Uniformity

CLEANING DATA IN PYTHON

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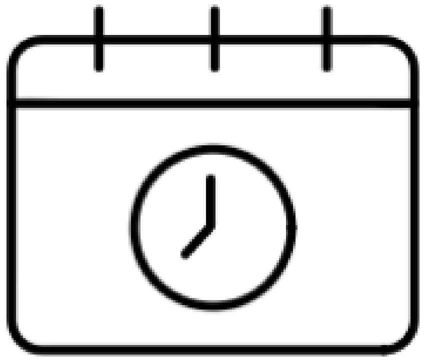
In this chapter

Chapter 3 - Advanced data problems

Data range constraints

Out of range movie ratings



Subscription dates in the future

Uniformity

Column	Unit
Temperature	`32°C` **is also** `89.6°F`
Weight	`70 Kg` **is also** `11 st.`
Date	`26-11-2019` **is also** `26, November, 2019`
Money	`100$` **is also** `10763.90¥`

An example

```
temperatures = pd.read_csv('temperature.csv')
temperatures.head()
```

```
       Date  Temperature
0  03.03.19         14.0
1  04.03.19         15.0
2  05.03.19         18.0
3  06.03.19         16.0
4  07.03.19         62.6
```

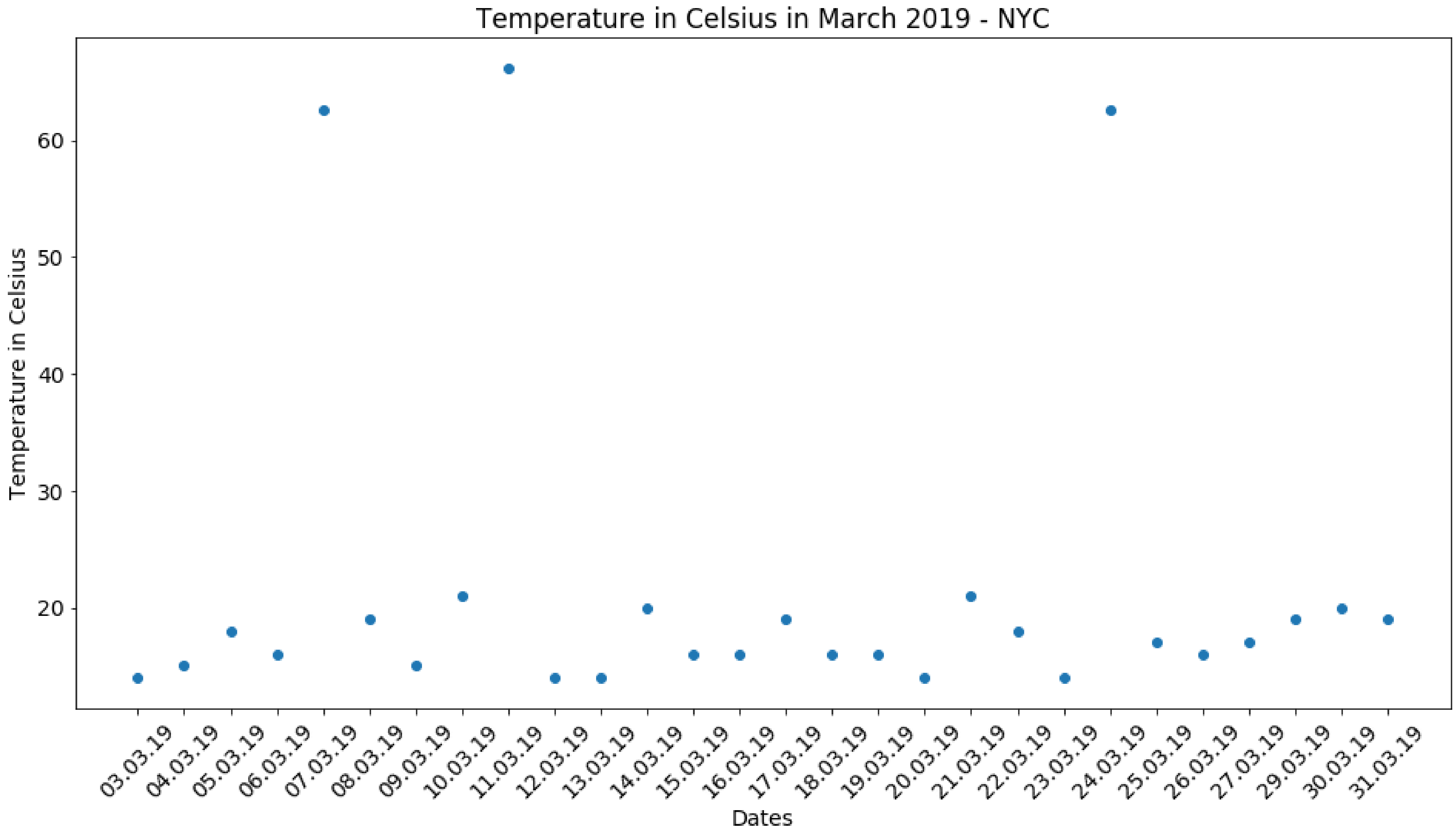
An example

```
temperatures = pd.read_csv('temperature.csv')
temperatures.head()
```

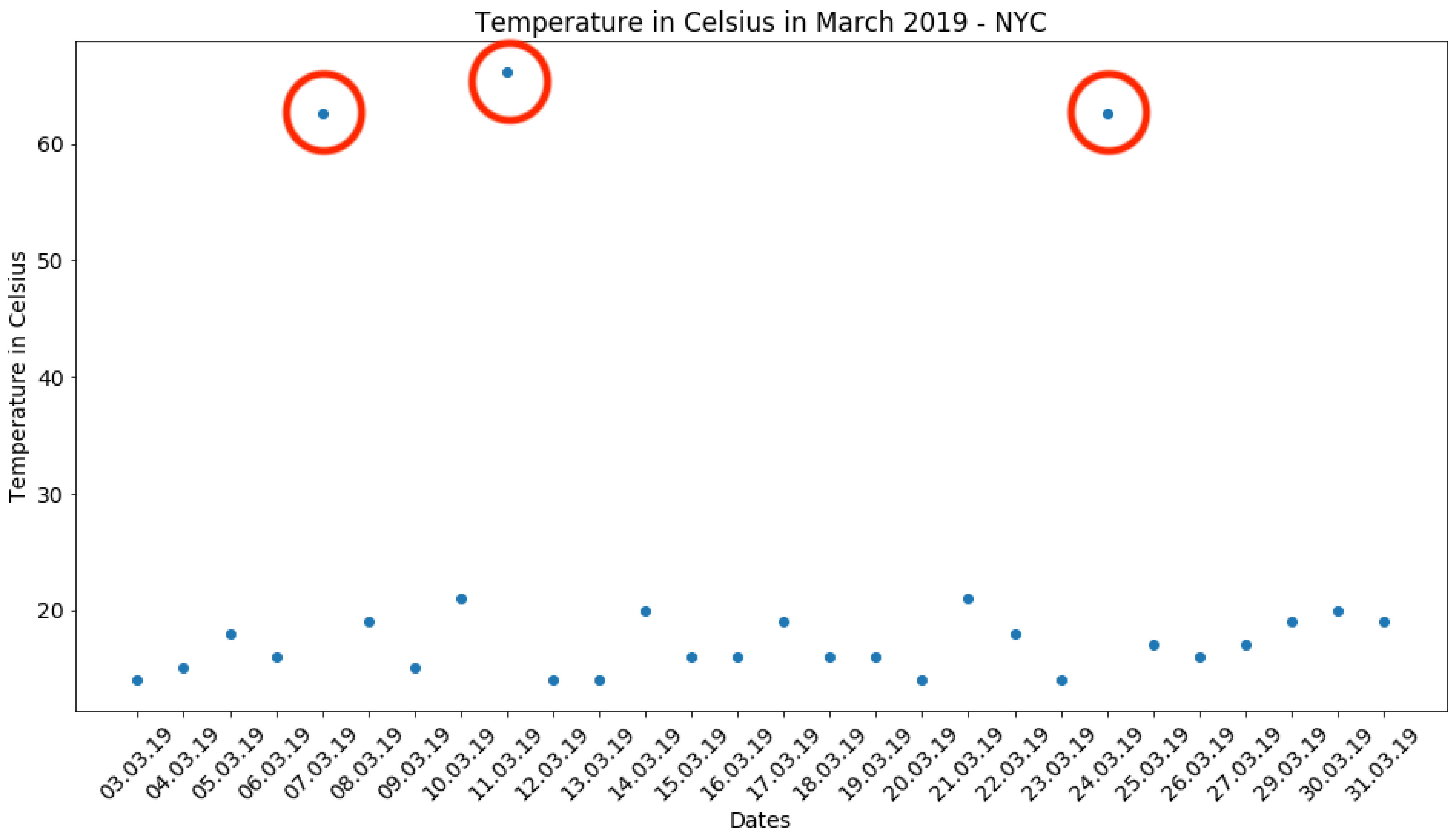
```
       Date  Temperature
0  03.03.19         14.0
1  04.03.19         15.0
2  05.03.19         18.0
3  06.03.19         16.0
4  07.03.19         62.6   <--
```

An example

```
# Import matplotlib
import matplotlib.pyplot as plt
# Create scatter plot
plt.scatter(x = 'Date', y = 'Temperature', data = temperatures)
# Create title, xlabel and ylabel
plt.title('Temperature in Celsius March 2019 - NYC')
plt.xlabel('Dates')
plt.ylabel('Temperature in Celsius')
# Show plot
plt.show()
```



Temperature in Celsius in March 2019 - NYC
Temperature in Celsius
20
30
40
50
60
Dates
03.03.19
04.03.19
05.03.19
06.03.19
07.03.19
08.03.19
09.03.19
10.03.19
11.03.19
12.03.19
13.03.19
14.03.19
15.03.19
16.03.19
17.03.19
18.03.19
19.03.19
20.03.19
21.03.19
22.03.19
23.03.19
24.03.19
25.03.19
26.03.19
27.03.19
29.03.19
30.03.19
31.03.19



Temperature in Celsius in March 2019 - NYC
Temperature in Celsius
60
50
40
30
20
03.03.19
04.03.19
05.03.19
06.03.19
07.03.19
08.03.19
09.03.19
10.03.19
11.03.19
12.03.19
13.03.19
14.03.19
15.03.19
16.03.19
17.03.19
18.03.19
19.03.19
20.03.19
21.03.19
22.03.19
23.03.19
24.03.19
25.03.19
26.03.19
27.03.19
29.03.19
30.03.19
31.03.19
Dates

Treating temperature data

$$C = (F - 32) \times \frac{5}{9}$$

```
temp_fah = temperatures.loc[temperatures['Temperature'] > 40, 'Temperature']
temp_cels = (temp_fah - 32) * (5/9)
temperatures.loc[temperatures['Temperature'] > 40, 'Temperature'] = temp_cels
```

```
# Assert conversion is correct
assert temperatures['Temperature'].max() < 40
```

10. Treating temperature data
A simple web search returns the formula for converting Fahrenheit to Celsius. To convert our temperature data, we isolate all rows of temperature column where it is above 40 using the loc method. We chose 40 because it's a common sense maximum for Celsius temperatures in New York City. We then convert these values to Celsius using the formula above, and reassign them to their respective Fahrenheit values in temperatures. We can make sure that our conversion was correct with an assert statement, by making sure the maximum value of temperature is less than 40.

Treating date data

```
birthdays.head()
```

```
         Birthday First name Last name
0        27/27/19      Rowan     Nunez
1        03-29-19      Brynn      Yang
2  March 3rd, 2019    Sophia    Reilly
3        24-03-19     Deacon    Prince
4        06-03-19   Griffith      Neal
```

Treating date data

```
birthdays.head()
```

```
          Birthday First name Last name
0         27/27/19      Rowan     Nunez
1         03-29-19      Brynn      Yang
2  March 3rd, 2019     Sophia   Reilly
3         24-03-19    Deacon    Prince
4         06-03-19  Griffith      Neal
```

??

MM-DD-YY

Month D, YYYY

Datetime formatting

`datetime` is useful for representing dates

Date	`datetime` format
25-12-2019	`%d-%m-%Y`
December 25th 2019	`%c`
12-25-2019	`%m-%d-%Y`
...	...

`pandas.to_datetime()`

- Can recognize most formats automatically
- Sometimes fails with erroneous or unrecognizable formats

13. Datetime formatting
We already discussed datetime objects. Without getting too much into detail, datetime accepts different formats that help you format your dates as pleased. The pandas to datetime function automatically accepts most date formats, but could raise errors when certain formats are unrecognizable. You don't have to memorize these formats, just know that they exist and are easily searchable!

Treating date data

```
# Converts to datetime - but won't work!
birthdays['Birthday'] = pd.to_datetime(birthdays['Birthday'])
```

```
ValueError: month must be in 1..12
```

```
# Will work!
birthdays['Birthday'] = pd.to_datetime(birthdays['Birthday'],
                        # Attempt to infer format of each date
                        infer_datetime_format=True,
                        # Return NA for rows where conversion failed
                        errors = 'coerce')
```

14. Treating date data

You can fix it by converting your date column to datetime. We can do this in pandas with the to_datetime function. However this isn't enough and will most likely return an error, since we have dates in multiple formats, especially the weird day/day/format which triggers an error with months. Instead we set the infer_datetime_format argument to True, and set errors equal to coerce. This will infer the format and return missing value for dates that couldn't be identified and converted instead of a value error.

Treating date data

```
birthdays.head()
```

```
    Birthday First name Last name
0        NaT      Rowan     Nunez
1 2019-03-29      Brynn      Yang
2 2019-03-03     Sophia    Reilly
3 2019-03-24     Deacon    Prince
4 2019-06-03   Griffith      Neal
```

Treating date data

```
birthdays['Birthday'] = birthdays['Birthday'].dt.strftime("%d-%m-%Y")
birthdays.head()
```

```
     Birthday First name Last name
0         NaT      Rowan     Nunez
1  29-03-2019      Brynn      Yang
2  03-03-2019     Sophia    Reilly
3  24-03-2019     Deacon    Prince
4  03-06-2019   Griffith      Neal
```

16. Treating date data
We can also convert the format of a datetime column using the dt dot strftime method, which accepts a datetime format of your choice. For example, here we convert the Birthday column to day month year, instead of year month day.

Treating ambiguous date data

17. Treating ambiguous date data
However a common problem is having ambiguous dates with vague formats. For example, is this date value set in March or August? Unfortunately there's no clear cut way to spot this inconsistency or to treat it. Depending on the size of the dataset and suspected ambiguities, we can either convert these dates to NAs and deal with them accordingly. If you have additional context on the source of your data, you can probably infer the format. If the majority of subsequent or previous data is of one format, you can probably infer the format as well. All in all, it is essential to properly understand where your data comes from, before trying to treat it, as it will make making these decisions much easier.

Is* `2019-03-08` *in August or March?

- Convert to `NA` and treat accordingly
- Infer format by understanding data source
- Infer format by understanding previous and subsequent data in DataFrame

Let's practice!

CLEANING DATA IN PYTHON

Cross field validation

CLEANING DATA IN PYTHON

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Motivation

```
import pandas as pd


flights = pd.read_csv('flights.csv')
flights.head()
```

We know that these columns have been collected and merged from different data sources, and a common challenge when merging data from different sources is data integrity, or more broadly making sure that our data is correct.

```
  flight_number  economy_class  business_class  first_class  total_passengers
0         DL140            100              60           40               200
1         BA248            130             100           70               300
2        MEA124            100              50           50               200
3        AFR939            140              70           90               300
4        TKA101            130             100           20               250
```

Cross field validation

*The use of **multiple** fields in a dataset to sanity check data integrity*

```
  flight_number  economy_class  business_class  first_class  total_passengers
0         DL140            100         +    60        +   40        =      200
1         BA248            130         +   100        +   70        =      300
2        MEA124            100         +    50        +   50        =      200
3        AFR939            140         +    70        +   90        =      300
4        TKA101            130         +   100        +   20        =      250
```

```
sum_classes = flights[['economy_class', 'business_class', 'first_class']].sum(axis = 1)
passenger_equ = sum_classes == flights['total_passengers']
# Find and filter out rows with inconsistent passenger totals
inconsistent_pass = flights[~passenger_equ]
consistent_pass = flights[passenger_equ]
```

3. Cross field validation

This is where cross field validation comes in. Cross field validation is the use of multiple fields in your dataset to sanity check the integrity of your data. ... This could be easily done in Pandas, by first subsetting on the columns to sum, then using the sum method with the axis argument set to 1 to indicate row wise summing. We then find instances where the total passengers column is equal to the sum of the classes. And find and filter out instances of inconsistent passenger amounts by subsetting on the equality we created with brackets and the tilde symbol.

Cross field validation

```
users.head()
```

```
   user_id  Age   Birthday
0    32985   22 1998-03-02
1    94387   27 1993-12-04
2    34236   42 1978-11-24
3    12551   31 1989-01-03
4    55212   18 2002-07-02
```

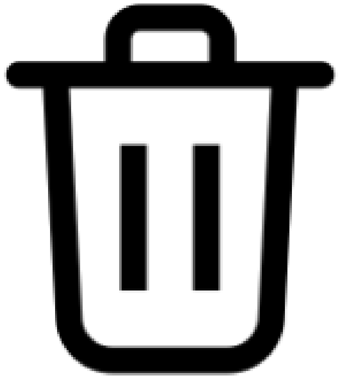
Cross field validation

```python
import pandas as pd
import datetime as dt

# Convert to datetime and get today's date
users['Birthday'] = pd.to_datetime(users['Birthday'])
today = dt.date.today()
# For each row in the Birthday column, calculate year difference
age_manual = today.year - users['Birthday'].dt.year
# Find instances where ages match
age_equ = age_manual == users['Age']
# Find and filter out rows with inconsistent age
inconsistent_age = users[~age_equ]
consistent_age = users[age_equ]
```

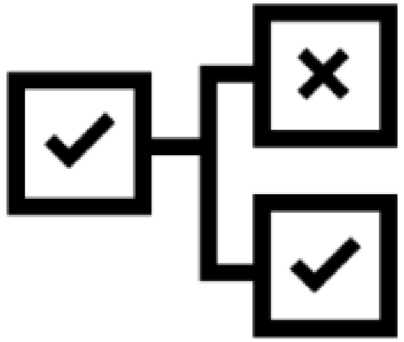
5. Cross field validation
We can do this by first making sure the Birthday column is converted to datetime with the pandas to datetime function. We then create an object storing today's date using the datetime package's date dot today function. We then calculate the difference in years between today's date's year, and the year of each birthday by using the dot dt dot year attribute of the user's Birthday column. We then find instances where the calculated ages are equal to the actual age column in the users DataFrame. We then find and filter out the instances where we have inconsistencies using subsetting with brackets and the tilde symbol on the equality we created.

What to do when we catch inconsistencies?



Dropping Data

Set to missing and impute



Apply rules from domain knowledge

Let's practice!

CLEANING DATA IN PYTHON

Completeness

CLEANING DATA IN PYTHON

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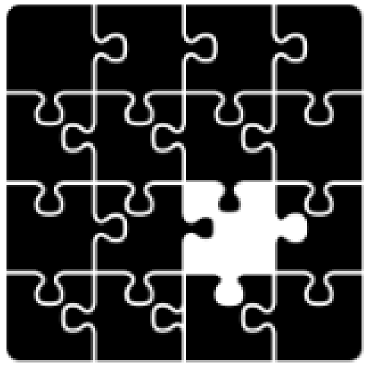
What is missing data?



Occurs when no data value is stored for a variable in an observation

Can be represented as `NA` , `nan` , `0` , `.` ...

Technical error

Human error

Airquality example

```python
import pandas as pd
airquality = pd.read_csv('airquality.csv')
print(airquality)
```

```
            Date  Temperature  CO2
987   20/04/2004         16.8  0.0
2119  07/06/2004         18.7  0.8
2451  20/06/2004        -40.0  NaN
1984  01/06/2004         19.6  1.8
8299  19/02/2005         11.2  1.2
...         ...           ...  ...
```

Airquality example

```python
import pandas as pd
airquality = pd.read_csv('airquality.csv')
print(airquality)
```

```
            Date  Temperature  CO2
987   20/04/2004         16.8  0.0
2119  07/06/2004         18.7  0.8
2451  20/06/2004        -40.0  NaN   <--
1984  01/06/2004         19.6  1.8
8299  19/02/2005         11.2  1.2
...        ...            ...  ...
```

Airquality example

```
# Return missing values
airquality.isna()
```

```
       Date  Temperature    CO2
987   False        False  False
2119  False        False  False
2451  False        False   True
1984  False        False  False
8299  False        False  False
```

Airquality example

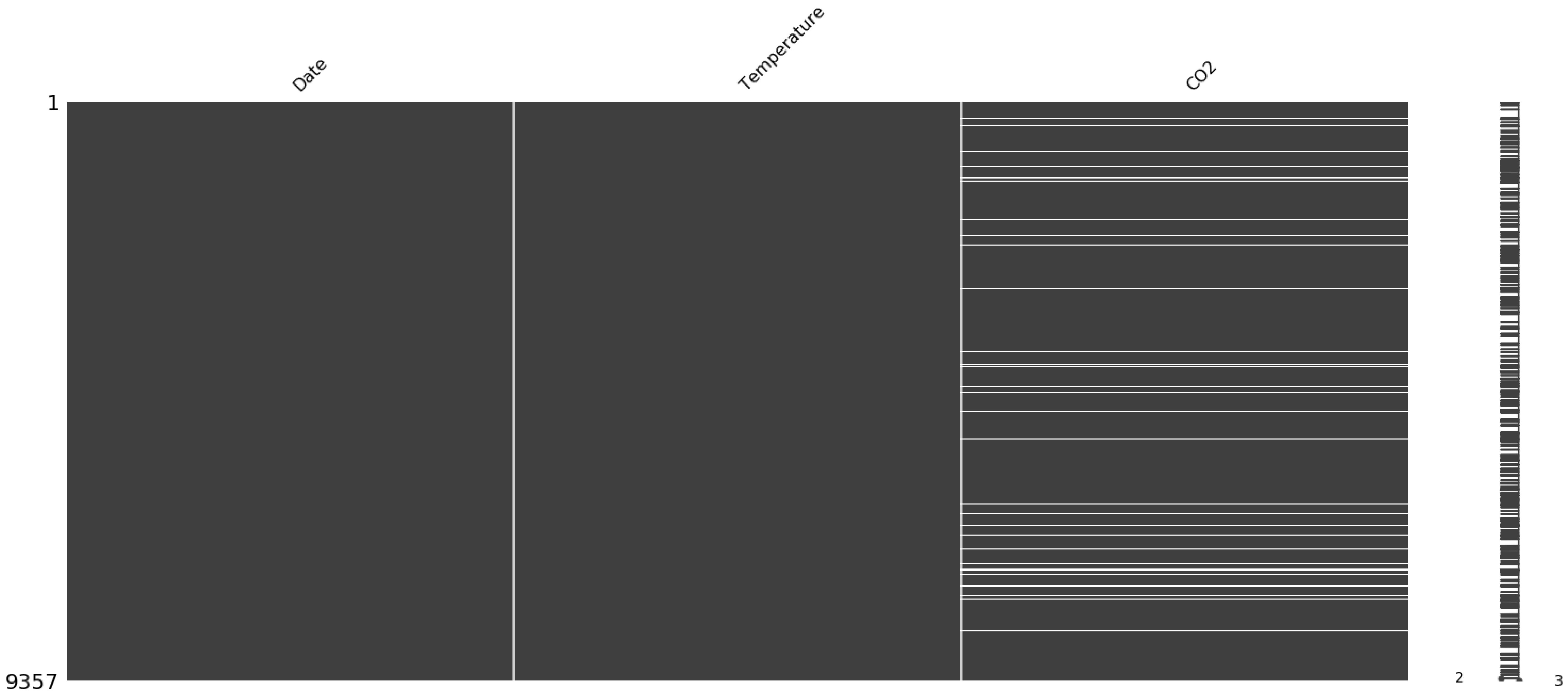
```
# Get summary of missingness
airquality.isna().sum()
```

```
Date              0
Temperature       0
CO2             366
dtype: int64
```

Missingno

Useful package for visualizing and understanding missing data

```
import missingno as msno
import matplotlib.pyplot as plt
# Visualize missingness
msno.matrix(airquality)
plt.show()
```


Date
Temperature
CO2
1
9357
2
3

Airquality example

```
# Isolate missing and complete values aside
missing = airquality[airquality['CO2'].isna()]
complete = airquality[~airquality['CO2'].isna()]
```

Airquality example

```
# Describe complete DataFramee
complete.describe()
```

```
       Temperature          CO2
count  8991.000000  8991.000000
mean     18.317829     1.739584
std       8.832116     1.537580
min      -1.900000     0.000000
...    ...          ...
max      44.600000    11.900000
```

```
# Describe missing DataFramee
missing.describe()
```

```
       Temperature  CO2
count   366.000000  0.0
mean    -39.655738  NaN
std       5.988716  NaN
min     -49.000000  NaN
...       ...        ...
max     -30.000000  NaN
```

Airquality example

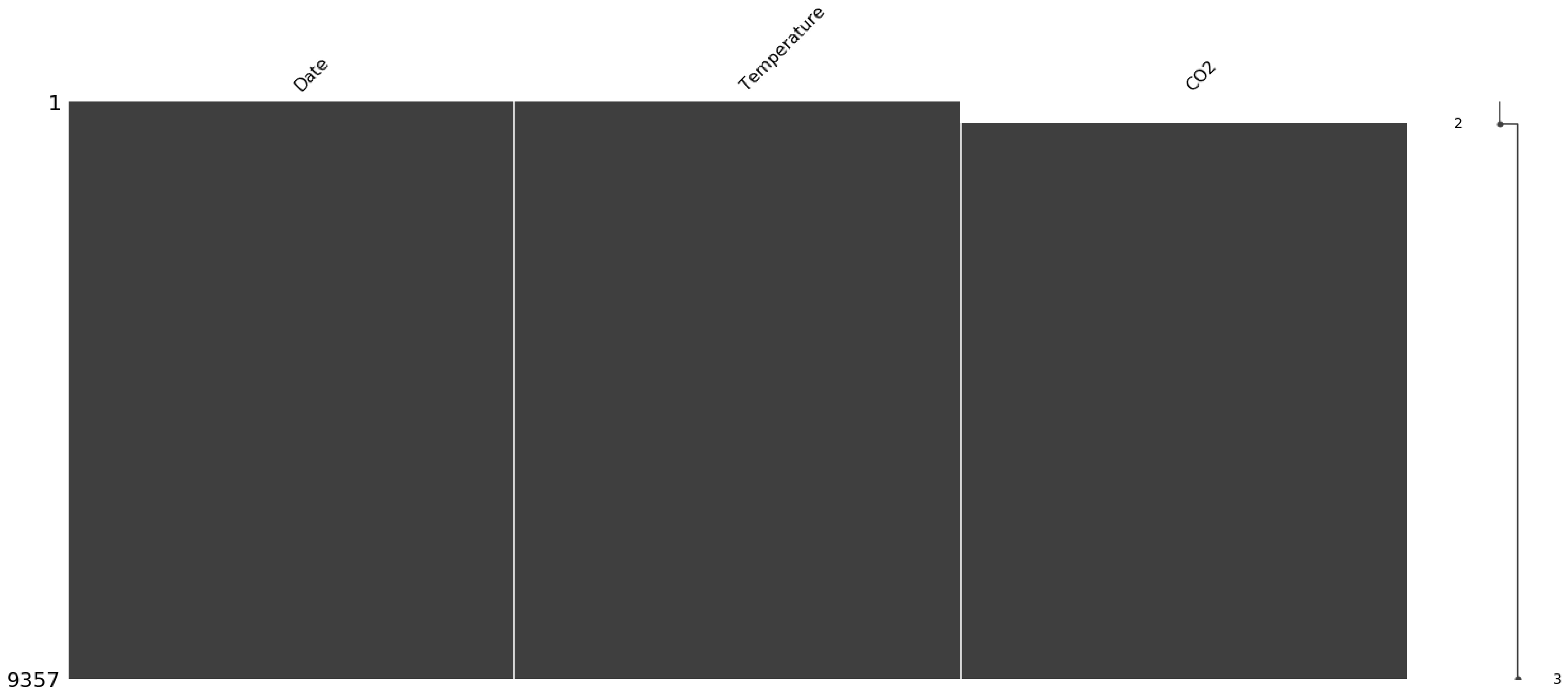
```
# Describe complete DataFramee
complete.describe()
```

```
         Temperature          CO2
count    8991.000000  8991.000000
mean       18.317829     1.739584
std         8.832116     1.537580
min        -1.900000     0.000000
...         ...          ...
max        44.600000    11.900000
```

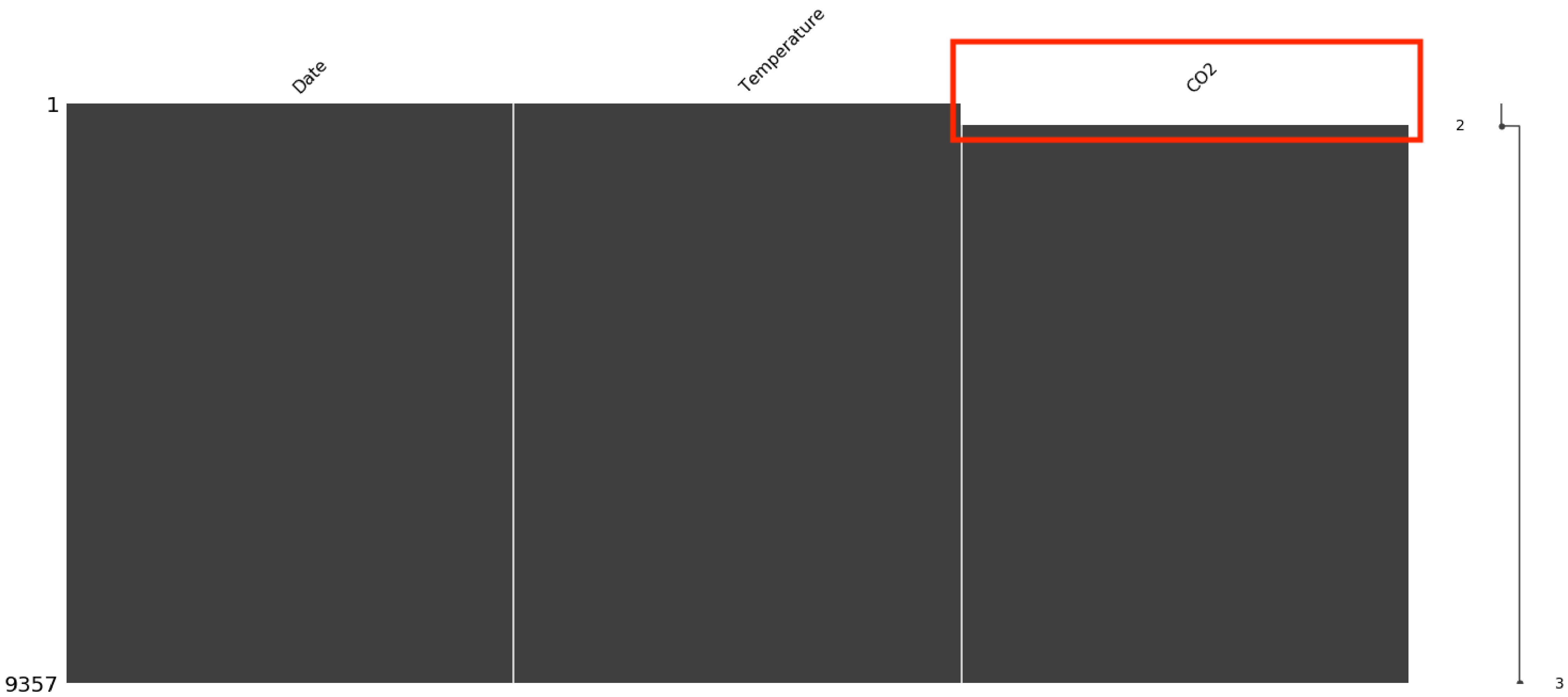
```
# Describe missing DataFramee
missing.describe()
```

```
        Temperature  CO2
count    366.000000  0.0
mean     -39.655738  NaN   <--
std        5.988716  NaN
min      -49.000000  NaN   <--
...         ...      ...
max      -30.000000  NaN   <--
```

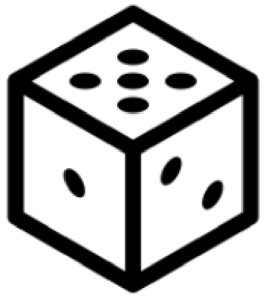
```
sorted_airquality = airquality.sort_values(by = 'Temperature')
msno.matrix(sorted_airquality)
plt.show()
```



```
sorted_airquality = airquality.sort_values(by = 'Temperature')
msno.matrix(sorted_airquality)
plt.show()
```

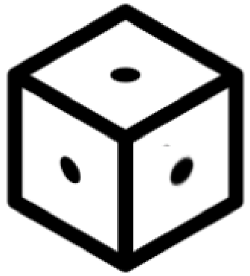


Missingness types



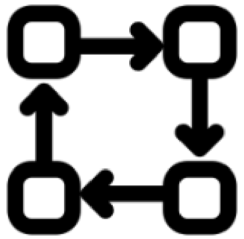
Missing Completely at Random

(MCAR)



Missing at Random

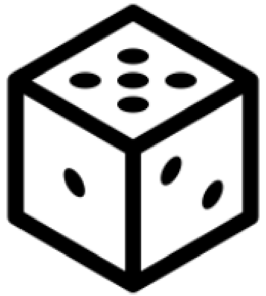
(MAR)



Missing Not at Random

(MNAR)

Missingness types

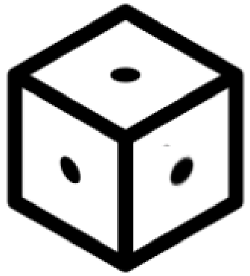


Missing Completely at Random

(MCAR)

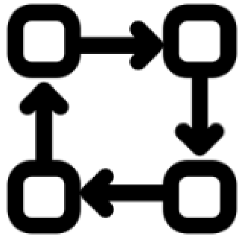
No systematic relationship between missing data and other values

Data entry errors when inputting data



Missing at Random

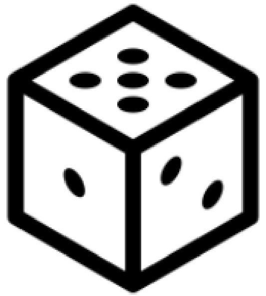
(MAR)



Missing Not at Random

(MNAR)

Missingness types

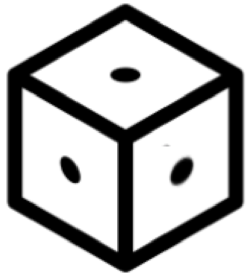


Missing Completely at Random

(MCAR)

No systematic relationship between missing data and other values

Data entry errors when inputting data

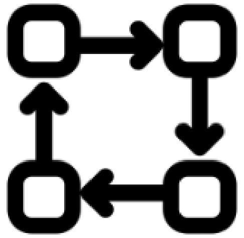


Missing at Random

(MAR)

*Systematic relationship between missing data and other **observed** values*

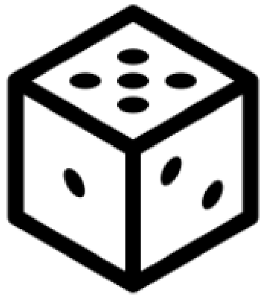
Missing ozone data for high temperatures



Missing Not at Random

(MNAR)

Missingness types

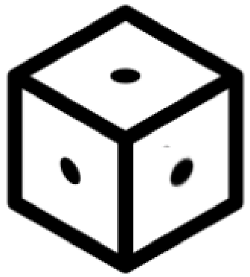


Missing Completely at Random

(MCAR)

No systematic relationship between missing data and other values

Data entry errors when inputting data

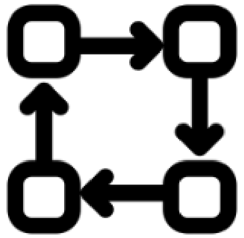


Missing at Random

(MAR)

Systematic relationship between missing data and other observed values

Missing ozone data for high temperatures



Missing Not at Random

(MNAR)

Systematic relationship between missing data and unobserved values

Missing temperature values for high temperatures

How to deal with missing data?

Simple approaches:

1. Drop missing data
2. Impute with statistical measures *(mean, median, mode..)*

More complex approaches:

1. Imputing using an algorithmic approach
2. Impute with machine learning models

Dealing with missing data

```
airquality.head()
```

```
         Date  Temperature  CO2
0  05/03/2005          8.5  2.5
1  23/08/2004         21.8  0.0
2  18/02/2005          6.3  1.0
3  08/02/2005        -31.0  NaN
4  13/03/2005         19.9  0.1
```

Dropping missing values

```
# Drop missing values
airquality_dropped = airquality.dropna(subset = ['CO2'])
airquality_dropped.head()
```

```
         Date  Temperature  CO2
0  05/03/2005          8.5  2.5
1  23/08/2004         21.8  0.0
2  18/02/2005          6.3  1.0
4  13/03/2005         19.9  0.1
5  02/04/2005         17.0  0.8
```

Replacing with statistical measures

```python
co2_mean = airquality['CO2'].mean()
airquality_imputed = airquality.fillna({'CO2': co2_mean})
airquality_imputed.head()
```

```
         Date  Temperature       CO2
0  05/03/2005          8.5  2.500000
1  23/08/2004         21.8  0.000000
2  18/02/2005          6.3  1.000000
3  08/02/2005        -31.0  1.739584
4  13/03/2005         19.9  0.100000
```

Let's practice!

CLEANING DATA IN PYTHON