Data Science

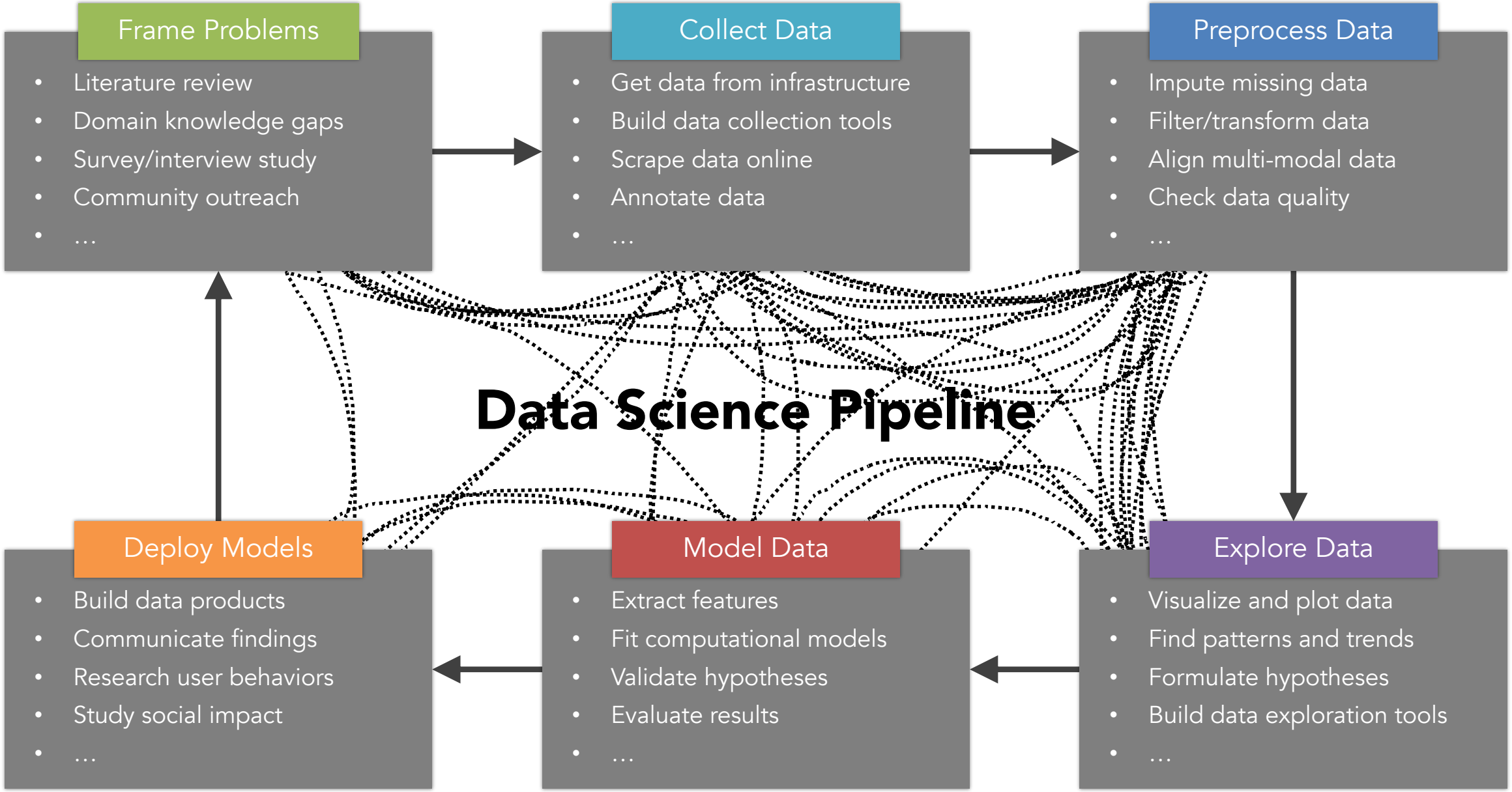
Lecture 2-1: Data Science Fundamentals (Pipeline)

UNIVERSITY OF AMSTERDAM

Lecturer: Yen-Chia Hsu

Date: Feb 2024

This lecture shows a typical data science pipeline and recaps data cleaning techniques.

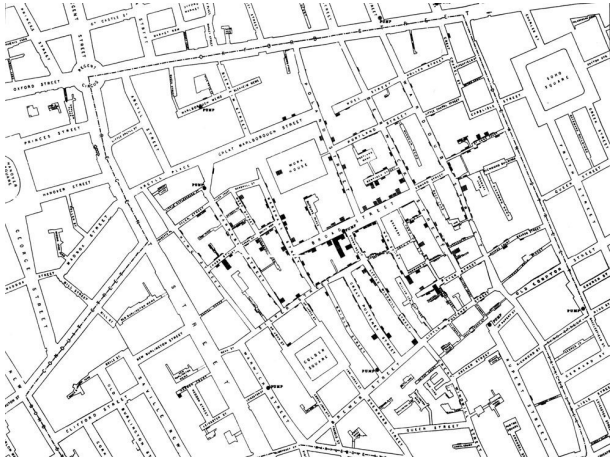


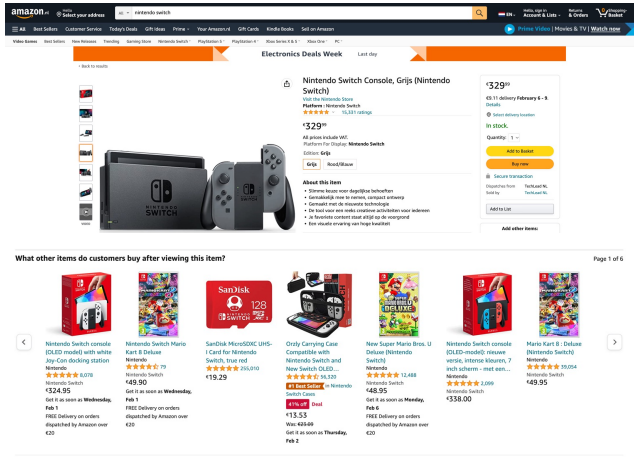
What people typically think : →

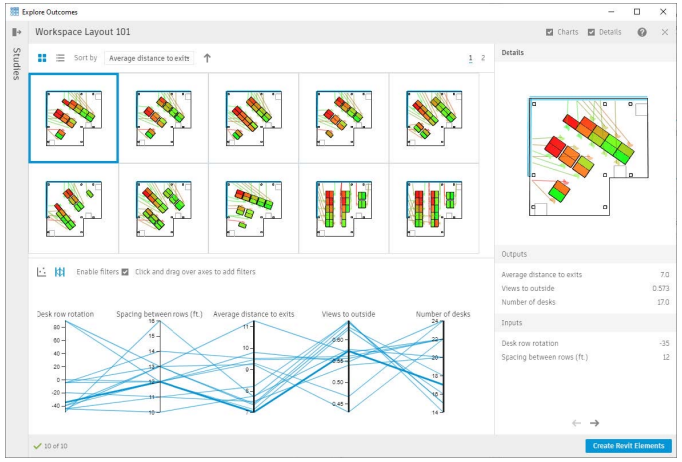
The reality of the data science pipeline: ·····

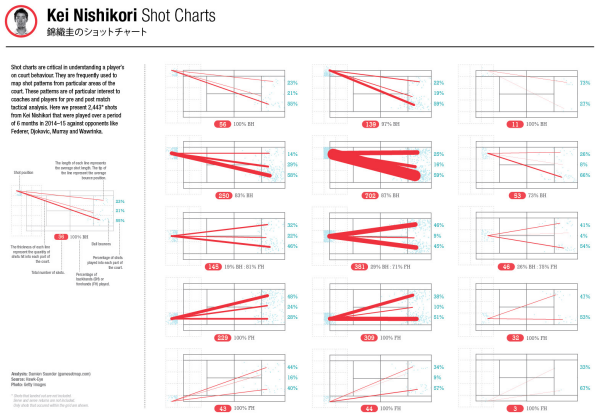
Frame Problems

This course will use existing scenarios and cases with well-defined problems. However, in the real world, we need to define and frame the problems first.









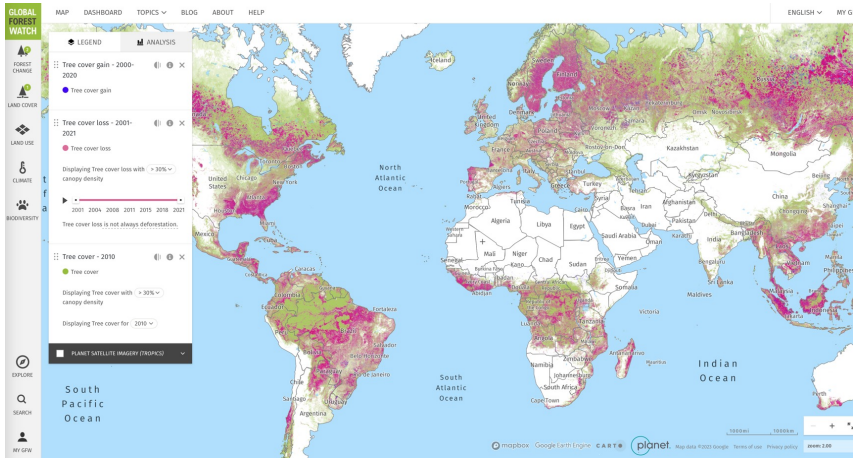
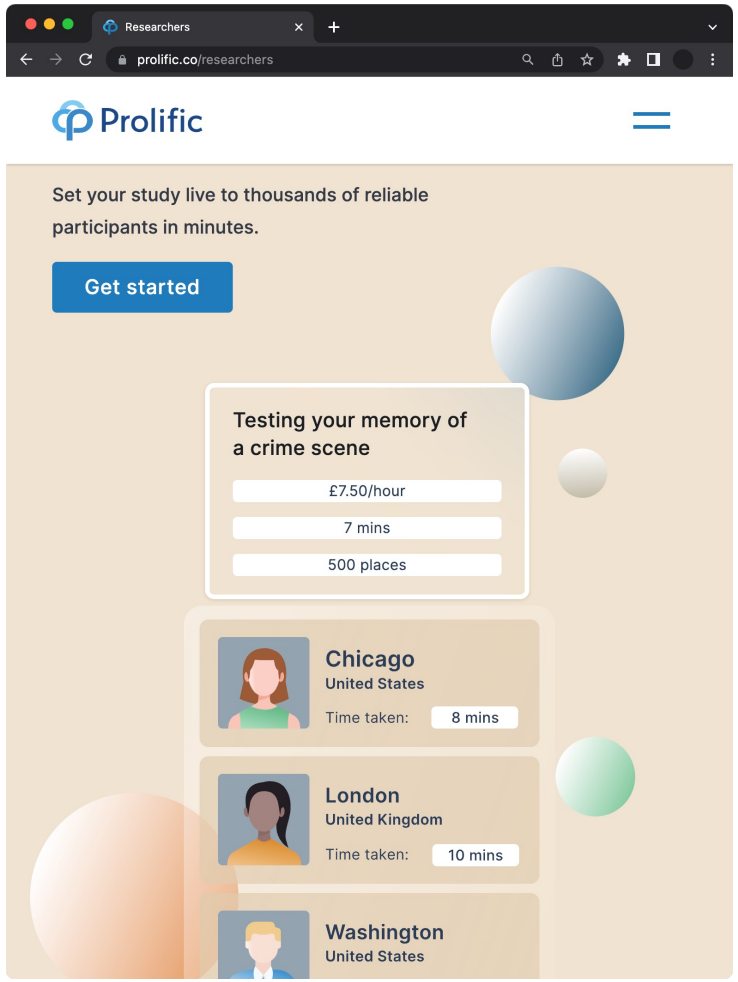


Figure sources are in the slides for the first lecture.

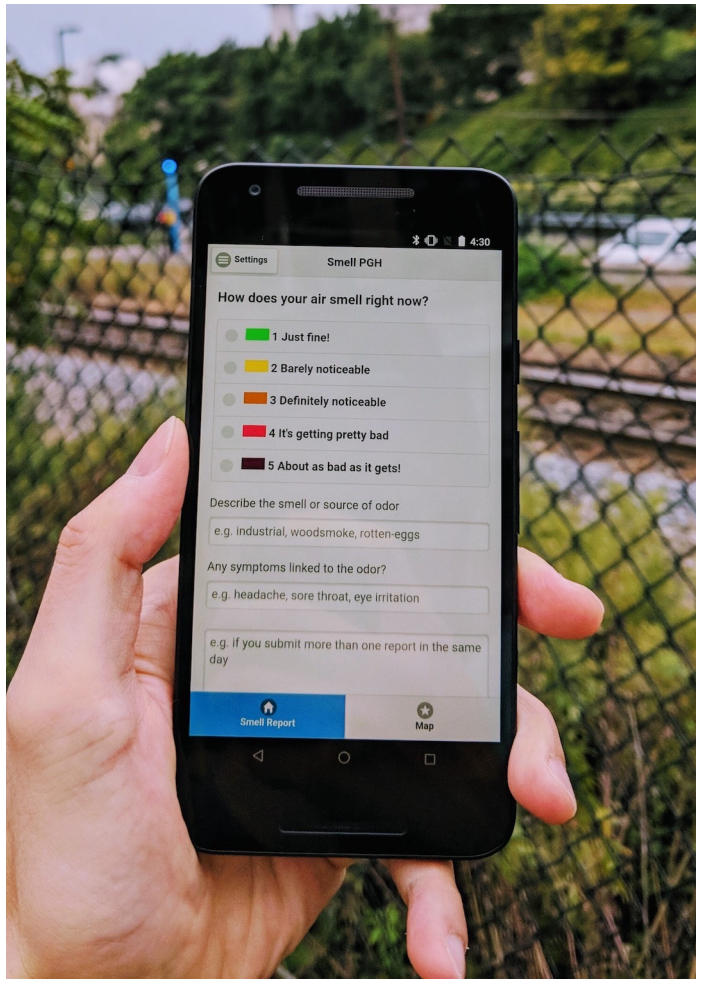
Collect Data

This course will assume that someone already collected the data for you. But we will briefly cover crowdsourcing and data annotation techniques.

GGD Amsterdam Data Portal



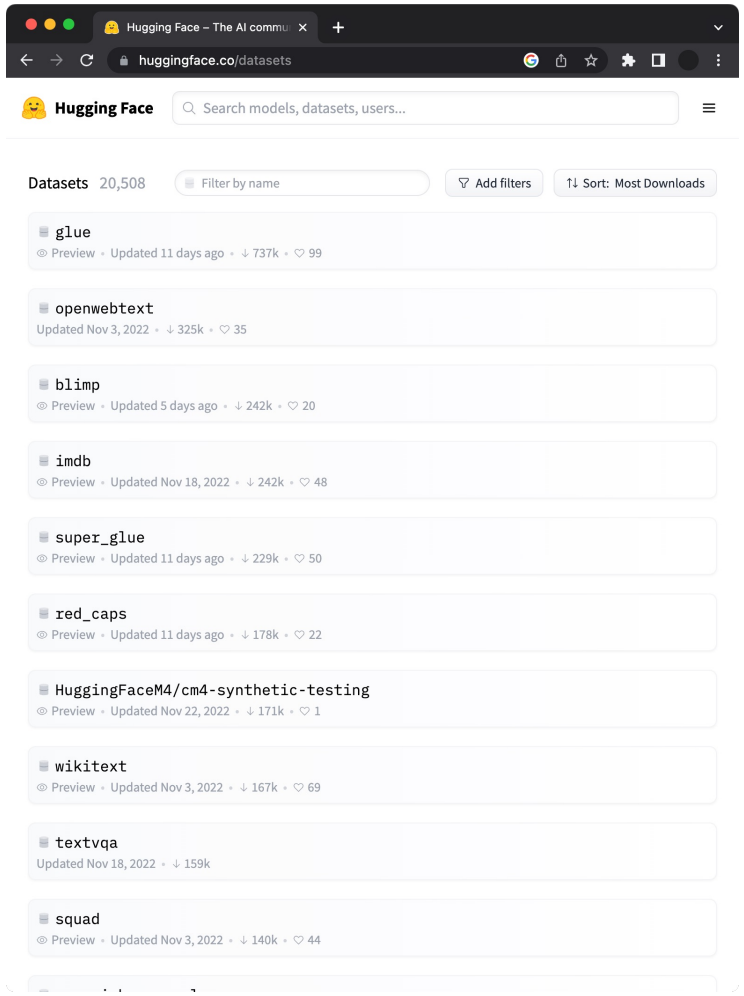
Prolific Tool for Data Annotation

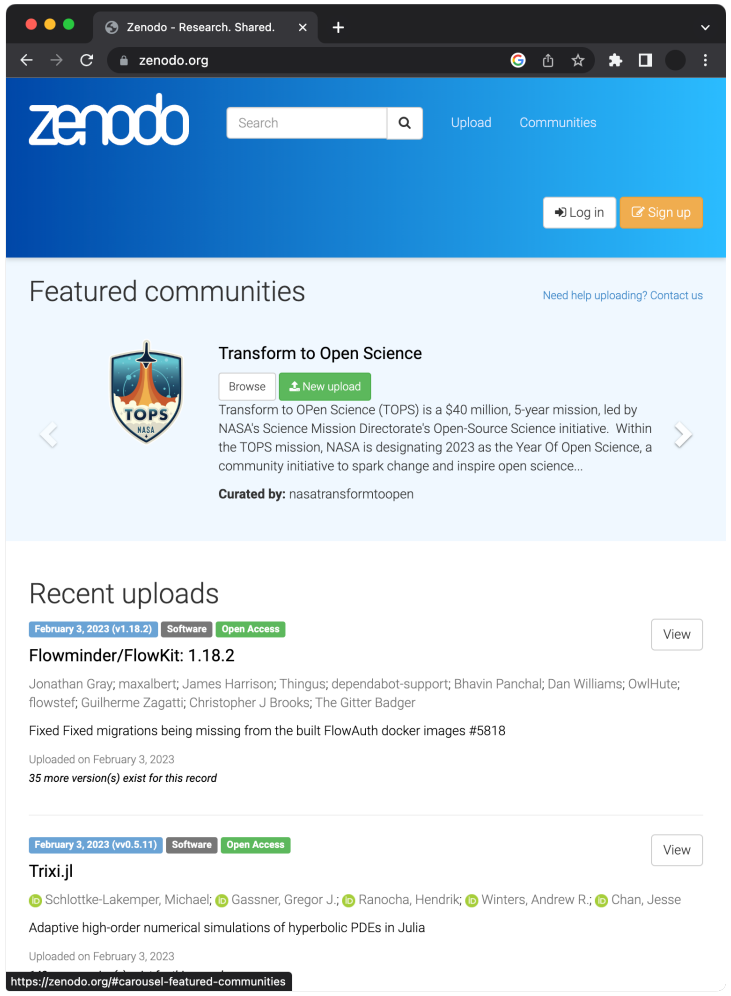


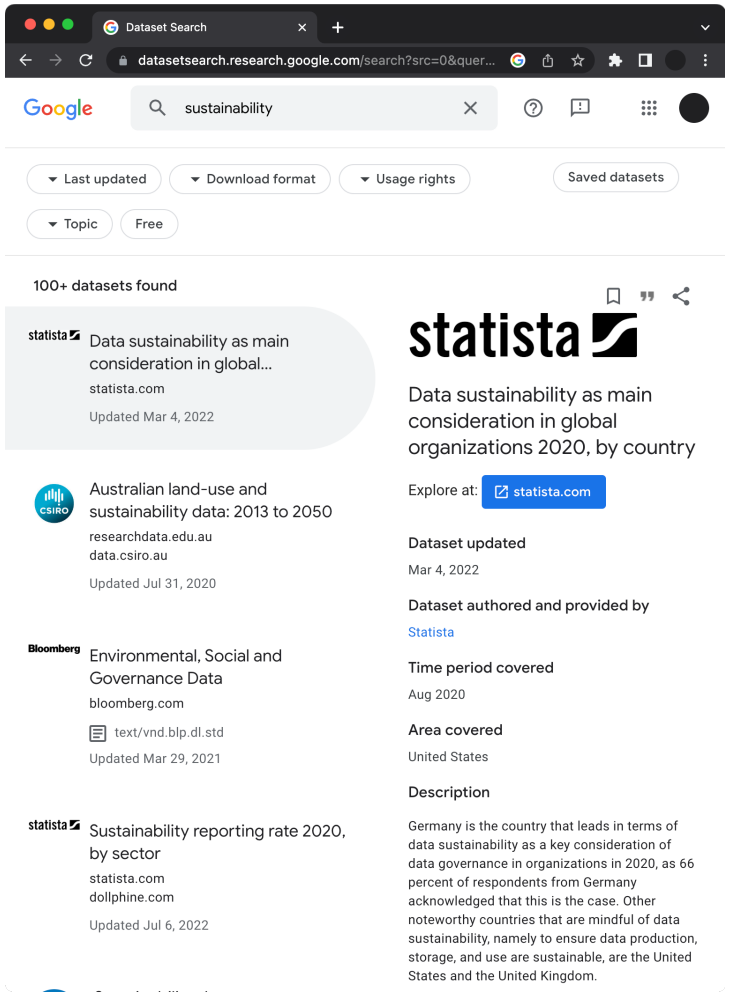
Mobile App Data Collection

Collect Data

There are also other sources for getting public datasets, such as Hugging Face, Zenodo, Google Dataset Search, government websites, etc.







Hugging Face

Zenodo

Google Dataset Search

Preprocess Data

This course will focus on pandas, which is a very handy Python library for preprocessing structured data. We will cover the following techniques:

- Filter unwanted data
- Aggregate data (e.g., sum)
- Group data based on a column
- Sort rows based on a column
- Concatenate data frames
- Merge and join data frames
- Quantize continuous values into bins
- Scale column values
- Resample time series data
- Apply a transformation function
- Use regular expressions
- Drop rows or columns
- Treat missing values

10 minutes to pandas -- https://pandas.pydata.org/docs/user_guide/10min.html

Preprocess Data

Filtering can reduce a set of data based on specific criteria. For example, the left table can be reduced to the right table using a population threshold.

D

city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439
Utrecht	344,384
Eindhoven	227,100
Tilburg	214,157

city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439

More about filtering data -- https://pandas.pydata.org/docs/user_guide/indexing.html

Preprocess Data

Aggregation reduces a set of data to a descriptive statistic. For example, the left table is reduced to a single number by computing the mean value.

D

city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439
Utrecht	344,384
Eindhoven	227,100
Tilburg	214,157

```
D["population"].mean()
```

population	467,496

More about aggregation -- https://pandas.pydata.org/pandas-docs/stable/reference/frame.html#computations-descriptive-stats

Grouping divides a table into groups by column values, which can be chained with data aggregation to produce descriptive statistics for each group.

D

city	province	population
Amsterdam	Noord-Holland	853,312
Rotterdam	Zuid-Holland	639,587
Den Haag	Zuid-Holland	526,439
Utrecht	Utrecht	344,384
Eindhoven	Noord-Brabant	227,100
Tilburg	Noord-Brabant	214,157

```
D.groupby("province").sum()
```

province	population
Noord-Holland	853,312
Zuid-Holland	1,166,026
Utrecht	344,384
Noord-Brabant	441,257

More about grouping -- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.groupby.html

Preprocess Data

Sorting rearranges data based on values in a column, which can be useful for inspection. For example, the right table is sorted by population.

D

city	population
Eindhoven	227,100
Den Haag	526,439
Tilburg	214,157
Rotterdam	639,587
Amsterdam	853,312
Utrecht	344,384

```
D.sort_values(by=["population"])
```

city	population
Tilburg	214,157
Eindhoven	227,100
Utrecht	344,384
Den Haag	526,439
Rotterdam	639,587
Amsterdam	853,312

More about sorting -- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.sort_values.html

Preprocess Data

Concatenation combines multiple datasets that have the same variables. For example, the two left tables can be concatenated into the right table.

A

city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439

B

city	population
Utrecht	344,384
Eindhoven	227,100
Tilburg	214,157

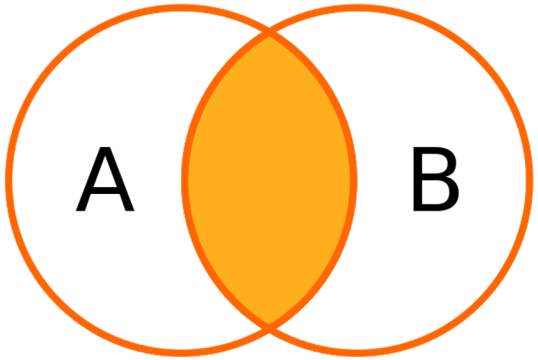
city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439
Utrecht	344,384
Eindhoven	227,100
Tilburg	214,157

More about concatenation -- https://pandas.pydata.org/docs/reference/api/pandas.concat.html

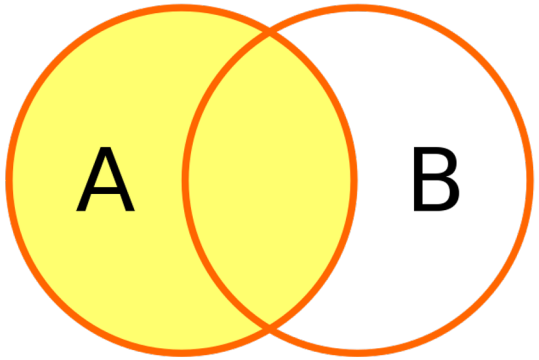
Preprocess Data

Merging and joining is a common method (in relational databases) to merge multiple data tables which have overlapping set of instances.

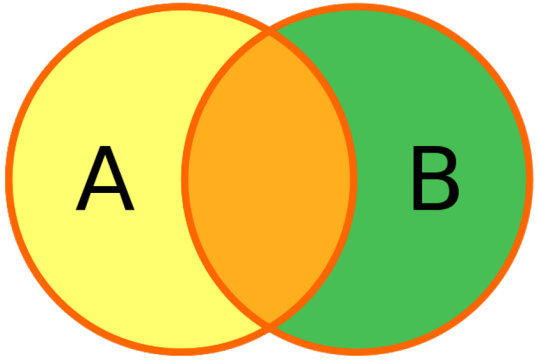
- Inner join



- Left (outer) join



- Outer join



- Right (outer) join

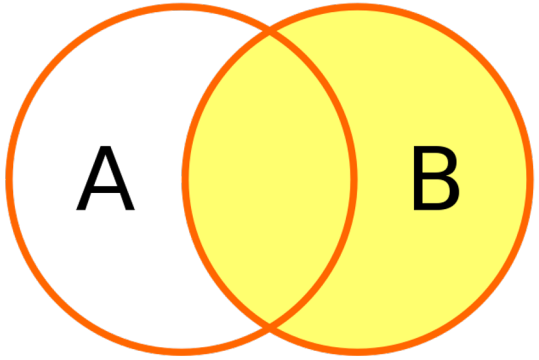


Figure source -- https://en.wikipedia.org/wiki/Join_(SQL)

A

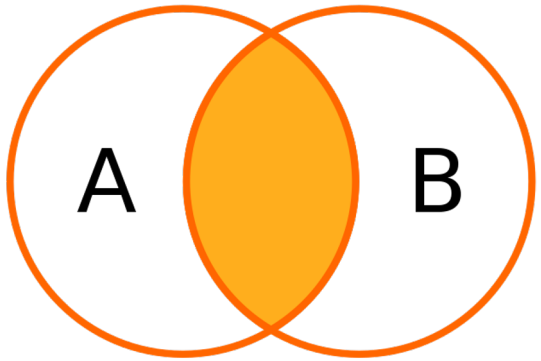
city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439
Utrecht	344,384
Eindhoven	227,100
Tilburg	214,157

B

city	air_quality
Amsterdam	42.4
Rotterdam	40.9
Den Haag	41.1
Utrecht	41.4
Eindhoven	43.8
Zwolle	40.9

Use "city" as the key to merge A and B

```
A.merge(B, how="inner", on="city")
```



- Inner join

city	population	air_quality
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8

More about merging -- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.merge.html

A

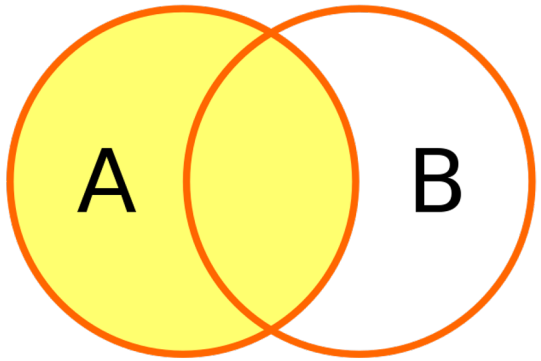
city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439
Utrecht	344,384
Eindhoven	227,100
Tilburg	214,157

B

city	air_quality
Amsterdam	42.4
Rotterdam	40.9
Den Haag	41.1
Utrecht	41.4
Eindhoven	43.8
Zwolle	40.9

Use "city" as the key to merge A and B

```
A.merge(B, how="left", on="city")
```



- Left join

city	population	air_quality
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8
Tilburg	214,157	NaN

More about merging -- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.merge.html

A

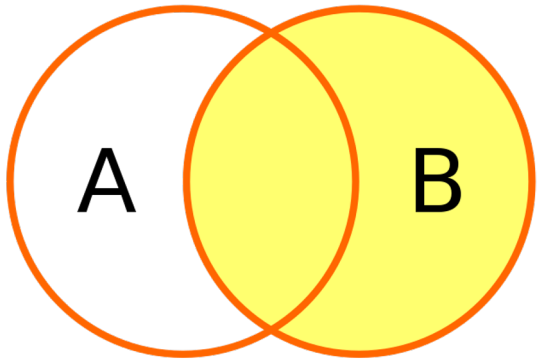
city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439
Utrecht	344,384
Eindhoven	227,100
Tilburg	214,157

B

city	air_quality
Amsterdam	42.4
Rotterdam	40.9
Den Haag	41.1
Utrecht	41.4
Eindhoven	43.8
Zwolle	40.9

Use "city" as the key to merge A and B

```
A.merge(B, how="right", on="city")
```



- Right join

city	population	air_quality
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8
Zwolle	NaN	40.9

More about merging -- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.merge.html

A

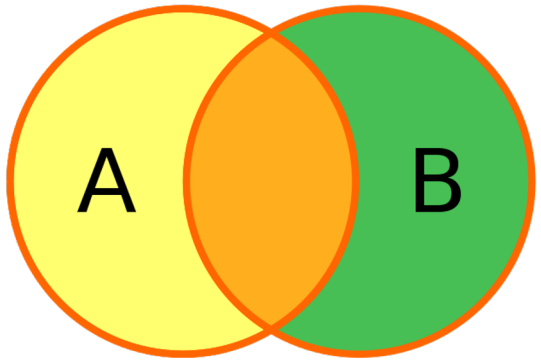
city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439
Utrecht	344,384
Eindhoven	227,100
Tilburg	214,157

B

city	air_quality
Amsterdam	42.4
Rotterdam	40.9
Den Haag	41.1
Utrecht	41.4
Eindhoven	43.8
Zwolle	40.9

Use "city" as the key to merge A and B

```
A.merge(B, how="outer", on="city")
```



- Outer join

city	population	air_quality
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8
Tilburg	214,157	NaN
Zwolle	NaN	40.9

More about merging -- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.merge.html

Preprocess Data

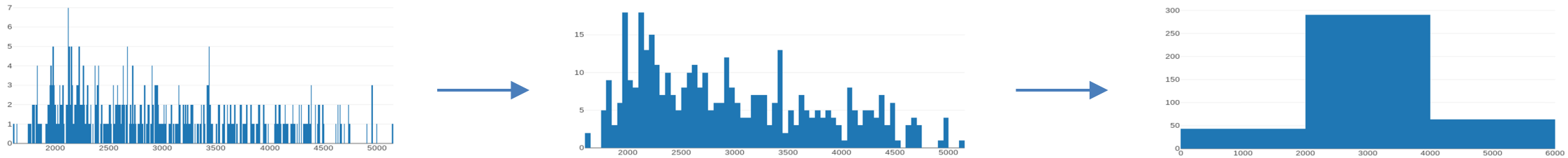
Quantization transforms a continuous set of values (e.g., integers) into a discrete set (e.g., categories). For example, age is quantized to age range.

D

name	age
Jantje	8
Piet	16
Maria	22
Renske	34
Donald	65

```
pandas.cut(D["age"], [0,20,50,200],
  labels=["1-20","21-50","51+"])
```

name	age
Jantje	1-20
Piet	1-20
Maria	21-50
Renske	21-50
Donald	51+



More about quantization -- https://pandas.pydata.org/docs/reference/api/pandas.cut.html

Preprocess Data

Scaling transforms variables to have another distribution, which puts variables at the same scale and makes the data work better on many models.

D

population	air_quality
853,312	42.4
639,587	40.9
526,439	41.1
344,384	41.4
227,100	43.8
214,157	39.1

- Z-score scaling (representing how many standard deviations from the mean)

```
(D-D.mean()) / D.std()
```

population	air_quality
1.5273	0.6039
0.6812	-0.3496
0.2333	-0.2225
-0.4874	-0.0318
-0.9516	1.4938
-1.0029	-1.4938

- Min-max scaling (making the value range between 0 and 1)

```
(D-D.min()) / (D.max()-D.min())
```

population	air_quality
1	0.7021
0.6656	0.3830
0.4886	0.4255
0.2037	0.4894
0.0203	1
0	0

More about scaling data -- https://scikit-learn.org/stable/modules/preprocessing.html

Preprocess Data

You can resample time series data (i.e., the data with time stamps) to a different frequency (e.g., hourly) using different aggregation methods (e.g., mean).

D

timestamp	v1
2016-10-31 07:30:00	52.6
2016-10-31 08:30:00	48.3
2016-10-31 08:53:20	44.2
2016-10-31 09:30:00	31.1

```
D.resample("60Min", label="right").mean()
```

timestamp	v1
2016-10-31 08:00:00	52.60
2016-10-31 09:00:00	46.25
2016-10-31 10:00:00	31.10

More information about the "resample" function -- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.resample.html

Preprocess Data

You can apply a transformation to rows or columns in the data frame.

D

wind_mph
3.6
NaN
5.1

```
def f(x):
    if pd.isna(x): return None
    else: return x<5
D["is_calm"] = D["wind_mph"].apply(f)
```

wind_mph	is_calm
3.6	True
NaN	None
5.1	False

D

wind_deg
343
351
359
5
41
25
⋮

Very slow if you have a lot of rows!

```
def f(x):
    return numpy.sin(numpy.deg2rad(x))
D["wind_sine"] = D["wind_deg"].apply(f)
```

```
D["wind_sine"] = np.sin(np.deg2rad(D["wind_deg"]))
```

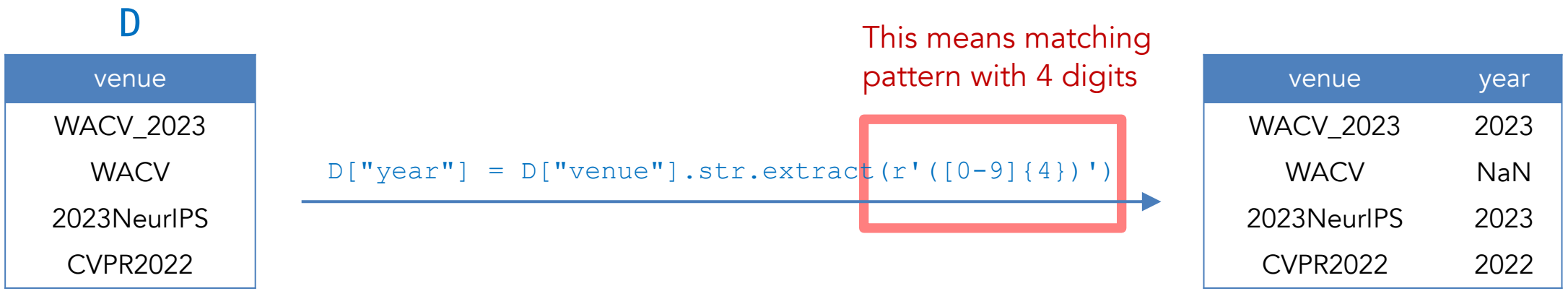
Better to transform the entire column directly!

wind_deg	wind_sine
343	-0.292372
351	-0.156434
359	-0.017452
5	0.087156
41	0.656059
25	0.422618
⋮	⋮

More information about the "apply" function -- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.apply.html

Preprocess Data

To extract data from text or match text patterns, you can use regular expression, which is a language to specify search patterns.



More information about regular expressions -- https://docs.python.org/3/library/re.html

Preprocess Data

We can drop data that we do not need, such as duplicate data records or those that are irrelevant to our research question.

city	population	year
Amsterdam	853,312	2018
Rotterdam	639,587	2018
Den Haag	526,439	2018

`pandas.drop(columns=["year"])`

city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439

	city	population	year
0	Amsterdam	853,312	2018
1	Rotterdam	639,587	2018
2	Den Haag	526,439	2018
3	Utrecht	344,384	2018
4	Eindhoven	227,100	2018
5	Amsterdam	862,965	2019
6	Utrecht	344,384	2018

`pandas.drop([5, 6])`

	city	population	year
0	Amsterdam	853,312	2018
1	Rotterdam	639,587	2018
2	Den Haag	526,439	2018
3	Utrecht	344,384	2018
4	Eindhoven	227,100	2018

More information on dropping data -- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.drop.html

Preprocess Data

We can either drop the rows (i.e., the records/observations) or the columns (i.e., the variables/attributes) that contain the missing values.

city	population	air_quality
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8
Tilburg	214,157	

drop column

city	population
Amsterdam	853,312
Rotterdam	639,587
Den Haag	526,439
Utrecht	344,384
Eindhoven	227,100
Tilburg	214,157

drop row

city	population	air_quality
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8

More information on dropping data -- https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.dropna.html

Preprocess Data

We can replace the missing values (i.e., imputation) with a constant, mean, or the most frequent value along the same column.

city	population	air_quality
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8
Tilburg	214,157	

constant imputation

city	population	air_quality
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8
Tilburg	214,157	-1

mean imputation

city	population	air_quality
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8
Tilburg	214,157	41.92

More information univariate imputation -- https://scikit-learn.org/stable/modules/impute.html#univariate-feature-imputation

Preprocess Data

We can model missing values, where y is the variable/column that has the missing values, X means other variables, and F is a regression function.

city	population (X)	air_quality (y)
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8
Tilburg	214,157	

$$y = F(X)$$

city	population (X)	air_quality (y)
Amsterdam	853,312	42.4
Rotterdam	639,587	40.9
Den Haag	526,439	41.1
Utrecht	344,384	41.4
Eindhoven	227,100	43.8
Tilburg	214,157	42.46

More information on multivariate imputation -- https://scikit-learn.org/stable/modules/impute.html#multivariate-feature-imputation

Preprocess Data

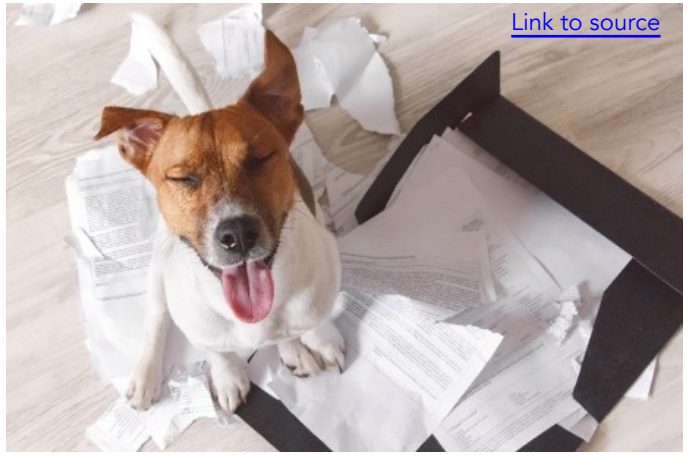
Different missing data may require different data cleaning methods.

Missing Not At Random is a big problem and cannot be solved simply with imputation.

MCAR

Missing Completely At Random:

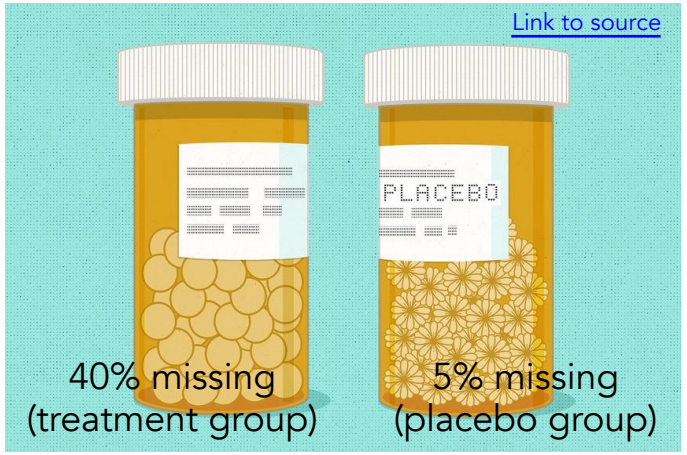
- Missing data is a completely random subset (no relations) of the entire dataset.



MAR

Missing at Random:

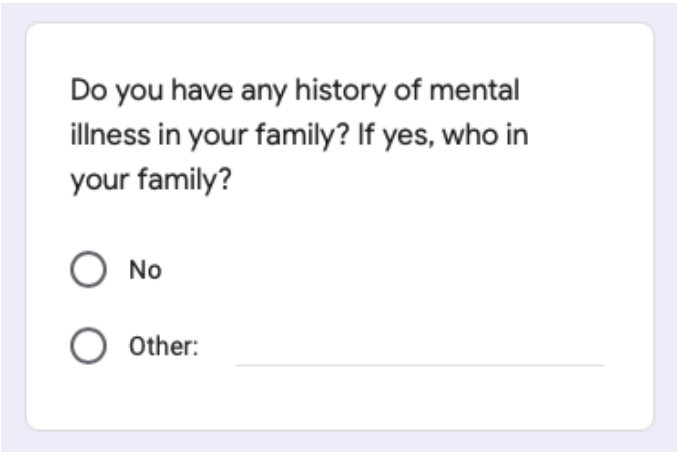
- Missing data is only related to variables other than the one having missing data.



MNAR

Missing Not At Random:

- Missing data is related to the variable that has the missing data. (e.g., sensitive questions)



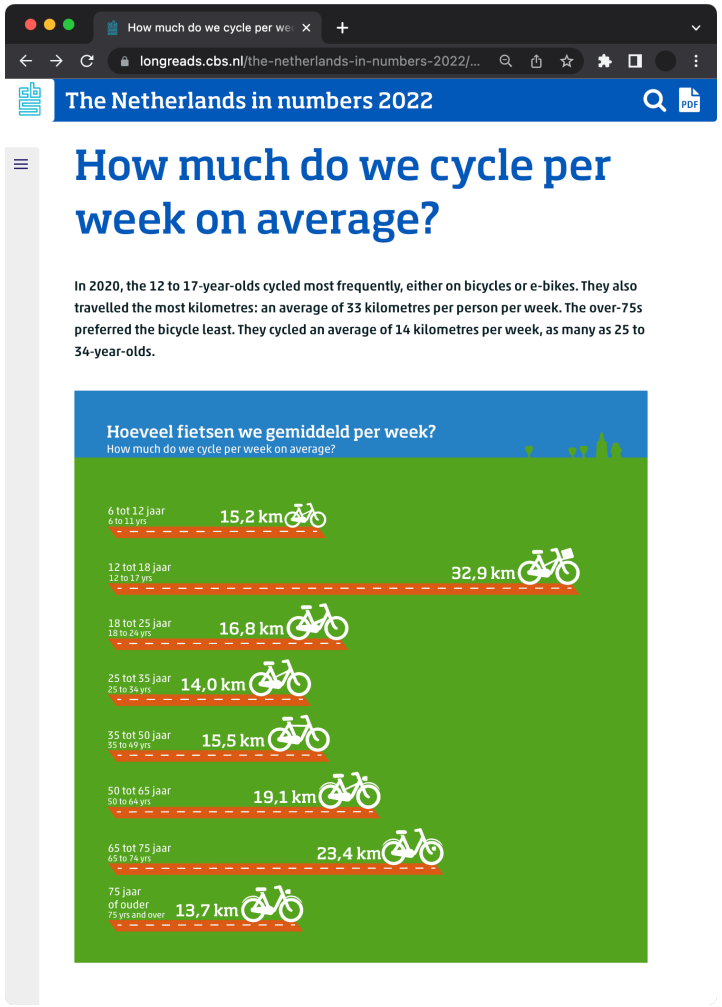
https://aph-qualityhandbook.org/set-up-conduct/process-analyze-data/3-2-quantitative-research/3-2-2-data-analysis/handling-missing-data/

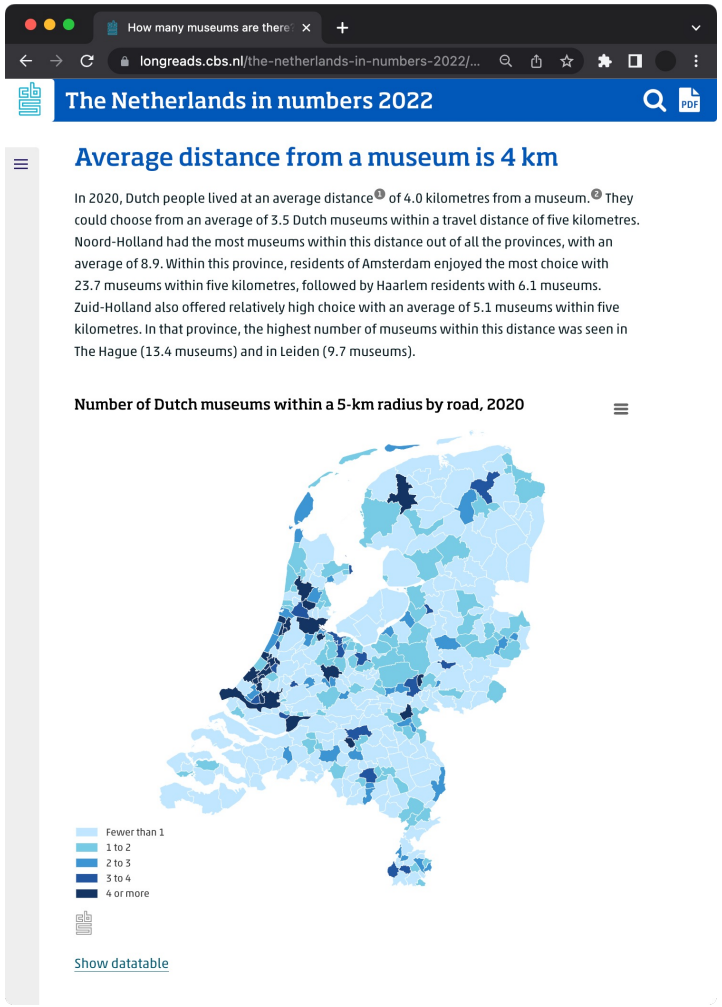
You really need to practice coding a lot to know and internalize how these things work!

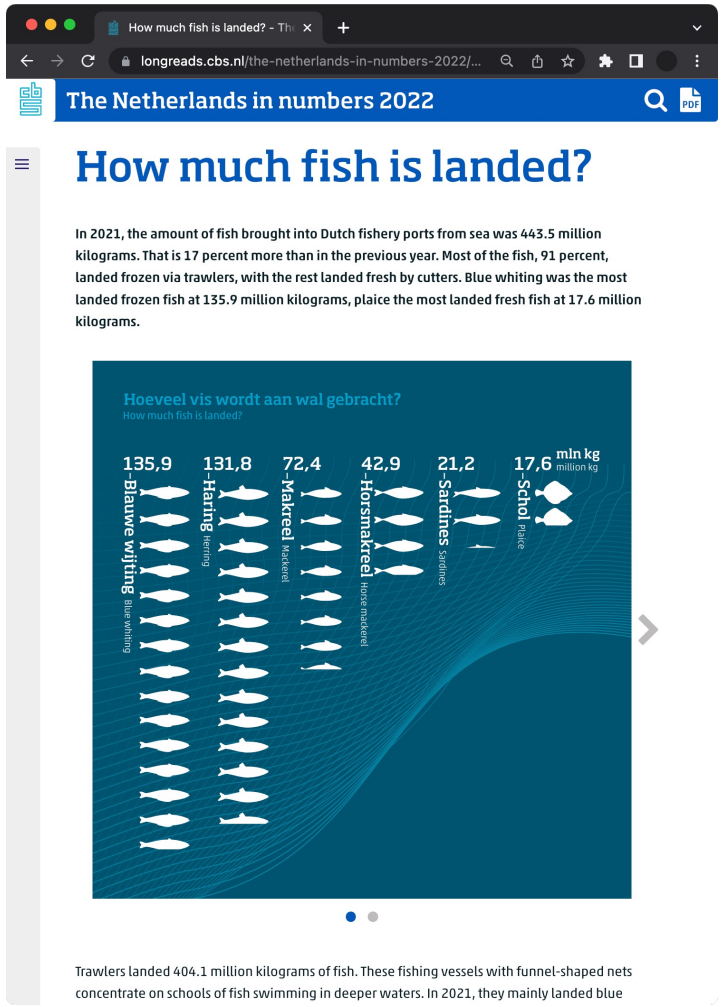
- Pandas exercises on GitHub
- Pandas exercises on Kaggle
- Pandas exercises on W3Schools
- Pandas exercises by UC Berkeley School of Information
- Pandas exercises on GeeksforGeeks
- Pandas exercises on w3resource

Explore Data

The course will use examples (i.e., the modules) to teach you how to explore different types of data, either using existing tools or Python.



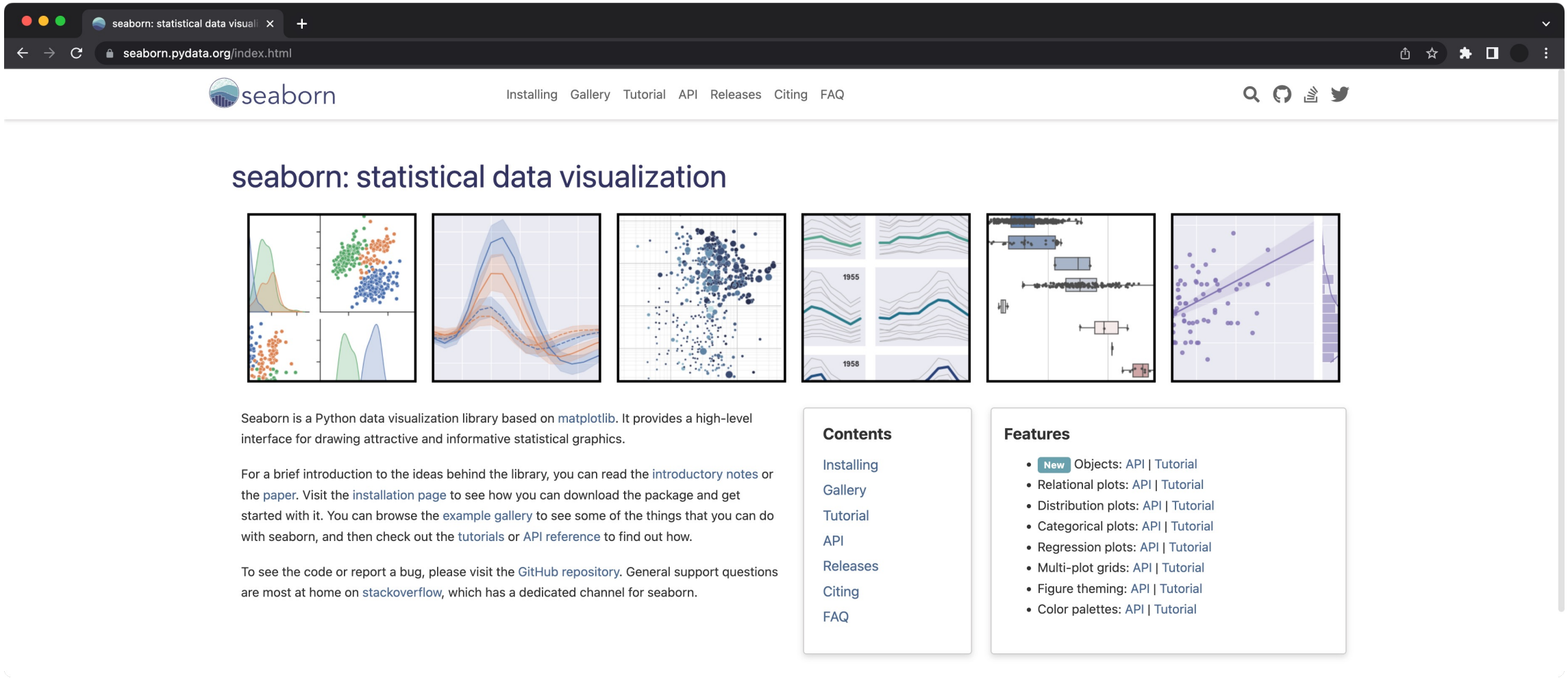




The Netherlands in Numbers -- https://longreads.cbs.nl/the-netherlands-in-numbers-2022/

Explore Data

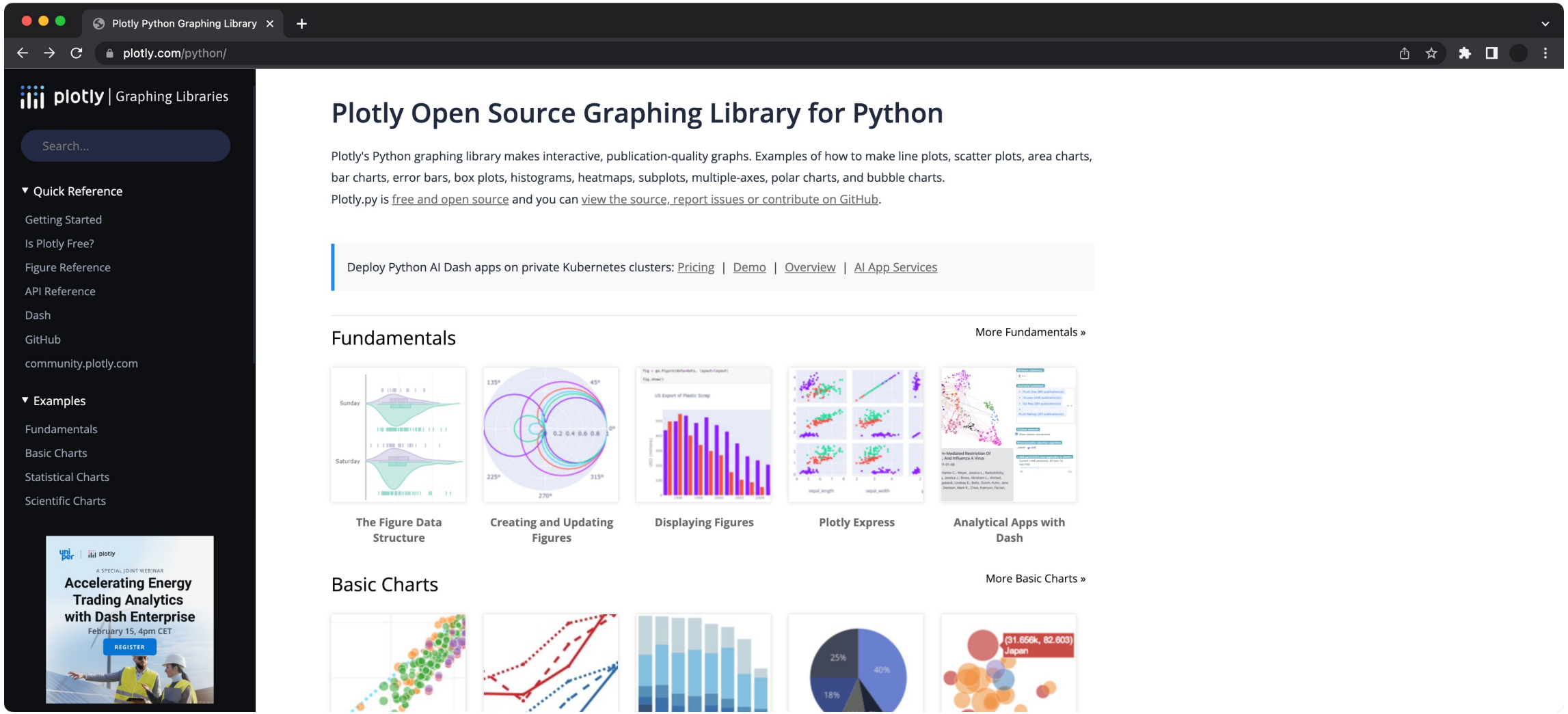
You can use the Python seaborn library (based on matplotlib) to quickly plot and explore structured data.



The Seaborn Library for Statistical Data Visualization -- https://seaborn.pydata.org/

Explore Data

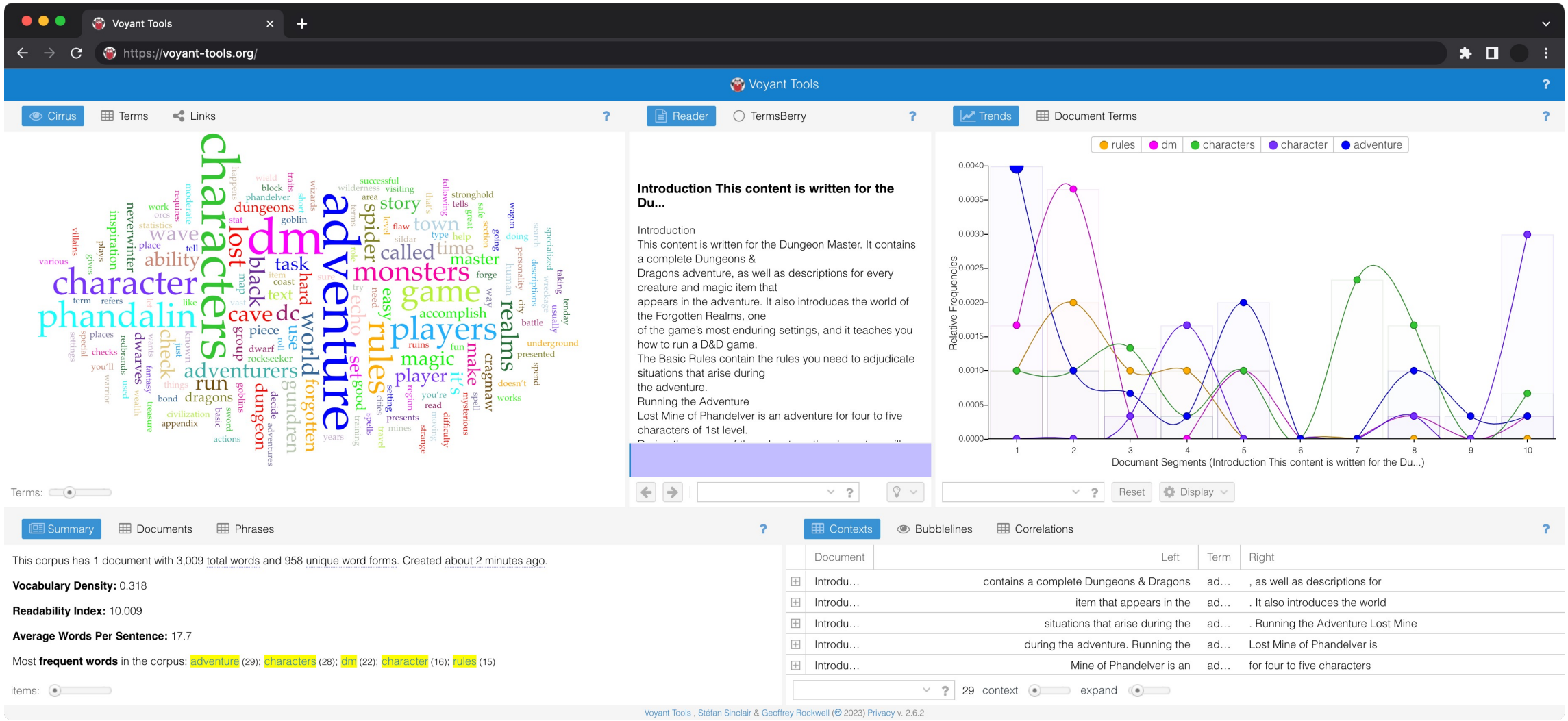
You can use the Python Plotly library to build interactive visualizations.



Plotly Open Source Graphing Library for Python -- https://plotly.com/python/

Explore Data

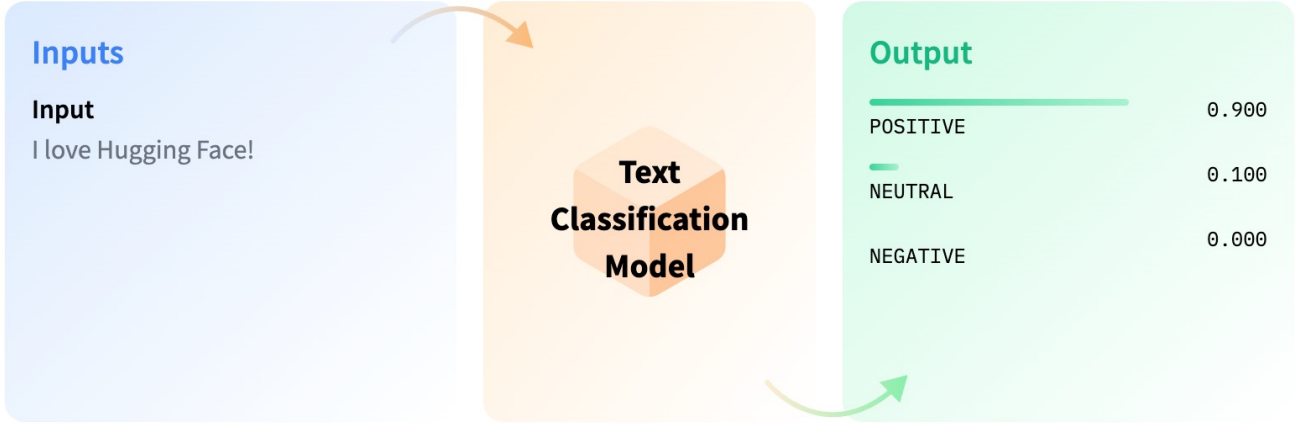
You can use the Voyant Tools to explore text data.

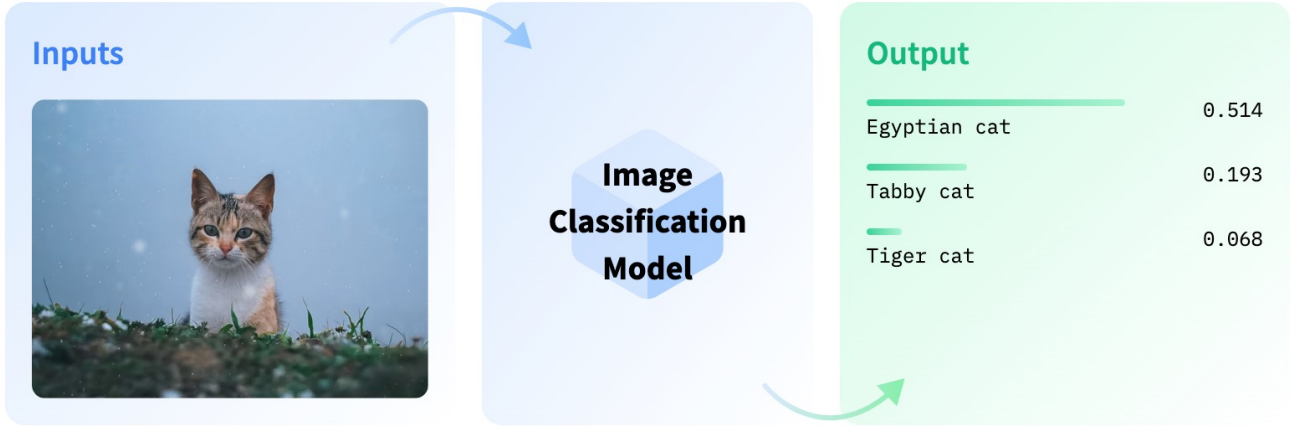


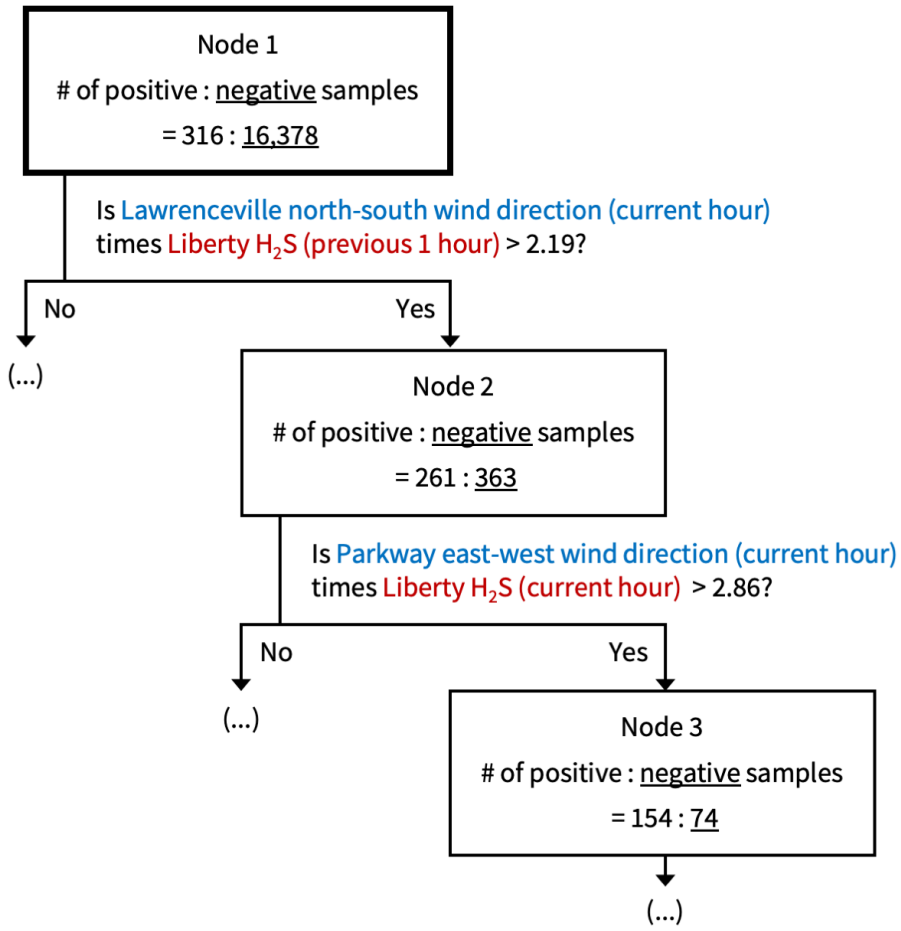
Voyant Tools -- https://voyant-tools.org/

Model Data

This course will teach you techniques for modeling structured, text, and image data through three modules from a practical point of view.





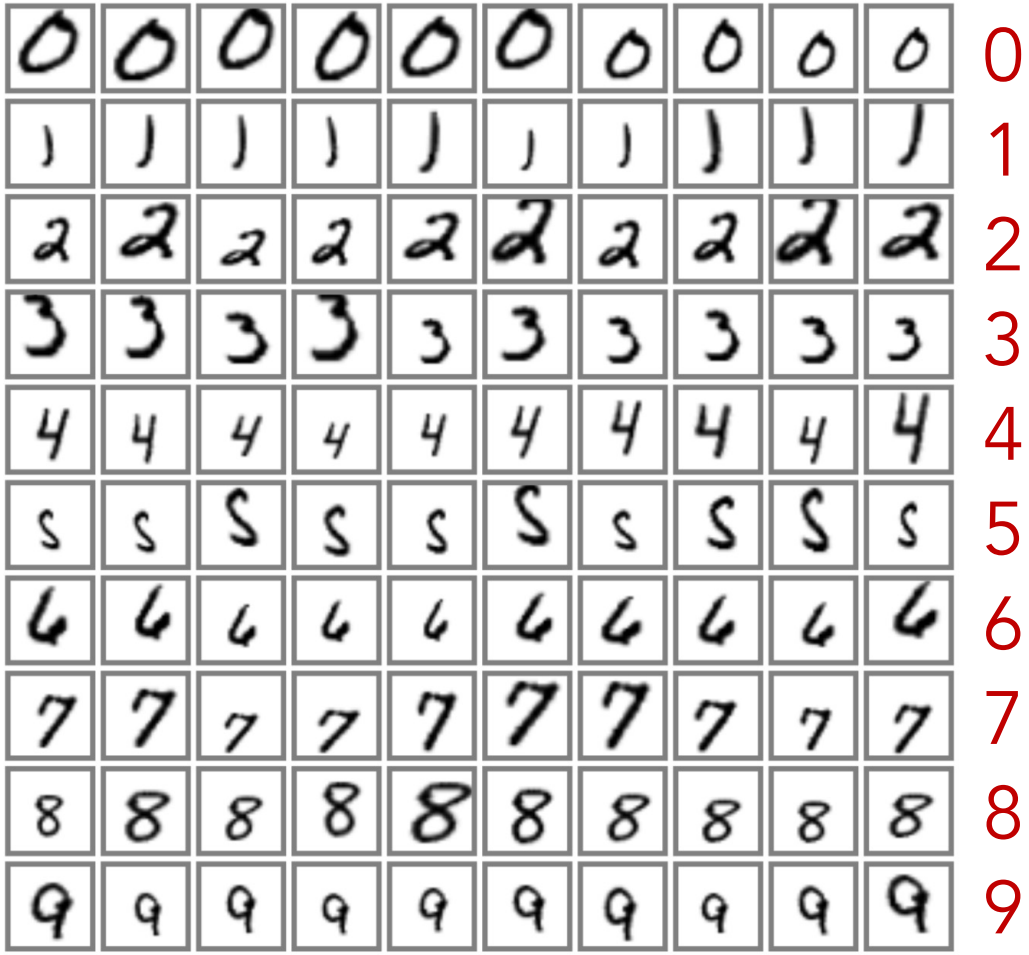


Source: https://huggingface.co/tasks

Source: https://smellpgh.org/

Model Data

One example of image classification is optical character recognition, such as recognizing digits from hand-written images.



LeCun et al. 1998. Gradient-based learning applied to document recognition. IEEE.

Model Data

A more complicated image classification task is fine-grained categorization, such as categorizing the types of birds.

Barred Owl

American Robin

American Crow

Rufous Hummingbird

Rock Pigeon

Canada Goose

Retrieved from https://ebird.org

Model Data

One example of text classification is sentiment analysis, such as identifying emotions from movie reviews.

Retrieved from https://www.rottentomatoes.com/m/star_wars_the_last_jedi

Model Data

A more complex text classification task is annotating paragraphs, such as categorizing the research aspect for each fragment in the paper abstract.

For successful infection, viruses must recognize their respective host cells. A common mechanism of host recognition by viruses is to utilize a portion of the host cell as a receptor. Bacteriophage Sf6, which infects Shigella flexneri, uses lipopolysaccharide as a primary receptor and then requires interaction with a secondary receptor, a role that can be fulfilled by either outer membrane proteins (Omp) A or C. Our previous work showed that specific residues in the loops of OmpA mediate Sf6 infection. To better understand Sf6 interactions with OmpA loop variants, we determined the kinetics of these interactions through the use of biolayer interferometry, an optical biosensing technique that yields data similar to surface plasmon resonance. Here, we successfully tethered whole Sf6 virions, determined the binding constant of Sf6 to OmpA to be 36 nM. Additionally, we showed that Sf6 bound to five variant OmpAs and the resulting kinetic parameters varied only slightly. Based on these data, we propose a model in which Sf6: Omp receptor recognition is not solely based on kinetics, but likely also on the ability of an Omp to induce a conformational change that results in productive infection.

Background

Purpose

Method

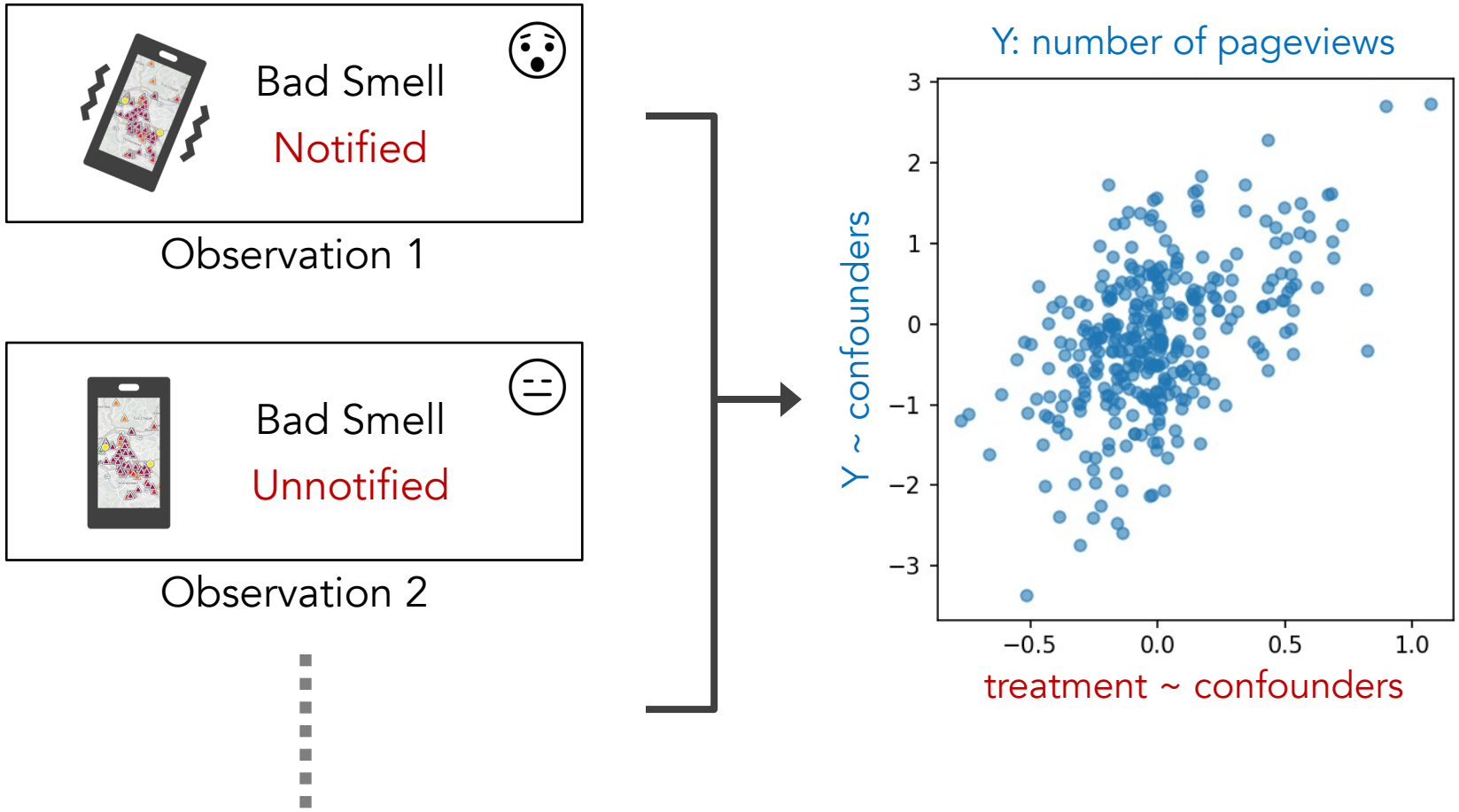
Finding

Other

Retrieved from https://arxiv.org/abs/2005.02367

Deploy Models

Deploying models in the wild can enable further quantitative or qualitative research with insights, such as the push notification study in Smell Pittsburgh.



Hsu, Y. C., et al. (2020). Smell Pittsburgh: Engaging Community Citizen Science for Air Quality. ACM TiiS.

Deploy Models

Another example is to study the behaviors of deployed systems to understand its social impact. For example, face recognition systems for recognizing gender did worst on darker-skin female images.

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%

Retrieved from the Gender Shades project on 2018 -- http://gendershades.org

Take-Away Messages

- The data science pipeline is not always linear. Be flexible and open-minded!
- Be aware of the step of framing problems. This course assumes that the problems are defined.
- Collecting data requires well-designed software/hardware infrastructure.
- Being familiar with pandas can speed up the data preprocessing step.
- Different types of missing data require different treatments.
- Besides using descriptive statistics, it is also a good idea to visualize and explore data.
- Different types of data need different modeling techniques. There is no “one solution for all”.
- It is important to study user behaviors and investigate the social impact of deployed models.

Questions?