,302	5,962	6,044	5,067	
Participation rate (%)	78.1	74.0	74.7	75.4	77.3	76.7	80.5	81.8	85.5	88.9	
Total participants	1,477	4,687	5,178	5,786	6,025	5,463	5,191	4,290	3,948	3,465	
Eligible participants	1,304	4,554	7,212	7,622	7,960	7,155	4,690	5,206	4,602	3,945	
Participation rate (%)	77.4	72.7	73.8	74.3	75.3	74.8	80.4	81.4	84.1	87.0	
Australian Capital Territory (Total)	Eligible participants	2,591	2,906	3,369	3,601	3,926	3,609	3,747	3,807	3,799	
Participation rate (%)	64.6	61.4	63.6	65.4	67.4	69.4	71.4	72.4	74.4	73.4	
Australia	Eligible participants	151,297	438,165	441,168	460,549	462,206	479,360	524,850	517,893	545,149	506,759
Participation rate (%)	75.1	77.8	73.9	73.7	75.1	76.4	76.5	80.3	81.3	84.9	87.3
Total	Eligible participants	201,439	638,909	646,516	665,250	658,446	660,841	681,850	659,150	664,720	597,386
Participation rate (%)	75.1	68.9	68.3	69.2	70.4	72.5	75.6	78.5	81.8	84.8	

(a) The Federal Electoral Divisions are current as at 24 August 2017

(b) Includes those aged 16 or unknown

(c) Includes Tasmania and the Cocos (Keeling) Islands

(d) Includes Norfolk Island

(e) Includes Jervis Bay

Return of the table junk

Survey-data-with-r-5d35cea07962

MS Excel or Die

Tidy Data

1. Each **variable** you measure should be in a single column

	A	B	C	D	E	F	G
1	ID	LastName	FirstName	Sex	City	State	Occupation
2	1004	Smith	Jane	female	Frederick	MD	Welder
3	4587	Nayef	Mohammed	male	Upper Darby	PA	Nurse
4	1727	Doe	Janice	female	San Diego	CA	Doctor
5	6879	Jordan	Alex	male	Birmingham	AL	Teacher

2. Every **observation** of a variable should be in a different row

	A	B	C	D	E	F	G
1	ID	LastName	FirstName	Sex	City	State	Occupation
2	1004	Smith	Jane	female	Frederick	MD	Welder
3	4587	Nayef	Mohammed	male	Upper Darby	PA	Nurse
4	1727	Doe	Janice	female	San Diego	CA	Doctor
5	6879	Jordan	Alex	male	Birmingham	AL	Teacher

3. There should be one table for each type of data

Demographic Survey Data

	A	B	C	D	E	F	G
1	ID	LastName	FirstName	Sex	City	State	Occupation
2	1004	Smith	Jane	female	Frederick	MD	Welder
3	4587	Nayef	Mohammed	male	Upper Darby	PA	Nurse
4	1727	Doe	Janice	female	San Diego	CA	Doctor
5	6879	Jordan	Alex	male	Birmingham	AL	Teacher

Doctor's Office Measurements Data

	A	D	E	F	G
1	ID	Height_inches	Weight_lbs	Insulin	Glucose
2	1004	65	180	0.60	163
3	4587	75	215	1.46	150
4	1727	62	124	0.72	177
5	6879	77	160	1.23	205

4. If you have multiple tables, they should include a column in each *with the same column label* that allows them to be joined or merged

	A	B	C	D	E	F	G
1	ID	LastName	FirstName	Sex	City	State	Occupation
2	1004	Smith	Jane	female	Frederick	MD	Welder
3	4587	Nayef	Mohammed	male	Upper Darby	PA	Nurse
4	1727	Doe	Janice	female	San Diego	CA	Doctor
5	6879	Jordan	Alex	male	Birmingham	AL	Teacher

	A	D	E	F	G
1	ID	Height_inches	Weight_lbs	Insulin	Glucose
2	1004	65	180	0.60	163
3	4587	75	215	1.46	150
4	1727	62	124	0.72	177
5	6879	77	160	1.23	205

Tidy data == rectangular data

A

	A	B	C	D	E
1	id	sex	glucose	insulin	triglyc
2	101	Male	134.1	0.60	273.4
3	102	Female	120.0	1.18	243.6
4	103	Male	124.8	1.23	297.6
5	104	Male	83.1	1.16	142.4
6	105	Male	105.2	0.73	215.7

Tidy Data Benefits

1. consistent data structure
2. foster tool development
3. require only a small set of tools to be learned
4. allow for datasets to be combined

TIDY data is **NOT** the same as **CLEAN** data

Clean Data

Data cleaning is the process of detecting and correcting/ removing data records that are

- incomplete,
- incorrect,
- inaccurate, or
- irrelevant

and often includes making sure missing data is correctly marked and that duplicate records and other errors are removed

Data that is **TIDY** and **CLEAN** is ready for use



A

ID	Last	First	height_m	height_f
1004	Smith	Jane	NA	65
4587	Nayef	Mohammed	72	NA
1727	Doe	Janice	NA	60
6879	Jordan	Alex	55	NA

B

ID	Last	First	height_m	height_f
1004	Smith	Jane		65
4587	Nayef	Mohammed	72	
1727	Doe	Janice		60
6879	Jordan	Alex	55	

C

ID	Last	First	sex	height
1004	Smith	Jane	female	65
4587	Nayef	Mohammed	male	72
1727	Doe	Janice	fem	60
6879	Jordan	Alex	male	55

D

ID	Last	First	sex	height
1004	Smith	Jane	F	65
4587	Nayef	Mohammed	M	72
1727	Doe	Janice	F	60
6879	Jordan	Alex	M	55

Which of these tables stores data best?



A



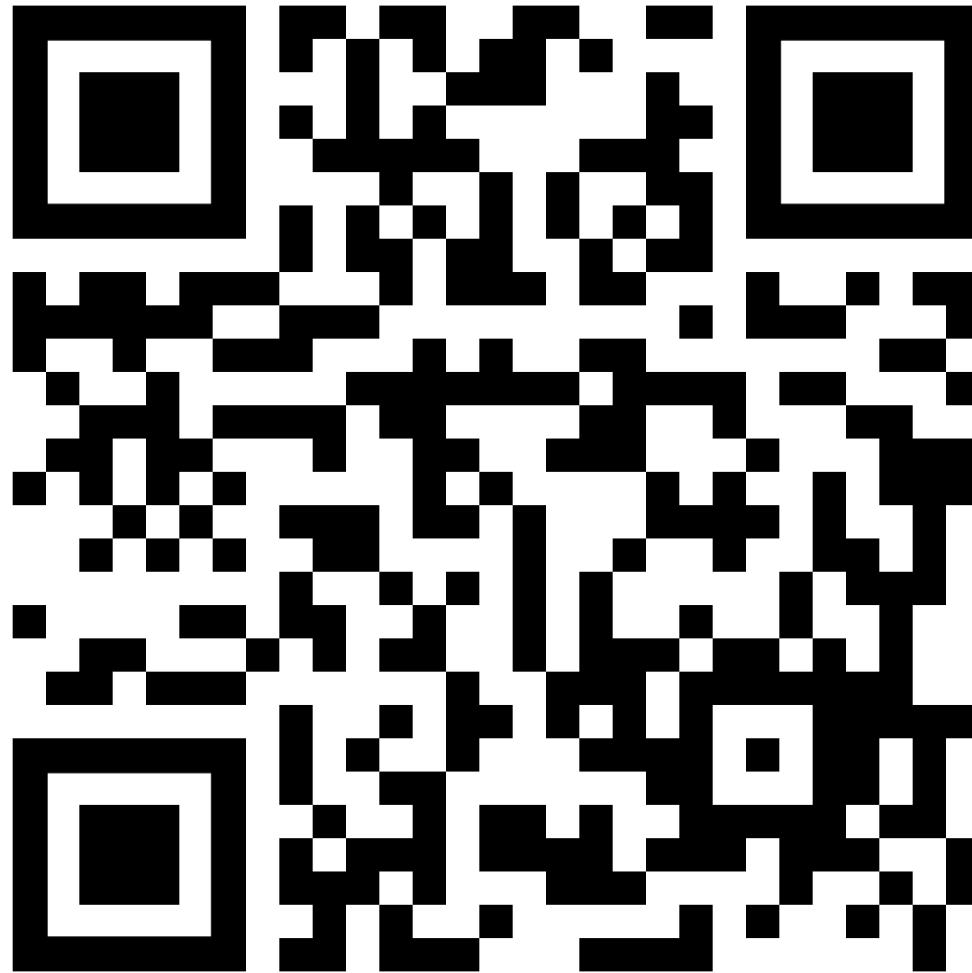
B



C



D



2024-2025



Mentor Sign-Ups

About EDGE Mentorship

Join the Society of Women Engineers and
Women in Computing at UC San Diego to:

- Give back to the community and have a rewarding experience
 - Attend 1 to 2 events per quarter
 - Be a role model to future women engineers!



Through EDGE, you will....

- Gain active membership to WIC and SWE
 - Build a community of empowered women in STEM

Mentor Application:

Deadline: 10/16/2024



For updates & more information
about EDGE:



@edge.ucsd



<https://edgeucsd.wixsite.com/edge>



 edge.ucsd@gmail.com



Clean

ID	Last	First	height_m	height_f
1004	Smith	Jane	NA	65
4587	Nayef	Mohammed	72	NA
1727	Doe	Janice	NA	60
6879	Jordan	Alex	55	NA

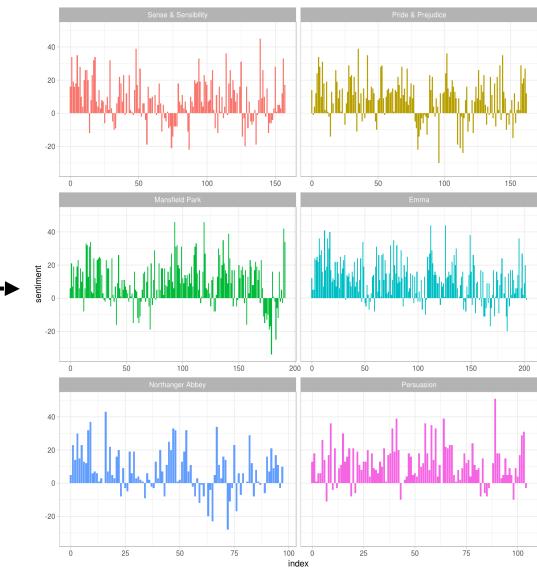
Tidy

ID	Last	First	sex	height
1004	Smith	Jane	female	65
4587	Nayef	Mohammed	male	72
1727	Doe	Janice	fem	60
6879	Jordan	Alex	male	55

Tidy + Clean

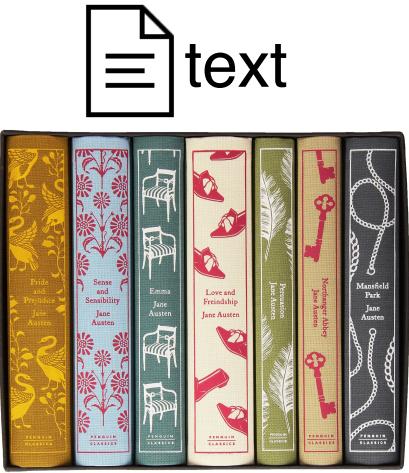
ID	Last	First	sex	height
1004	Smith	Jane	F	65
4587	Nayef	Mohammed	M	72
1727	Doe	Janice	F	60
6879	Jordan	Alex	M	55

results



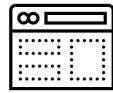
tidy dataset

Word	Novel	Frequency
good	Emma	359
young	Emma	192
friend	Emma	166



text





website

JAN. 21 "I wasn't a fan of Iraq. I didn't want to go to war." (A reporter for Time magazine — and I have been here since day one) to me: "I didn't want to be in a room where the talk was of 'war against Iraq'." (There was a moment of honest silence before he continued.) "I didn't want to be in a room where the talk was of 'war against Iraq'." (There was a moment of honest silence before he continued.)

JAN. 22 "Revenue is down and I really think voters expect us to tax the popular vote." (There is no evidence of that.)

JAN. 23 "Now, the audience was the biggest ever. But once we started, look back at how it grew. This crowd was massive." (Official aerial photos show Obamas 2009 inauguration was the most heavily attended.)

JAN. 24 "Take a look at the Pew reports (which show voter fraud)." (The report never mentioned voter fraud.)

JAN. 25 "No, he's not." (No, he's not.)

JAN. 26 "No, look, when President Obama had his two weeks ago making a speech, very nice speech. Two people were shot and killed during his speech. You can't say that." (Two people were killed during the inauguration ceremony in China this year.)

JAN. 26 "Who takes in a few of thousands of people? We leave nothing like that there. There are no people left there. They take in a few hundred thousand people. Who leaves nothing like that there? You see what I mean?" (Wrong. Just as in 2009.)

JAN. 27 "Out of hundreds of millions of dollars for one particular place, hundreds of millions of dollars is a short period of time. I would like to point, like, weeks, hours, less than hours, and more, many hundreds of millions of dollars. And the plan's going to be better. (There is no evidence of that.)

JAN. 28 "It's not a coincidence that he's coming to the White House. He's coming to the White House because he's been invited by the president. He's not going to be there because he's been invited by the Senate majority whip or by the departing senator or by the incoming senator." (The Coloradan was invited to the president's inauguration.)

JAN. 29 "Only 100 people or so of 30,000 were detained and held for questioning. Big problems at airports were caused by Delta computer malfunctions. (At least 100 people were detained and arrested, and the number was much higher.)

JAN. 30 "Professional associations, things and people who are involved in politics, they're not going to be here. (The Coloradan was invited to the White House.)

JAN. 31 "We're going to apologize for it but not because of any who's winning the election. (The FAZ-MINIS government is still lost.)" (It never concluded.)

FEB. 1 "We had 300 people out of hundreds of thousands and all we did was we had three people very, very ready!" (Official White House website claims that 300 people were ready.)

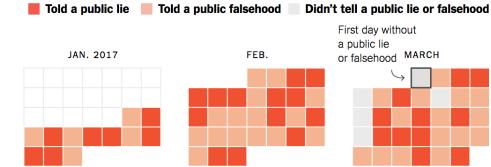
FEB. 1 "I had already written that that little statement which I put forward in the explanation on the FBN... (The Coloradan was interviewed, and the transcript was not available.)

FEB. 1 "To quote to a point where it's not even being reported. And in most cases, the very top-dictated from [which] had to report it."

tidy dataset

date	lie	explanation	url
0 Jan 21, 2017	I wasn't a fan of Iraq. I didn't want to go to war...	He was for an invasion before he was against it.	https://www.buzzfeed.com/andrewkaczynski/in-20...
1 Jan 21, 2017	A reporter for Time magazine — and I have been...	Trump was on the cover 11 times and Nixon 11 times and Nixon apple...	http://nation.time.com/2013/11/06/10-things-yo...
2 Jan 23, 2017	Between 3 million and 5 million illegal votes ...	There's no evidence of illegal voting.	https://www.nytimes.com/2017/01/23/us/politics...
3 Jan 25, 2017	Now, the audience was the biggest ever. But th...	Official aerial photos show Obamas 2009 inaug...	https://www.nytimes.com/2017/01/21/us/politics...
4 Jan 25, 2017	Take a look at the Pew reports (which show vot...	The report never mentioned voter fraud.	https://www.nytimes.com/2017/01/24/us/politics...

results



text (lyrics)

ThePudding "I'll be analyzing the repetitiveness of a dataset of 15,000 songs that charted on the Billboard Hot 100 between 1958 and 2017."



AN EXERCISE IN LANGUAGE COMPRESSION

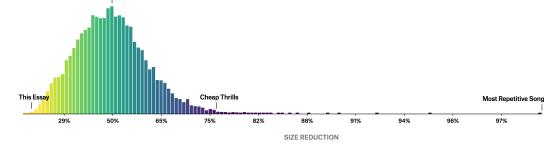
Are Pop Lyrics Getting More Repetitive?

By Colin Morris

tidy dataset

song	Artist	Released	Reduction
Cheap Thrills	Sia	2016	76
Around The World	Daft Punk	1997	98
Everybody Dies	J. Cole	2018	27

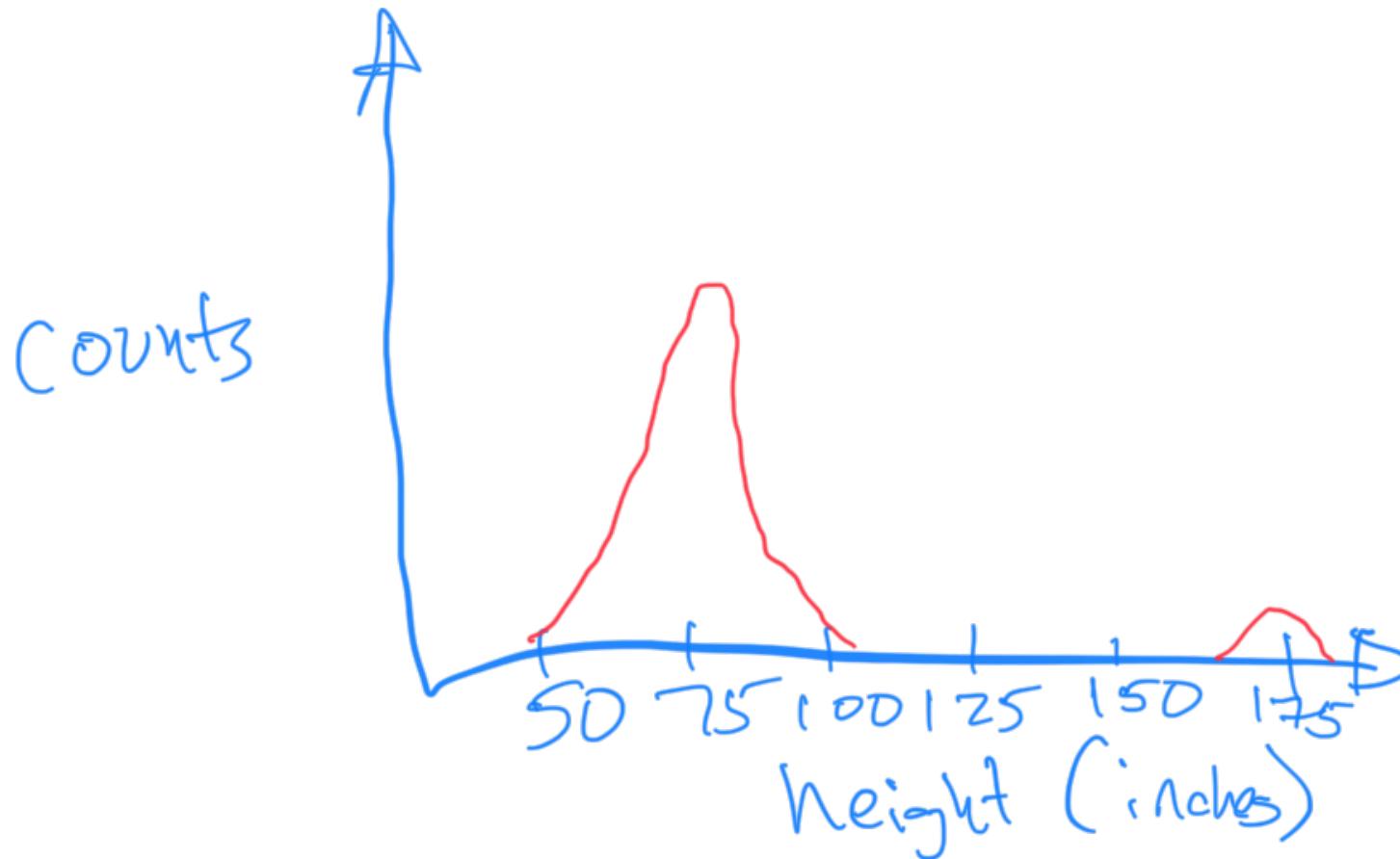
results



What are these uber-repetitive outliers? *Around The World* by Daft Punk gets reduced a whopping 98%. It goes from 2,610 characters to 61. Small enough to fit in a tweet - twice!

Data Intuition

Why do you need intuition?

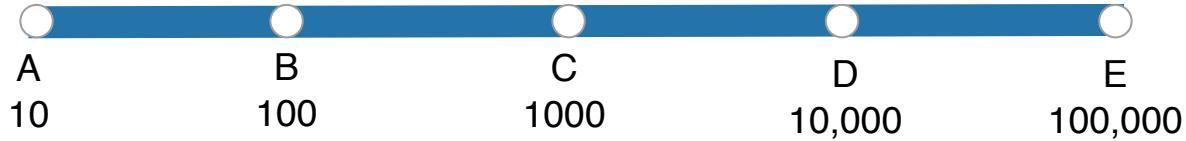




Fermi Estimation

<https://forms.gle/C982naWtU9RvHqAb7>

Approximately how many piano tuners do you think there are
in the city of Chicago?





<https://www.youtube.com/watch?v=0YzvupOX8ls>



Fermi Estimation

<https://forms.gle/shS84W1tai4SDrVF9>



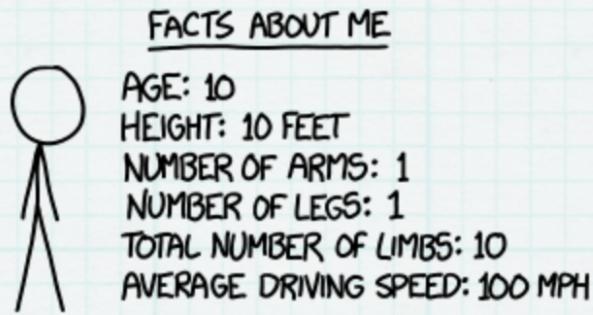
Has humanity produced enough paint to cover the entire land area of the Earth?



This answer is pretty straightforward. We can look up the size of the world's paint industry, extrapolate backward to figure out the total amount of paint produced. We'd also need to make some assumptions about how we're painting the ground. Note: When we get to the Sahara desert, I recommend not using a brush.



But first, let's think about different ways we might come up with a guess for what the answer will be. In this kind of thinking—often called **Fermi estimation**—all that matters is getting in the right ballpark; that is, the answer should have about the right number of digits. In Fermi estimation, you can round [1] all your answers to the nearest order of magnitude:



Let's suppose that, on average, everyone in the world is responsible for the existence of two rooms, and they're both painted. My living room has about 50 square meters of paintable area, and two of those would be 100 square meters. 7.15 billion people times 100 square meters per person is a little under a trillion square meters —an area smaller than Egypt.

NOT ENOUGH	EXACTLY ENOUGH	MORE THAN ENOUGH
/		

Let's make a wild guess that, on average, one person out of every thousand spends their working life painting things. If I assume it would take me three hours to paint the room I'm in, [2] and 100 billion people have ever lived, and each of them spent 30 years painting things for 8 hours a day, we come up with 150 trillion square meters ... just about exactly the land area of the Earth.

NOT ENOUGH	EXACTLY ENOUGH	MORE THAN ENOUGH
/	/	

How much paint does it take to paint a house? I'm not enough of an adult to have any idea, so let's take another Fermi guess.

Based on my impressions from walking down the aisles, home improvement stores stock about as many light bulbs as cans of paint. A normal house might have about 20 light bulbs, so let's assume a house needs about 20 gallons of paint.^[3] Sure, that sounds about right.

The average US home costs about \$200,000. Assuming each gallon of paint covers about 300 square feet, that's a square meter of paint per \$300 of real estate. I vaguely remember that the world's real estate has a combined value of something like \$100 trillion, [4] which suggests there's about 300 billion square meters of paint on the world's real estate. That's about one New Mexico.

NOT ENOUGH	EXACTLY ENOUGH	MORE THAN ENOUGH
//	/	

Of course, both of the building-related guesses could be overestimates (lots of buildings are not painted) or underestimates (lots of things that are not buildings [5] are painted) But from these wild Fermi estimates, my guess would be that there probably isn't enough paint to cover all the land.

So, how did Fermi do?

According to the report [**The State of the Global Coatings Industry**](#), the world produced 34 billion liters of paints and coatings in 2012.

There's a neat trick that can help us here. If some quantity—say, the world economy—has been growing for a while at an annual rate of n —say, 3% (0.03)—then the most recent year's share of the whole total so far is $1 - \frac{1}{1+n}$, and the whole total so far is the most recent year's amount times $1 + \frac{1}{n}$.

If we assume paint production has, in recent decades, followed the economy and grown at about 3% per year, that means the total amount of paint produced equals the current yearly production times 34.^[6] That comes out to a little over a trillion liters of paint. At 30 square meters per gallon,^[7] that's enough to cover 9 trillion square meters—about the area of the United States.

So the answer is no; there's not enough paint to cover the Earth's land, and—at this rate—probably won't be enough until the year 2100.

Data Intuition

1. Think about your question and your expectations
2. Do some Fermi calculations (back of the envelope calculations)
3. Write code & look at outputs <- think about those outputs
4. Use your gut instinct / background knowledge to guide you
5. Review code & fix bugs

<https://forms.gle/CREcpMkYDLYTUp2s6>

<https://forms.gle/CREcpMkYDLYTUp2s6>

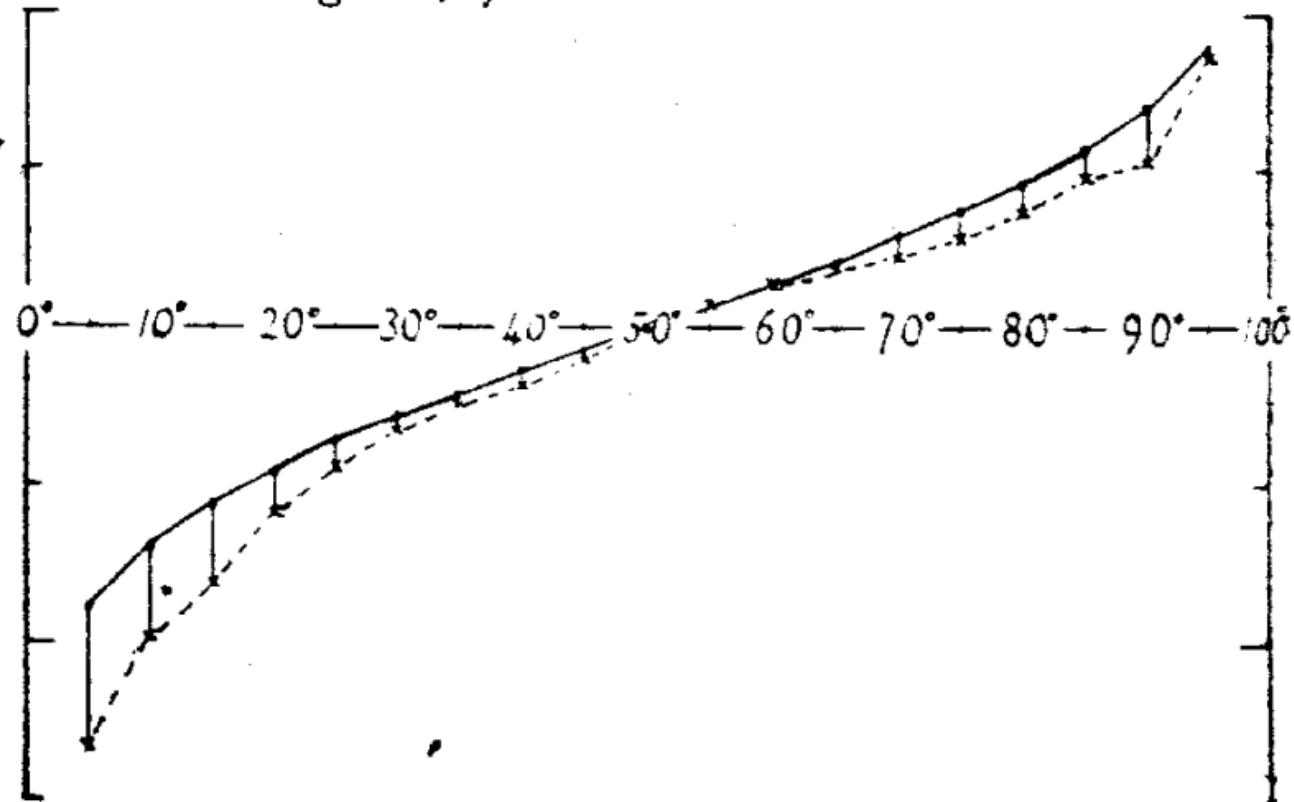


6 min think
6 min pair
6 share

Other kinds of
guessing and
intuitions

Diagram, from the tabular values.

Vox Populi



The Wisdom of the Crowds

- Diversity of opinion: Each person should have private information....even if it's just an eccentric interpretation of the known facts
- Independence: People's opinions aren't determined by the opinions of those around them
- Decentralization: People are able to specialize and draw on local knowledge
- Aggregation: Some mechanism exists for turning private judgements into a collective decision

