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CSC380: Principles of Data Science

Data Analysis, Collection, and Visualization 1

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credit: Jason Pacheco, Kwang-Sung Jun's slides & Watkins, J. "Intro. to the Science of Statistics"

Data Analysis, Exploration, and Visualization

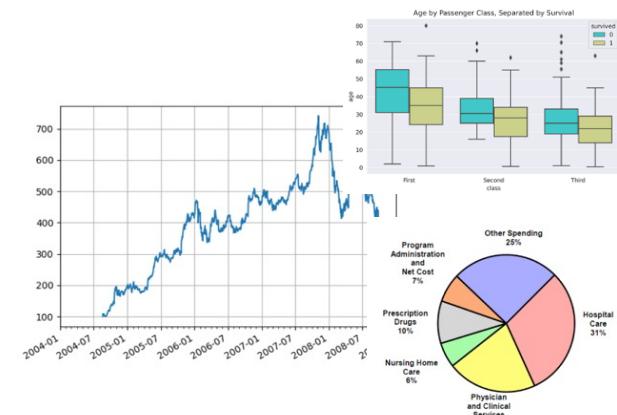
```

141 137 134 134 132 130 129 129 131 135 130 128 129 126 128 128 130
138 136 134 134 135 133 131 129 132 139 133 128 130 128 127 129 131
135 135 134 133 133 132 130 128 132 136 134 130 131 131 132 132 133
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153 153 153 153 154 154 154 154 154 154 154 154 153 153 153 152 155
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```

Encoding

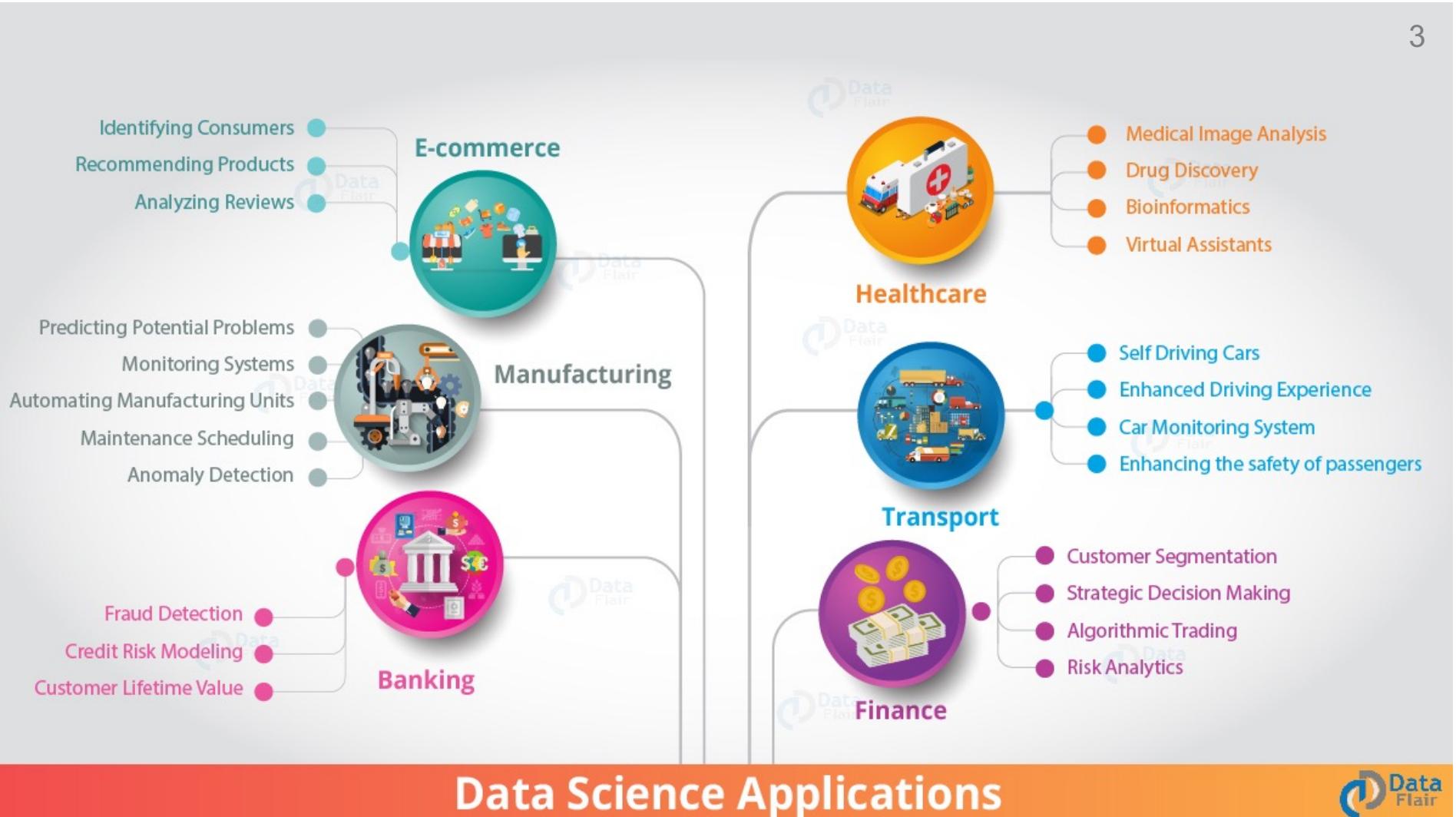
Iterate



Visual Perception

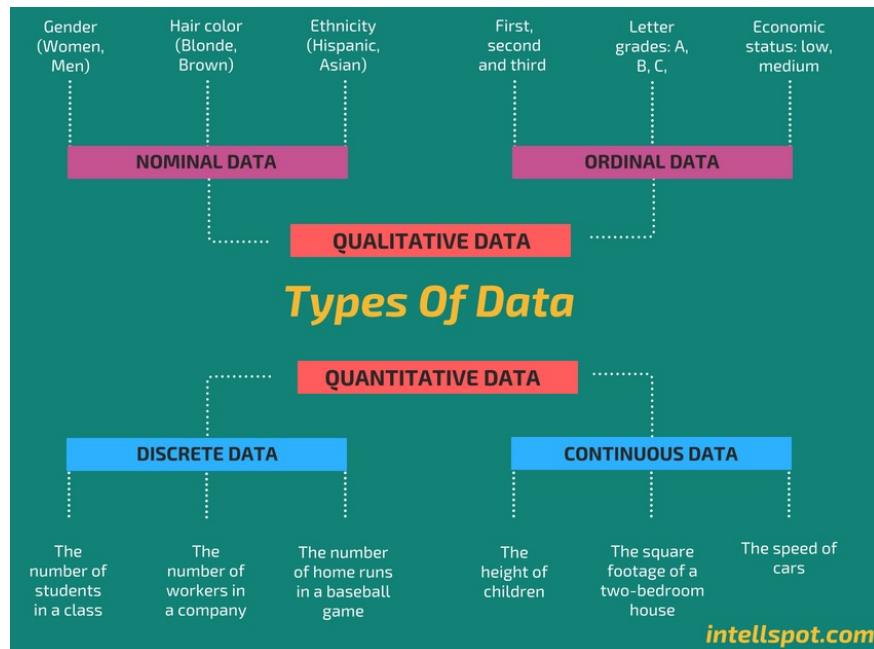
Understanding





Types of Data

Data come in many forms, each requiring different approaches & models



Qualitative or categorical : can partition data into classes

Quantitative : can perform mathematical operations (e.g., addition, subtraction)

*We often refer to different types of data as **variables***

Categorical Variables

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Examples

- Roll of a die: 1,2,3,4,5 or 6 ← **Numerical data can be categorical or quantitative depending on context**
- Blood Type: A, B, AB, or O
- Political Party: Democrat, Republican, etc.
- Type of Rock: Igneous, Sedimentary, or Metamorphic
- Word Identity: NP, VP, N, V, Adj, Adv, etc.

Conversion: Quantitative data can be converted to categorical by defining ranges:

- Small [0, 10mm), Medium [10, 100mm), Large [100mm, 1m), XL [1m, -)
- Low [less than -100dB), Moderate [-100dB, -50dB), Loud [over -50dB)

Introduction to Pandas

Open source library for data handling and manipulation in high-performance environments.



Installation If you are using Anaconda package manager,

```
conda install pandas
```

Or if you are using PyPi (pip) package manager,

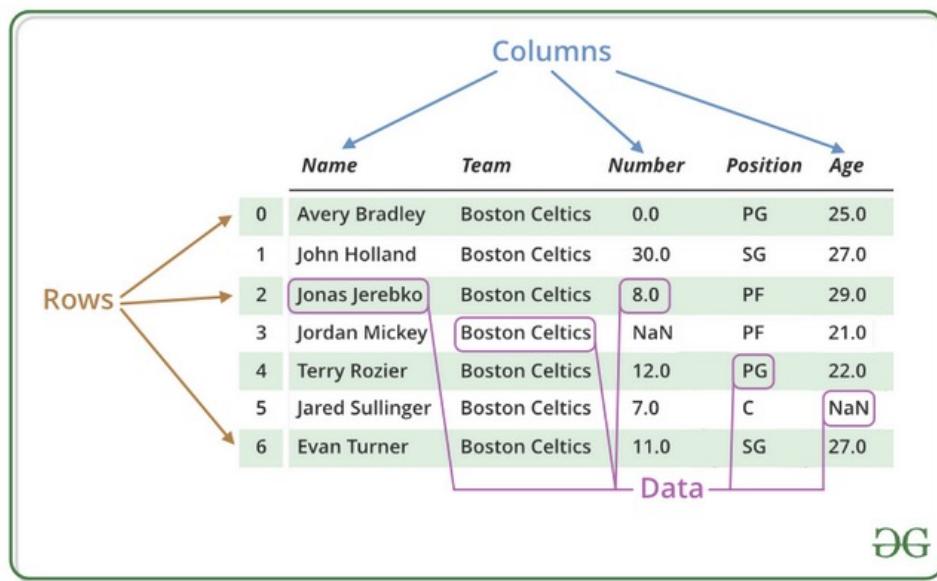
```
pip install pandas
```

See Pandas documentation for more detailed instructions
https://pandas.pydata.org/docs/getting_started/install.html

DataFrame

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Primary data structure : Essentially a table



Q: how is it different from 2d numpy array?

[Source: <https://www.geeksforgeeks.org/python-pandas-dataframe/>]

DataFrame Example

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Create and print an entire DataFrame

```
# import pandas as pd
import pandas as pd

# list of strings
lst = ['Geeks', 'For', 'Geeks', 'is',
       'portal', 'for', 'Geeks']

# Calling DataFrame constructor on list
df = pd.DataFrame(lst)
print(df)
```

0
0 Geeks
1 For
2 Geeks
3 is
4 portal
5 for
6 Geeks

[Source: <https://www.geeksforgeeks.org/python-pandas-dataframe/>]

DataFrame Example

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Can create named columns using dictionary

```
import pandas as pd

# initialise data of lists.
data = {'Name':['Tom', 'nick', 'krish', 'jack'],
        'Age':[20, 21, 19, 18]}

# Create DataFrame
df = pd.DataFrame(data)

# Print the output.
print(df)
```

	Name	Age
0	Tom	20
1	nick	21
2	krish	19
3	jack	18

all data must have the same length

[Source: <https://www.geeksforgeeks.org/python-pandas-dataframe/>]

DataFrame : Selecting Columns

11

Select columns to print by name,

```
# Import pandas package
import pandas as pd

# Define a dictionary containing employee data
data = {'Name':['Jai', 'Princi', 'Gaurav', 'Anuj'],
        'Age':[27, 24, 22, 32],
        'Address':['Delhi', 'Kanpur', 'Allahabad', 'Kannauj'],
        'Qualification':['Msc', 'MA', 'MCA', 'Phd']}

# Convert the dictionary into DataFrame
df = pd.DataFrame(data)

# select two columns
print(df[['Name', 'Qualification']])
```

	Name	Qualification
0	Jai	Msc
1	Princi	MA
2	Gaurav	MCA
3	Anuj	Phd

access columns by name, not the column index!

[Source: <https://www.geeksforgeeks.org/python-pandas-dataframe/>]

DataFrame : Selecting Columns

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```
[35]: import pandas as pd  
data = {'Name': ['tom', 'nick'], 'Age': [10,20]}  
df = pd.DataFrame(data)
```

```
[36]: df[['Name']]
```

```
[36]:  
      Name  
0    tom  
1   nick
```

```
[37]: df['Name']
```

```
[37]: 0    tom  
1   nick  
Name: Name, dtype: object
```

```
[38]: type(df[['Name']]), type(df['Name'])
```

```
[38]: (pandas.core.frame.DataFrame, pandas.core.series.Series)
```

pandas.Series

```
class pandas.Series(data=None, index=None, dtype=None, name=None, copy=False,  
fastpath=False)
```

One-dimensional ndarray with axis labels (including time series).

Labels need not be unique but must be a hashable type. The object supports both integer- and label-based indexing and provides a host of methods for performing operations involving the index. Statistical methods from ndarray have been overridden to automatically exclude missing data (currently represented as NaN).

still a DataFrame

essentially, a 'named' array

[Source: <https://www.geeksforgeeks.org/python-pandas-dataframe/>]

DataFrame : Selecting Rows

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Select rows by df.loc,

```
import pandas as pd
import numpy as np

# Define a dictionary containing employee data
data = {'Name':['Jai', 'Princi', 'Gaurav', 'Anuj'],
        'Age':[27, 24, 22, 32],
        'Address':['Delhi', 'Kanpur', 'Allahabad', 'Kannauj'],
        'Qualification':['Msc', 'MA', 'MCA', 'Phd']}

# Convert the dictionary into DataFrame
df = pd.DataFrame(data)

# Print rows 1 & 2    2nd and 3rd row!
row = df.loc[1:2]
print(row)
```

Output

	Name	Age	Address	Qualification
1	Princi	24	Kanpur	MA
2	Gaurav	22	Allahabad	MCA

(still a DataFrame)

1:2 includes 2! annoying! this is not python standard!!!

DataFrame : Selecting Rows

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df.loc[1:1] is DataFrame object , but df.loc[1] is a Series object

```
[6]: import pandas as pd  
data = {'Name': ['tom', 'nick'], 'Age': [10,20]}  
df = pd.DataFrame(data)
```

```
[19]: df.loc[1:1]
```

```
[19]:   Name  Age  
1    nick   20
```

```
[20]: df.loc[1]
```

```
[20]: Name      nick  
      Age       20  
      Name: 1, dtype: object
```

```
[21]: type(df.loc[1:1]), type(df.loc[1])
```

```
[21]: (pandas.core.frame.DataFrame, pandas.core.series.Series)
```

<= array with access to the member by name
instead of the numeric index

DataFrame : Selecting Rows

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head() and tail() select rows from beginning / end

```
import pandas as pd
import numpy as np

# Define a dictionary containing employee data
data = {'Name':['Jai', 'Princi', 'Gaurav', 'Anuj'],
        'Age':[27, 24, 22, 32],
        'Address':['Delhi', 'Kanpur', 'Allahabad', 'Kannauj'],
        'Qualification':['Msc', 'MA', 'MCA', 'Phd']}

# Convert the dictionary into DataFrame
df = pd.DataFrame(data)

# Print first / last rows
first2 = df.head(2)
last2 = df.tail(2)
print(first2)
print('\n', last2)
```

Output

	Name	Age	Address	Qualification
0	Jai	27	Delhi	Msc
1	Princi	24	Kanpur	MA

	Name	Age	Address	Qualification
2	Gaurav	22	Allahabad	MCA
3	Anuj	32	Kannauj	Phd

Reading Data from Files

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Easy reading / writing of standard formats,

```
df = pd.read_json("data.json")
print(df)
df.to_csv("data.csv", index=False)
df_csv = pd.read_csv("data.csv")
print(df_csv.head(2))
```

example: twitter api returns search results in json format.

	index ↓	Output			
		Duration	Pulse	Maxpulse	Calories
0	0	60	110	130	409.1
1	1	60	117	145	479.0
2	2	60	103	135	340.0
3	3	45	109	175	282.4
4	4	45	117	148	406.0

	164	60	105	140	290.8
	165	60	110	145	300.4
	166	60	115	145	310.2
	167	75	120	150	320.4
	168	75	125	150	330.4
[169 rows x 4 columns]					
		Duration	Pulse	Maxpulse	Calories
0	0	60	110	130	409.1
1	1	60	117	145	479.0

Data Structure Conversions

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Working with DataFrames outside of Pandas can be tricky,

```
df['Duration']
```

Q: does it return a DataFrame object or Series object?

We can easily convert to built-in types,
for example to a list.

```
0    60
1    60
2    60
3    45
4    45
..
164   60
165   60
166   60
167   75
168   75
Name: Duration, Length: 169, dtype: int64
```

```
L = df['Duration'].to_list()
print(L)
```

```
[60, 60, 60, 45, 45, 60, 60, 45, 30, 60, 60, 60, 60, 60, 60, 60, 60, 60, 60, 45, 60, 45, 60, 45, 60, 45, 60, 45, 60, 60, 60, 60, 60, 60, 60, 60, 60, 60, 60, 45, 60, 60, 60, 60, 60, 60, 60, 60, 60, 60, 60, 45, 45, 60, 60, 60, 80, 60, 60, 30, 60, 60, 45, 2
0, 45, 210, 160, 160, 45, 20, 180, 150, 150, 20, 300, 150, 60, 90, 150, 45, 90, 45, 45, 120, 270, 30, 45, 30, 120, 4
5, 30, 45, 120, 45, 20, 180, 45, 30, 15, 20, 20, 30, 25, 30, 90, 20, 90, 90, 30, 30, 180, 30, 90, 210, 60, 45, 1
5, 45, 60, 60, 60, 60, 60, 30, 45, 60, 60, 60, 60, 60, 60, 90, 60, 60, 60, 60, 60, 60, 60, 20, 45, 45, 45, 20, 60, 6
0, 45, 45, 60, 45, 60, 30, 60, 60, 60, 60, 60, 60, 60, 30, 30, 45, 45, 45, 60, 60, 75, 75]
```

Data Structure Conversions

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Or, to a numpy array.

```
[6]: import pandas as pd  
data = {'Name': ['tom', 'nick'], 'Age': [10, 20]}  
df = pd.DataFrame(data)
```

```
[29]: df
```

```
[29]:   Name  Age  
0      tom    10  
1     nick    20
```

```
[31]: df.to_numpy()
```

```
[31]: array([['tom', 10],  
           ['nick', 20]], dtype=object)
```

```
[40]: df['Name'].to_numpy()
```

```
[40]: array(['tom', 'nick'], dtype=object)
```

Summary Statistics

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Easily compute summary statistics on data

```
print('Min: ', df['Duration'].min())
print('Max: ', df['Duration'].max())
print('Median: ', df['Duration'].median())

Min: 15
Max: 300
Median: 60.0
```

if we were using numpy array,
then A[:,2].min()

60	79
45	35
30	16
20	9
90	8
150	4
120	3
180	3
15	2
75	2
160	2
210	2
270	1
25	1
300	1
80	1

Name: Duration, dtype: int64

Can also count occurrences of
unique values,

```
df['Duration'].value_counts()
```

- 
- s = df['Duration'].value_counts()
 - then s is a Series object. Note: s[60]=79;
 - can further convert s to a dictionary by calling dict(s)

Summary Statistics

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- use `describe()` to get a summary of the data

```
[42]: import pandas as pd  
data = {'Name': ['tom', 'nick'], 'Age': [10,20], 'Height': [6.2, 5.5]}  
df = pd.DataFrame(data)  
df
```

```
[42]:    Name  Age  Height  
0      tom    10      6.2  
1     nick    20      5.5
```

```
[43]: df.describe()
```

```
[43]:      Age      Height  
count  2.000000  2.000000  
mean  15.000000  5.850000  
std   7.071068  0.494975  
min   10.000000  5.500000  
25%   12.500000  5.675000  
50%   15.000000  5.850000  
75%   17.500000  6.025000  
max   20.000000  6.200000
```

- Many database operations are available
 - You can specify index, which can speed up some operations
 - You can do ‘join’
 - You can do ‘where’ clause to filter the data
 - You can do ‘group by’

More on Pandas

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Doing it yourself helps a lot!

Search the docs ...

[Installation](#)

[Package overview](#)

[Getting started tutorials](#)

^

[What kind of data does pandas handle?](#)

[How do I read and write tabular data?](#)

[How do I select a subset of a `DataFrame` ?](#)

[How to create plots in pandas?](#)

[How to create new columns derived from existing columns?](#)

[How to calculate summary statistics?](#)

[How to reshape the layout of tables?](#)

[How to combine data from multiple tables?](#)

[How to handle time series data with ease?](#)

[How to manipulate textual data?](#)



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CSC380: Principles of Data Science

Data Analysis, Collection, and Visualization 2

- Data Visualization
- Data Summarization
- Data Collection and Sampling

- Data Visualization
- Data Summarization
- Data Collection and Sampling

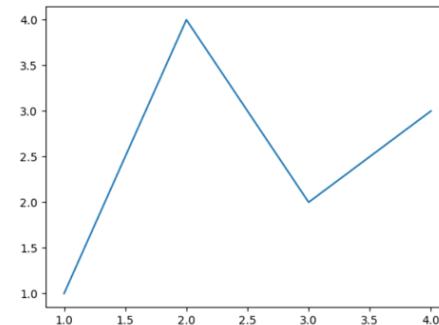
Data visualization in Python...



```
import matplotlib.pyplot as plt
import numpy as np
```

Create a simple figure with an axis object,

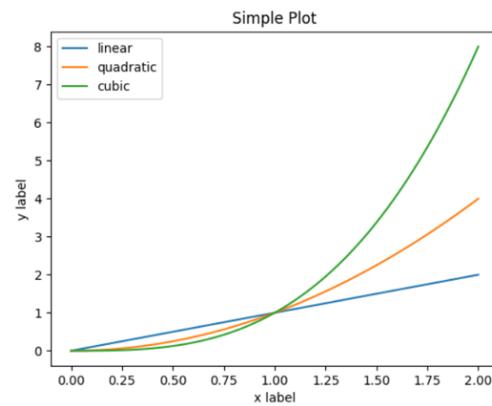
```
fig, ax = plt.subplots() # Create a figure containing a single axes.
ax.plot([1, 2, 3, 4], [1, 4, 2, 3]) # Plot some data on the axes.
```



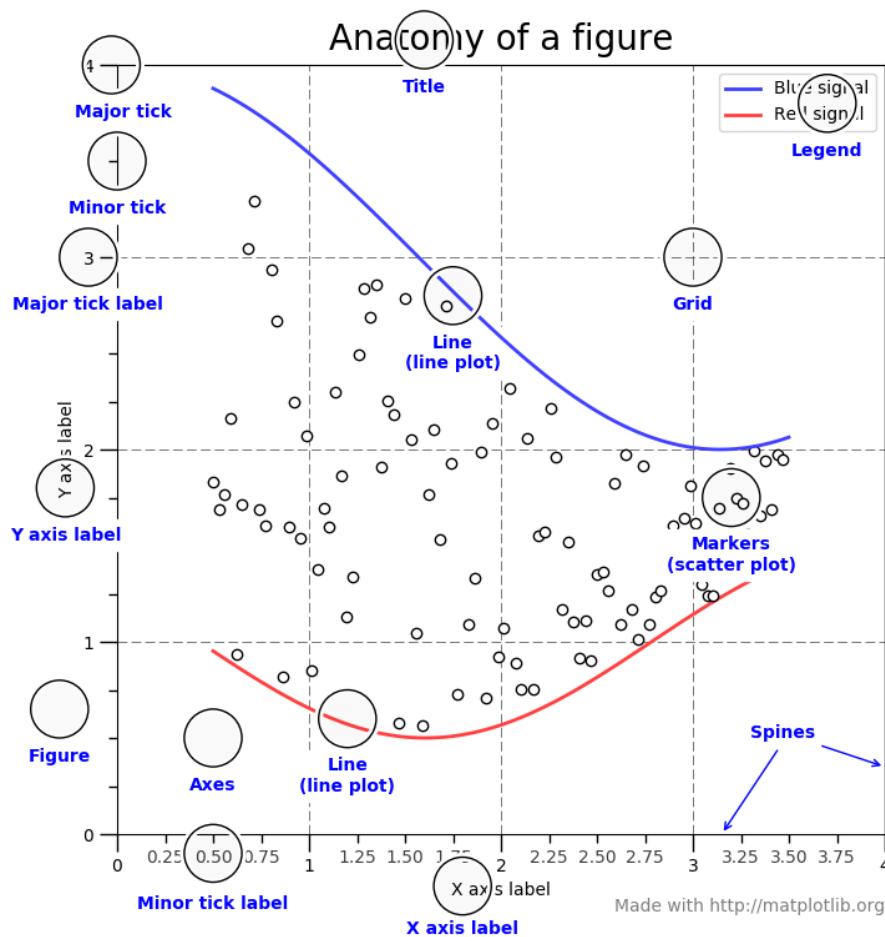
A more complicated plot...

```
x = np.linspace(0, 2, 100)

# Note that even in the OO-style, we use `pyplot.figure` to create the figure.
fig, ax = plt.subplots() # Create a figure and an axes.
ax.plot(x, x, label='linear') # Plot some data on the axes.
ax.plot(x, x**2, label='quadratic') # Plot more data on the axes...
ax.plot(x, x**3, label='cubic') # ... and some more.
ax.set_xlabel('x label') # Add an x-label to the axes.
ax.set_ylabel('y label') # Add a y-label to the axes.
ax.set_title("Simple Plot") # Add a title to the axes.
ax.legend() # Add a legend.
```



matplotlib²⁷



May need to **show** the plot with,

```
plt.show()
```

Typically, a **blocking** event.

Workaround: plt.ion()

If you are using JupyterLab, don't worry about it.

Documentation + tutorials:

<https://matplotlib.org/>

JupyterLab

File Edit View Run Kernel Tabs Settings Help

Lorenz.ipynb Terminal 1 Console 1 Data.ipynb README.md Python 3 (ipykernel)

We explore the Lorenz system of differential equations:

$$\begin{aligned}\dot{x} &= \sigma(y - x) \\ \dot{y} &= \rho x - y - xz \\ \dot{z} &= -\beta z + xy\end{aligned}$$

Let's change (σ, β, ρ) with ipywidgets and examine the trajectories.

```
[2]: from lorenz import solve_lorenz
interactive(solve_lorenz, sigma=(0.0,50.0), rho=(0.0,50.0))
```

Output View

sigma	10.00
beta	2.67
rho	28.00

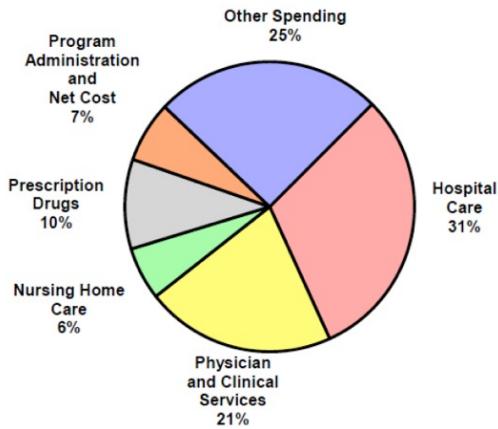
```

9 def solve_lorenz(sigma=10.0, beta=8./3, rho=28.0):
10     """Plot a solution to the Lorenz differential equations."""
11     fig = plt.figure()
12     ax = fig.add_axes([0, 0, 1, 1], projection='3d')
13     ax.axis('off')
14
15     # prepare the axes limits
16     ax.set_xlim((-25, 25))
17     ax.set_ylim((-35, 35))
18     ax.set_zlim((5, 55))
19
20     def lorenz_deriv(x_y_z, t0, sigma=sigma, beta=beta, rho=rho):
21         """Compute the time-derivative of a Lorenz system."""
22         x, y, z = x_y_z
23         return [sigma * (y - x), x * (rho - z) - y, x * y - beta * z]
24
25     # Choose random starting points, uniformly distributed from -15 to 15
26     np.random.seed(1)
27     x0 = -15 + 30 * np.random(N, 3)
28

```

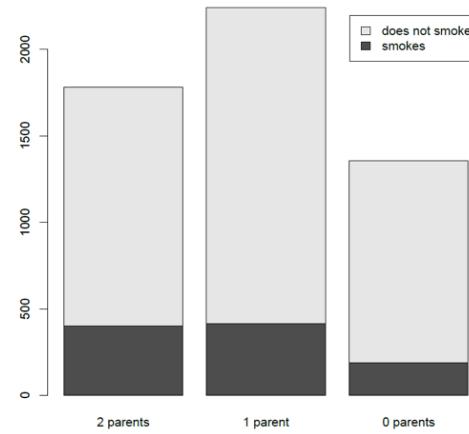
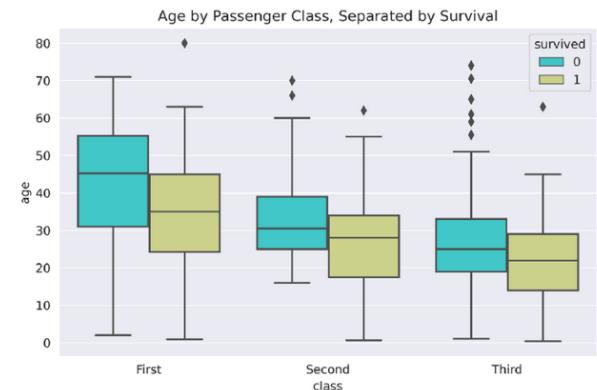
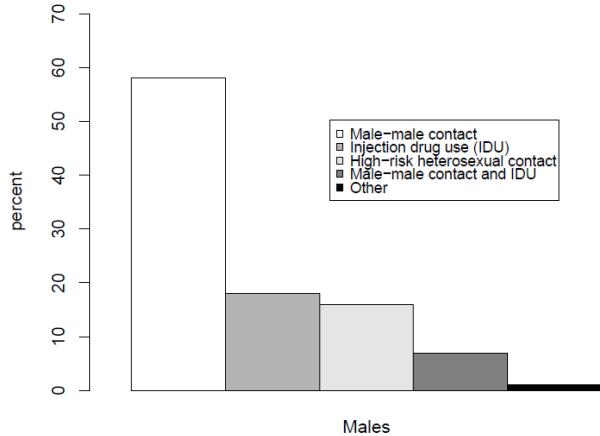
Simple 3 \$ 0 Python 3 (ipykernel) | Idle Mode: Command Ln 1, Col 1 Lorenz.ipynb

Visualizing Data



	student smokes	student does not smoke	total
2 parents smoke	400	1380	1780
1 parent smokes	416	1823	2239
0 parents smoke	188	1168	1356
total	1004	4371	5375

Proportion of AIDS Cases by Sex and Transmission Category
Diagnosed – USA, 2005



Pie Chart

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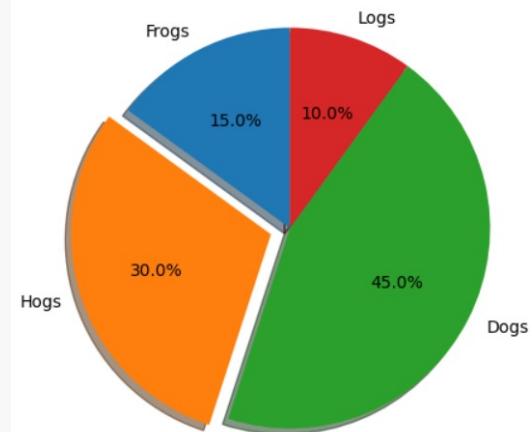
Circular chart divided into sectors, illustrating relative magnitudes in frequencies or percentage. In a pie chart, the area is proportional to the quantity it represents.

```
import matplotlib.pyplot as plt

# Pie chart, where the slices will be ordered and plotted counter-clockwise:
labels = 'Frogs', 'Hogs', 'Dogs', 'Logs'
sizes = [15, 30, 45, 10]
explode = (0, 0.1, 0, 0) # only "explode" the 2nd slice (i.e. 'Hogs')

fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%',
         shadow=True, startangle=90)
ax1.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circle.

plt.show()
```



'sizes` will be normalized to sum to 1 (see the API doc for exception)

Maybe the biggest problem with pie charts is that they have been so often done poorly...

Google search results for "bad pie charts":

Search terms: bad pie charts

Filter: Images

Results:

- wrong
- media
- example
- data visualization
- male female
- economy florida
- 2016 presidential election
- attractive
- advanced

1. Yet another bad pie chart : dataisugly reddit.com

453,737,086,67%

2. death to pie charts — storytellingwithdata... storytellingwithdata.com

3. Pie charts: the bad, the worst and the ... visuanalyze.wordpress.com

4. Best Practices for Using Pie Charts

5. "Using data visualizations' bad guy: pie charts" martinraffaeiner.blog

Bar Chart

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We perceive differences in height / length better than area...

`plt.bar()`

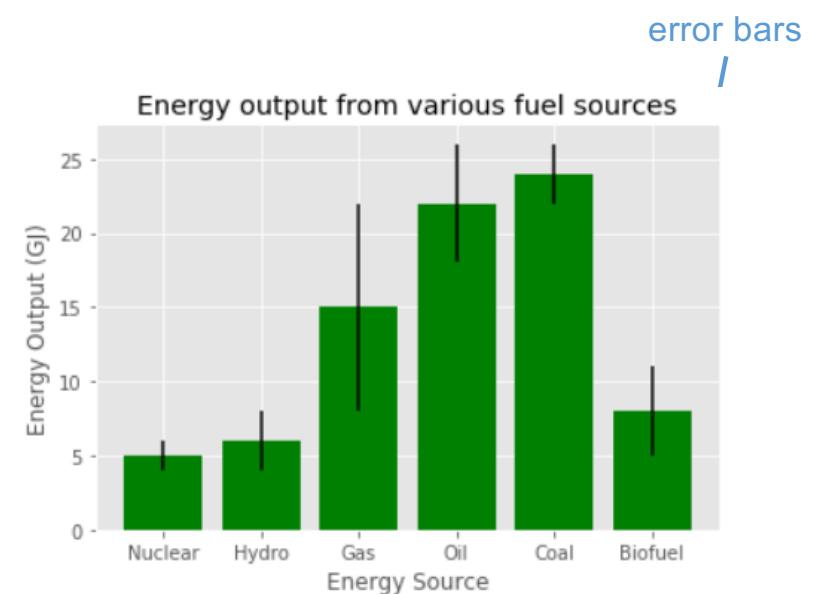
```
[42]: x = ['Nuclear', 'Hydro', 'Gas', 'Oil', 'Coal', 'Biofuel']
energy = [5, 6, 15, 22, 24, 8]
stddev = [1, 2, 7, 4, 2, 3]

x_pos = [i for i, _ in enumerate(x)]

plt.bar(x_pos, energy, color='green', yerr=stddev)
plt.xlabel("Energy Source")
plt.ylabel("Energy Output (GJ)")
plt.title("Energy output from various fuel sources")

plt.xticks(x_pos, x)

plt.show()
```



[Source: <https://benalexkeen.com/bar-charts-in-matplotlib/>]

Bar Chart

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Horizontal version.

`plt.barch()`

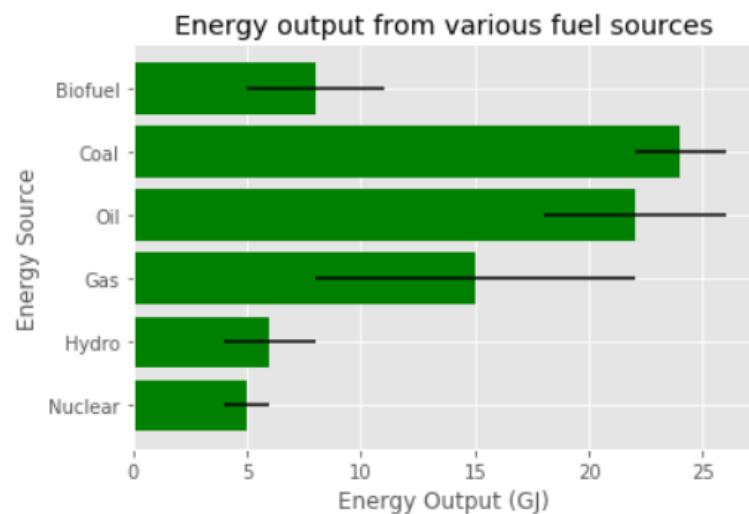
```
[45]: x = ['Nuclear', 'Hydro', 'Gas', 'Oil', 'Coal', 'Biofuel']
energy = [5, 6, 15, 22, 24, 8]
stddev = [1, 2, 7, 4, 2, 3]

x_pos = [i for i, _ in enumerate(x)]

plt.barch(x_pos, energy, color='green', xerr=stddev)
plt.xlabel("Energy Source")
plt.ylabel("Energy Output (GJ)")
plt.title("Energy output from various fuel sources")

plt.yticks(x_pos, x)

plt.show()
```



[Source: <https://benalexkeen.com/bar-charts-in-matplotlib/>]

Bar Chart

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Multiple groups of bars...

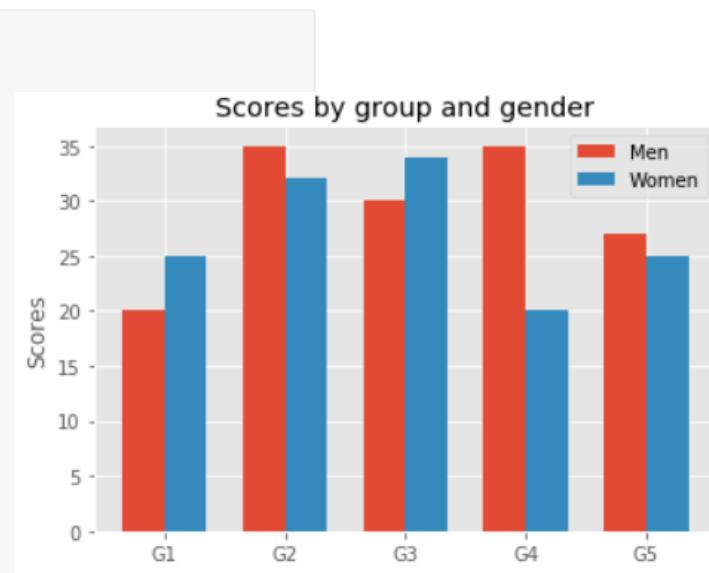
```
import numpy as np

N = 5
men_means = (20, 35, 30, 35, 27)
women_means = (25, 32, 34, 20, 25)

ind = np.arange(N) // [0,1,2,3,4]
width = 0.35
plt.bar(ind, men_means, width, label='Men')
plt.bar(ind + width, women_means, width,
        label='Women')      add the offset here

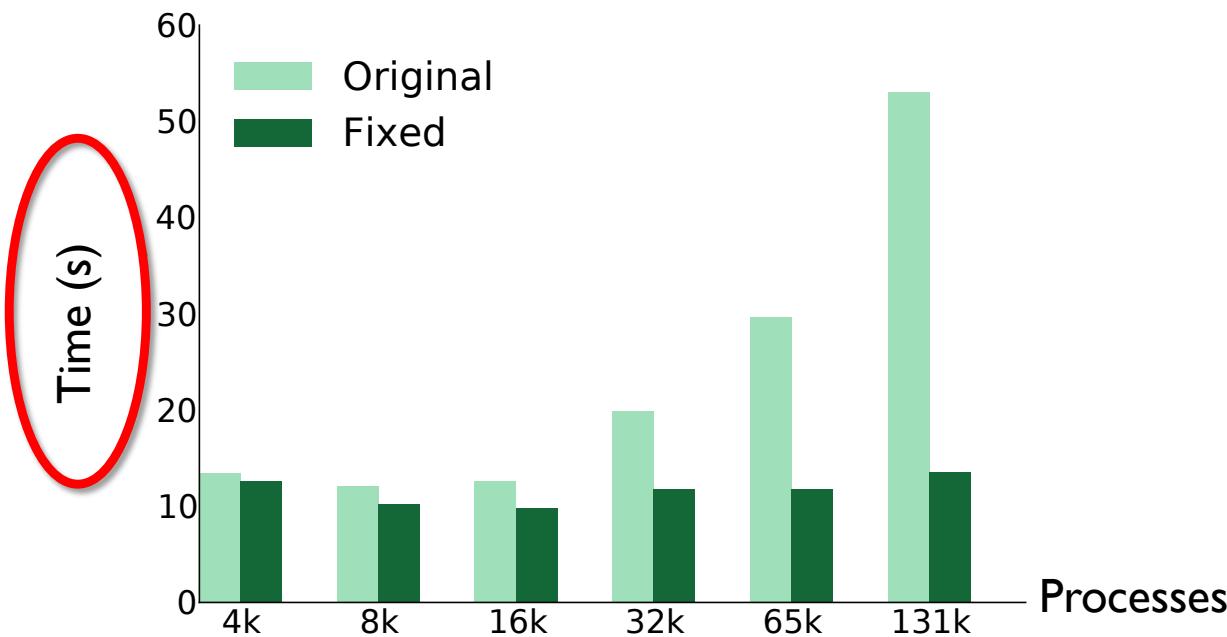
plt.ylabel('Scores')
plt.title('Scores by group and gender')

plt.xticks(ind + width / 2, ('G1', 'G2', 'G3', 'G4', 'G5'))
plt.legend(loc='best')
plt.show()
```

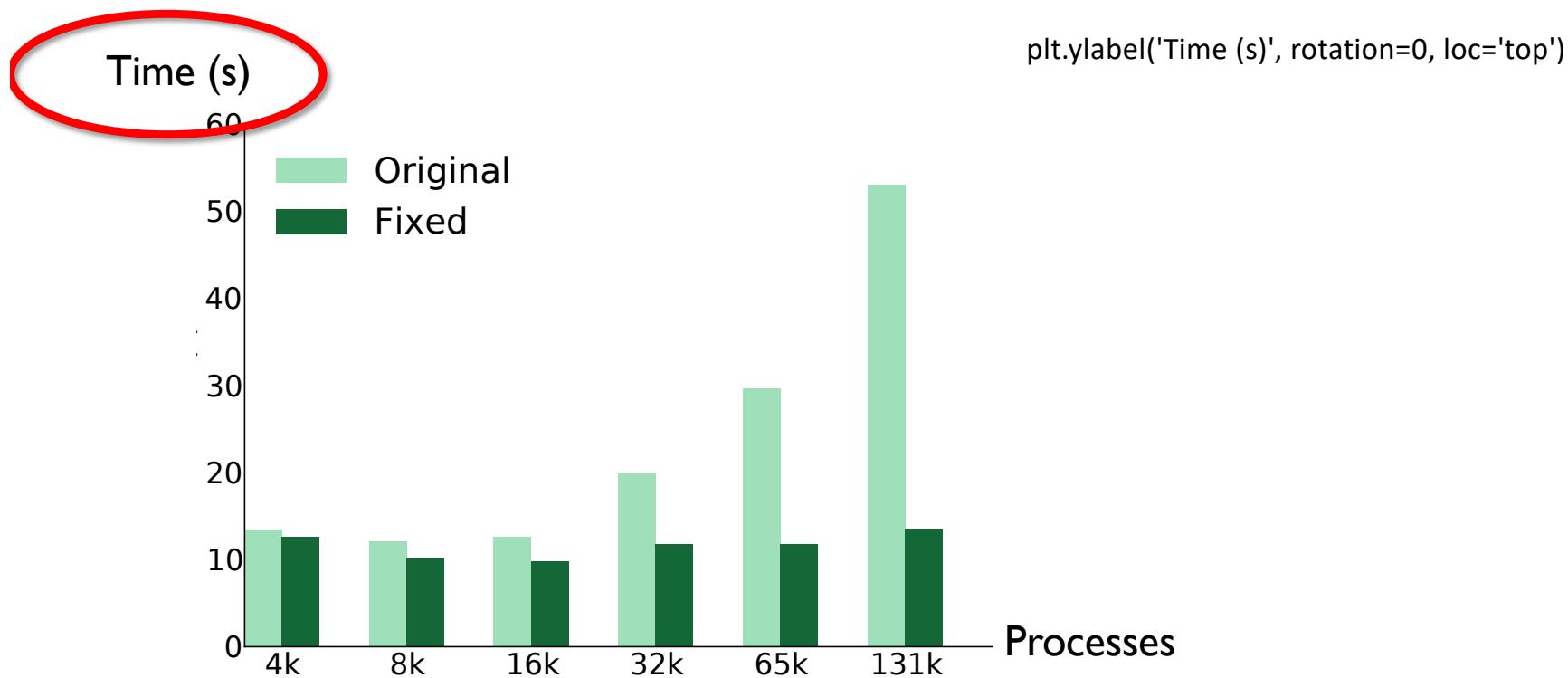


[Source: <https://benalexkeen.com/bar-charts-in-matplotlib/>]

Labels on the y-axis need not be vertical



Labels on the y-axis need not be vertical



Stacked Bar Chart

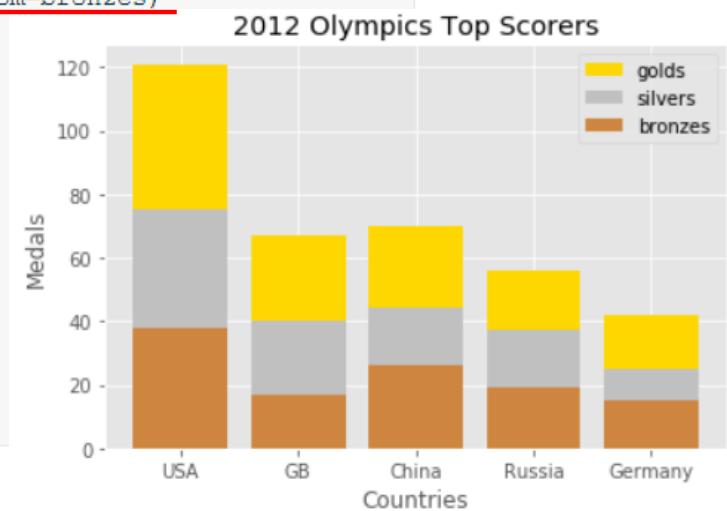
37

```
countries = ['USA', 'GB', 'China', 'Russia', 'Germany']
bronzes = np.array([38, 17, 26, 19, 15])
silvers = np.array([37, 23, 18, 18, 10])
golds = np.array([46, 27, 26, 19, 17])
ind = [x for x, _ in enumerate(countries)]

plt.bar(ind, golds, width=0.8, label='golds', color='gold', bottom=silvers+bronzes)
plt.bar(ind, silvers, width=0.8, label='silvers', color='silver', bottom=bronzes)
plt.bar(ind, bronzes, width=0.8, label='bronzes', color='#CD853F')

plt.xticks(ind, countries)
plt.ylabel("Medals")
plt.xlabel("Countries")
plt.legend(loc="upper right")
plt.title("2012 Olympics Top Scorers")

plt.show()
```



[Source: <https://benalexkeen.com/bar-charts-in-matplotlib/>]

Two-Way Table

38

Also called contingency table or cross tabulation table...

Count

	student smokes	student does not smoke	total
2 parents smoke	400	1380	1780
1 parent smokes	416	1823	2239
0 parents smoke	188	1168	1356
total	1004	4371	5375

Two-Way Table

39

Also called contingency table or cross tabulation table...

		Frequency		total
Row Variable	2 parents smoke	7.4%	25.7%	33.1%
	1 parent smokes	7.7%	33.9%	41.7%
	0 parents smoke	3.5%	21.8%	25.2%
total		18.7%	81.3%	100%

Column Variable

Marginal Distribution Of Row Variable

Marginal Distribution Of Column Variable

Joint Distribution

Q: how do you compute the conditional probability $P(\text{student smokes} \mid 2 \text{ parents smoke})$?

Two-Way Table

```

data = [[ 66386, 174296, 75131, 577908, 32015],
        [ 58230, 381139, 78045, 99308, 160454],
        [ 89135, 80552, 152558, 497981, 603535],
        [ 78415, 81858, 150656, 193263, 69638],
        [139361, 331509, 343164, 781380, 52269]]

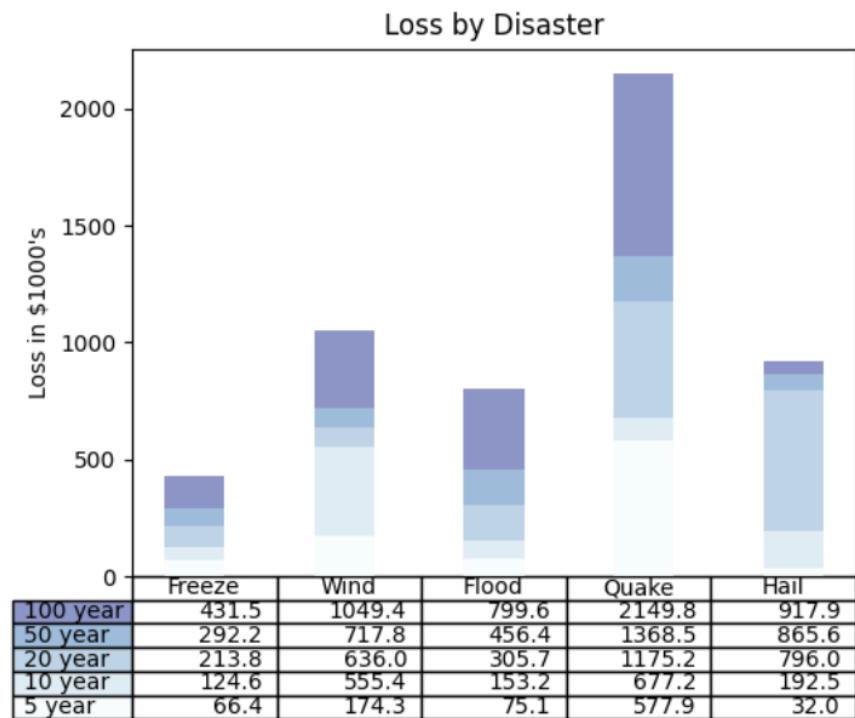
columns = ('Freeze', 'Wind', 'Flood', 'Quake', 'Hail')
rows = ['%d year' % x for x in (100, 50, 20, 10, 5)]
colors = plt.cm.BuPu(np.linspace(0, 0.5, len(rows)))

the_table = plt.table(cellText=cell_text,
                      rowLabels=rows,
                      rowColours=colors,
                      colLabels=columns,
                      loc='bottom')

```

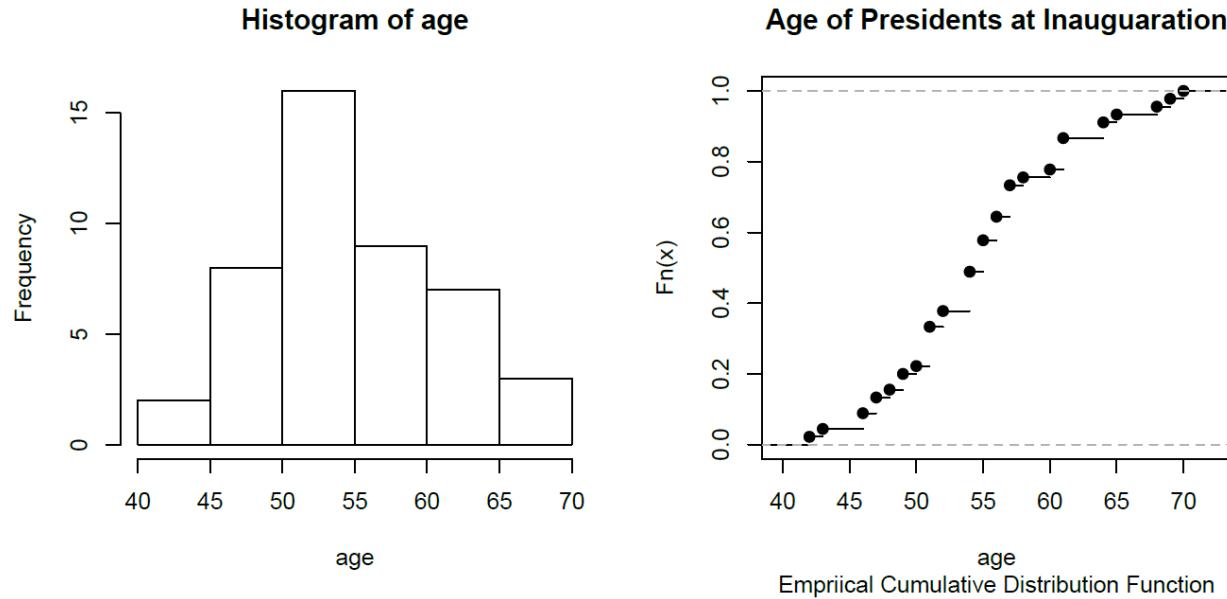
Adding stacked bars requires more steps, full code here:

https://matplotlib.org/stable/gallery/misc/table_demo.html



Histogram

Empirical approximation of (quantitative) data generating distribution



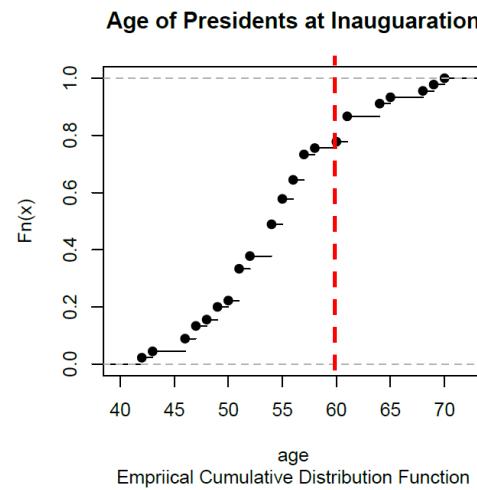
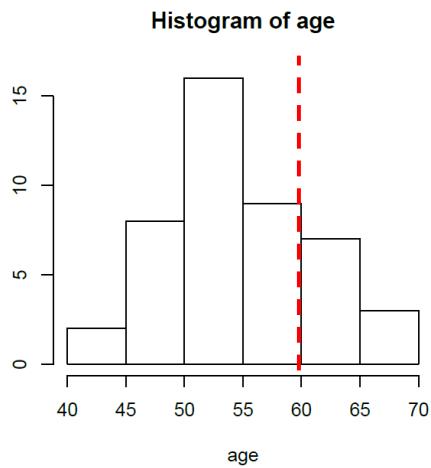
Empirical CDF for each x gives $P(X < x)$,

$$F_n(x) = \frac{1}{n} \#(\text{observations less than or equal to } x)$$

Quantile / Percentile

42

Question Is 60yrs old for a US president? Why or why not?



Empirical CDF for each x gives $P(X < x)$,

$$F_n(x) = \frac{1}{n} \#(\text{observations less than or equal to } x)$$

Compute probability of being <60,

$$F_n(60) \approx 0.8$$

0.8 Quantile or 80th Percentile → About 80% of presidents younger than 60

Histogram

43

```
import numpy as np
import matplotlib.pyplot as plt

np.random.seed(19680801)

# example data
mu = 100 # mean of distribution
sigma = 15 # standard deviation of distribution
x = mu + sigma * np.random.randn(437)

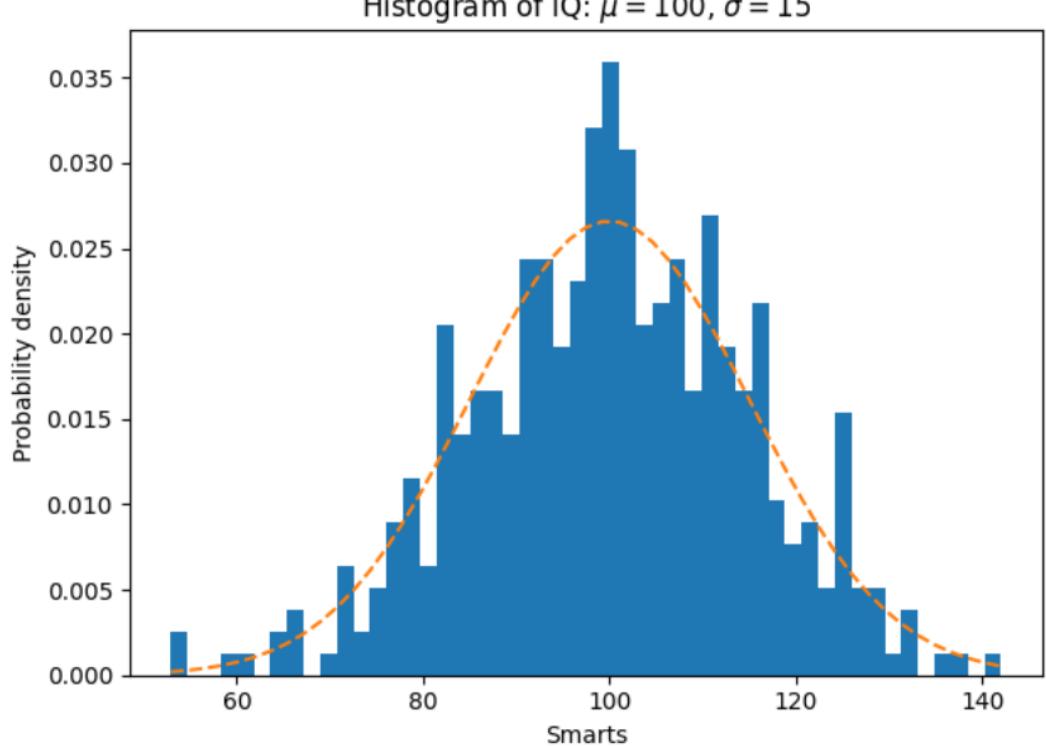
num_bins = 50

fig, ax = plt.subplots()

# the histogram of the data
n, bins, patches = ax.hist(x, num_bins, density=True)

# add a 'best fit' line
y = ((1 / (np.sqrt(2 * np.pi) * sigma)) *
     np.exp(-0.5 * (1 / sigma * (bins - mu))**2))
ax.plot(bins, y, '--')
ax.set_xlabel('Smarts')
ax.set_ylabel('Probability density')
ax.set_title(r'Histogram of IQ: $\mu=100$', '$\sigma=15$')

# Tweak spacing to prevent clipping of ylabel
fig.tight_layout()
plt.show()
```





44

CSC380: Principles of Data Science

Data Analysis, Collection, and Visualization 3

Kyoungseok Jang

credit: Jason Pacheco, Kwang-Sung Jun's slides & Watkins, J. "Intro. to the Science of Statistics"

- We will release the midterm score on Mar. 16th.
- We will also post the HW5 on Mar. 16th.
- About the final, it will be the **cumulative exam.**
 - You should study all chapters for the final exam.
 - Some questions in the midterm may re-appear in the final exam.

- Data Visualization
- Data Summarization
- Data Collection and Sampling

- Data Visualization
 - Tools (Matplotlib, JupyterLab)
 - Visualization methods
 - Bar chart, stacked bar chart
 - Pie chart
 - Two-way table
 - Quantiles
 - Histogram

- Data Visualization
 - Explanatory, target variables and scatterplot
 - Timeseries
 - Log-scale
- Data Summarization
- Data Collection and Sampling

Explanatory, response variable

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Example: Say we study the relationship between **Smoking** vs **Cancer**
or **the Age of Parents** vs **de novo mutations**

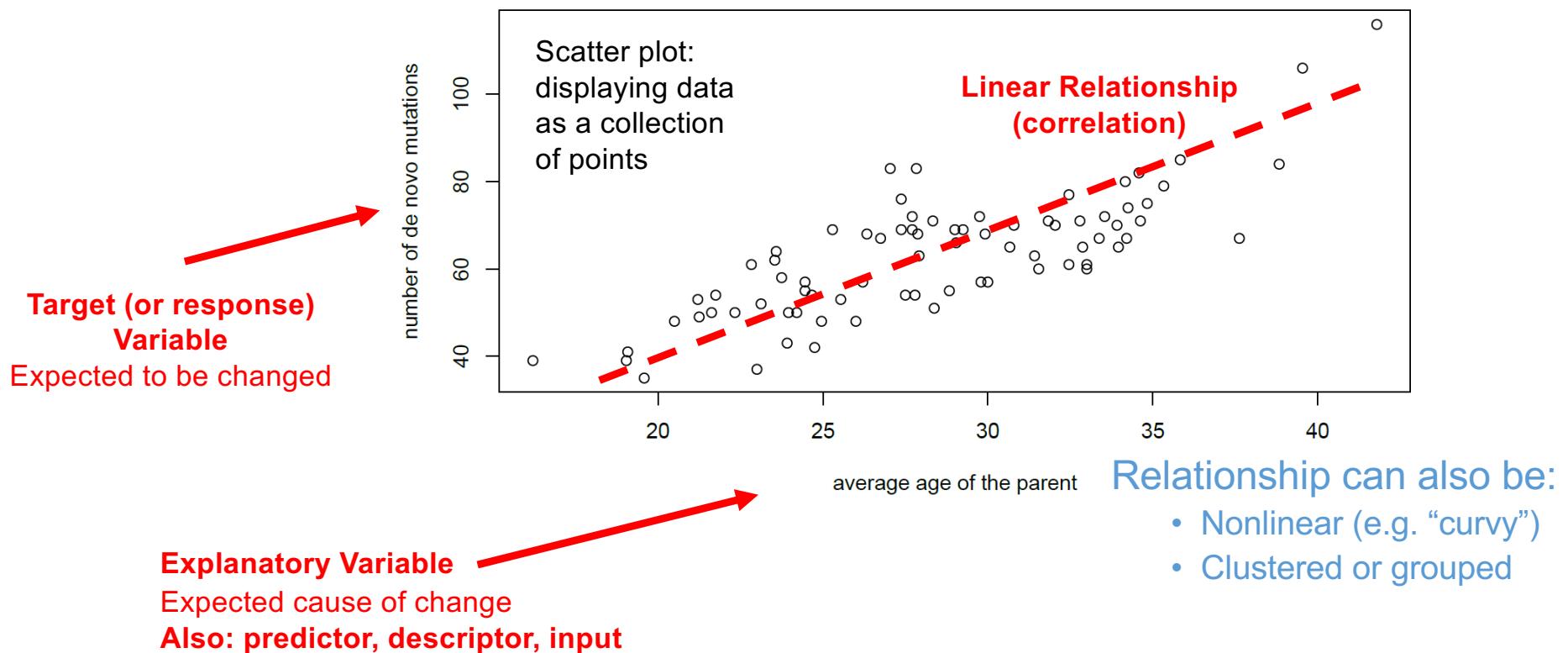
Independent variable: variables that are manipulated or are changed by researchers,
cause of the changes
= **explanatory variable**

Dependent variable: the variable that depends on independent variable (or
speculated to do so). The outcome of the manipulation.
= **response variable**

Scatter Plot

50

Compares relationship between two quantitative variables...



Scatterplot

51

```
import numpy as np
import matplotlib.pyplot as plt

# Fixing random state for reproducibility
np.random.seed(19680801)

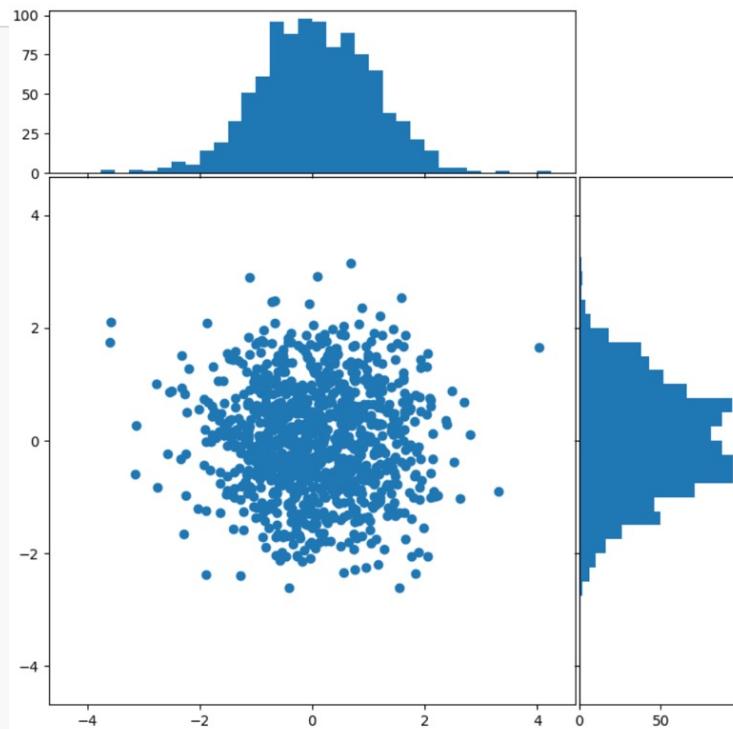
# some random data
x = np.random.randn(1000)
y = np.random.randn(1000)

def scatter_hist(x, y, ax, ax_histx, ax_histy):
    # no labels
    ax_histx.tick_params(axis="x", labelbottom=False)
    ax_histy.tick_params(axis="y", labelleft=False)

    # the scatter plot:
    ax.scatter(x, y)

    # now determine nice limits by hand:
    binwidth = 0.25
    xymax = max(np.max(np.abs(x)), np.max(np.abs(y)))
    lim = (int(xymax/binwidth) + 1) * binwidth

    bins = np.arange(-lim, lim + binwidth, binwidth)
    ax_histx.hist(x, bins=bins)
    ax_histy.hist(y, bins=bins, orientation='horizontal')
```



Full Code:

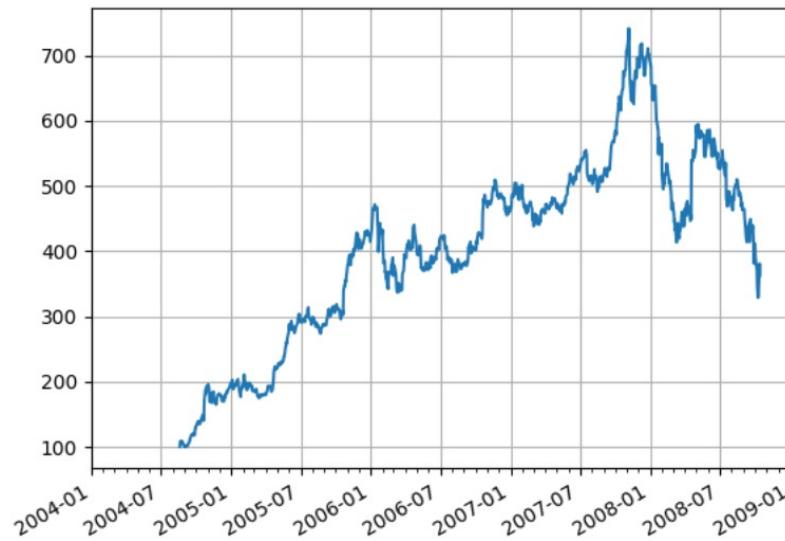
https://matplotlib.org/stable/gallery/lines_bars_and_markers/scatter_hist.html

Timeseries and line chart

52

Time series: a series of data points indexed (or listed or graphed) in time order.

- Ex) - stock prices
- changes in a baby's height over time



Usually plotted via line charts (the plot that connect data points by lines)
→ Possible since there is an 'order'

Timeseries

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```
fig, ax = plt.subplots()
ax.plot('date', 'adj_close', data=data)
# Major ticks every 6 months.
fmt_half_year = mdates.MonthLocator(interval=6)
ax.xaxis.set_major_locator(fmt_half_year)

# Minor ticks every month.
fmt_month = mdates.MonthLocator()
ax.xaxis.set_minor_locator(fmt_month)

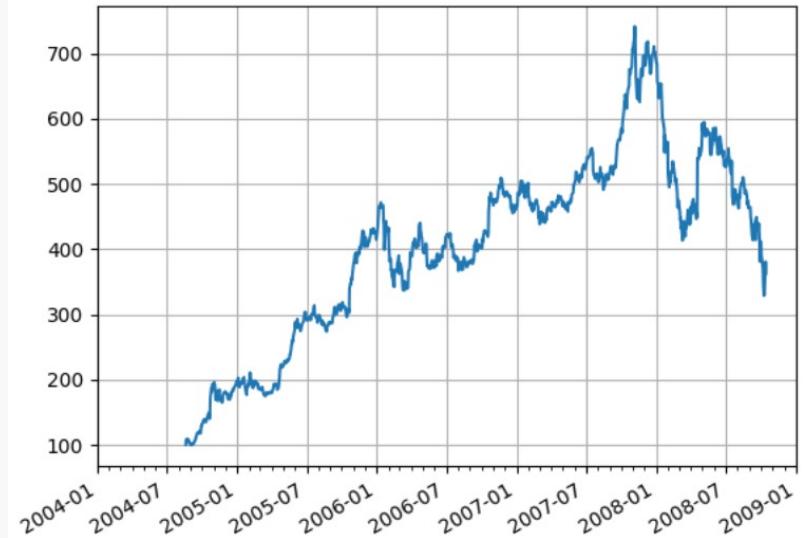
# Text in the x axis will be displayed in 'YYYY-mm' format.
ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m'))

# Round to nearest years.
datemin = np.datetime64(data['date'][0], 'Y')
datemax = np.datetime64(data['date'][-1], 'Y') + np.timedelta64(1, 'Y')
ax.set_xlim(datemin, datemax)

# Format the coords message box, i.e. the numbers displayed as the cursor moves
# across the axes within the interactive GUI.
ax.format_xdata = mdates.DateFormatter('%Y-%m')
ax.format_ydata = lambda x: f'${x:.2f}' # Format the price.
ax.grid(True)

# Rotates and right aligns the x labels, and moves the bottom of the
# axes up to make room for them.
fig.autofmt_xdate()

plt.show()
```



Logarithm Scale

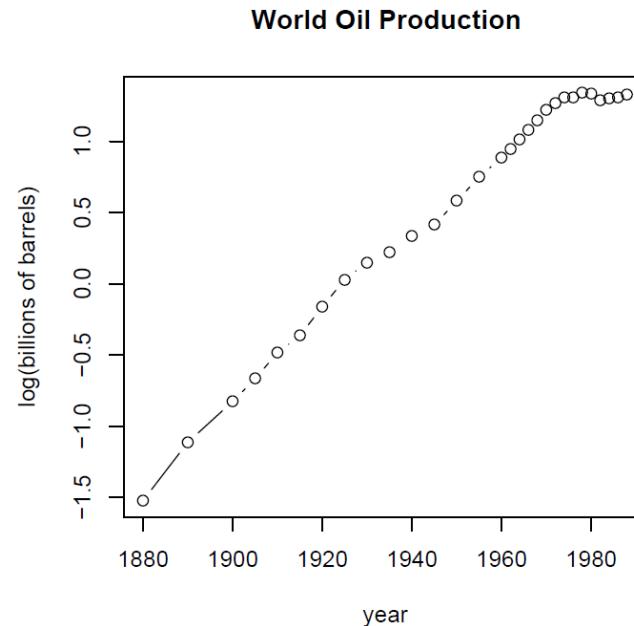
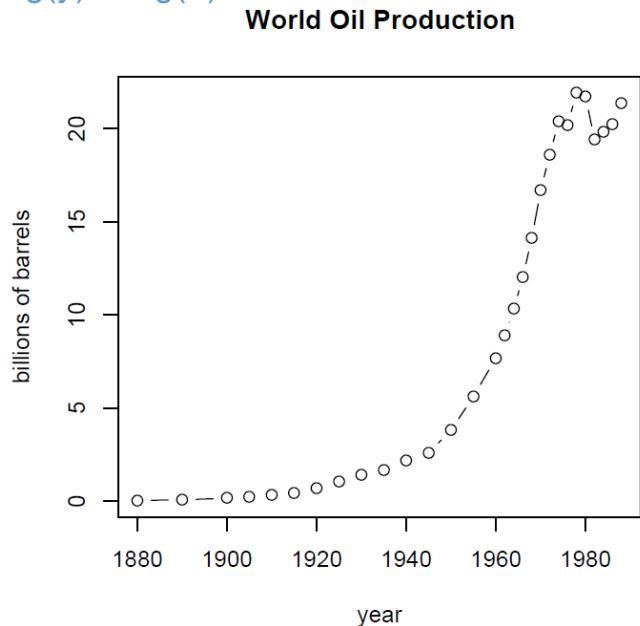
54

Changing limits and base of y-scale highlights different aspects...

if $y = e^x$, then $\log(y) = x$

if $y = b^x$, then $\log(y) = \log(b)*x$

=> becomes linear in x



...log-scale emphasizes relative changes in smaller quantities

Line Plots in Log-Domain

55

```
# Data for plotting
t = np.arange(0.01, 20.0, 0.01)

# Create figure
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2)

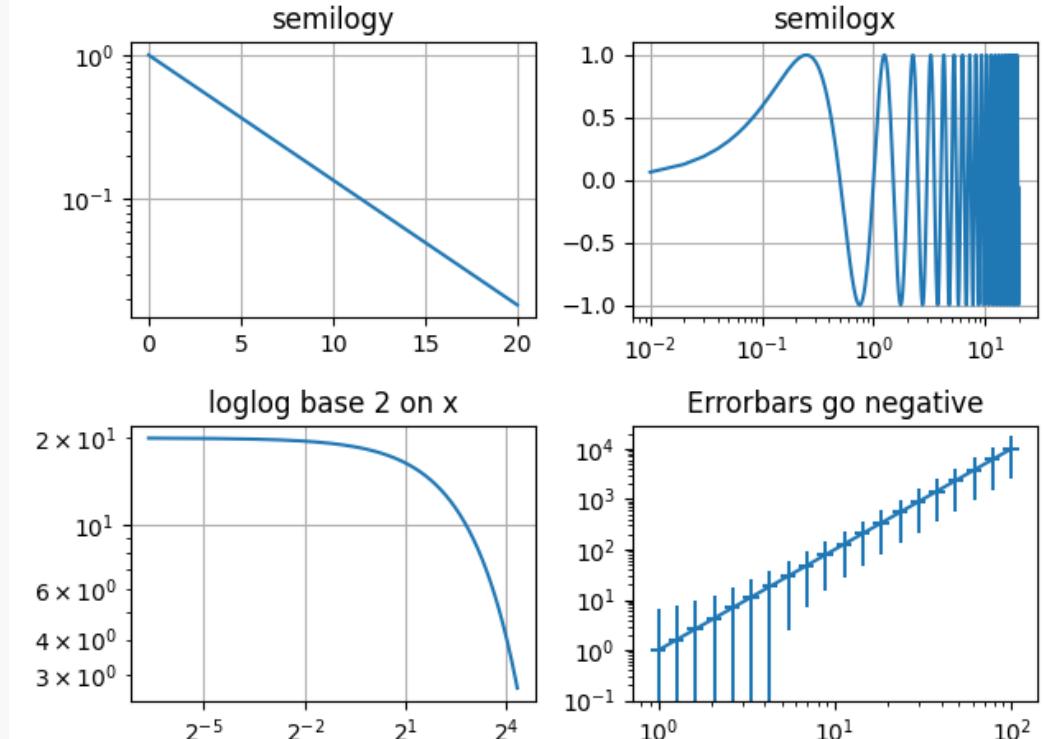
# Log y axis
ax1.semilogy(t, np.exp(-t / 5.0))
ax1.set(title='semilogy')
ax1.grid()

# Log x axis
ax2.semilogx(t, np.sin(2 * np.pi * t))
ax2.set(title='semilogx')
ax2.grid()

# Log x and y axis
ax3.loglog(t, 20 * np.exp(-t / 10.0))
ax3.set_xscale('log', base=2)
ax3.set(title='loglog base 2 on x')
ax3.grid()

# With errorbars: clip non-positive values
# Use new data for plotting
x = 10.0**np.linspace(0.0, 2.0, 20)
y = x**2.0

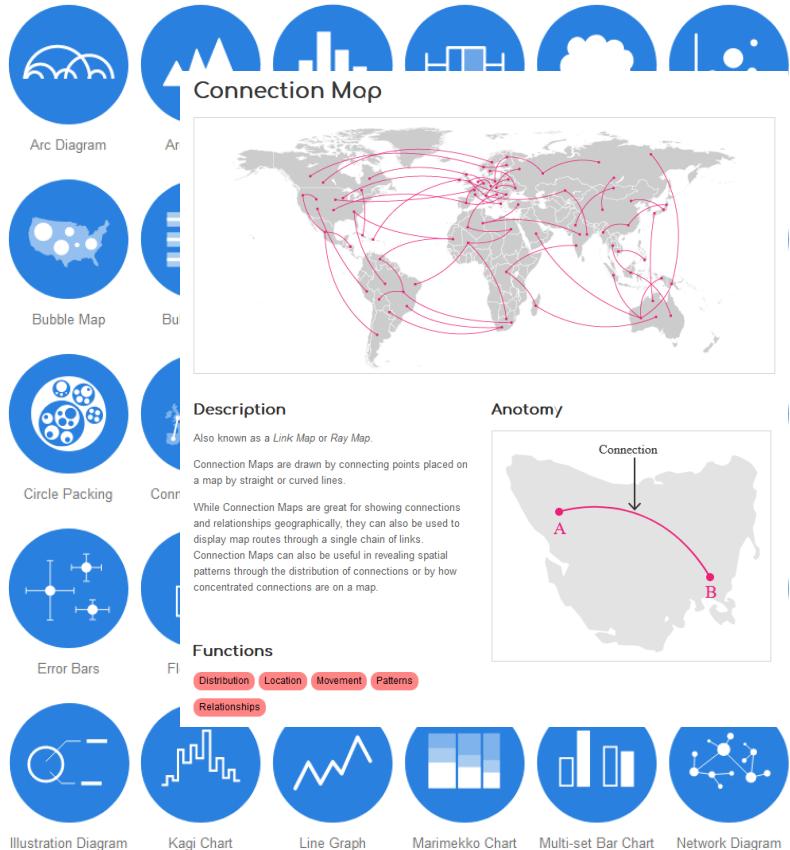
ax4.set_xscale("log", nonpositive='clip')
ax4.set_yscale("log", nonpositive='clip')
ax4.set(title='Errorbars go negative')
ax4.errorbar(x, y, xerr=0.1 * x, yerr=5.0 + 0.75 * y)
# ylim must be set after errorbar to allow errorbar to autoscale limits
ax4.set_ylim(bottom=0.1)
```



More Visualization Resources

56

datavizcatalogue.com



matplotlib

matplotlib.org



scikit-learn.org

- Data Visualization
- Data Summarization
 - Median, Sample mean
 - Quantile and box plot
- Data Collection and Sampling

- Raw data are hard to interpret
- Visualizations summarize important aspects of the data
- The *empirical distribution* estimates the distribution on data, but can be hard to interpret
- **Summary statistics** characterize aspects of the data distribution like:
 - Location / center
 - Scale / spread
 - Skew

Measuring Location

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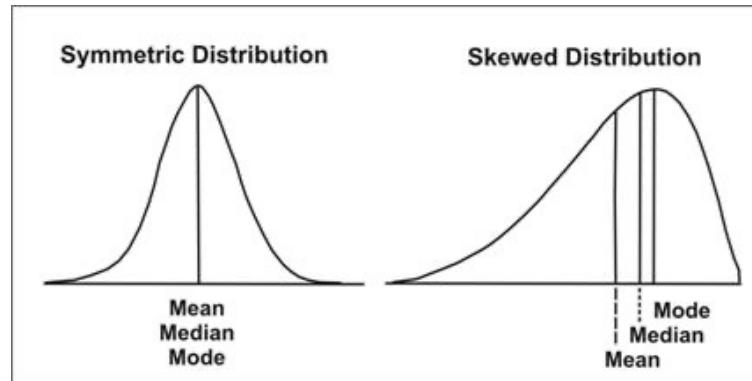
Three common measures of the distribution location...

Mean Average (expected value) of the data distribution

Median Midpoint – 50% of the probability is below and 50% above

Mode Value of highest probability (mass or density)

E.g., [1,2,3] vs [0,10,11]
compute mean and median



...align with symmetric distributions, but diverge with asymmetry

For data x_1, x_2, \dots, x_N sort the data,

$$x_{(1)}, x_{(2)}, \dots, x_{(n)}$$

- Notation $x_{(i)}$ means the i-th *lowest* value, e.g. $x_{(i-1)} \leq x_{(i)} \leq x_{(i+1)}$
- $x_{(1)}, x_{(2)}, \dots, x_{(n)}$ are called *order statistics*  not summary info, but rather a transformation

If n is **odd** then find the middle datapoint,

$$\text{median}(x_1, \dots, x_n) = x_{((n+1)/2)}$$

If n is **even** then average between both middle datapoints,

$$\text{median}(x_1, \dots, x_n) = \frac{1}{2} (x_{(n/2)} + x_{(n/2+1)})$$

What is the median of the following data?

1, 2, 3, 4, 5, 6, 8, 9 **4.5**

What is the median of the following data?

1, 2, 3, 4, 5, 6, 8, 100 **4.5**

Median is *robust* to outliers

Sample Mean

62

Empirical estimate of the true mean of the data distribution,

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$

Alternative definition: if the value x occurs $n(x)$ times in the data then,

$$\bar{x} = \frac{1}{N} \sum_x x n(x) = \sum_x x p(x) \quad \text{where} \quad p(x) = \frac{n(x)}{N}$$

Recall

for the unique values of $\{x_1, \dots, x_N\}$

Empirical Distribution

- Law of Large Numbers says \bar{x} goes to mean $E[X]$
- Central Limit Theorem says \bar{x} has Normal distribution, asymptotically.

Example 2.1. For the data set $\{1, 2, 2, 2, 3, 3, 4, 4, 4, 5\}$, we have $n = 10$ and the sum

$$\begin{aligned}1 + 2 + 2 + 2 + 3 + 3 + 4 + 4 + 4 + 5 &= 1n(1) + 2n(2) + 3n(3) + 4n(4) + 5n(5) \\&= 1(1) + 2(3) + 3(2) + 4(3) + 5(1) = 30\end{aligned}$$

Thus, $\bar{x} = 30/10 = 3$.

Sample Mean

64

↓ (bacterium)

Example 2.2. For the data on the length in microns of wild type *Bacillus subtilis* data, we have

length x	frequency $n(x)$	proportion $p(x)$	product $xp(x)$
1.5	18	0.090	0.135
2.0	71	0.355	0.710
2.5	48	0.240	0.600
3.0	37	0.185	0.555
3.5	16	0.080	0.280
4.0	6	0.030	0.120
4.5	4	0.020	0.090
sum	200	1	2.490

So the sample mean $\bar{x} = 2.49$.

Sample Mean

65

For any real-valued function $h(x)$ we can compute the mean as,

$$\overline{h(x)} = \frac{1}{N} \sum_{i=1}^N h(x_i)$$

Note $\overline{h(x)} \neq h(\bar{x})$ in general.

Example Compute the average of the square of values,

$$\{ 1, 2, 3, 4, 5, 5, 6 \}$$

$$\overline{x^2} = \frac{1}{7}(1 + 2^2 + 3^2 + 4^2 + 2(5^2) + 6^2) \approx 16.57$$

$$(\bar{x})^2 \approx 13.80$$

Weighted Mean

66

In some cases we may weight data differently,

$$\sum_{i=1}^N w_i x_i \quad \text{where} \quad \sum_{i=1}^N w_i = 1 \quad 0 \leq w_i \text{ for } i = 1, \dots, N$$

Sample mean: $w_i = \frac{1}{N}$ for all $i = 1, \dots, N$

For example, grades in a class:

$$\text{Grade} = 0.2 \cdot x_{\text{midterm}} + 0.2 \cdot x_{\text{final}} + 0.6 \cdot x_{\text{homework}}$$

Grading Breakdown (example)

- Homework: 60%
- Midterm: 20%
- Final: 20%

We have seen estimates of spread via the sample variance,

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2 \quad \text{Biased}$$
$$s^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2 \quad \text{Unbiased}$$

But you might be interested in more detailed information about the spread.

For example, fraction of people with heights ≤ 5 feet

Quantile divides data into 4 equally-sized bins,

- **1st Quantile** : Lowest 25% of data
- **2nd Quantile** : Median (lowest 50% of data)
- **3rd Quantile** : 75% of data is below 3rd quartile
- **4th Quantile** : All the data... not useful

Compute using `np.quantile()` :

various interpolation methods,
but linear is the standard.

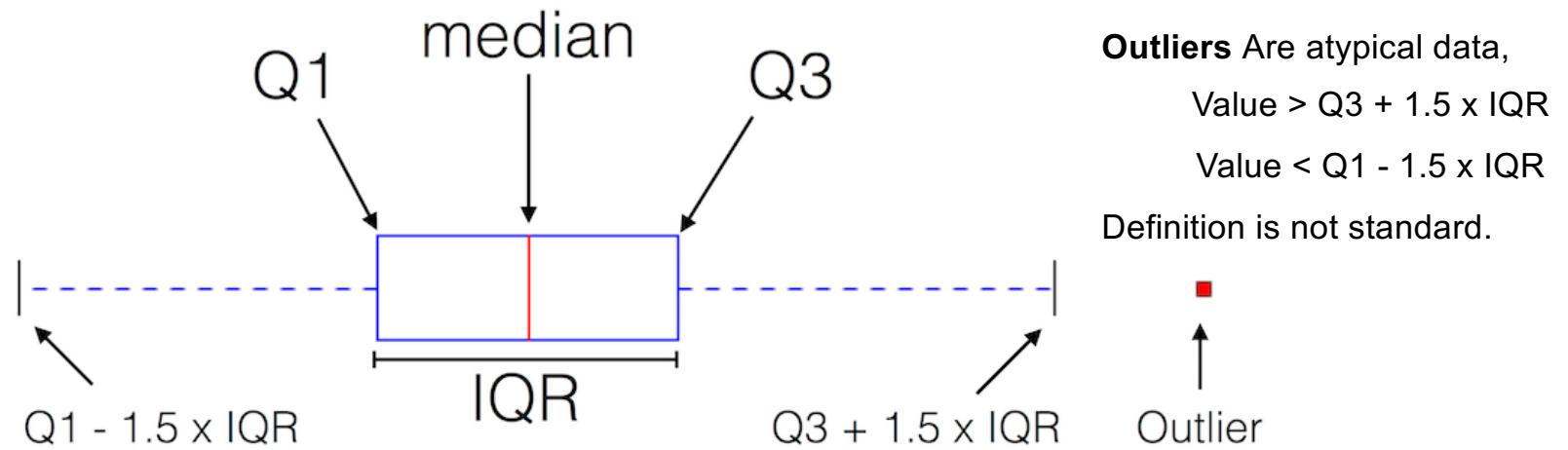
```
x = np.random.rand(10) * 100
q = np.quantile(x, (0.25, 0.5, 0.75))
np.set_printoptions(precision=1)
print("X: ", x)
print("Q: ", q)
```

X: [90.7 73.9 31.7 2.8 56.3 95.7 15.6 75.8 4.1 19.5]
Q: [16.6 44. 75.3]

Box Plot

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A way of displaying the distribution of data based on quantiles



Interquartile-Range (IQR) Measures interval containing 50% of data

$$IQR = Q_3 - Q_1$$

Region of *typical* data

Box Plot

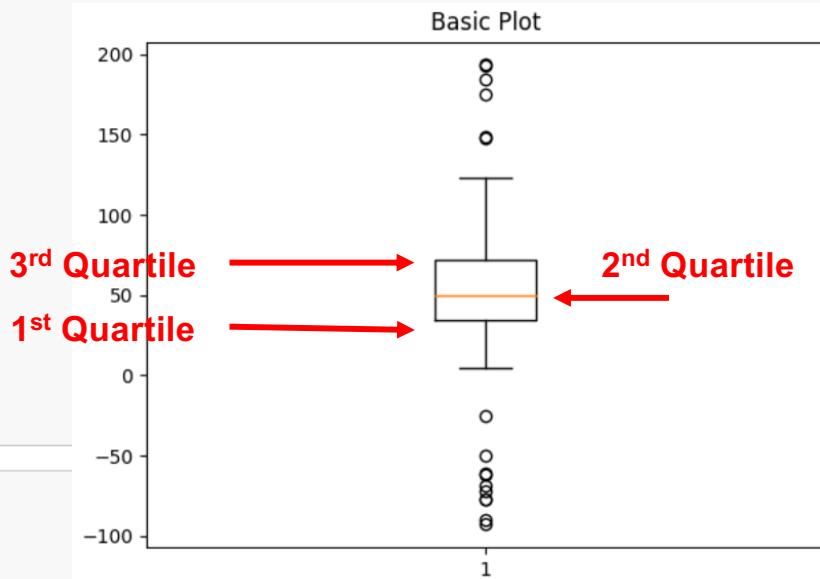
70

```
import numpy as np
import matplotlib.pyplot as plt

# Fixing random state for reproducibility
np.random.seed(19680801)

# fake up some data
spread = np.random.rand(50) * 100
center = np.ones(25) * 50
flier_high = np.random.rand(10) * 100 + 100
flier_low = np.random.rand(10) * -100
data = np.concatenate((spread, center, flier_high, flier_low))
```

```
fig1, ax1 = plt.subplots()
ax1.set_title('Basic Plot')
ax1.boxplot(data)
```

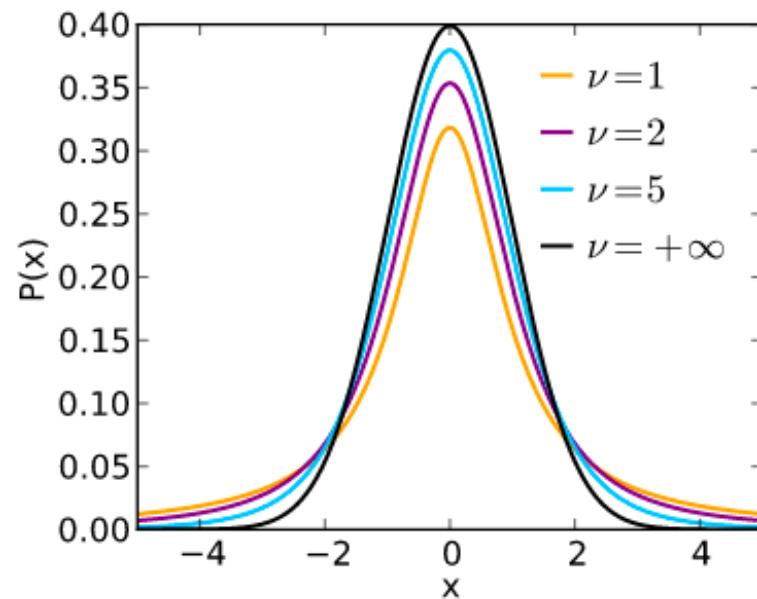


Box Plot

71

Recall t distribution: degrees of freedom determines the thickness of tail

- 1000 samples $\mathcal{N}(0,1)$ vs “t-distribution(0,scale=1/ $\sqrt{3}$,dof=3)”
- both distribution has the same variance



Box Plot

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Recall t distribution: degrees of freedom determines the thickness of tail

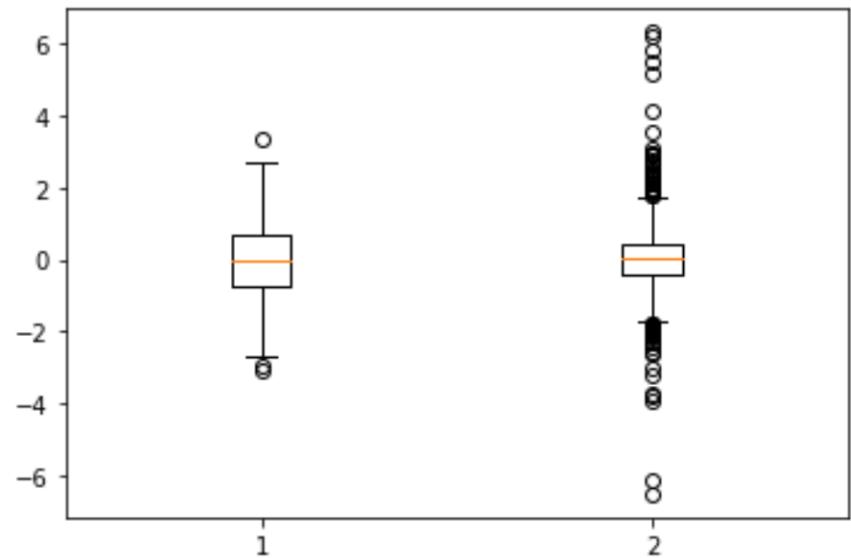
- 1000 samples $\mathcal{N}(0,1)$ vs “t-distribution(0,scale=1/ $\sqrt{3}$,dof=3)”
- both distribution has the same variance

```
import numpy as np
import matplotlib.pyplot as plt
import numpy.random as ra

x1 = ra.randn(1000)
x2 = ra.standard_t(3, size=1000)/np.sqrt(3)
print([np.var(x1),np.var(x2)])
data = [x1,x2]
fig,ax = plt.subplots()
ax.boxplot(data)
```

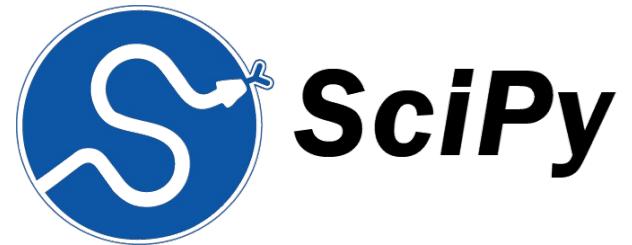
output: [1.04, 0.98]

What's happening here?



Variance is “a” measure of spread. Does not encode ‘thickness’ of the tails.

*Python-based ecosystem for math, science
and engineering.*



As usual, install with Anaconda:

```
> conda install scipy
```

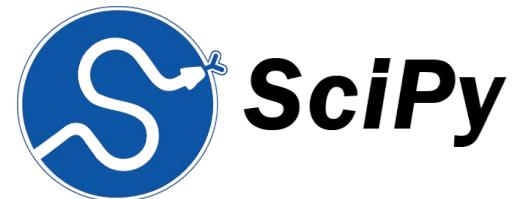
Or with PyPI:

```
> pip install scipy
```

SciPy includes some libraries that directly works with:



SciPy is a large library, so we import it in bits and pieces...



```
>>> from scipy import stats
```

Access the object norm and call its function mean(): stats.norm.mean()

In some cases, you will import only the functions that you need:

```
>>> from scipy.stats import norm
```

contains information about the standard normal distribution

```
>>> norm.mean(), norm.std(), norm.var()  
(0.0, 1.0, 1.0)  
>>> norm.stats(moments="mv")  
(array(0.0), array(1.0))
```

norm.ppf(0.975) returns 0.975-quantile, which is ≈ 1.96



To compute summary stats (e.g., **mode**):

[numpy has mean, but not mode.](#)

- [numpy](#) provides popular numerical functions.
- [scipy](#) provides more serious & specialized functions.

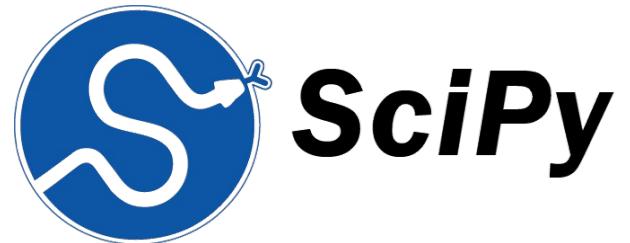
```
>>> import numpy as np
>>> a = np.array([[3, 0, 3, 7],
...                 [3, 2, 6, 2],
...                 [1, 7, 2, 8],
...                 [3, 0, 6, 1],
...                 [3, 2, 5, 5]])
>>> from scipy import stats
>>> stats.mode(a, keepdims=True)
ModeResult(mode=array([[3, 0, 6, 1]]), count=array([[4, 2, 2, 1]]))
```

If there's a multiple candidate for the modal value, the function outputs the smallest element.

Compute the mode of the whole array set `axis=None`:

```
>>> stats.mode(a, axis=None, keepdims=True)
ModeResult(mode=[3], count=[5])
>>> stats.mode(a, axis=None, keepdims=False)
ModeResult(mode=3, count=5)
```

When `axis=None`, it computes the modal value over the whole array.



Other useful summary statistics:

`moment(a[, moment, axis, nan_policy])`

Calculate the nth moment
about the mean for a sample.

`trim_mean(a, proportiontocut[, axis])`

Return mean of array after trimming distribution from both
tails.

`iqr(x[, axis, rng, scale, nan_policy, ...])`

Compute the interquartile range of the data along the
specified axis.

`bootstrap(data, statistic, *[, vectorized, ...])`

Compute a two-sided bootstrap confidence interval of a
statistic.

...

Anscomb's Quartet : The Data

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This example shows risk of relying on statistics only, not the actual data or visualization.

Four distinct datasets of X and Y...

I		II		III		IV	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

[Source: <https://www.geeksforgeeks.org/anscombes-quartet/>]

Anscomb's Quartet : Summary Statistics

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```
# Import the csv file
df = pd.read_csv("anscombe.csv")

# Convert pandas dataframe into pandas series
list1 = df['x1']
list2 = df['y1']

# Calculating mean for x1
print('%.1f' % statistics.mean(list1))

# Calculating standard deviation for x1
print('%.2f' % statistics.stdev(list1))

# Calculating mean for y1
print('%.1f' % statistics.mean(list2))

# Calculating standard deviation for y1
print('%.2f' % statistics.stdev(list2))

# Calculating pearson correlation
corr, _ = pearsonr(list1, list2)
print('%.3f' % corr)

# Similarly calculate for the other 3 samples

# This code is contributed by Amiya Rout
```

Start by computing summary statistics, e.g. Dataset 1:

Mean X1: 9.0

STDEV X1: 3.32

Mean Y1: 7.5

STDEV Y1: 2.03

Correlation: 0.816

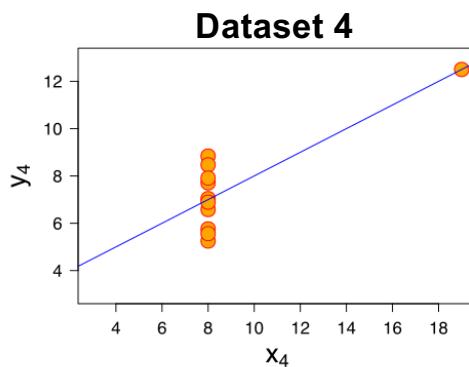
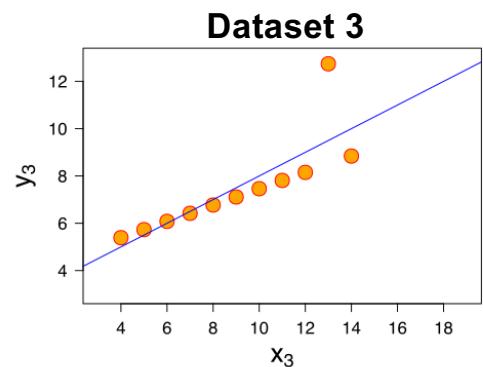
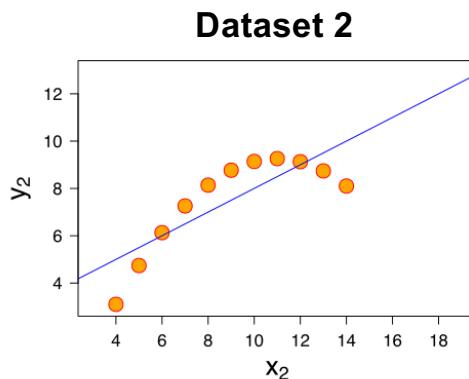
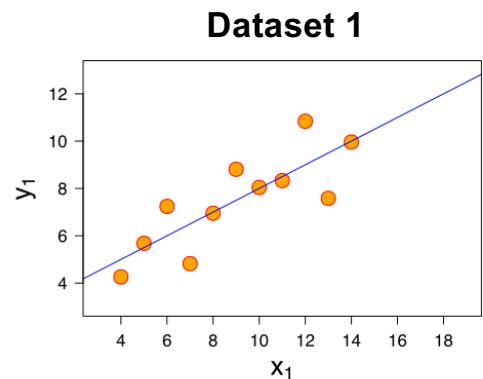
Actually, all datasets have the same statistics...

Question What can we conclude about these data? Are they the same?

[Source: <https://www.geeksforgeeks.org/anscombes-quartet/>]

Anscomb's Quartet : Visualization

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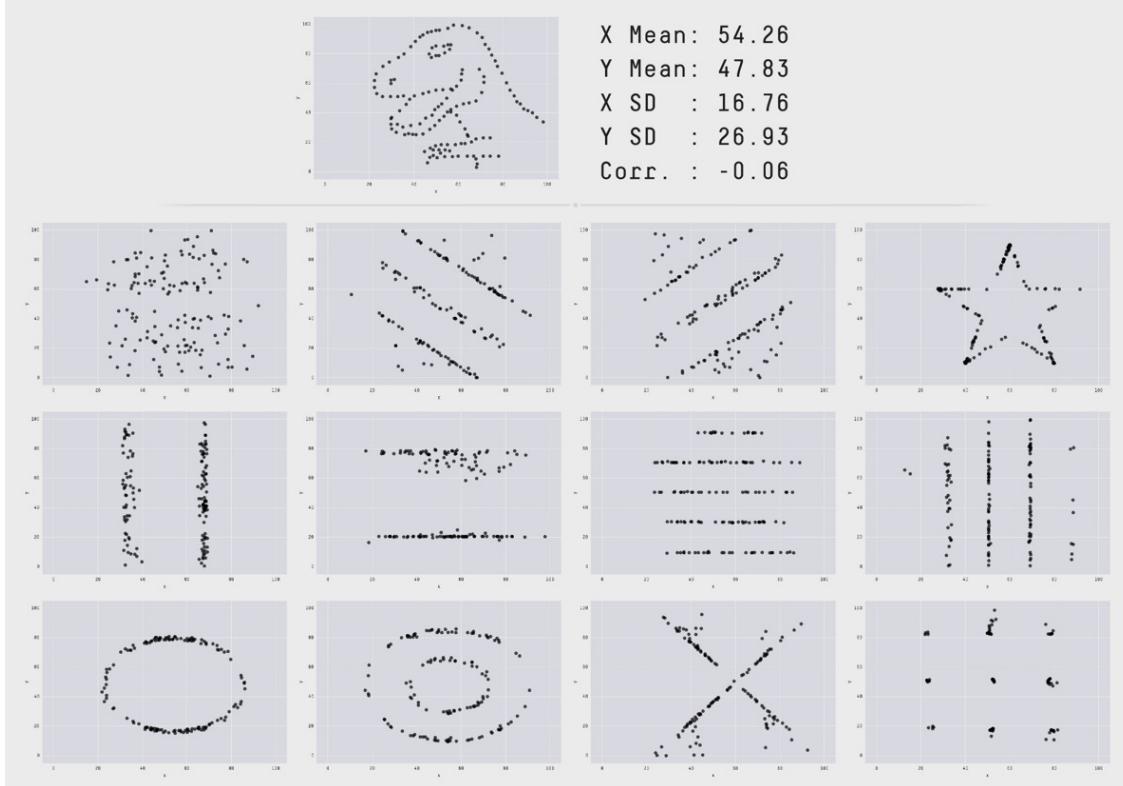


Visualizing data clearly indicates that these are *very different* datasets...

...this highlights the **importance of visualizing data**

Datasaurus

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13 datasets that all have the same summary statistics, but look very different in simple visualizations

Can be very difficult to see differences in high dimensions, however

[Source: [Alberto Cairo](#)]

- Data Visualization
- Data Summarization
- Data Collection and Sampling

Much of the content in this section from Scribbr.com and Shona McCombes

Motivation

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Not understanding how data are collected is one of the top reasons behind bad data science...

How Bad Data Is
Undermining Big Data
Analytics

Forbes

How to be a bad data scientist!

Pascal Potvin Feb 27, 2018

**8 telltale signs of
a bad data scientist**

InfoWorld

**If Your Data Is Bad, Your
Machine Learning Tools
Are Useless**

by Thomas C. Redman

...we will not do data collection or experimental design, but students should be familiar with the basics

1. Plan research design
2. Collect data (essentially, sampling)
3. Visualize and summarize the data (plots and summary stats)
4. Make inferences from data (i.e., estimate stuff, test hypotheses, ...)
5. Interpret results

1. Plan research design
2. Collect data (essentially, sampling)
3. Visualize and summarize the data (plots and summary stats)
4. Make inferences from data (i.e., estimate stuff, test hypotheses, ...)
5. Interpret results

Have touched on these already...

1. Plan research design
Will focus on these
2. Collect data (essentially, sampling)
3. Visualize and summarize the data (plots and summary stats)
4. Make inferences from data (i.e. estimate stuff, test hypotheses, ...)
5. Interpret results

Randomized Control. Researcher controls treatment among groups. Used to assess *causal* relationships. Stronger than correlational study but difficult to conduct. (e.g., clinical trials)

Observational. Collect data by “observing” passively. Individuals/samples are not under the control of the researcher.

- **Natural Experiment.** Observe naturally-occurring phenomena. Approximates a controlled study, despite the researcher not having control of any groups.

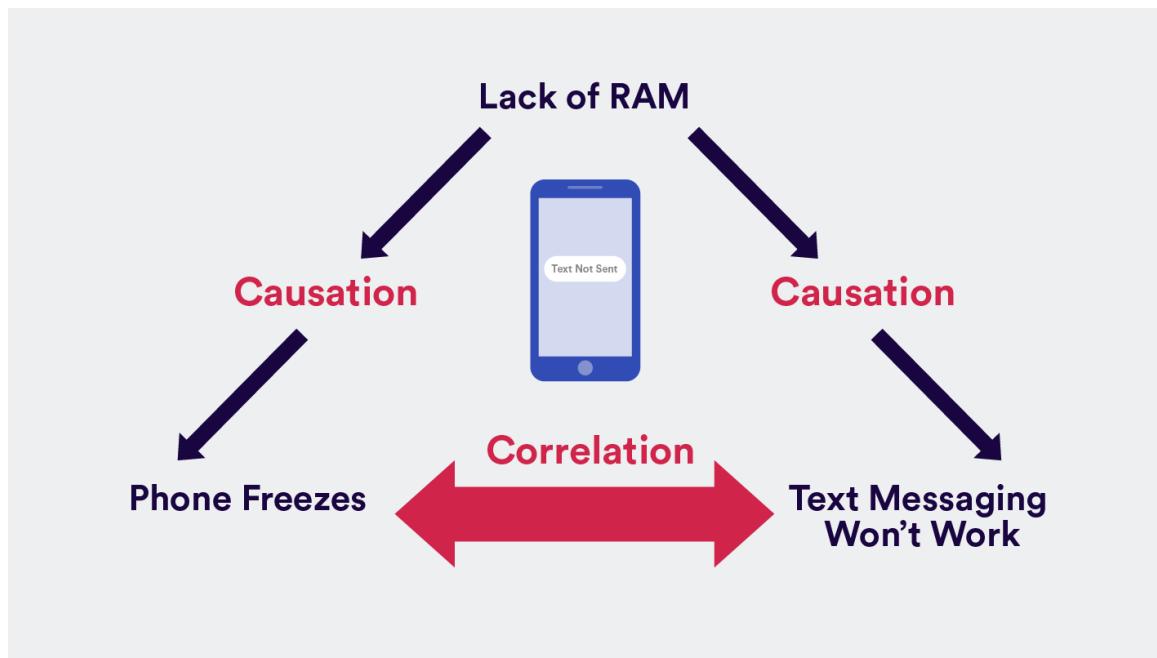
E.g.) Helena, Montana banned smoking ban in all public spaces for six months – before/after this ban

- **Case Studies and Surveys.** Analysis based on previously-collected data. E.g., Analysis of US census data, or US current population survey (CPS)

Causation vs. Correlation

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Studies generally try to show *either* correlation (association) or causation, but they are not the same...



background explained: https://www.explainxkcd.com/wiki/index.php/925:_Cell_Phones

Recall: Explanatory, response variable

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Example: Say we study the relationship between **Smoking** vs **Cancer**

Independent variable: variables that are manipulated or are changed by researchers and whose effects are measured and compared.

= **explanatory variable**

Dependent variable: the variable that depends on independent variable (or speculated to do so).

= **response variable**

Confounding Variables

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A variable that influences the *response* but is unaccounted for in data collection

Example: You are studying whether **birth order** affects **Down's Syndrome** in the child. You collect samples of children, their birth order, and cases of Down's syndrome.

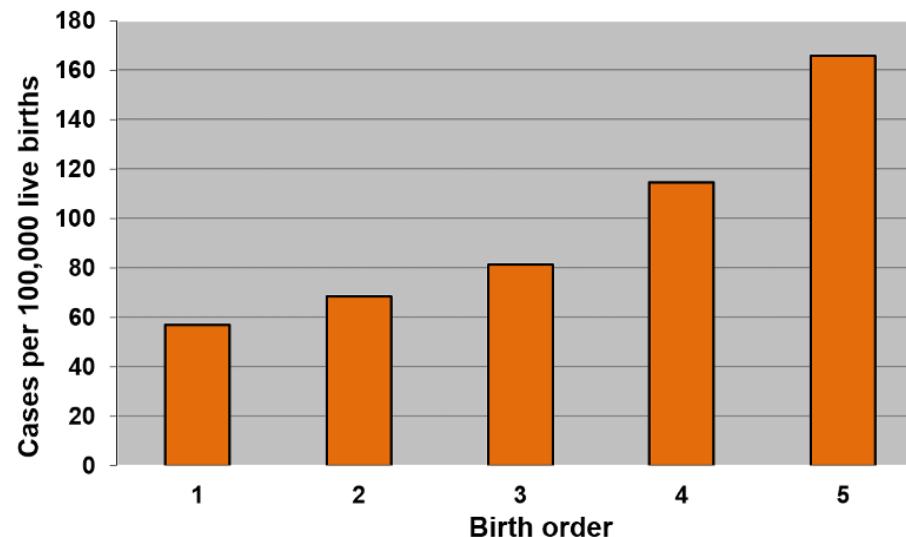


chart from <https://sphweb.bumc.bu.edu/otlt MPH-Modules/PH717-QuantCore/PH717-Module11-Confoundin g-EMM/PH717-Module11-Confoundin g-EMM3.html>

Confounding Variables

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A variable that influences the *response* but is unaccounted for in data collection

Example: You are studying whether **birth order** affects **Down's Syndrome** in the child. You collect samples of children, their birth order, and cases of Down's syndrome.

Explanation: Maternal age (confounder) was not recorded. Two scenarios:

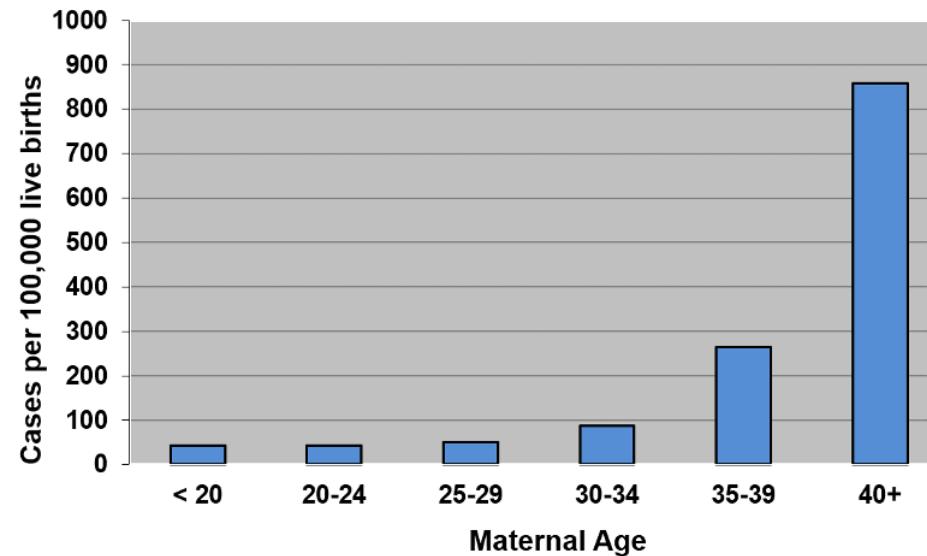
1. Higher maternal age is directly associated with Down's syndrome, regardless of birth order.
2. Maternal age directly assoc. with birth order (mother is older with later children), but not directly associated with Down's syndrome.



Confounding Variables

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- You went on to collecting the maternal age data.



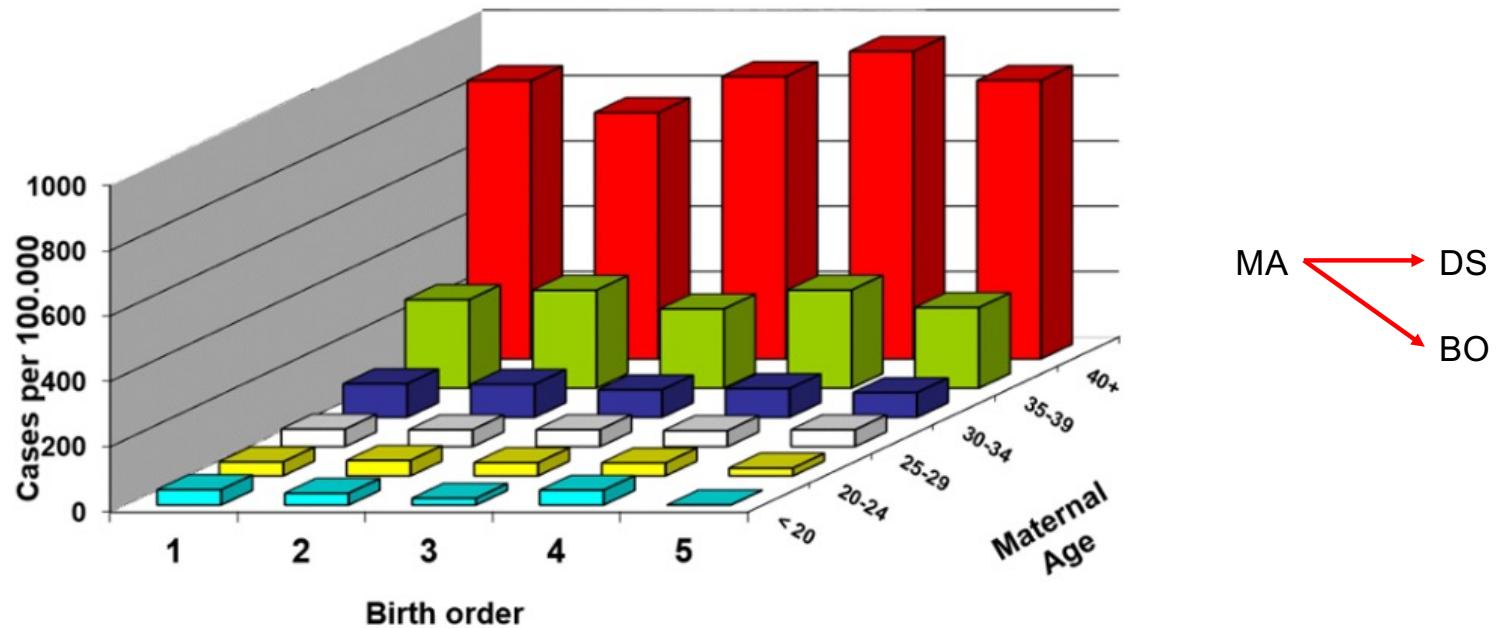
So.. both maternal age and birth order is associated with Down's syndrome?

Controlling for Confounders

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Stratified Sampling: Divide population into smaller groups.

Previous example can divide population of children by maternal age at birth and collect data from each stratum



Approach

1. **Control** confounders: design treatments
2. **Randomize** the assignment of subjects to treatments to eliminate bias due to systematic differences in categories
3. **Replicate** experiment on many subjects, to obtain statistically meaningful results

Example: Pfizer COVID Phase 3 Vaccine Trials

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the tendency of any medication or treatment, even an inert or ineffective one, to exhibit results simply because the recipient believes that it will work.

1. **Placebo Control:** Subjects are randomly selected to receive either the vaccine or an injection of saline solution
2. **Randomize:** Stratified sampling with age strata: 12-15yrs, 16-55yrs, 55+yrs
3. **Replicate:** Experiment is repeated at multiple sites in several countries

Full statistical procedures are published and publicly available:

https://cdn.pfizer.com/pfizercom/2020-11/C4591001_Clinical_Protocol_Nov2020.pdf

Example: Pfizer COVID Phase 3 Vaccine Trials

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The landmark phase 3 clinical trial enrolled **46,331** participants at **153** clinical trial sites around the world.

Trial Geography



Our trial sites are located in **Argentina, Brazil, Germany, Turkey, South Africa** and the **United States**.

Participant Diversity

Approximately **42%** of overall and **30%** of U.S. participants have diverse backgrounds.

Participants	Overall Study	U.S. Only
Asian	5%	6%
Black	10%	10%
Hispanic/Latinx	26%	13%
Native American	1.0%	1.3%

49.1% of participants are male and **50.9%** are female

Participant Age



Ages 12-15 2,260

Ages 16-17 754

Ages 18-55 25,427

Ages 56+ 17,879

Example: Polio Vaccine

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In 1954 the National Foundation of Infantile Paralysis (**NFIP**) tested Jonas Salk's Polio vaccine in a controlled trial with the following cohorts:

- Vaccinate all 2nd grade children with parental consent
- Use grades 1 and 3 as control (unvaccinated)

Do you see anything wrong with this design?

To address study flaws the US Public Health Service (**PHS**) conducted a new randomized control study:

- Flip coin for each child (randomized control)
- Kids in control get salt water injection
- Diagnosticians not told what group each child is in (double blind)



- placebo
- polio spreads through contact
- consent = higher income
(low income => low infection rate)

	PHS		NFIP	
	Size	Rate	Size	Rate
Treatment	200,000	28	225,000	25
Control	200,000	71	725,000	54
No consent	350,000	46	125,000	44

Source: Watkins, J.

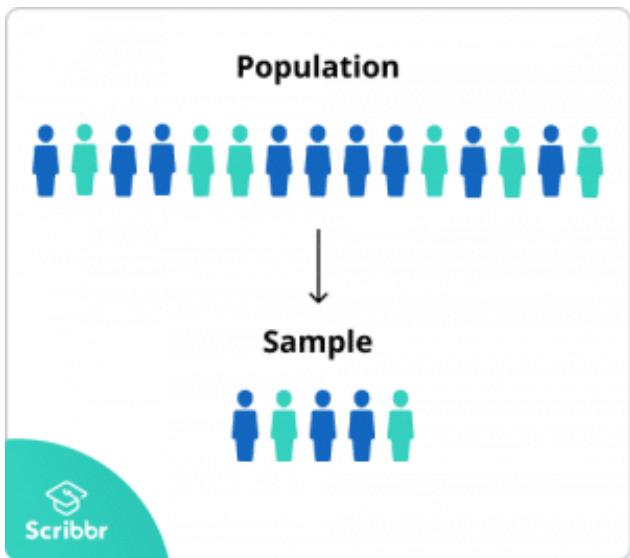
Data collection

- What can I measure?
- What *shall* I measure?
- How shall I measure it?
- How frequently shall I measure it?
- What obstacles prevent reliable measurement?

Population vs. Sample

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Generally infeasible to collect data from entire *population*



Population Entire group that we want to draw conclusions about.

Can be defined in terms of location, age, income, etc.

Sample Specific group that we collect data from.

Examples of Population vs. Sample

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Population	Sample
Advertisements for IT jobs in the Netherlands	The top 50 search results for advertisements for IT jobs in the Netherlands on May 1, 2020
Songs from the Eurovision Song Contest	Winning songs from the Eurovision Song Contest that were performed in English
Undergraduate students in the Netherlands	300 undergraduate students from three Dutch universities who volunteer for your psychology research study
All countries of the world	Countries with published data available on birth rates and GDP since 2000

Keep in mind: You could easily collect biased data

Necessity It is usually impractical or impossible to collect data from an entire population due to size or inaccessibility.

Cost-effectiveness There are fewer participant, laboratory, equipment, and researcher costs involved.

Manageability Storing data and running statistical analyses is easier on smaller datasets.

Population Parameter vs. Sample Statistic

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Population parameter A measure that describes *the whole population*.

Sample statistic A measure that describes the sample and reflects the population parameter.

Example We are studying student ***political attitudes*** and ask students to rate themselves on a scale: 1, very liberal, to 7, very conservative. The ***population parameter*** of interest is the average political leaning. The sample mean, say 3.2, is our ***statistic***.

The *sampling error* is the difference between the population parameter and the sample statistic.

- Sampling errors are **normal**, but we want them to be low
- Samples are **random**, so sample statistics are estimates and thus subject to random noise
- **Sample bias** occurs when the sample is not representative of the population (for various reasons)

Sampling must be conducted properly, to avoid sample bias

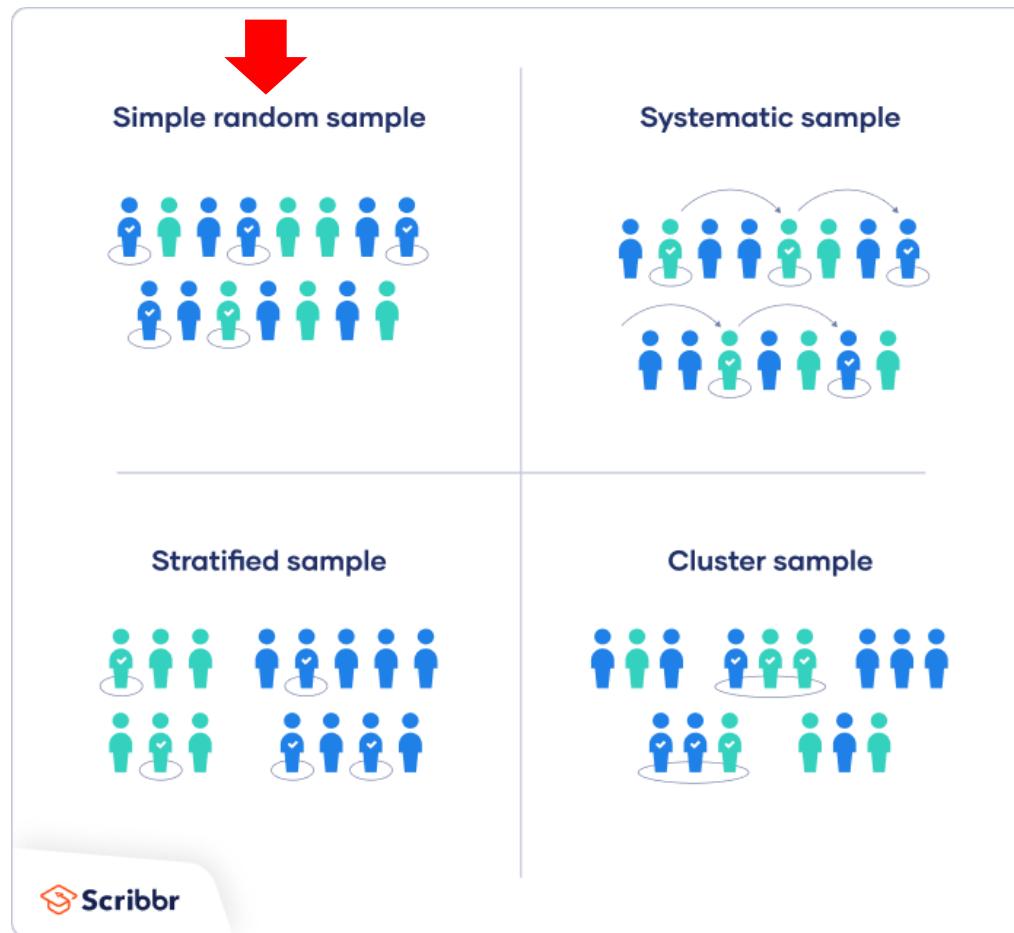
Two primary types of sampling...

Probability Sampling Random selection allowing strong statistical inferences about the population

Non-Probability Sampling Based on convenience or other criteria to easily collect data (but no random sampling)

Probability Sampling

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Simple Random Sample (SRS)

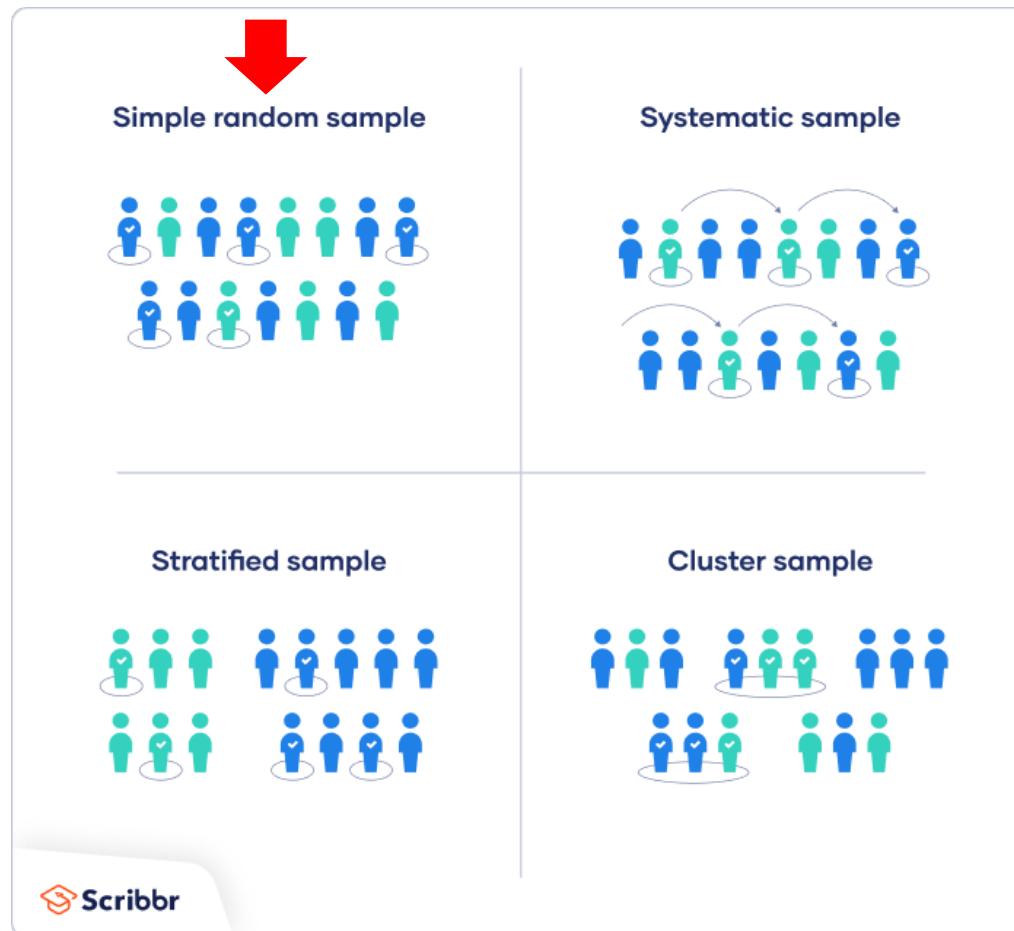
Each member of the population has the *same chance* of being selected (i.e., uniform over the population)

Example : American Community Survey (ACS)

Each year the US Census Bureau use *simple random sampling* to select individuals in the US. They follow those individuals for 1 year to draw conclusions about the US population as a whole.

Probability Sampling

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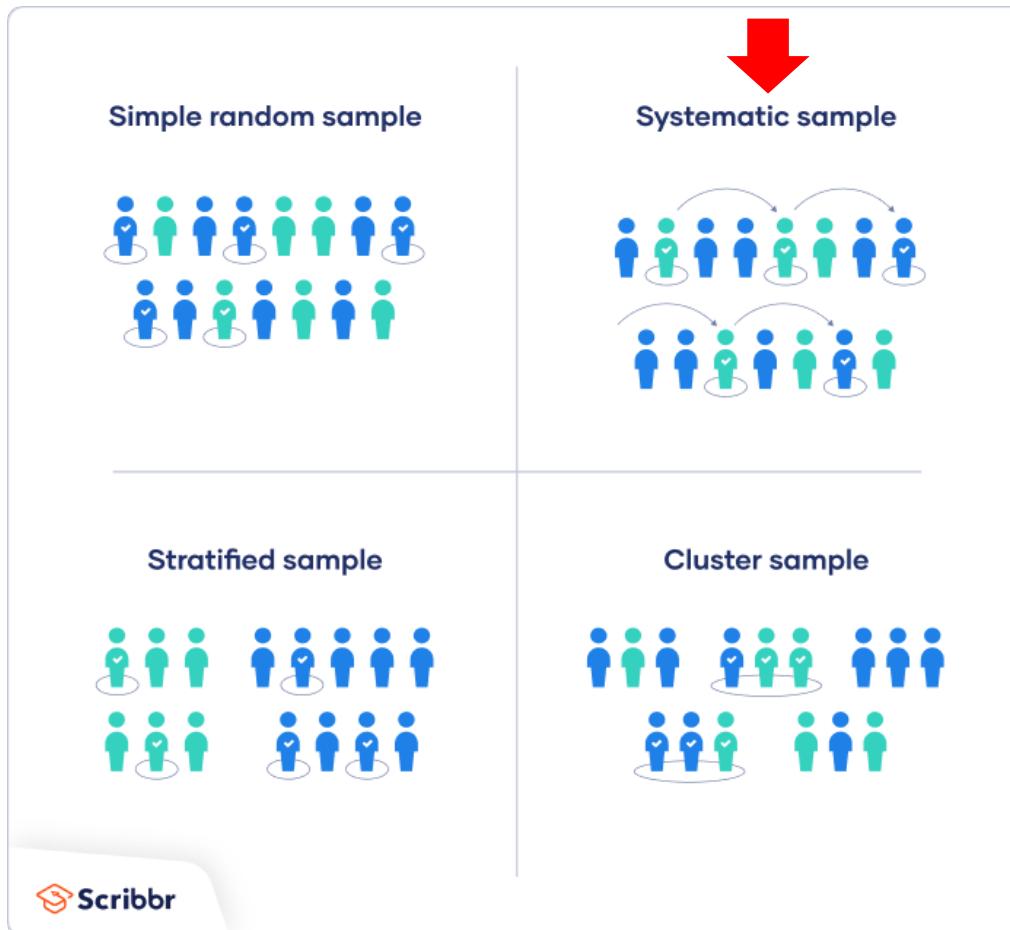
Simple Random Sample (SRS)

Each member of the population has the *same chance* of being selected (i.e., uniform over the population)

- Most straightforward probability sampling method
- Impractical unless you have a complete list of every member of population

Probability Sampling

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Systematic Sample

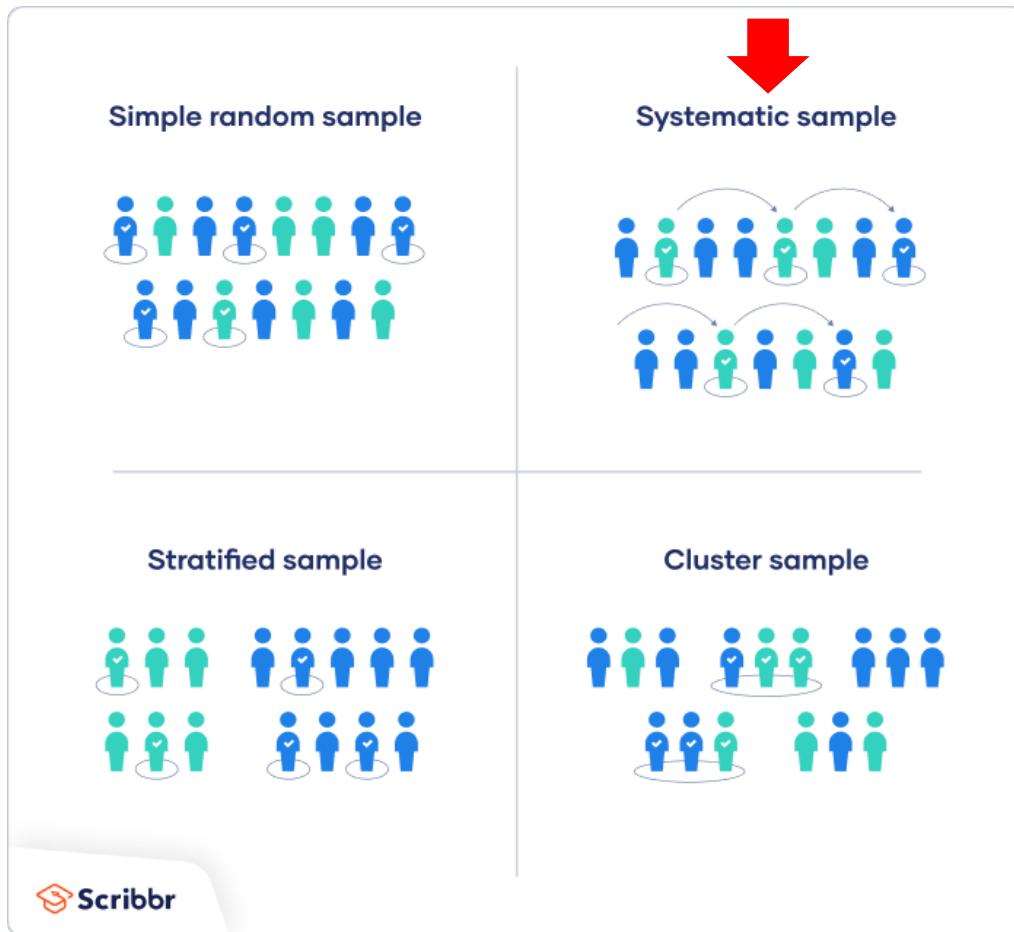
Select members of population at a regular interval, determined in advance

Example You own a grocery store and want to study customer satisfaction. You ask every 20th customer at checkout about their level of satisfaction.

Note We cannot itemize the whole population in this example, so SRS is not possible.

Probability Sampling

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Systematic Sample

Select members of population at a regular interval, determined in advance

- Imitates SRS but is easier in practice
- **Do not** use when there can be a pattern. E.g., survey at the exit of a rollercoaster with N seats but with every N-th customer.

Alternative: use a Bernoulli(p) (e.g., $p=1/20$)

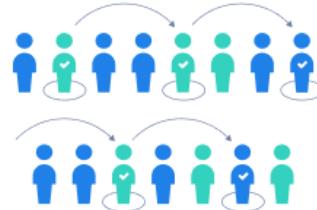
Probability Sampling

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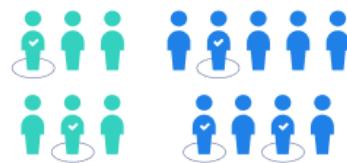
Simple random sample



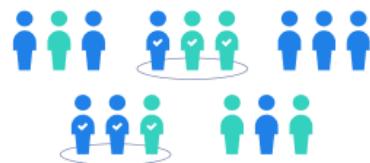
Systematic sample



Stratified sample



Cluster sample



Stratified Sample

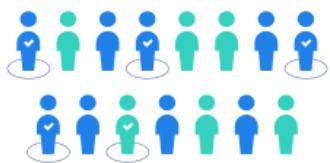
Divide population into *homogeneous* subpopulations (strata). Probability sample the strata.

Example We wish to solicit opinions of UA CS freshman by asking 100 of them, but they are about 14% women. SRS could easily fail to capture adequate number of women. We divide into men / women and perform SRS within each group.

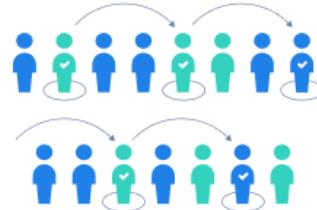
Probability Sampling

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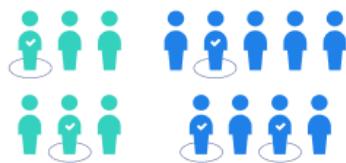
Simple random sample



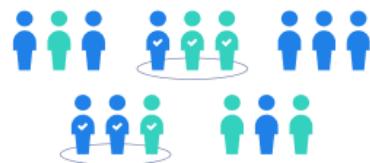
Systematic sample



Stratified sample



Cluster sample



Stratified Sample

Divide population into *homogeneous* subpopulations (strata). Probability sample the strata.

- Use when population is diverse and want to accurately capture characteristic of each group
- Ensures similar variance across subgroups
- Lowers overall variance in the population

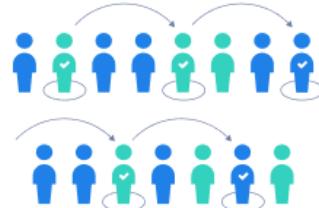
Probability Sampling

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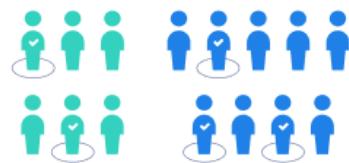
Simple random sample



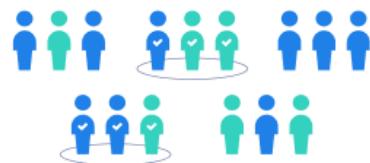
Systematic sample



Stratified sample



Cluster sample



Cluster Sample

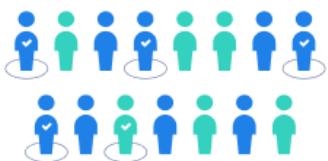
Divide population into subgroups (clusters). Randomly select entire clusters.

Example We wish to study the average reading level of *all 7th graders in the city* (population). Create a list of all schools (clusters) then randomly select a subset of schools and test every student.

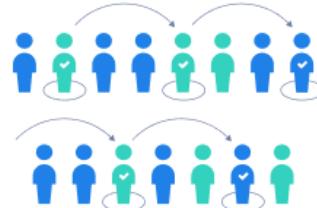
Probability Sampling

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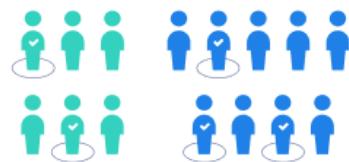
Simple random sample



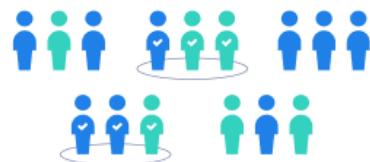
Systematic sample



Stratified sample



Cluster sample



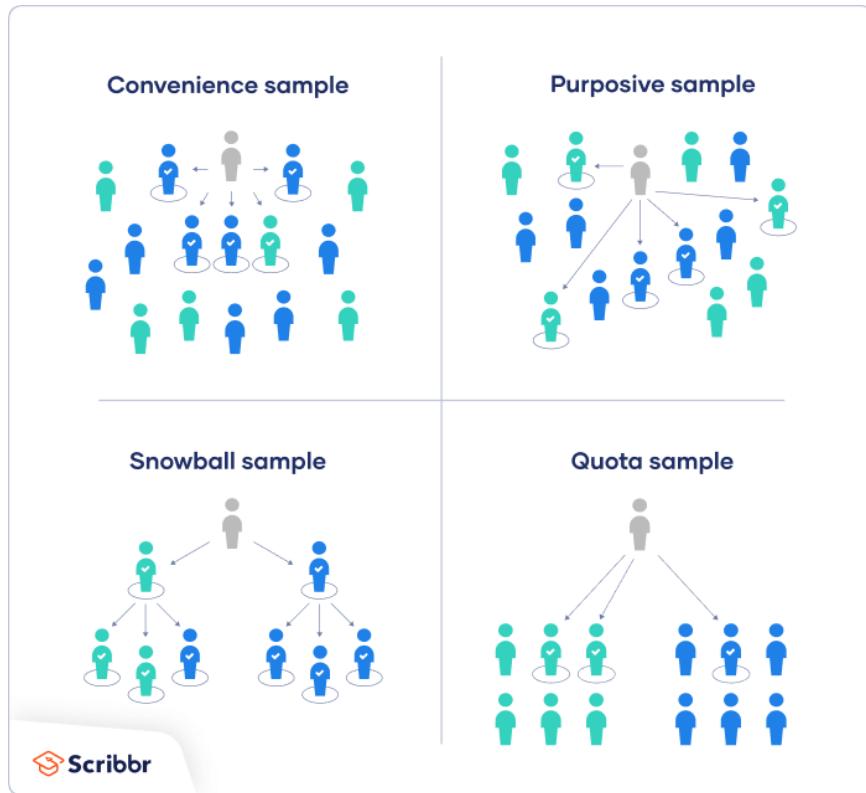
Cluster Sample

Divide population into subgroups (clusters). Randomly select entire clusters.

- This is *single-stage* cluster sampling
- *Multi-stage* avoids sampling every member of a group
- Related to stratified sampling, but groups are not homogeneous

Non-Probability Sampling

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Easier to access data, but higher risk of *sample bias* compared to probability sampling

Usually used to perform *qualitative research* (e.g., gathering student opinions, experiences, etc.)

We will not focus on these, but you should be aware if your data are from non-probability methods

Review Questions

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- When can we use SRS and when can we not? quiz candidates
- What's the alternative?
- When do we want to use stratified sampling?

Sampling Bias

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Occurs if data are collected in a way that some members of the population have lower/higher probability of being sampled than others

Sometimes is unavoidable (e.g., not all members are equally accessible) but

- (1) you should be aware of it
- (2) must be corrected if possible at all

Example We conduct a poll by randomly calling numbers in a phone book. People that have less time are less likely to respond. Called **non-response bias**.

Common Types of Sampling Bias

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Self-selection: Possible whenever members (typically people) under study have control over whether to participate.

- E.g., online or phone-in poll—user can choose whether to initiate participation.

Exclusion: a researcher exclude certain groups from the sample.

- E.g., longitudinal data collection for 2 years in a town where we exclude groups that move in or out.

Survivorship: Only surviving subjects are selected.

- E.g., during WW2, the military wanted to find out the vulnerable spots on the aircraft, so they counted the bullet holes on the planes in their air base. Now, where should we put additional armor to protect aircraft?



(Wikipedia)

Example of Bias in a Simple Random Sample

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SRS is least prone to bias, but not always...

You want to study procrastination and social anxiety levels in undergraduate students at your university using a simple random sample. You assign a number to every student in the research participant database from 1 to 1500 and use a random number generator to select 120 numbers.

What is the cause of bias in this simple random sample?

<https://www.scribbr.com/methodology/sampling-bias/>

Example of Bias in a Simple Random Sample

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SRS is least prone to bias, but not always...

You want to study procrastination and social anxiety levels in undergraduate students at your university using a simple random sample. You assign a number to every student in the research participant database from 1 to 1500 and use a random number generator to select 120 numbers.

Although you used a random sample, not every member of your target population –undergraduate students at your university – had a chance of being selected. Your sample misses anyone who did not sign up to be contacted about participating in research. This may bias your sample towards people who have less social anxiety and are more willing to participate in research.

<https://www.scribbr.com/methodology/sampling-bias/>

- Data Visualization
 - matplotlib.pyplot; see the documentation & tutorials
- Data Summarization
 - summary statistics – location, spread, skew
 - scipy for more advanced functionality
 - Anscomb's quartet: importance of visualization.
- Research Design
 - Randomized control, observational, natural experiment.
 - Correlation vs causation
 - Confounding variables: could cause correlation that may disappear after observing the confounding variable.
- Data Collection and Sampling
 - Sampling methods: SRS, systematic, stratified, cluster.
 - Look out for the bias: self-selection, exclusion, survivorship.