dm22s1

Topic 04 : Exploratory Data Analysis

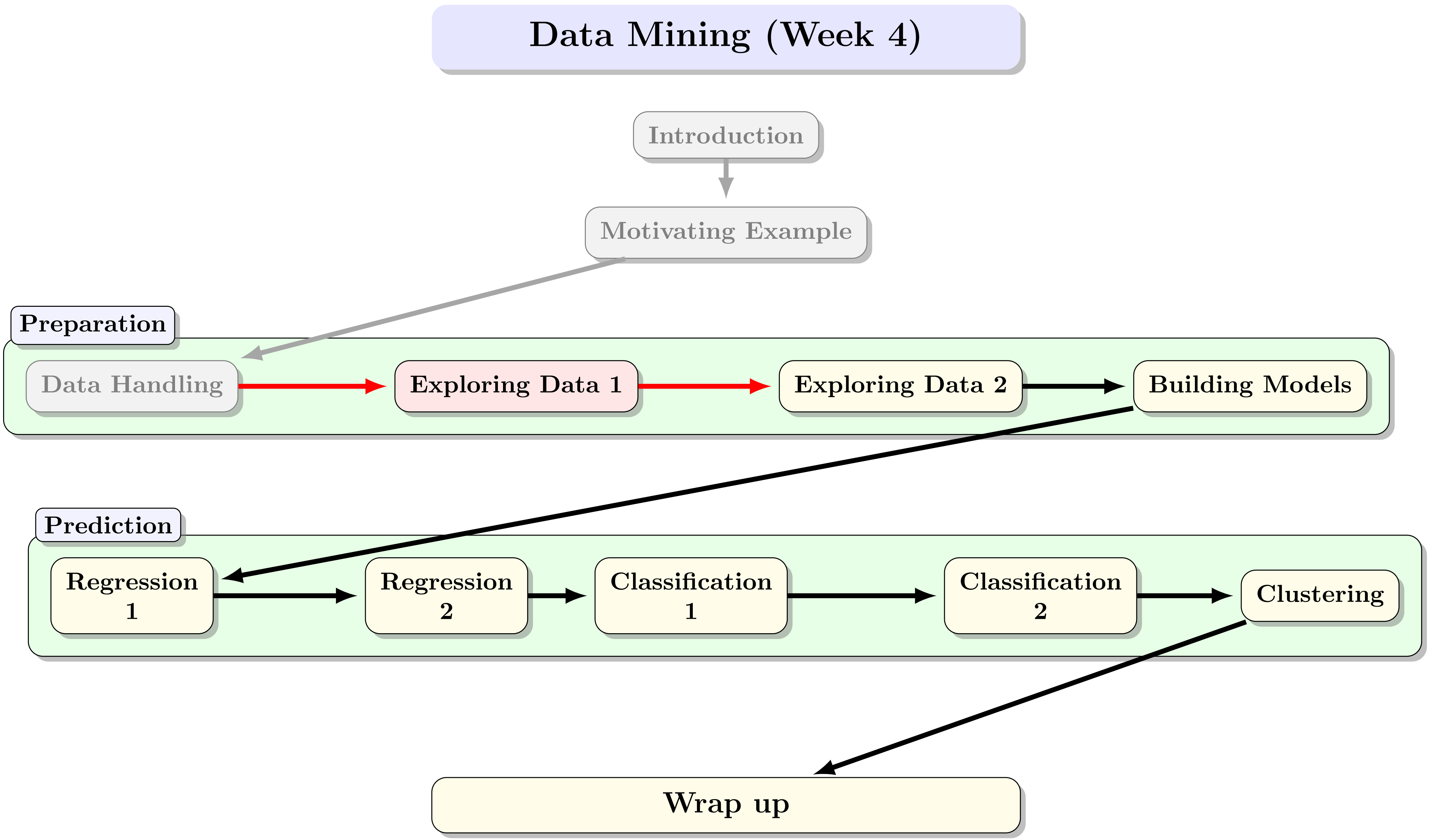
Part 01 : Exploratory Data Analysis

Dr Bernard Butler
Department of Computing and Mathematics, WIT.
(bernard.butler@setu.ie)

Autumn Semester, 2022

Outline

- EDA Process
- Datasets = Tips, Titanic and Algae Blooms


Data Mining (Week 4)
Introduction
Motivating Example
Preparation
Data Handling
Exploring Data 1
Exploring Data 2
Building Models
Prediction
Regression 1
Regression 2
Classification 1
Classification 2
Clustering
Wrap up

Exploratory Data Analysis — Summary

Acknowledgment

A big thanks to Dr Kieran Murphy, who provided many of the slides for today's lecture.

Introduction

Exploratory Data Analysis (EDA)

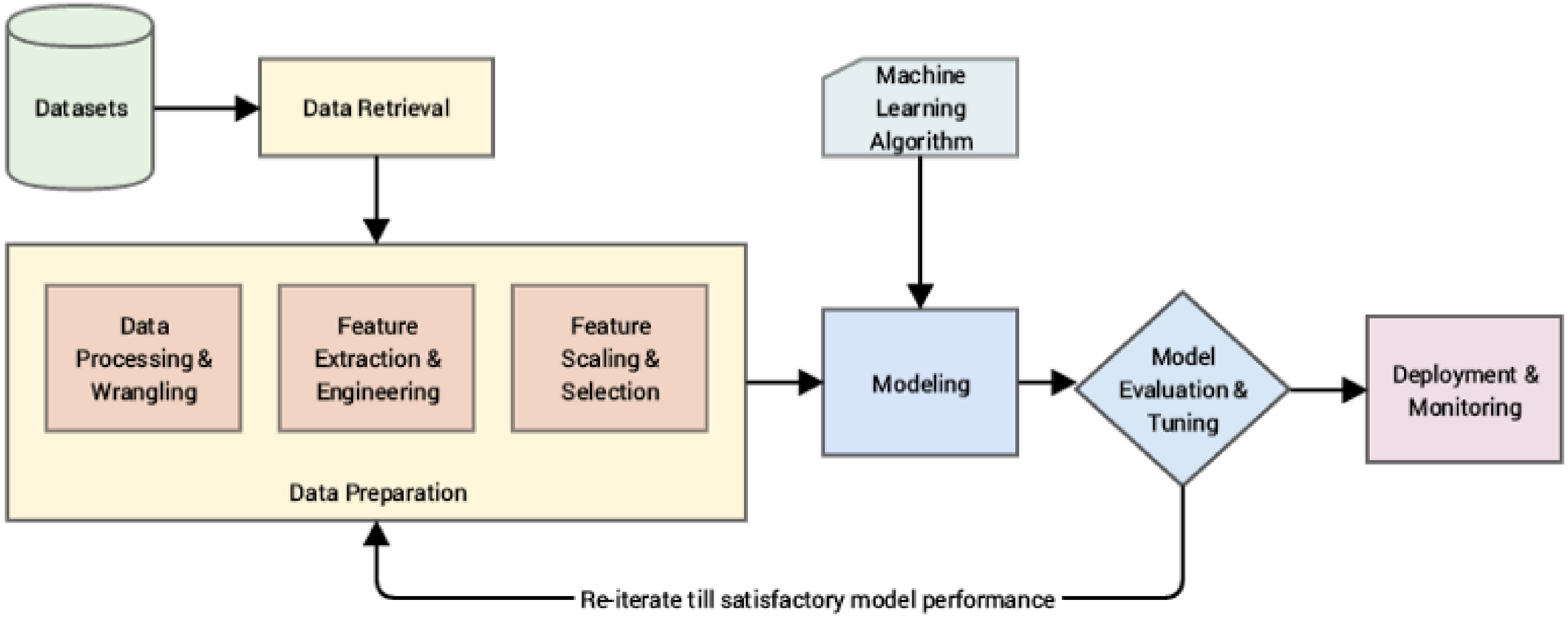
Aim

To understand and summarise a dataset to ensure that the features which are feed to machine learning algorithms are refined and that the results are valid and can correctly interpreted.

Benefits

- Develop insight about the dataset and understanding of the underlying structure.
- Extract important parameters and relationships that hold between them.
- Test underlying assumptions.
- Identify issues that affect model performance — outliers, missing values.

Data Pipeline



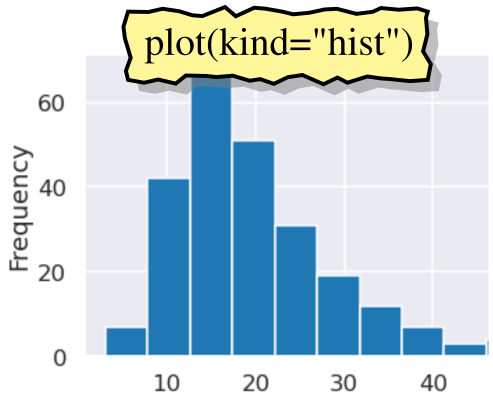
- Data preparation is the core of the data mining pipeline (typical estimates >50% of the time/effort).
- EDA is the data processing and wrangling.
- EDA informs the feature extraction, engineering, transformation and selection.

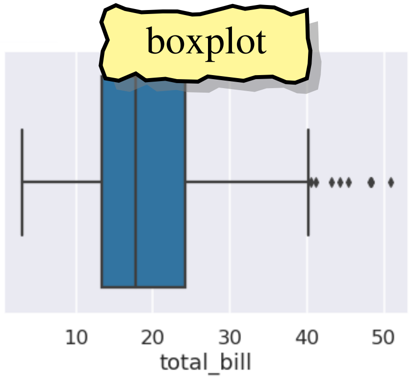
The Bad News — ‘The curse of choice’

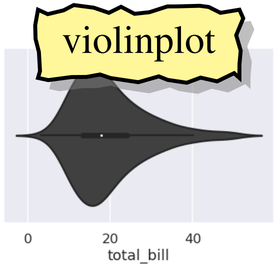
What questions to ask?

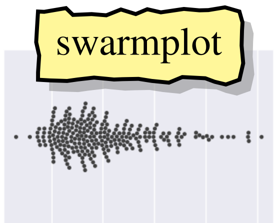
Dataset global questions: How many features? How many observations? What is the data type of each feature? Any null values? ... Feature specific questions: What is the distribution of each variable? Do there appear to be outliers? What features are related? ... Missing value questions: Are null value a result of the way data was recorded? Can we drop the rows with null values without it significantly affecting your analysis? Can we justify filling in the missing values with the mean or median for that variable? If the data is time-series data, can we fill the missing values with interpolation? Are there so many missing values for a variable that we should drop that variable from the dataset? ... Outlier questions: Why are outliers present? Do the outliers represent real observations (i.e. not errors)? Should we exclude these observations? If not, should we winsorise the values? ... Correlations/Relationships questions: Which variables are most correlated with your target variable? (If applicable) Is there multicollinearity? (Two features that have a correlation > 0.8) How will this affect your model? Do you have variables that represent the same information? Can one be dropped? ...

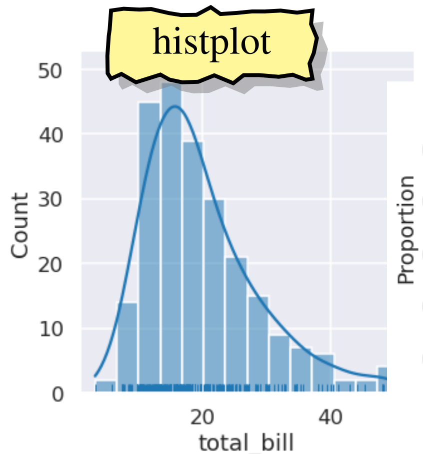
What visualisations to build?

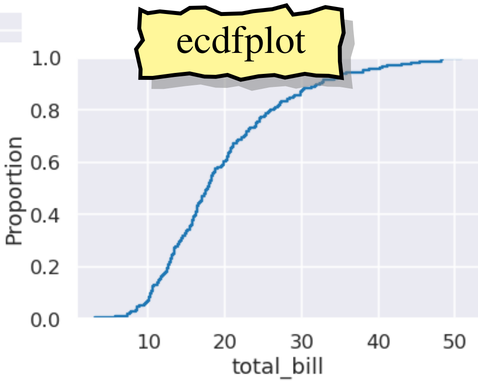












Have a plan, be selective, understand strengths/weaknesses of metrics/visualisations

Terminology / Notation

$n+1$ columns / variables

$\mathbf{X}$

n features / attributes / dimensions

$\mathbf{y}$ target

m observations / instances / cases / rows

PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Survived
1	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S	0
2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C	1
3	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	1
4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S	1
5	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S	0
6	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q	0
7	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S	0
8	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S	0
9	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S	1
10	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C	1
11	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G6	S	1

$\mathbf{x}^{(i)}$

$\mathbf{x}_j$

- A labeled dataset consists of m rows $\times$ $(n+1)$ columns / variables.
- Use bold to represent vectors and matrices.
- Use subscripts to indicate particular feature / attribute / column . . . . $\mathbf{x}_j$
- Use superscript in parenthesis to indicate particular observation / instance/ case / row . . . . $\mathbf{x}^{(i)}$
- So $x_j^{(i)}$ (or $x_{i,j}$) is the i-th observation in the j-th feature . . . . $x_j^{(i)}$

Example Datasets

We will use a few datasets today to illustrate the various features:

Tips

- Small dataset of total bills, and tips for different servers with gender, day, time and group size.
- Clean, no missing values, some outliers.
- Task: exploratory data analysis

Titanic

- Classic dataset with passenger information for the Titanic's fatal voyage, and whether they survived.
- Has missing values and information rich text fields (Name, ticket number).
- Task: classification — predict whether a passenger survived.

Algae Blooms

- Water quality study where samples were taken from different rivers over time.
- Recorded levels of (seven) chemical substances and population of (six) algae species and other information on the sample conditions.
- Task: regression — predict algae population level (7 separate populations).

Tips dataset

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4
5	25.29	4.71	Male	No	Sun	Dinner	4
6	8.77	2.00	Male	No	Sun	Dinner	2
7	26.88	3.12	Male	No	Sun	Dinner	4
8	15.04	1.96	Male	No	Sun	Dinner	2
9	14.78	3.23	Male	No	Sun	Dinner	2

No target column, so mainly just an exploratory data analysis problem. But questions of interest:

- How do factors `sex`, `smoker`, `day`, `time`, or `size` affect tip / percentage tip?
- Does `size` vary with `day`, `time`, `smoker`?

But some questions don't make sense

- What is the relationship between `sex` and `smoker`? — why should they be related?

This is the downside of automatic EDA tools such as `pandas-profiling` — you will drowned in statistics / charts.

Algae Blooms dataset

	Season	Size	Speed	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1	a2	a
0	winter	small	medium	8.00	9.8	60.800	6.238	578.00000	105.00000	170.00000	50.000	0.0	0.0	0.0
1	spring	small	medium	8.35	8.0	57.750	1.288	370.00000	428.75000	558.75000	1.300	1.4	7.6	4.8
2	autumn	small	medium	8.10	11.4	40.020	5.330	346.66699	125.66700	187.05701	15.600	3.3	53.6	1.9
3	spring	small	medium	8.07	4.8	77.364	2.302	98.18200	61.18200	138.70000	1.400	3.1	41.0	18.
4	autumn	small	medium	8.06	9.0	55.350	10.416	233.70000	58.22200	97.58000	10.500	9.2	2.9	7.5
5	winter	small	high	8.25	13.1	65.750	9.248	430.00000	18.25000	56.66700	28.400	15.1	14.6	1.4
6	summer	small	high	8.15	10.3	73.250	1.535	110.00000	61.25000	111.75000	3.200	2.4	1.2	3.2
7	autumn	small	high	8.05	10.6	59.067	4.990	205.66701	44.66700	77.43400	6.900	18.2	1.6	0.0
8	winter	small	medium	8.70	3.4	21.950	0.886	102.75000	36.30000	71.00000	5.544	25.4	5.4	2.5
9	winter											7.0	0.0	0.0
10	spring	small	high	7.70	10.2	8.000	1.527	21.57100	12.75000	20.75000	0.800	16.6	0.0	0.0
11	summer	small	high	7.45	11.7	8.690	1.588	18.42900	10.66700	19.00000	0.600	32.1	0.0	0.0
12	winter	small	high	7.74	9.6	5.000	1.223	27.28600	12.00000	17.00000	41.000	43.5	0.0	2.1
13	summer	small	high	7.72	11.8	6.300	1.470	8.00000	16.00000	15.00000	0.500	31.1	1.0	3.4
14	winter	small	high	7.90	9.6	3.000	1.448	46.20000	13.00000	61.60000	0.300	52.2	5.0	7.8
15	autumn	small	high	7.55	11.5	4.700	1.320	14.75000	4.25000	98.25000	1.100	69.9	0.0	1.7
16	winter	small	high	7.78	12.0	7.000	1.420	34.33300	18.66700	50.00000	1.100	46.2	0.0	0.0
17	spring	small	high	7.61	9.8	7.000	1.443	31.33300	20.00000	57.83300	0.400	31.8	0.0	3.1
18	summer	small	high	7.35	10.4	7.000	1.718	49.00000	41.50000	61.50000	0.800	50.6	0.0	9.9
19	spring	small	medium	7.79	3.2	64.000	2.822	8777.59961	564.59998	771.59998	4.500	0.0	0.0	0.0

How well can we predict the (7) different algae population levels using water sample information?

Titanic dataset

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C
10	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G6	S
11	12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	S
12	13	0	3	[illegible] Henry	male	20.0	0	0	A/5. 2151	8.0500	NaN	S
13	14	0	3	Andersson, Mr. Anders Johan	male	39.0	1	5	347082	31.2750	NaN	S
14	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14.0	0	0	350406	7.8542	NaN	S
				Hewlett, Mrs. (Mary D								

How well can we predict a passenger's survival using information at time of departure?

Before we start ... Loading libraries

We start by loading in the core data science modules...

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

`matplotlib` is an excellent visualisation library but some plots needs additional configuration. `seaborn` sits above `matplotlib` and has a collection of visualisations optimised for statistical analysis. ...

```
import seaborn as sns
```

Next, we import some statistical modules ...

```
import scipy.stats as stats
import statsmodels.api as sm
import pingouin as pg
```

`scipy.stats` has a large number of distributions, parametric and nonparametric statistical tests, and descriptive statistics.
`statsmodels` is more focused on estimating statistical models.
`pingouin` overlaps with bits of `scipy.stats` and `statsmodels` but generates more details and nicer visualisations.

Finally we set options ...

```
plt.style.use("seaborn-darkgrid")
```

Before we start . . . auto EDA using `pandas−profiling`

```
from pandas_profiling import ProfileReport
profile = ProfileReport(df, title="Tips Report", html={"style": {"full_width": True}}, sort="None")
profile
```

`pandas−profiling` is nice, but see how slow it is on this tiny dataset. What would happen if we had 100K rows x 100 columns?

Summarize dataset: 100% 21/21 [00:05<00:00, 4.00it/s, Completed]

Generate report structure: 100% 1/1 [00:02<00:00, 2.78s/it]

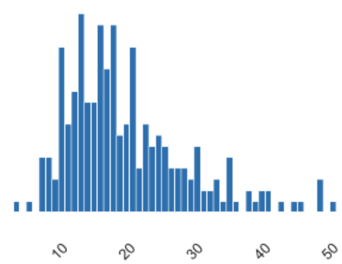
Render HTML: 100% 1/1 [00:00<00:00, 1.72it/s]

Tips Report — Overview | Variables | Interactions | Correlations | Missing values | Sample | Duplicate rows

Variables

total_bill
Real number ($\mathbb{R}_{\geq 0}$)

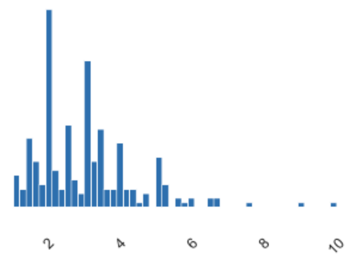
Distinct	229	Mean	19.78594262
Distinct (%)	93.9%	Minimum	3.07
Missing	0	Maximum	50.81
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%
Infinite (%)	0.0%	Memory size	1.9 KiB



Toggle details

tip
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	123	Mean	2.998278689
Distinct (%)	50.4%	Minimum	1
Missing	0	Maximum	10
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%
Infinite (%)	0.0%	Memory size	1.9 KiB



Before we start . . . zero-code EDA using `dtale`

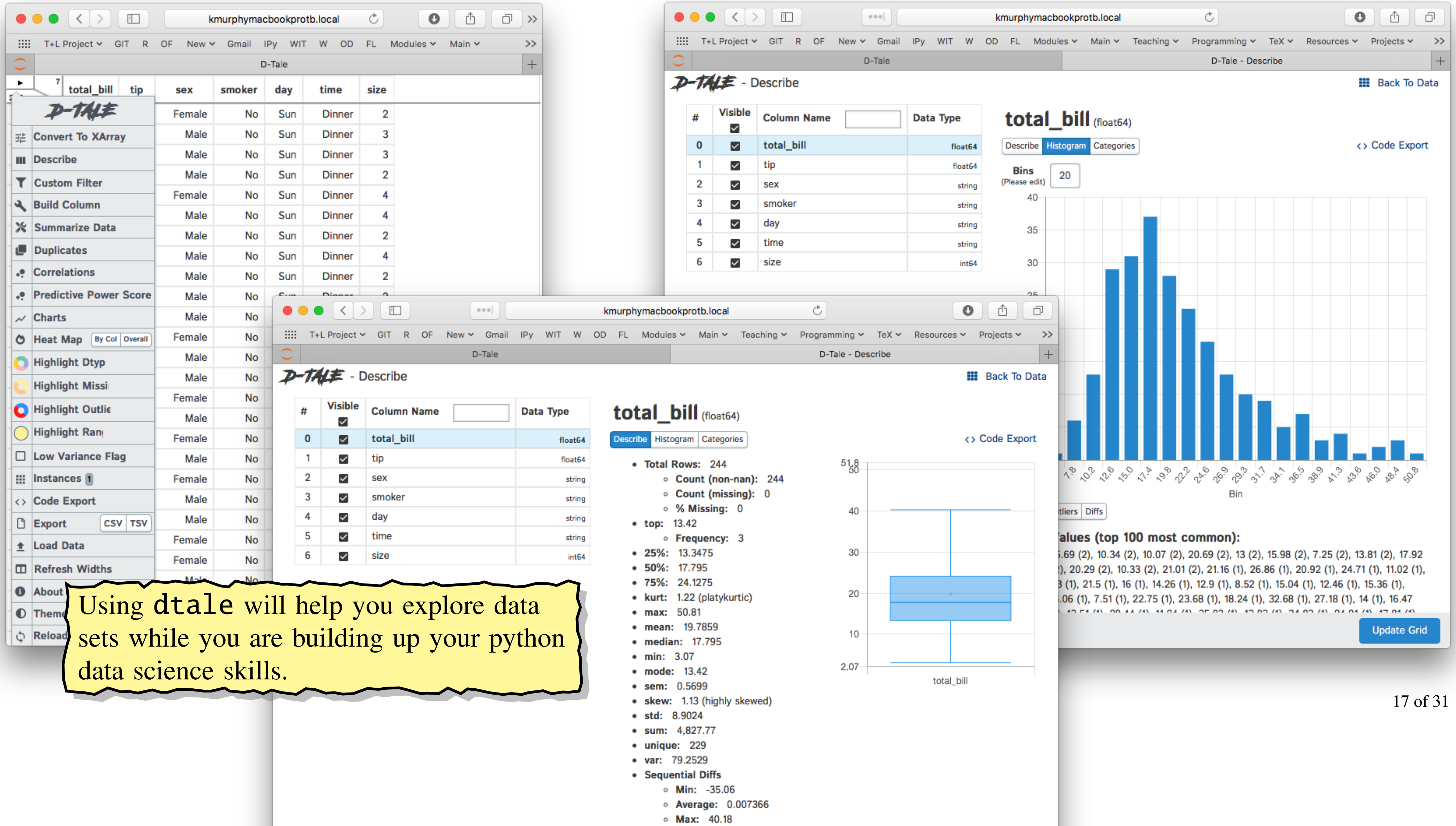
Well, almost zero code....

```
import pandas as pd
import dtale

# Read the Tips data into a dataframe, check it looks OK
df = pd.read_csv('tips.csv')
df.head()

# Run dtale to visualize the structure of the dataframe
dtale.show(df)
```

Before we start . . . zero-code EDA using `dtale`



Using `dtale` will help you explore data sets while you are building up your python data science skills.

First Pass — Load Dataset and Initial Clean

- Load dataset
- Check variables names
- Verify variable types
- Identify (and possibly address) missing values

Tips — Load

```
df = pd.read_csv("tips.csv")
print(df.shape)
df.head(10)
```

```
(244, 7)
```

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4
5	25.29	4.71	Male	No	Sun	Dinner	4
6	8.77	2.00	Male	No	Sun	Dinner	2
7	26.88	3.12	Male	No	Sun	Dinner	4
8	15.04	1.96	Male	No	Sun	Dinner	2
9	14.78	3.23	Male	No	Sun	Dinner	2

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   total_bill  244 non-null    float64
 1   tip         244 non-null    float64
 2   sex         244 non-null    object
 3   smoker      244 non-null    object
 4   day         244 non-null    object
 5   time        244 non-null    object
 6   size        244 non-null    int64
dtypes: float64(2), int64(1), object(4)
memory usage: 13.5+ KB
```

Issue: categorical data treated as object (string).

Tips — Fix Data Types I

```
df.sex.unique()
```

```
array(['Female', 'Male'], dtype=object)
```

```
df.sex = pd.Categorical(df.sex)
df.sex.unique()
```

```
['Female', 'Male']
Categories (2, object): ['Female', 'Male']
```

```
df.smoker.unique()
```

```
array(['No', 'Yes'], dtype=object)
```

```
df.smoker = pd.Categorical(df.smoker)
df.smoker.unique()
```

```
['No', 'Yes']
Categories (2, object): ['No', 'Yes']
```

```
df.day.unique()
```

```
array(['Sun', 'Sat', 'Thur', 'Fri'], dtype=object)
```

```
df.day = pd.Categorical(df.day, categories=['Thur', 'Fri','Sun', 'Sat'], ordered=True)
df.day.unique()
```

```
['Sun', 'Sat', 'Thur', 'Fri']
Categories (4, object): ['Thur' < 'Fri' < 'Sun' < 'Sat']
```

Tips — fix datatypes II

```
df.time = pd.Categorical(df.time, categories=['Lunch', 'Dinner'], ordered=True)
df.time.unique()
```

```
['Dinner', 'Lunch']
Categories (2, object): ['Lunch' < 'Dinner']
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   total_bill  244 non-null    float64
 1   tip         244 non-null    float64
 2   sex         244 non-null    category
 3   smoker      244 non-null    category
 4   day         244 non-null    category
 5   time        244 non-null    category
 6   size        244 non-null    int64
dtypes: category(4), float64(2), int64(1)
memory usage: 7.4 KB
```

Converting to category will:

- Simplify visualisation (order can be preserved).
- Reduce memory usage (not that big a deal for us).
- Speed up I/O (depending on file format).

⇒ Convert to category is a bigger deal for features where the levels have an order.

`Titanic` — load

- Dataset is split into two parts:
  - `train.csv` — 891 rows with `Survived` column, used in EDA and model training.
  - `test.csv` — 418 rows without the `Survived` column, used in competition scoring.

```python
df = pd.read_csv("train.csv")
print(df.shape)
df.head(25)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarke
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
											C123	S
											NaN	S
											NaN	Q
											E46	S
											NaN	S
											NaN	S
											NaN	C
											G6	S
											C103	S
											NaN	S
											NaN	S
											NaN	S
											NaN	S
											NaN	Q
											NaN	S
18	19	0	3	Vander Planke, Mrs. Julius (Emelia Maria Vande...	female	31.0	1	0	345763	18.0000	NaN	S
19	20	1	3	Masselmani, Mrs. Fatima	female	NaN	0	0	2649	7.2250	NaN	C
20	21	0	2	Fynney, Mr. Joseph J	male	35.0	0	0	239865	26.0000	NaN	S
21	22	1	2	Beesley, Mr. Lawrence	male	34.0	0	0	248698	13.0000	D56	S
22	23	1	3	McGowan, Miss. Anna "Annie"	female	15.0	0	0	330923	8.0292	NaN	Q
23	24	1	1	Sloper, Mr. William Thompson	male	28.0	0	0	113788	35.5000	A6	S

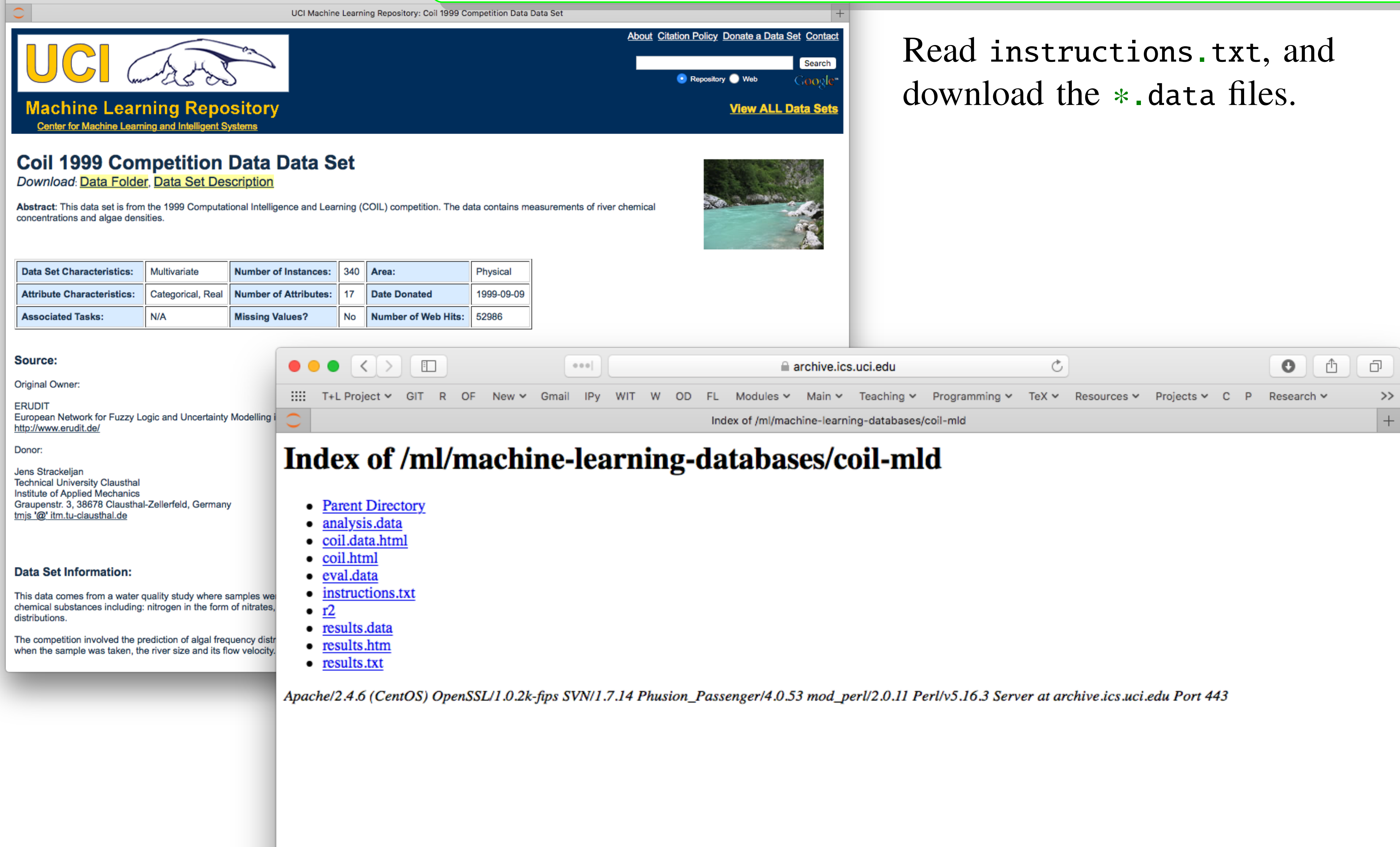
- We could convert `Sex` or `Embarked`, to a category, but since their levels are not ordered there is no big advantage.
- We don't want to convert `Name`, `Ticket` and `Cabin` since we want to perform further text processing on these columns. For example, extracting title (Capt, Mr, Miss, etc.) out of `Name`.
- We have missing values (**that are plausibly linked to target**) that we need to deal with.

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

`Algae_Blooms` – load I

https://archive.ics.uci.edu/ml/datasets/Coil+1999+Competition+Data



Read `instructions.txt`, and download the `*.data` files.

Algae_Blooms — load (1st attempt) II

Pandas function pd.read_table, is a more general function than read_csv.

```
df = pd.read_table('src/Analysis.txt')
print(df.shape)
df.head()
```

```
(199, 1)
```

	winter small medium 8.00000 9.80000 60.80000 6.23800 578.00000 105.00000 170.00000 50.00000 0.00000 0.00000 0.00000 0.00000 34.20000 8.30000 0.00000
0	spring small medium 8.35000 ...
1	autumn small medium 8.10000 1...
2	spring small medium 8.07000 ...
3	autumn small medium 8.06000 ...
4	winter small high 8.25000 13....

Two problems, first row was treated as column headers, and we need to specify the character(s) used to separate columns

`Algae_Blooms` — load (2nd attempt) III

```python
df = pd.read_table('src/Analysis.txt', sep='\s+', header=None)
print(df.shape)
df.head()
```

```
(200, 18)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	winter	small	medium	8.00000	9.80000	60.80000	6.23800	578.00000	105.00000	170.00000	50.00000	0.0	0.0	0.0	0.0	34.2	8.3
1	spring	small	medium	8.35000	8.00000	57.75000	1.28800	370.00000	428.75000	558.75000	1.30000	1.4	7.6	4.8	1.9	6.7	0.0
2	autumn	small	medium	8.10000	11.40000	40.02000	5.33000	346.66699	125.66700	187.05701	15.60000	3.3	53.6	1.9	0.0	0.0	0.0
3	spring	small	medium	8.07000	4.80000	77.36400	2.30200	98.18200	61.18200	138.70000	1.40000	3.1	41.0	18.9	0.0	1.4	0.0
4	autumn	small	medium	8.06000	9.00000	55.35000	10.41600	233.70000	58.22200	97.58000	10.50000	9.2	2.9	7.5	0.0	7.5	4.1

- Now, notice that the number of data row changed from 199 to 200 since the first row is now counted as a data row. And now we are using default columns names.
- The "\s+" matches one or more spaces. This is an example of a regex.
- We need to name the columns.

`Algae_Blooms` — load (3rd attempt) IV

```python
names = ('Season','Size','Speed','max_pH','min_O2','mean_Cl', 'mean_NO3', 'mean_NH4', 'mean_oPO4',
         'mean_PO4', 'mean_Chlor', 'a1', 'a2', 'a3', 'a4', 'a5', 'a6', 'a7')

df = pd.read_table('src/Analysis.txt', sep='\s+', names=names)
print(df.shape)
df.head()
```

```
(200, 18)
```

	Season	Size	Speed	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1	a2	a3
0	winter	small	medium	8.00000	9.80000	60.80000	6.23800							
1	spring	small	medium	8.35000	8.00000	57.75000	1.28800							
2	autumn	small	medium	8.10000	11.40000	40.02000	5.33000							
3	spring	small	medium	8.07000	4.80000	77.36400	2.30200							
4	autumn	small	medium	8.06000	9.00000	55.35000	10.41600							

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 18 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Season       200 non-null    object
 1   Size         200 non-null    object
 2   Speed        200 non-null    object
 3   max_pH       200 non-null    object
 4   min_O2       200 non-null    object
 5   mean_Cl      200 non-null    object
 6   mean_NO3     200 non-null    object
 7   mean_NH4     200 non-null    object
 8   mean_oPO4    200 non-null    object
 9   mean_PO4     200 non-null    object
 10  mean_Chlor   200 non-null    object
 11  a1           200 non-null    float64
 12  a2           200 non-null    float64
```

Dataframe looks a bit better, but why are numeric columns converted as `object`?
Reading `instructions.txt` we see that missing values are indicated by `XXXXXXX`.

`Algae_Blooms` — load (4th attempt)

```python
names = ('Season','Size','Speed','max_pH','min_O2','mean_Cl', 'mean_NO3', 'mean_NH4', 'mean_oPO4',
         'mean_PO4', 'mean_Chlor', 'a1', 'a2', 'a3', 'a4', 'a5', 'a6', 'a7')

df = pd.read_table('src/Analysis.txt', sep='\s+', names=names, na_values='XXXXXXX')
print(df.shape)
df.head()
```

```
(200, 18)
```

	Season	Size	Speed	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1	a2	a3
0	winter	small	medium	8.00	9.8	60.800	6.238	578.00000	105.000	170.00000	50.0	0.0	0.0	0.0
1	spring	small	medium	8.35	8.0	57.750	1.288	[illegible]						
2	autumn	small	medium	8.10	11.4	40.020	5.330	[illegible]						
3	spring	small	medium	8.07	4.8	77.364	2.302	[illegible]						
4	autumn	small	medium	8.06	9.0	55.350	10.416	[illegible]						

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 18 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Season      200 non-null    object
 1   Size        200 non-null    object
 2   Speed       200 non-null    object
 3   max_pH      199 non-null    float64
 4   min_O2      198 non-null    float64
 5   mean_Cl     190 non-null    float64
 6   mean_NO3    198 non-null    float64
 7   mean_NH4    198 non-null    float64
 8   mean_oPO4   198 non-null    float64
 9   mean_PO4    198 non-null    float64
 10  mean_Chlor  188 non-null    float64
 11  a1          200 non-null    float64
 12  a2          200 non-null    float64
```

Now some variables have missing values

Also we should convert `Season`, `Size` and `Speed` to category and ensure the levels are ordered.

`Algae_Blooms` — Fix Data Types II

The three categorical variables have levels with a natural order ⇒ convert to `category` and specify order:

```
df.Season = pd.Categorical(df.Season, categories=['spring', 'summer', 'autumn', 'winter'], ordered=Tr
print(df.Season.unique())
```

```
['winter', 'spring', 'autumn', 'summer']
Categories (4, object): ['spring' < 'summer' < 'autumn' < 'winter']
```

```
df.Size = pd.Categorical(df.Size, categories=['small', 'medium', 'large'], ordered=True)
print(df.Size.unique())
```

```
['small', 'medium', 'large']
Categories (3, object): ['small' < 'medium' < 'large']
```

```
df.Speed = pd.Categorical(df.Speed, categories=['low', 'medium', 'high'], ordered=True)
print(df.Speed.unique())
```

```
['medium', 'high', 'low']
Categories (3, object): ['low' < 'medium' < 'high']
```

`Algae_Blooms` — Identification of Missing Values (NA)

1 Which columns have missing values?

```
df.isna().sum()
```

```
Season        0
Size          0
Speed         0
max_pH        1
min_O2        2
mean_Cl      10
mean_NO3      2
mean_NH4      2
mean_oPO4     2
mean_PO4      2
mean_Chlor   12
a1            0
a2            0
a3            0
a4            0
a5            0
a6            0
a7            0
dtype: int64
```

- Two columns (features) account for 22 NAs, but cannot just drop them as will lose a lot of information.
- Two rows (observations) account for 12 NAs ⇒ remove.
- Removing other rows with a NA will result in a los of 14 rows (7% of the data), instead will impute later.

2 ~~Which rows have missing values?~~
How many NAs per row?

```
df.isna().sum(axis=1).value_counts()
```

```
0    184
1      7
2      7
6      2
dtype: int64
```

4 Rows / ~~Cols~~ to drop?

```
df.loc[df.isna().sum(axis=1)==6]
```

	Season	Size	Speed	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor
61	summer	small	medium	6.4	NaN	NaN	NaN	NaN	NaN	14.0	NaN
198	winter	large	medium	8.0	7.6	NaN	NaN	NaN	NaN	NaN	NaN

```
df = df.loc[df.isna().sum(axis=1)<6].copy()
print(df.shape)
```

```
(198, 18)
```

After Loading and Initial Clean — Where are we? I

Tips

- ✔ Loaded data, corrected dtypes (categorical with order levels)
- ✔ Sanitised column names — not needed, but note column name `size` shadows pandas dataframe function `size` ⇒ so use `df["size"]` instead of `df.size`.
- ✔ No missing values

Titanic

- ✔ Loaded data — no conversion of dtypes needed . . . . (but if you don't plots/crosstab order won't agree)
- ✔ Sanitised column names — not needed,
- Missing values in `Age` (177/891=20%), `Cabin` (687/891=77%), and `Embarked` (2/891=0.2%).
  - A feature with 77% missing values should be considered for deletion, but what if the presence of a missing value actually tells us something? ⇒ convert to a boolean feature.

Algae Blooms

- ✔ Loaded data, corrected dtypes (categorical with ordered levels)
- ✔ Sanitised column names.
- Missing values
  - Removed two rows with 6 NA each, accounted for 12/33=36% of the missing values.
  - Remaining, 21 NAs are concentrated in `mean_CL` (8) and `mean_Chlor` (10). EDA will suggest options.

After Loading and Initial Clean — Where are we? II

Next we might

- Save result of initial clean:
  - To either a CSV (if we don't mind losing `dtype` metadata)

```
df.to_csv('data/Analysis.csv', index=False)
```

  - To (say) pickle format (to keep `dtype` metadata)

```
df.to_pickle('data/Analysis.pkl')
```

  Later can read dataframe back in using

```
df = pd.read_pickle('data/Analysis.pkl')
print(df.shape)
df.head(1)
```

- If the dataset is large (>100K rows), save a (reproducible) sample of the dataset for later EDA to speed up calculations (especially visualisations).

```
df.sample(frac=.25, random_state=42).to_pickle('data/Analysis_sample.pkl')
```