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# Analysing Data Using Pandas a Vademecum

Prof. Fabio Ciravegna  
Dipartimento di Informatica  
Università di Torino  
fabio.ciravegna@unito.it



# Load data from CSV

```
import pandas as pd
```

```
df = pd.read_csv('../rollercoasters.csv')
```

```
df
```

-

# Load data from mongoldb

```
import pymongo
import pandas as pd
from pymongo import MongoClient
```

```
client = MongoClient()
db = client.database_name
collection = db.collection_name
```

```
# Query MongoDB with specific fields and convert to DataFrame
results = collection.find({sport: 'tennis', tournament: 'davis cup'},
    # Fetch only sport and tournament excluding '_id'
    {'_id': 0, 'sport': 1, 'tournament': 1})
```

```
data = pd.DataFrame(list(results))
```

# Some recommendations

- Query Optimization:
  - Depending on the size of the collection, fetching all data at once might not be efficient
  - You might want to use query filters (like `collection.find({})`)
    - to fetch only the necessary data or limit the number of results using `limit()`
- Data Types:
  - MongoDB stores data in BSON format, so ensure that the data types are appropriate when converted to a DataFrame.
- Memory Usage:
  - If the collection is large, fetching all the data at once might consume a lot of memory
  - Consider fetching data in batches

# Check the shape

- **df.shape**

- will give you the number of rows and columns

- why you should use it?

- so to make sure that the data you have loaded is what you expect
    - a typical error is to have no or very few rows
      - typically a wrong query

```
In 140 1 df.shape
Executed at 2023.11.24 14:49:27 in 10ms

Out 140 (142, 21)
```

# Checking the types

- **df.dtypes**

- why you should use it:
  - some fields may just have an apparent correct type:
    - e.g. some dates may appear as "12/03/2024"
  - but some of them may be represented as a string rather than a daytime
    - check the types to make sure they are what you expect

```
In 141 1 df.dtypes
Executed at 2023.11.24 14:49:28 in 13ms

Out 141 ✓
max_speed      int64
avg_speed      int64
ride_time      int64
ride_length    int64
max_pos_gs     float64
max_neg_gs     float64
max_lateral_gs float64
total_air_time float64
drops          int64
highest_drop_height int64
inversions     int64
dtype: object
```

# To convert

- How to convert:
  - in general:
    - `df[column_name] = df[column_name].astype('int')`
      - replace `int` with the type you need
  - to convert to a date time:
    - `pd.to_datetime(df[column_name])`
  - This will modify the entire column

# Accessing

- A column

```
df['custom_design']
```

- A row

```
df.loc[0]
```

```
In 142 1 df['custom_design']
```

Executed at 2023.11.24 14:49:29 in 76ms

```
Out 142 0 0
1 0
2 0
3 0
4 0
..
137 1
138 1
139 1
140 1
141 1
Name: custom_design, Length: 142, dtype: int64
```

```
In 143 1 df.loc[0]
```

Executed at 2023.11.24 14:49:30 in 14ms

```
Out 143 max_speed 59
avg_speed 12
ride_time 63
ride_length 1496
max_pos_gs 2.59
max_neg_gs -0.27
max_lateral_gs 1.71
total_air_time 0.0
drops 2
highest_drop_height 19
inversions 0
Name: 0, dtype: object
```



# Setting a column as an index

- Normally the indexes in a data frame are integer from 0 to num\_columns
  - however we can assign specific indexes to each row, typically by using some unique ides, generally provided by a database relation
    - e.g.

```
df.set_index('park_id')
```

- this removes park\_id from the columns
  - simplifying any queries and results
  - and identifies each element row using its id

# Checking the name of the columns

`df.columns`

- why it is important
  - to remember their name when you type commands that require the name of columns
  - to change the names in order to make the code easier to read
    - e.g. a column originally called AVG\_TMP could be renamed into Average\_Temperature
    - making the programme easier to read and interpret

# Creating a view on a DF

```
df[['park_id', 'theme', 'rollercoaster_type',  
    'custom_design', 'excitement']]
```

- Why you should use it
  - to work with smaller (apparent) data and focus only on the parts of the data you really need
  - if you do not need the rest of the data, just reassign the view to the original df variable
    - `df = df[['park_id', ...`

```
df[['park_id', 'theme', 'rollercoaster_type', 'custom_design', 'excitement']]
```

Executed at 2023.11.24 13:26:16 in 226ms

	park_id	theme	rollercoaster_type	custom_de
1	0	Barony Bridge	Dinghy Slide	
2	0	Barony Bridge	Wild Mouse	
3	0	Barony Bridge	Wooden Roller Coaster	
4	1	Forest Frontiers	Junior Roller Coaster	
...	...	...	...	
137	30	Botany Breakers	Spiral Coaster	

# Understanding the data

- Describing a number column

```
df['max_speed'].describe()
```

- Why you should use it?
  - to check the actual distribution of the data. For example it returns the 25/50/75 percentile mean
    - which tells you if some data has outliers
      - in the image, to 25% corresponds an increase by 4 or 5
        - but the max is 89, so it is probably an outlier

```
df['max_speed'].describe()
```

Executed at 2023.11.24 13:26:16 in 215ms

count	142.000000
mean	43.570423
std	8.980197
min	29.000000
25%	38.000000
50%	42.500000
75%	47.000000
max	89.000000

Name: max\_speed, dtype: float64

# Get all rows that match a condition

- You must create a filter
  - `df[condition]`
- and then apply it to the dataframe
  - `df[filter]`
- so in total it is
  - `df[[condition]]`
- e.g.

```
df.loc[df['max_speed'] > 42]
```

```
df.loc[df['max_speed'] > 42]
```

Executed at 2023.11.24 14:55:30 in 36ms

11 rows ▾ 71 rows x 21 columns pd.DataFrame ▶					CSV ▾	⬇	↗	👁
⬆	park_id ▾	theme	⬆	rollercoaster_type	⬆	custo		
3	0	Barony Bridge		Wooden Roller Coaster				

# Better: use query

- This is easier to use  
`df.query( 'max_speed>42' )`
- Note that use of the quotes are around the entire condition

```
df.loc[df['max_speed'] > 42]
```

Executed at 2023.11.24 14:55:30 in 36ms

11 rows × 21 columns `pd.DataFrame`

CSV ↓ ↗ 🔍

	park_id	theme	rollercoaster_type	custo
3	0	Barony Bridge	Wooden Roller Coaster	
6	2	Haunted Harbour	Wooden Roller Coaster	
13	4	Pacific Pyramids	Vertical Drop Coaster	
15	5	Mel's World	Inverted Roller Coaster	
17	5	Mel's World	Suspended Swinging Coaster	

# Checking for invalid values

- Some values in some rows can be invalid
  - i.e. None, NaT, Nan...

```
df.isna()
```

- will return all the rows with a None value
- not very useful. Typically you would check the value in specific columns

```
df['max_speed'].isna()
```

```
In 82 1 df['max_speed'].isna()
      Executed at 2023.11.24 13:26:16 in 159ms

Out 82 0      False
      1      False
      2      False
      3      False
      4      False
      ...
      137     False
      138     False
      139     False
      140     False
      141     False
      Name: max_speed, Length: 142, dtype: bool
```

# What to do with NAs?

- Several strategies, e.g.
  - remove the rows from the df (note the negation of the filter using ~)

```
df = df.loc[~df['max_speed'].isna()]
```

- insert the average of the column

```
df.loc[df['max_speed'].isna()].max_speed = df['max_speed'].mean()
```



# Finding Duplicates

- Why you should use it?
  - because duplicates
    - can be errors (information repeated)
    - can influence measures such as means and standard deviation
  - two types of duplications
    - full duplication (entire element - typically an error in input), The filter is:  
`df.duplicated()`
    - partial duplication
      - the significant columns such as id and name are identical
      - some minor information is different
        - e.g. date of creation - in that case it may mean that there is uncertainty on the information
      - the filter is:

```
df.duplicated(subset=['column_1', 'column_2', ..., 'column_n'])
```

# Inspecting duplicates

```
# you can do loc on it because it is a filter
df.loc[~df.duplicated(subset=['theme', 'rollercoaster_type'])]
```

```
2 df.loc[df.duplicated(subset=['theme', 'rollercoaster_type'])]
```

```
3
```

Executed at 2023.11.24 13:26:16 in 284ms

Out 90

7 rows x 21 columns pd.DataFrame					CSV				
	park_id	theme	rollercoaster_type	custom					
36	10	Karts And Coasters	Wooden Roller Coaster						
40	11	Three Monkeys Park	Looping Roller Coaster						
41	11	Three Monkeys Park	Looping Roller Coaster						
46	12	Crumbly Woods	Corkscrew Roller Coaster						
52	14	Canry Mines	Vertical Drop Coaster						
115	26	Paradise Pier	Looping Roller Coaster						
120	27	Swamp Cove	Inverted Roller Coaster						

# Check the duplicates and remove them

```
df = df.loc[~df.duplicated(subset=['theme', 'rollercoaster_type'])]
```

# Univariate analysis

- you can analyse the distribution of a column by writing
  - `df[column_name].value_counts()`
- e.g. how many rollercoasters were built per year
  - you may want to reduce that to the top 10
    - just use `.head` on the `value_counts` call
      - and if you want to plot it, you can
-

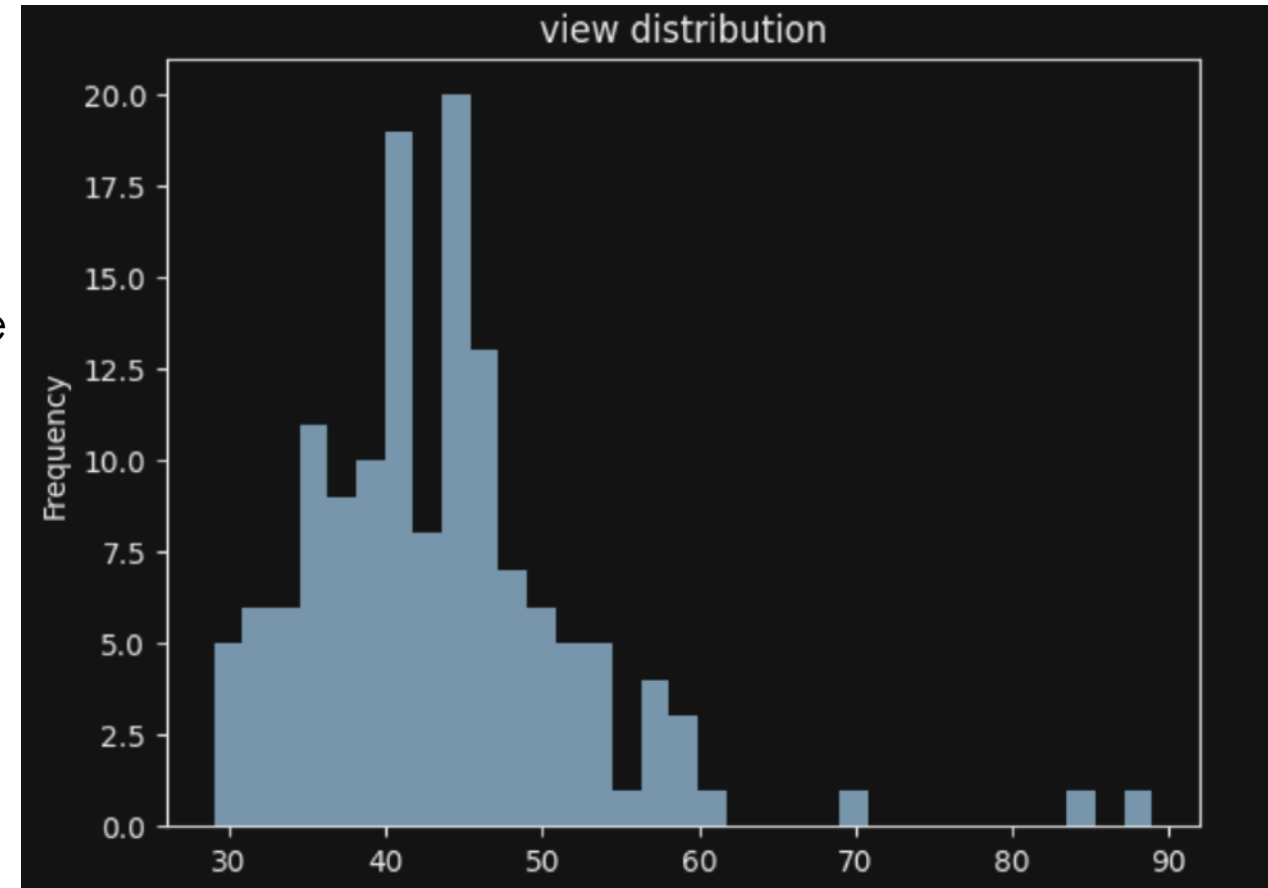
# Studying the distribution: Histograms

```
import matplotlib.pyplot as plt
```

```
ax = df['max_speed'].plot(kind='hist', bins=33, title='view distribution')
ax.x_label = "Max Speed"
ax.y_label = "Total number"
plt.show()
```

This will create an histogram dividing the data into 33 bins regularly paced

The image shows a generally normal distribution with a few outliers on the right hand side  
(the latter ones are elements of interest to investigate)



# Check the outliers

- Being an outlier does not mean being an error. Some outliers are just fully justified
  - check them one by one

```
df.loc[df['max_speed']>80]
```

In 9 1 `df.loc[df['max_speed']>80]`  
Executed at 2023.11.27 12:43:01 in 40ms

Out 9 ▾

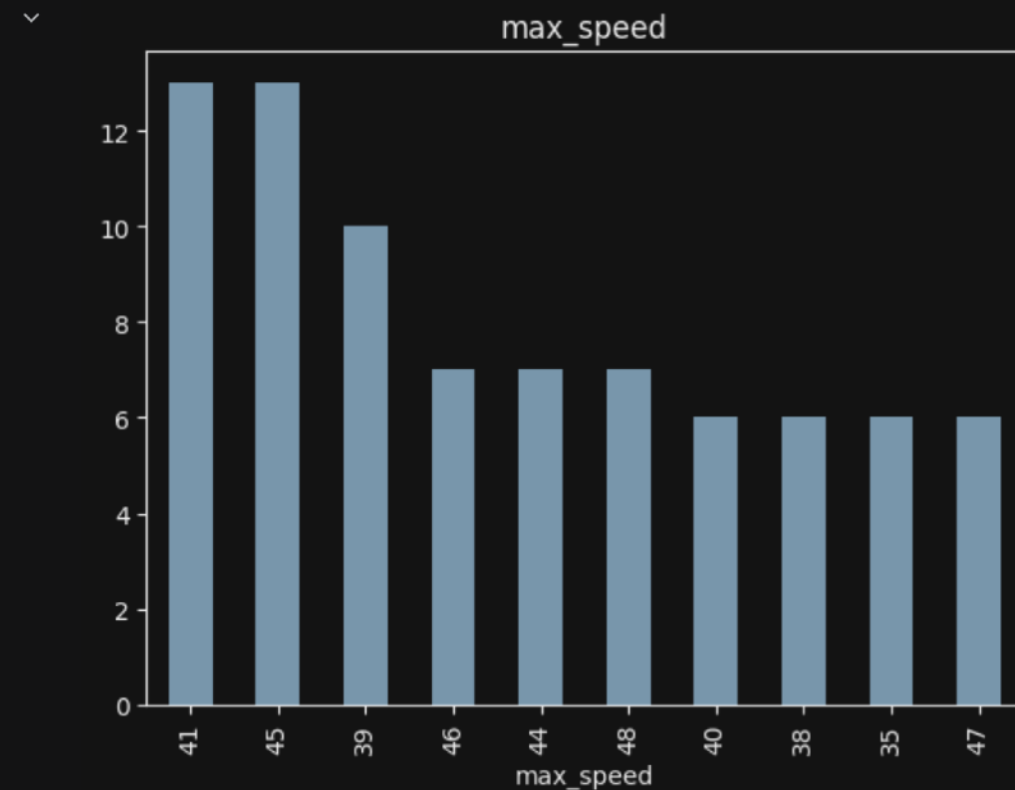
	park_id	theme	rollercoaster_type	custom_design	excitement	excite
66	19	Razor Rocks	Air Powered Vertical Coaster	0	8.42	Very H
85	21	Vertigo Views	Hypercoaster	0	9.48	Very H

```
axis = df['max_speed'].value_counts() \
        .head(10) \
        .plot(kind='bar', title="max_speed")
```

### Note!

The values on the x axis are sorted by the value of the y values

```
In 164 1 axis = df['max_speed'].value_counts() \
        2         .head(10) \
        3         .plot(kind='bar', title="max_speed")
        Executed at 2023.11.24 15:44:09 in 111ms
```



# How to fix the outliers"

- How to fix an outlier

- remove all elements above a specific reasonable manual value

```
df = df.loc[~df['max_speed']>1000]
```

- insert a reasonable manual value into these elements

```
df.loc[df['max_speed']>1000].max_speed = 1000
```

I have not checked these operations  
there may be minor errors

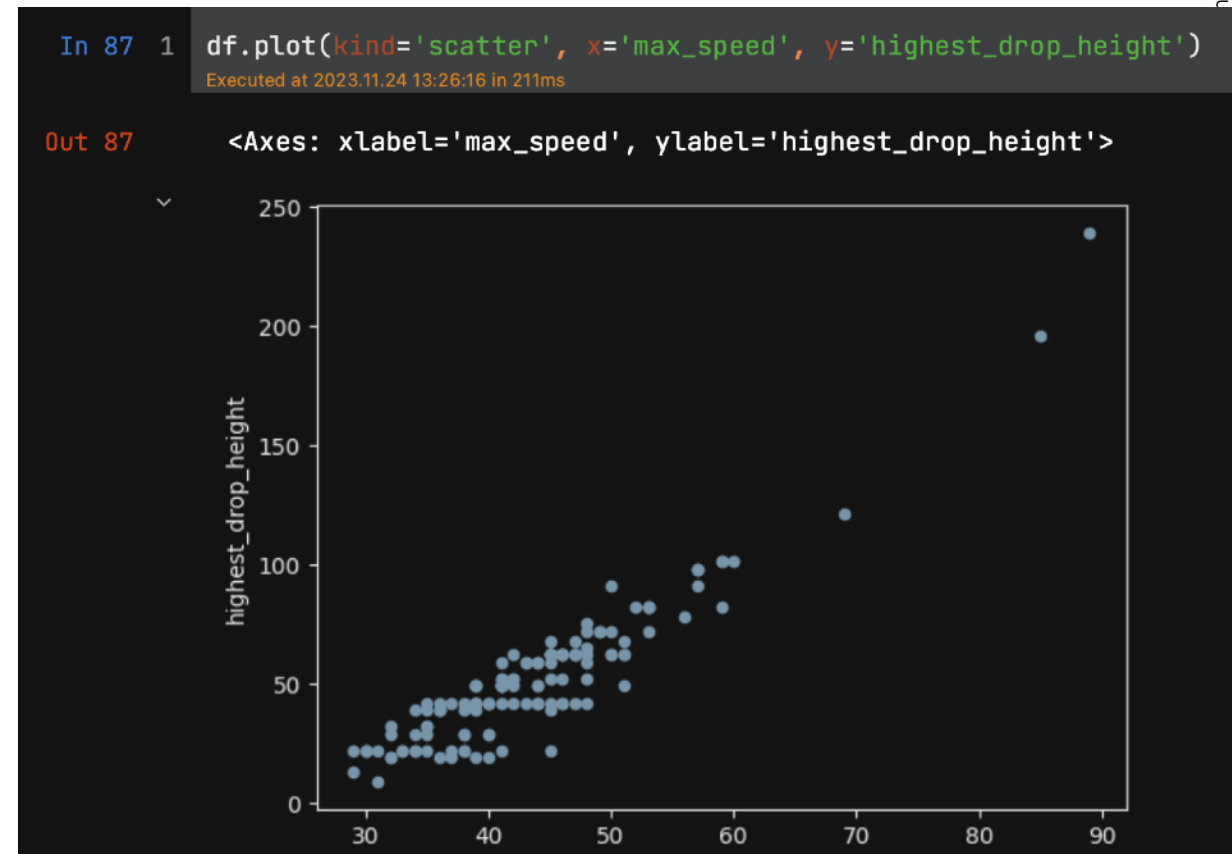


# Analysing correlations

- you can use scatterplots to see correlation between two variables (e.g. max speed and highest drop height)

```
df.plot(kind='scatter', x='max_speed', y='highest_drop_height')
```

- why you should use it?
  - a correlation between two variables is an important information about the data
    - it shows if two variables may be dependent or not
    - note! correlation is not causation!!!
      - it is just an hypothesis to be verified!



# Correlations using the confusion matrix

```
df[['nausea', 'excitement']].dropna().corr()
```

```
# correlations
```

In 166 1

```
df[['nausea', 'excitement']].dropna().corr()
```

Executed at 2023.11.24 15:47:03 in 38ms

Out 166 ▾

|< < 2 rows ▾ > >| 2 rows x 2 columns **pd.DataFrame** ▶

	nausea ▾	excitement ▾
nausea	1.000000	0.349712
excitement	0.349712	1.000000

# Group by and aggregation

- Grouping allow to study the rows that meet a specific condition, e.g. the same value on a column

```
df.groupby('theme')
```

- Groups can be described (as we did for columns)

```
df.groupby('theme').describe()
```

Out 97

30 rows x 128 columns <code>pd.DataFrame</code>							CSV			
theme	park_id count	mean	std	min	25%	50%				
Adrenaline Heights	6.0	29.0	0.000000	29.0	29.0	29.0				
Arid Heights	9.0	20.0	0.000000	20.0	20.0	20.0				
Barony Bridge	4.0	0.0	0.000000	0.0	0.0	0.0				
Botany Breakers	8.0	30.0	0.000000	30.0	30.0	30.0				
Bumbly Bazaar	4.0	24.0	0.000000	24.0	24.0	24.0				
Butterfly Dam	3.0	17.0	0.000000	17.0	17.0	17.0				

# Groups by multiple columns values

```
df.groupby(['country_of_origin', 'programming_language']).describe()
```

In 170 1 `df.groupby(['country_of_origin', 'programming_language']).describe()`

2

Executed at 2023.11.24 15:51:56 in 28ms

Out 170

10 rows x 4 columns <code>pd.DataFrame</code>					CSV			
		experience count	unique	top				
country_of_origin	programming_language							
Italy	Python	1	1	pro				
Nigeria	Java	2	2	good				
	Python	1	1	good				
The Netherlands	Javascript	1	1	good				
	Kotlin	2	2	good				

# getting a group

```
df.groupby('country_of_origin').get_group('USA')
```

- it returns a group that can be accessed as a data frame

In 133 1 `df.groupby('country_of_origin').get_group('USA')`

Executed at 2023.11.24 13:51:44 in 18ms

Out 133 ▾

2 rows × 3 columns <code>pd.DataFrame</code>					CSV ▾	⬇
	programming_language	country_of_origin	experience			
0	Pyhon	USA	intermediate			
4	Javascript	USA	intermediate			

- e.g.

```
df.groupby('country_of_origin').get_group('Nigeria')['experience'].value_counts()
```

# A complex example

```
# Filter the DataFrame for programmers who know Kotlin
kotlin_programmers = df[df['programming_language'] == 'Kotlin']

# Group by country and count Kotlin programmers for each country
kotlin_programmers_by_country =
kotlin_programmers.groupby('country_of_origin').size().reset_index(
    name='kotlin_programmers_count')

# Calculate the total programmers for each country
total_programmers_by_country =
df.groupby('country_of_origin').size().reset_index(name='total_programmers')

# Merge the two dataframes on 'country_of_origin'
merged_df = pd.merge(kotlin_programmers_by_country, total_programmers_by_country,
on='country_of_origin')

# Calculate the percentage for each country
merged_df['percentage_kotlin_programmers'] = (merged_df['kotlin_programmers_count'] / merged_df[
    'total_programmers']) * 100
merged_df
```



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# Questions?

