



03

Pandas, Matplotlib & Seaborn

Pandas

Pandas is a package commonly used to deal with data analysis. It simplifies the loading of data from external sources such as text files and databases, as well as providing ways of analyzing and manipulating them (its features simplify a lot of the common tasks that would take many lines of code to write in the basic Python language). Pandas just like NumPy is written internally in C so it can work fast to process large datasets. Pandas is best suited for structured, labelled data, in other words, tabular data, that has headings associated with each column of data. The official Pandas website describes Pandas' data-handling strengths as:

- Tabular data with heterogeneously-typed columns, as in an SQL table or Excel spreadsheet.
- Ordered and unordered (not necessarily fixed-frequency) time series data.
- Arbitrary matrix data (homogeneously typed or heterogeneous) with row and column labels.
- Any other form of observational / statistical data sets. The data actually need not be labelled at all to be placed into a pandas data structure.

Pandas Data Structure

- Series

Series is a one-dimensional labelled data structure which can hold data such as strings, integers and even other Python objects.

index	values
A	6
B	3.14
C	-4
D	0

- DataFrame

DataFrame is composed of one or more Series. The names of the Series form the column names, and the row labels form the Index.

<i>index</i>	←	<i>columns</i>	→
	foo	bar	baz
A	x	6	True
B	y	10	True
C	z	NaN	False

Creating Create

```
import pandas as pd
s1 = pd.Series([1, 2, 3, 4])
s2 = pd.Series([1, 2, 3, 4], index=['A', 'B', 'C', 'D'])
```

s1		s2	
0	1	A	1
1	2	B	2
2	3	C	3
3	4	D	4
dtype: int64		dtype: int64	

Column Selection

df	df['foo']	df['bar']
	0 x 1 y 2 z Name: foo, dtype: object	0 6.0 1 10.0 2 NaN Name: bar, dtype: float64
	df['baz']	df[['foo', 'bar']]
	0 True 1 True 2 False Name: baz, dtype: bool	foo bar 0 x 6.0 1 y 10.0 2 z NaN

Creating Dataframe

```
df = pd.DataFrame({
    'foo': ['x', 'y', 'z'],
    'bar': [6, 10, None],
    'baz': [True, True, False]
})
```

df

	foo	bar	baz
0	x	6.0	True
1	y	10.0	True
2	z	NaN	False

Conditional Filtering

df	df[df['baz']]
	foo bar baz
0 x 6.0 True	0 x 6.0 True
1 y 10.0 True	1 y 10.0 True
2 z NaN False	
	df[(df['foo'] == 'x') (df['foo'] == 'z')]
	foo bar baz
	0 x 6.0 True
	2 z NaN False

Row Selection

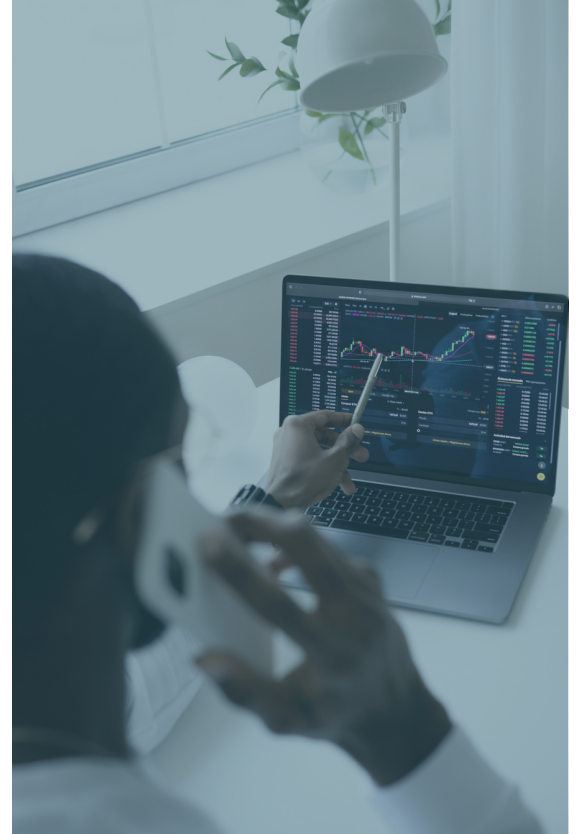
df	df.loc[0]	df.loc[1:2]
	foo x bar 6.0 baz True Name: 0, dtype: object	foo bar baz 1 y 10.0 True 2 z NaN False

Data Alignment

index_names = ['A', 'B', 'C', 'D', 'E']	df1	df2	df1+df2
df1 = pd.DataFrame({ 'a': [0, 1, 2, 3], 'b': [1, 2, 3, 4], 'c': [2, 3, 4, 5]}, index=index_names[0:4])	a b c A 0 1 2 B 1 2 3 C 2 3 4 D 3 4 5	a b A 0 1 B 1 2 C 2 3 D 3 4 E 4 5	a b c A 0.0 2.0 NaN B 2.0 4.0 NaN C 4.0 6.0 NaN D 6.0 8.0 NaN E NaN NaN NaN
df2 = pd.DataFrame({ 'a': [0, 1, 2, 3, 4], 'b': [1, 2, 3, 4, 5]}, index=index_names)			

Handling Missing Values

df	Drop row(s) that contain Null new_df = df.dropna() new_df	Drop column(s) that contain Null new_df = df.dropna(axis=1) new_df																																	
<table border="1"> <thead> <tr><th>foo</th><th>bar</th><th>baz</th></tr> </thead> <tbody> <tr><td>0</td><td>x</td><td>6.0 True</td></tr> <tr><td>1</td><td>y</td><td>10.0 True</td></tr> <tr><td>2</td><td>z</td><td>NaN False</td></tr> </tbody> </table>	foo	bar	baz	0	x	6.0 True	1	y	10.0 True	2	z	NaN False	<table border="1"> <thead> <tr><th>foo</th><th>bar</th><th>baz</th></tr> </thead> <tbody> <tr><td>0</td><td>x</td><td>6.0 True</td></tr> <tr><td>1</td><td>y</td><td>10.0 True</td></tr> </tbody> </table>	foo	bar	baz	0	x	6.0 True	1	y	10.0 True	<table border="1"> <thead> <tr><th>foo</th><th>bar</th><th>baz</th></tr> </thead> <tbody> <tr><td>0</td><td>x</td><td>6.0 True</td></tr> <tr><td>1</td><td>y</td><td>10.0 True</td></tr> <tr><td>2</td><td>z</td><td>0.0 False</td></tr> </tbody> </table>	foo	bar	baz	0	x	6.0 True	1	y	10.0 True	2	z	0.0 False
foo	bar	baz																																	
0	x	6.0 True																																	
1	y	10.0 True																																	
2	z	NaN False																																	
foo	bar	baz																																	
0	x	6.0 True																																	
1	y	10.0 True																																	
foo	bar	baz																																	
0	x	6.0 True																																	
1	y	10.0 True																																	
2	z	0.0 False																																	



Indexing

Use:

- `iloc[]` to select rows and columns by their position
- `loc[]` to select by name

df = pd.DataFrame({ 'foo': ['a', 'b', 'c', 'd'], 'bar': [6, 10, -2, 1], 'baz': [True, True, False, True] })	df	df.index															
	<table border="1"> <thead> <tr><th>foo</th><th>bar</th><th>baz</th></tr> </thead> <tbody> <tr><td>0</td><td>a</td><td>6 True</td></tr> <tr><td>1</td><td>b</td><td>10 True</td></tr> <tr><td>2</td><td>c</td><td>-2 False</td></tr> <tr><td>3</td><td>d</td><td>1 True</td></tr> </tbody> </table>	foo	bar	baz	0	a	6 True	1	b	10 True	2	c	-2 False	3	d	1 True	RangeIndex(start=0, stop=4, step=1)
foo	bar	baz															
0	a	6 True															
1	b	10 True															
2	c	-2 False															
3	d	1 True															

df = df.set_index('foo')
df

df.loc['a']

df.iloc[0]

	bar	baz
foo		
a	6	True
b	10	True
c	-2	False
d	1	True

bar	6
baz	True

Name: a, dtype: object

bar	6
baz	True

Name: a, dtype: object

df = df.set_index(['one', 'one', 'two', 'two'], df.index)
df

one = df.loc['one']
one

	bar	baz
foo		
a	6	True
b	10	True
c	-2	False
d	1	True

a	6	True
b	10	True

Data Visualization



The human brain excels at finding patterns in visual representations of the data; so in this section, we will learn how to visualize data that will help us better understand our data.

Python features many libraries that provide useful tools for visualization.

The most well-known, Matplotlib, enables users to generate visualizations like histograms, scatterplots, bar charts, pie charts and much more.

Seaborn is another useful visualization library that is built on top of Matplotlib. It provides data visualizations that are typically more aesthetic and statistically sophisticated.

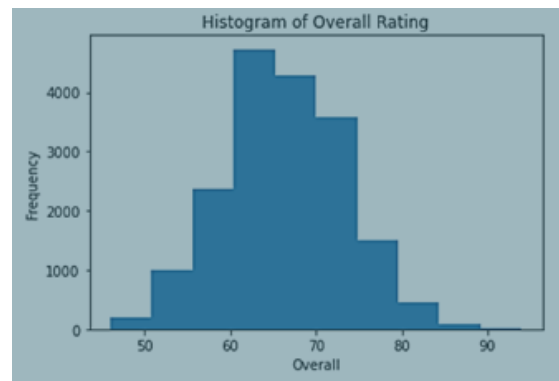
Having a solid understanding of how to use both of these libraries is essential for any data scientist or data analyst as they both provide easy methods for visualizing data for insight.

- Generating histograms

When analyzing a new data set, researchers are often interested in the distribution of values for a set of columns. One way to do so is through a histogram.

```
import matplotlib.pyplot as plt
df = pd.read_csv('fifa_e19.csv')
df.head()
```

	ID	Name	Age	Nationality	Overall	Potential	Club	Value	Wage
0	158023	L. Messi	31	Argentina	94	94	FC Barcelona	110500.0	565.0
1	20801	Cristiano Ronaldo	33	Portugal	94	94	Juventus	77000.0	405.0
2	190871	Neymar Jr	26	Brazil	92	93	Paris Saint-Germain	118500.0	290.0
3	193080	De Gea	27	Spain	91	93	Manchester United	72000.0	260.0
4	192985	K. De Bruyne	27	Belgium	91	92	Manchester City	102000.0	355.0

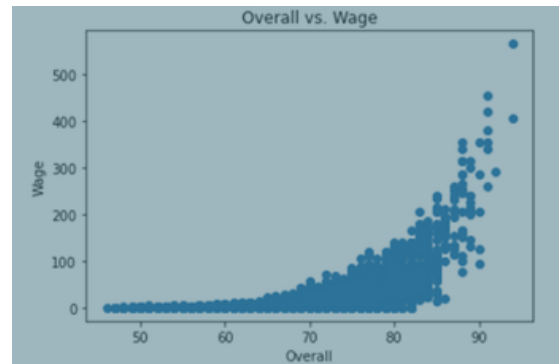


```
plt.hist(df['Overall'])
plt.xlabel('Overall')
plt.ylabel('Frequency')
plt.title('Histogram of Overall Rating')
plt.show()
```

- Generating scatterplots

Scatterplots are a useful data visualization tool that helps with identifying variable dependence.

```
plt.scatter(df['Overall'], df['Wage'])
plt.title('Overall vs. Wage')
plt.ylabel('Wage')
plt.xlabel('Overall')
plt.show()
```



- Generating bar charts

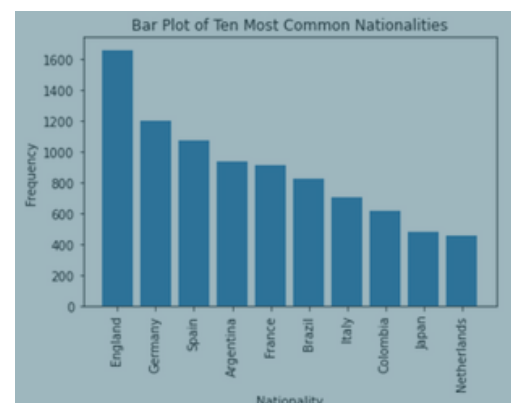
Bar charts are another useful visualization tool for analyzing categories in data. For example, we want to see the most common nationalities found in our FIFA19 data set.

```
# creating new series of no. of players based on their nationality
nationality_count = df.Nationality.value_counts()
nationality_count
```

England	1662
Germany	1198
Spain	1072
Argentina	937
France	914
...	
Puerto Rico	1
Fiji	1
St Lucia	1
Palestine	1
Lebanon	1

Name: Nationality, Length: 164, dtype: int64

```
plt.bar(nationality_count.index[0:10], nationality_count.values[0:10]) # we only look at the first 10
plt.xlabel('Nationality')
plt.ylabel('Frequency')
plt.title('Bar Plot of Ten Most Common Nationalities')
plt.xticks(rotation=90)
plt.show()
```



- Generating pie charts

Pie charts are a useful way to visualize proportions in your data. For example, in this data set, we can use a pie chart to visualize the proportion of players from England, Germany and Spain.

```
# add column named Nationality2
# assign value to each row satisfying the condition
# loc[rows where the condition is satisfied, column]
# here we create 4 categories of Nationality2

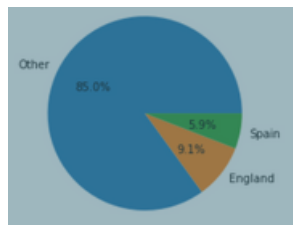
df.loc[df.Nationality == 'England', 'Nationality2'] = 'England'
df.loc[df.Nationality == 'Spain', 'Nationality2'] = 'Spain'
df.loc[df.Nationality == 'Germany', 'Nationality2'] = 'Germany'
df.loc[~df.Nationality.isin(['England', 'German', 'Spain']), 'Nationality2'] = 'Other'

# count values in Nationality2 column
nationality2_count = df['Nationality2'].value_counts()
# same as df.value_counts(['Nationality2']) or df.Nationality2.value_counts()
nationality2_count
```

Other	15473
England	1662
Spain	1072

Name: Nationality2, dtype: int64

```
plt.pie(nationality2_count, labels=nationality2_count.index,
        autopct='%1.1f%%')
plt.show()
```



Seaborn



Seaborn is a library built on top of Matplotlib that enables more sophisticated visualization and aesthetic plot formatting. Once you've mastered Matplotlib, you may want to move up to Seaborn for more complex visualizations. For example, simply using the Seaborn `set()` method can dramatically improve the appearance of your Matplotlib plots. Let's take a look.

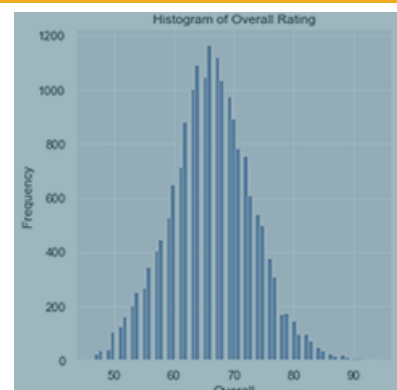
First, import Seaborn as `sns`

```
import seaborn as sns
```

- Generating histograms

We can also generate all of the same visualizations we did in Matplotlib using Seaborn. To regenerate our histogram of the overall column, we use the `displot` method on the Seaborn object:

```
sns.displot(df['Overall'])
plt.xlabel('Overall')
plt.ylabel('Frequency')
plt.title('Histogram of Overall Rating')
plt.show()
```

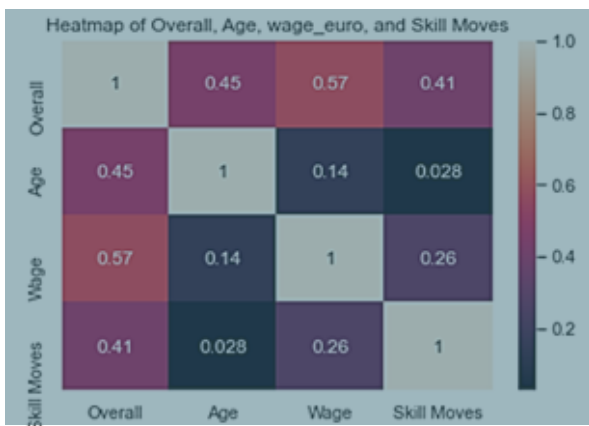


- Generating heatmaps

Seaborn is also known for making correlation heatmaps, which can be used to identify variable dependence. To generate one, first we need to calculate the correlation between a set of numerical columns. Let's do this for age, overall, wage_euro and skill moves.

These correlation values can help us selecting features later on when we learn more about machine learning. Features/variables with high correlation are more linearly dependent and hence have almost the same effect. So, when two features have high correlation, we can drop one of the two features.

```
corr = df[['Overall', 'Age', 'Wage', 'Skill Moves']].corr()
sns.heatmap(corr, annot=True)
plt.title('Heatmap of Overall, Age, wage_euro, and Skill Moves')
plt.show()
```



- Generating scatterplots

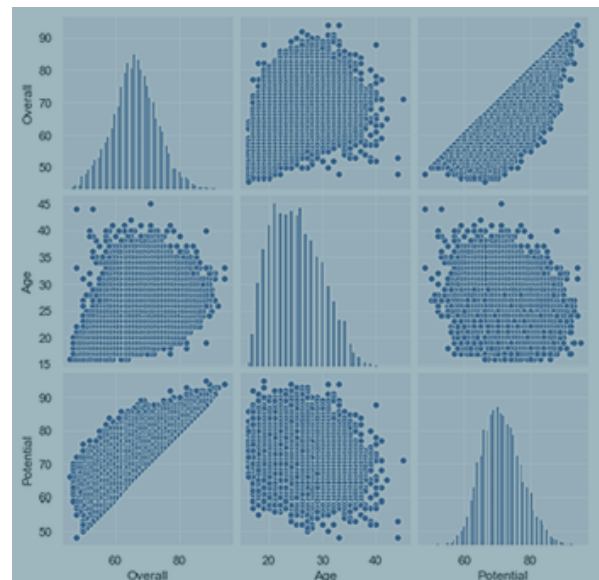
```
sns.scatterplot(x=df['Overall'], y=df['Wage'])
plt.title('Overall vs. Wage')
plt.ylabel('Wage')
plt.xlabel('Overall')
plt.show()
```



- Generating pair plots

The last Seaborn tool we'll discuss is the pairplot method. This allows you to generate a matrix of distributions and scatter plots for a set of numerical features. Let's do this for age, overall and potential:

```
data = df[['Overall', 'Age', 'Potential']]
sns.pairplot(data)
plt.show()
```



Picture Source

- https://upload.wikimedia.org/wikipedia/en/thumb/5/56/Matplotlib_logo.svg/2560px-Matplotlib_logo.svg.png
- https://seaborn.pydata.org/_static/logo-wide-lightbg.svg
- [pexels.com](https://www.pexels.com)