

Introduction to Data Science with Python

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Preface

This book is developed for the course STAT303-1 (Data Science with Python-1). The first two chapters of the book are a review of python, and will be covered very quickly. Students are expected to know the contents of these chapters beforehand, or be willing to learn it quickly. Students may use the STAT201 book (https://nustat.github.io/Intro_to_programming_for_data_sci/) to review the python basics required for the STAT303 sequence. The core part of the course begins from the third chapter - *Reading data*.

Please feel free to let the instructors know in case of any typos/mistakes/general feedback in this book.

Part I

Quick overview: Python programming

1 Introduction to Python and Jupyter Notebooks

This chapter is a very brief introduction to python and Jupyter notebooks. If you have not taken STAT201 (Introduction to programming for data science), which is now a pre-requisite for the data science major / minor program, please review the python programming section (chapters 1-6) from the [STAT201 book](#). It is assumed that you are already comfortable with this content. Some of the content of these chapters is reviewed briefly in the first two chapters of this book.

1.1 Installation

Anaconda: If you are new to python, we recommend downloading the [Anaconda installer](#) and following the instructions for installation. Once installed, we'll use the Jupyter Notebook interface to write code.

Quarto: We'll use Quarto to publish the *.ipynb* file containing text, python code, and the output. Download and install Quarto from [here](#).

1.2 Jupyter notebook

1.2.1 Introduction

Jupyter notebook is an interactive platform, where you can write code and text, and make visualizations. You can access Jupyter notebook from the Anaconda Navigator, or directly open the Jupyter Notebook application itself. It should automatically open up in your default browser. The figure below shows a Jupyter Notebook opened with Google Chrome. This page is called the *landing page* of the notebook.

```
<IPython.core.display.Image object>
```

To create a new notebook, click on the **New** button and select the **Python 3** option. You should see a blank notebook as in the figure below.

```
<IPython.core.display.Image object>
```

1.2.2 Writing and executing code

Code cell: By default, a cell is of type *Code*, i.e., for typing code, as seen as the default choice in the dropdown menu below the *Widgets* tab. Try typing a line of python code (say, `2+3`) in an empty code cell and execute it by pressing *Shift+Enter*. This should execute the code, and create a new code cell. Pressing *Ctrl+Enter for Windows (or Cmd+Enter for Mac)* will execute the code without creating a new cell.

Commenting code in a code cell: Comments should be made while writing the code to explain the purpose of the code or a brief explanation of the tasks being performed by the code. A comment can be added in a code cell by preceding it with a `#` sign. For example, see the comment in the code below.

Writing comments will help other users understand your code. It is also useful for the coder to keep track of the tasks being performed by their code.

```
#This code adds 3 and 5
3+5
```

8

Markdown cell: Although a comment can be written in a code cell, a code cell cannot be used for writing headings/sub-headings, and is not appropriate for writing lengthy chunks of text. In such cases, change the cell type to *Markdown* from the dropdown menu below the *Widgets* tab. Use any markdown cheat sheet found online, for example, [this one](#) to format text in the markdown cells.

Give a name to the notebook by clicking on the text, which says ‘Untitled’.

1.2.3 Saving and loading notebooks

Save the notebook by clicking on **File**, and selecting **Save as**, or clicking on the **Save and Checkpoint** icon (below the **File** tab). Your notebook will be saved as a file with an extension *ipynb*. This file will contain all the code as well as the outputs, and can be loaded and edited by a Jupyter user. To load an existing Jupyter notebook, navigate to the folder of the notebook on the *landing page*, and then click on the file to open it.

1.2.4 Rendering notebook as HTML

We'll use Quarto to print the `**ipynb*` file as HTML. Check the procedure for rendering a notebook as HTML [here](#). You have several options to format the file.

You will need to open the command prompt, navigate to the directory containing the file, and use the command: `quarto render filename.ipynb --to html`.

In-class exercise

1. Create a new notebook.
2. Save the file as `In_class_exercise1`.
3. Give a heading to the file - `First HTML file`.
4. Print `Today is day 1 of class`.
5. Compute and print the number of hours of this course in the quarter (that will be 10 weeks x 2 classes per week x 1.33 hours per class).

The HTML file should look like the picture below.

```
<IPython.core.display.Image object>
```

1.3 Python language basics

1.3.1 Object Oriented Programming

Python is an object-oriented programming language. In layman terms, it means that every number, string, data structure, function, class, module, etc., exists in the python interpreter as a python object. An object may have attributes and methods associated with it. For example, let us define a variable that stores an integer:

```
var = 2
```

The variable `var` is an object that has attributes and methods associated with it. For example a couple of its attributes are `real` and `imag`, which store the real and imaginary parts respectively, of the object `var`:

```
print("Real part of 'var': ",var.real)
print("Real part of 'var': ",var.imag)
```

```
Real part of 'var': 2
Real part of 'var': 0
```

Attribute: An attribute is a value associated with an object, defined within the class of the object.

Method: A method is a function associated with an object, defined within the class of the object, and has access to the attributes associated with the object.

For looking at attributes and methods associated with an object, say `obj`, press tab key after typing `obj..`

Consider the example below of a class *example_class*:

```
class example_class:
    class_name = 'My Class'
    def my_method(self):
        print('Hello World!')

e = example_class()
```

In the above class, `class_name` is an attribute, while `my_method` is a method.

1.3.2 Assigning variable name to object

When an object is assigned to a variable name, the variable name serves as a reference to the object. For example, consider the following assignment:

```
x = [5,3]
```

The variable name `x` is a reference to the memory location where the object `[5, 3]` is stored. Now, suppose we assign `x` to a new variable `y`:

```
y = x
```

In the above statement the variable name `y` now refers to the same object `[5,3]`. The object `[5,3]` does **not** get copied to a new memory location referred by `y`. To prove this, let us add an element to `y`:

```
y.append(4)
print(y)
```

```
[5, 3, 4]
```

```
print(x)
```

```
[5, 3, 4]
```

When we changed `y`, note that `x` also changed to the same object, showing that `x` and `y` refer to the same object, instead of referring to different copies of the same object.

1.3.3 Importing libraries

There are several [built-in functions](#) in python like `print()`, `abs()`, `max()`, `sum()` etc., which do not require importing any library. However, these functions will typically be insufficient for analyzing data. Some of the popular libraries and their primary purposes are as follows:

1. **NumPy**: Performing numerical operations and efficiently storing numerical data.
2. **Pandas**: Reading, cleaning and manipulating data.
3. **Matplotlib, Seaborn**: Visualizing data.
4. **SciPy**: Performing scientific computing such as solving differential equations, optimization, statistical tests, etc.
5. **Scikit-learn**: Data pre-processing and machine learning, with a focus on prediction.
6. **Statsmodels**: Developing statistical models with a focus on inference

A library can be imported using the `import` keyword. For example, a NumPy library can be imported as:

```
import numpy as np
```

Using the `as` keyword, the NumPy library has been given the name `np`. All the functions and attributes of the library can be called using the '`np.`' prefix. For example, let us generate a sequence of whole numbers upto 10 using the NumPy function `arange()`:

```
np.arange(8)
```

```
array([0, 1, 2, 3, 4, 5, 6, 7])
```

1.3.4 Built-in objects

There are several [built-in objects, modules and functions in python](#). Below are a few examples:

Scalar objects: Python has some built-in datatypes for handling scalar objects such as number, string, boolean values, and date/time. The built-in function `type()` function can be used to determine the datatype of an object:

```
var = 2.2
type(var)
```

float

range(): The `range()` function returns a sequence of evenly-spaced integer values. It is commonly used in `for` loops to define the sequence of elements over which the iterations are performed.

Below is an example where the `range()` function is used to create a sequence of whole numbers upto 10:

```
print(list(range(1,10)))
```

[1, 2, 3, 4, 5, 6, 7, 8, 9]

Date time: Python has a built-in `datetime` module for handling date/time objects:

```
import datetime as dt

#Defining a date-time object
dt_object = dt.datetime(2022, 9, 20, 11,30,0)
```

Information about date and time can be accessed with the relevant attribute of the `datetime` object.

```
dt_object.day
```

20

```
dt_object.year
```

2022

The `strftime` method of the `datetime` module formats a `datetime` object as a string. There are several types of formats for representing date as a string:

```
dt_object.strftime('%m/%d/%Y')
```

```
'09/20/2022'
```

```
dt_object.strftime('%m/%d/%y %H:%M')
```

```
'09/20/22 11:30'
```

```
dt_object.strftime('%h-%d-%Y')
```

```
'Sep-20-2022'
```

1.3.5 Control flow

As in other languages, python has [built-in keywords](#) that provide conditional flow of control in the code.

If-elif-else: The `if-elif-else` statement can check several conditions, and execute the code corresponding to the condition that is true. Note that there can be as many `elif` statements as required.

```
#Example of if-elif-else
x = 5
if x>0:
    print("x is positive")
elif x==0:
    print("x is zero")
else:
    print("X is negative")
    print("This was the last condition checked")
```

```
x is positive
```

for loop: A `for` loop iterates over the elements of an object, and executes the statements within the loop in each iteration. For example, below is a `for` loop that prints odd natural numbers upto 10:

```
for i in range(10):  
    if i%2!=0:  
        print(i)
```

1
3
5
7
9

while loop: A **while** loop iterates over a set of statements *while* a condition is satisfied. For example, below is a **while** loop that prints odd numbers upto 10:

```
i=0  
while i<10:  
    if i%2!=0:  
        print(i)  
    i=i+1
```

1
3
5
7
9

2 Data structures

In this chapter we'll learn about the python data structures that are often used or appear while analyzing data.

2.1 Tuple

Tuple is a sequence of python objects, with two key characteristics: (1) the number of objects are fixed, and (2) the objects are immutable, i.e., they cannot be changed.

Tuple can be defined as a sequence of python objects separated by commas, and enclosed in rounded brackets (). For example, below is a tuple containing three integers.

```
tuple_example = (2,7,4)
```

We can check the data type of a python object using the in-built python function *type()*. Let us check the data type of the object *tuple_example*.

```
type(tuple_example)
```

tuple

Elements of a tuple can be extracted using their index within square brackets. For example the second element of the tuple *tuple_example* can be extracted as follows:

```
tuple_example[1]
```

7

Note that an element of a tuple cannot be modified. For example, consider the following attempt in changing the second element of the tuple *tuple_example*.

```
tuple_example[1] = 8
```

```
TypeError: 'tuple' object does not support item assignment
```

The above code results in an error as tuple elements cannot be modified.

2.1.1 Concatenating tuples

Tuples can be concatenated using the `+` operator to produce a longer tuple:

```
(2,7,4) + ("another", "tuple") + ("mixed","datatypes",5)
```

```
(2, 7, 4, 'another', 'tuple', 'mixed', 'datatypes', 5)
```

Multiplying a tuple by an integer results in repetition of the tuple:

```
(2,7,"hi") * 3
```

```
(2, 7, 'hi', 2, 7, 'hi', 2, 7, 'hi')
```

2.1.2 Unpacking tuples

If tuples are assigned to an expression containing multiple variables, the tuple will be unpacked and each variable will be assigned a value as per the order in which it appears. See the example below.

```
x,y,z = (4.5, "this is a string", (("Nested tuple",5)))
```

```
x
```

```
4.5
```

```
y
```

```
'this is a string'
```

```
z
```

```
('Nested tuple', 5)
```

If we are interested in retrieving only some values of the tuple, the expression `*_` can be used to discard the other values. Let's say we are interested in retrieving only the first and the last two values of the tuple:

```
x,*_,y,z = (4.5, "this is a string", ("Nested tuple",5)), "99", 99)
```

```
x
```

```
4.5
```

```
y
```

```
'99'
```

```
z
```

```
99
```

2.1.3 Tuple methods

A couple of useful tuple methods are `count`, which counts the occurrences of an element in the tuple and `index`, which returns the position of the first occurrence of an element in the tuple:

```
tuple_example = (2,5,64,7,2,2)
```

```
tuple_example.count(2)
```

```
3
```

```
tuple_example.index(2)
```

```
0
```

Now that we have an idea about tuple, let us try to think where it can be used.

```
<IPython.core.display.HTML object>
```

2.2 List

List is a sequence of python objects, with two key characteristics that differentiates it from tuple: (1) the number of objects are variable, i.e., objects can be added or removed from a list, and (2) the objects are mutable, i.e., they can be changed.

List can be defined as a sequence of python objects separated by commas, and enclosed in square brackets []. For example, below is a list consisting of three integers.

```
list_example = [2,7,4]
```

2.2.1 Adding and removing elements in a list

We can add elements at the end of the list using the *append* method. For example, we append the string 'red' to the list *list_example* below.

```
list_example.append('red')
```

```
list_example
```

```
[2, 7, 4, 'red']
```

Note that the objects of a list or a tuple can be of different datatypes.

An element can be added at a specific location of the list using the *insert* method. For example, if we wish to insert the number 2.32 as the second element of the list *list_example*, we can do it as follows:

```
list_example.insert(1,2.32)
```

```
list_example
```

```
[2, 2.32, 7, 4, 'red']
```

For removing an element from the list, the *pop* and *remove* methods may be used. The *pop* method removes an element at a particular index, while the *remove* method removes the element's first occurrence in the list by its value. See the examples below.

Let us say, we need to remove the third element of the list.

```
list_example.pop(2)
```

```
7
```

```
list_example
```

```
[2, 2.32, 4, 'red']
```

Let us say, we need to remove the element 'red'.

```
list_example.remove('red')
```

```
list_example
```

```
[2, 2.32, 4]
```

```
#If there are multiple occurrences of an element in the list, the first occurrence will be removed
list_example2 = [2,3,2,4,4]
list_example2.remove(2)
list_example2
```

```
[3, 2, 4, 4]
```

For removing multiple elements in a list, either *pop* or *remove* can be used in a *for* loop, or a *for* loop can be used with a condition. See the examples below.

Let's say we need to remove integers less than 100 from the following list.

```
list_example3 = list(range(95,106))
list_example3
```

[95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105]

```
#Method 1: For loop with remove
list_example3_filtered = list(list_example3) #
for element in list_example3:
    if element<100:
        list_example3_filtered.remove(element)
print(list_example3_filtered)
```

[100, 101, 102, 103, 104, 105]

Q1: What's the need to define a new variable `list_example3_filtered` in the above code?

A1: Replace `list_example3_filtered` with `list_example3` and identify the issue.

```
#Method 2: For loop with condition
[element for element in list_example3 if element>=100]
```

[100, 101, 102, 103, 104, 105]

2.2.2 List comprehensions

List comprehension is a compact way to create new lists based on elements of an existing list.

Example: Create a list that has squares of natural numbers from 5 to 15.

```
sqrt_natural_no_5_15 = [(x**2) for x in range(5,16)]
print(sqrt_natural_no_5_15)
```

[25, 36, 49, 64, 81, 100, 121, 144, 169, 196, 225]

Example: Create a list of tuples, where each tuple consists of a natural number and its square, for natural numbers ranging from 5 to 15.

```
sqrt_natural_no_5_15 = [(x,x**2) for x in range(5,16)]  
print(sqrt_natural_no_5_15)
```

$[(5, 25), (6, 36), (7, 49), (8, 64), (9, 81), (10, 100), (11, 121), (12, 144), (13, 169), (14, 196), (15, 225), (16, 256), (17, 289), (18, 324), (19, 361), (20, 400), (21, 441), (22, 484), (23, 529), (24, 576), (25, 625), (26, 676), (27, 729), (28, 784), (29, 841), (30, 900), (31, 961), (32, 1024), (33, 1089), (34, 1156), (35, 1225), (36, 1296), (37, 1369), (38, 1444), (39, 1521), (40, 1600), (41, 1681), (42, 1764), (43, 1849), (44, 1936), (45, 2025), (46, 2116), (47, 2209), (48, 2304), (49, 2401), (50, 2500), (51, 2601), (52, 2704), (53, 2809), (54, 2916), (55, 3025), (56, 3136), (57, 3249), (58, 3364), (59, 3481), (60, 3600), (61, 3721), (62, 3844), (63, 3969), (64, 4096), (65, 4225), (66, 4356), (67, 4489), (68, 4624), (69, 4761), (70, 4900), (71, 5041), (72, 5184), (73, 5329), (74, 5476), (75, 5625), (76, 5776), (77, 5929), (78, 6084), (79, 6241), (80, 6400), (81, 6561), (82, 6724), (83, 6889), (84, 7056), (85, 7225), (86, 7396), (87, 7569), (88, 7744), (89, 7921), (90, 8100), (91, 8281), (92, 8464), (93, 8649), (94, 8836), (95, 9025), (96, 9216), (97, 9409), (98, 9604), (99, 9801), (100, 10000)]$

2.2.3 Practice exercise 1

Below is a list consisting of responses to the question: “At what age do you think you will marry?” from students of the STAT303-1 Fall 2022 class.

```
exp_marriage_age=['24','30','28','29','30','27','26','28','30+', '26','28','30','30','30',
```

Use list comprehension to:

2.2.3.1

Remove the elements that are not integers - such as *'probably never'*, *'30+'*, etc. What is the length of the new list?

Hint: The built-in python function of the `str` class - `isdigit()` may be useful to check if the string contains only digits.

Solution:

```
exp_marriage_age_num = [x for x in exp_marriage_age if x.isdigit()==True]
print("Length of the new list = ",len(exp_marriage_age_num))
```

Length of the new list = 181

2.2.3.2

Cap the values greater than 80 to 80, in the clean list obtained in (1). What is the mean age when people expect to marry in the new list?

```
exp_marriage_age_capped = [min(int(x),80) for x in exp_marriage_age_num]
print("Mean age when people expect to marry = ", sum(exp_marriage_age_capped)/len(exp_marriage_age_capped))
```

Mean age when people expect to marry = 28.955801104972377

2.2.3.3

Determine the percentage of people who expect to marry at an age of 30 or more.

```
print("Percentage of people who expect to marry at an age of 30 or more =", str(100*sum([1
```

Percentage of people who expect to marry at an age of 30 or more = 37.01657458563536 %

2.2.4 Concatenating lists

As in tuples, lists can be concatenated using the + operator:

```
import time as tm

list_example4 = [5,'hi',4]
list_example4 = list_example4 + [None,'7',9]
list_example4
```

[5, 'hi', 4, None, '7', 9]

For adding elements to a list, the **extend** method is preferred over the + operator. This is because the + operator creates a new list, while the **extend** method adds elements to an existing list. Thus, the **extend** operator is more memory efficient.

```
list_example4 = [5,'hi',4]
list_example4.extend([None, '7', 9])
list_example4
```

[5, 'hi', 4, None, '7', 9]

2.2.5 Sorting a list

A list can be sorted using the **sort** method:

```
list_example5 = [6,78,9]
list_example5.sort(reverse=True) #the reverse argument is used to specify if the sorting i
list_example5
```

[78, 9, 6]

2.2.6 Slicing a list

We may extract or update a section of the list by passing the starting index (say **start**) and the stopping index (say **stop**) as **start:stop** to the index operator []. This is called *slicing* a list. For example, see the following example.

```
list_example6 = [4,7,3,5,7,1,5,87,5]
```

Let us extract a slice containing all the elements from the 3rd position to the 7th position.

```
list_example6[2:7]
```

```
[3, 5, 7, 1, 5]
```

Note that while the element at the **start** index is included, the element with the **stop** index is excluded in the above slice.

If either the **start** or **stop** index is not mentioned, the slicing will be done from the beginning or until the end of the list, respectively.

```
list_example6[:7]
```

```
[4, 7, 3, 5, 7, 1, 5]
```

```
list_example6[2:]
```

```
[3, 5, 7, 1, 5, 87, 5]
```

To slice the list relative to the end, we can use negative indices:

```
list_example6[-4:]
```

```
[1, 5, 87, 5]
```

```
list_example6[-4:-2:]
```

```
[1, 5]
```

An extra colon (':') can be used to slice every *n*th element of a list.

```
#Selecting every 3rd element of a list  
list_example6[::3]
```

[4, 5, 5]

```
#Selecting every 3rd element of a list from the end  
list_example6[::-3]
```

[5, 1, 3]

```
#Selecting every element of a list from the end or reversing a list  
list_example6[::-1]
```

[5, 87, 5, 1, 7, 5, 3, 7, 4]

2.2.7 Practice exercise 2

Start with the list [8,9,10]. Do the following:

2.2.7.1

Set the second entry (index 1) to 17

```
L = [8,9,10]  
L[1]=17
```

2.2.7.2

Add 4, 5, and 6 to the end of the list

```
L = L+[4,5,6]
```

2.2.7.3

Remove the first entry from the list

```
L.pop(0)
```

8

2.2.7.4

Sort the list

```
L.sort()
```

2.2.7.5

Double the list (concatenate the list to itself)

```
L=L+L
```

2.2.7.6

Insert 25 at index 3

The final list should equal [4,5,6,25,10,17,4,5,6,10,17]

```
L.insert(3,25)  
L
```

```
[4, 5, 6, 25, 10, 17, 4, 5, 6, 10, 17]
```

Now that we have an idea about lists, let us try to think where it can be used.

<IPython.core.display.HTML object>

Now that we have learned about lists and tuples, let us compare them.

Q2: A list seems to be much more flexible than tuple, and can replace a tuple almost everywhere. Then why use tuple at all?

A2: The additional flexibility of a list comes at the cost of efficiency. Some of the advantages of a tuple over a list are as follows:

1. Since a list can be extended, space is over-allocated when creating a list. A tuple takes less storage space as compared to a list of the same length.
2. Tuples are not copied. If a tuple is assigned to another tuple, both tuples point to the same memory location. However, if a list is assigned to another list, a new list is created consuming the same memory space as the original list.
3. Tuples refer to their element directly, while in a list, there is an extra layer of pointers that refers to their elements. Thus it is faster to retrieve elements from a tuple.

The examples below illustrate the above advantages of a tuple.

```
#Example showing tuples take less storage space than lists for the same elements
tuple_ex = (1, 2, 'Obama')
list_ex = [1, 2, 'Obama']
print("Space taken by tuple =",tuple_ex.__sizeof__()," bytes")
print("Space taken by list =",list_ex.__sizeof__()," bytes")
```

Space taken by tuple = 48 bytes
 Space taken by list = 64 bytes

```
#Examples showing that a tuples are not copied, while lists can be copied
tuple_copy = tuple(tuple_ex)
print("Is tuple_copy same as tuple_ex?", tuple_ex is tuple_copy)
list_copy = list(list_ex)
print("Is list_copy same as list_ex?",list_ex is list_copy)
```

Is tuple_copy same as tuple_ex? True
 Is list_copy same as list_ex? False

```
#Examples showing tuples takes lesser time to retrieve elements
import time as tm
tt = tm.time()
list_ex = list(range(1000000)) #List containinig whole numbers upto 1 million
a=(list_ex[::-2])
print("Time take to retrieve every 2nd element from a list = ", tm.time()-tt)

tt = tm.time()
tuple_ex = tuple(range(1000000)) #tuple containinig whole numbers upto 1 million
a=(tuple_ex[::-2])
print("Time take to retrieve every 2nd element from a tuple = ", tm.time()-tt)
```

```
Time take to retrieve every 2nd element from a list = 0.03579902648925781
Time take to retrieve every 2nd element from a tuple = 0.02684164047241211
```

2.3 Dictionary

A dictionary consists of key-value pairs, where the keys and values are python objects. While values can be any python object, keys need to be immutable python objects, like strings, intergers, tuples, etc. Thus, a list can be a value, but not a key, as elements of list can be changed. A dictionary is defined using the keyword `dict` along with curly braces, colons to separate keys and values, and commas to separate elements of a dictionary:

```
dict_example = {'USA': 'Joe Biden', 'India': 'Narendra Modi', 'China': 'Xi Jinping'}
```

Elements of a dictionary can be retrieved by using the corresponding key.

```
dict_example['India']
```

```
'Narendra Modi'
```

2.3.1 Adding and removing elements in a dictionary

New elements can be added to a dictionary by defining a key in square brackets and assigning it to a value:

```
dict_example['Japan'] = 'Fumio Kishida'
dict_example['Countries'] = 4
dict_example
```

```
{'USA': 'Joe Biden',
 'India': 'Narendra Modi',
 'China': 'Xi Jinping',
 'Japan': 'Fumio Kishida',
 'Countries': 4}
```

Elements can be removed from the dictionary using the `del` method or the `pop` method:

```
#Removing the element having key as 'Countries'
del dict_example['Countries']
```

```
dict_example
```

```
{'USA': 'Joe Biden',  
 'India': 'Narendra Modi',  
 'China': 'Xi Jinping',  
 'Japan': 'Fumio Kishida'}
```

```
#Removing the element having key as 'USA'  
dict_example.pop('USA')
```

```
'Joe Biden'
```

```
dict_example
```

```
{'India': 'Narendra Modi', 'China': 'Xi Jinping', 'Japan': 'Fumio Kishida'}
```

New elements can be added, and values of existing keys can be changed using the `update` method:

```
dict_example = {'USA': 'Joe Biden', 'India': 'Narendra Modi', 'China': 'Xi Jinping', 'Countries': 3}  
dict_example
```

```
{'USA': 'Joe Biden',  
 'India': 'Narendra Modi',  
 'China': 'Xi Jinping',  
 'Countries': 3}
```

```
dict_example.update({'Countries': 4, 'Japan': 'Fumio Kishida'})
```

```
dict_example
```

```
{'USA': 'Joe Biden',  
 'India': 'Narendra Modi',  
 'China': 'Xi Jinping',  
 'Countries': 4,  
 'Japan': 'Fumio Kishida'}
```

2.3.2 Iterating over elements of a dictionary

The `items()` attribute of a dictionary can be used to iterate over elements of a dictionary.

```
for key,value in dict_example.items():  
    print("The Head of State of",key,"is",value)
```

```
The Head of State of USA is Joe Biden  
The Head of State of India is Narendra Modi  
The Head of State of China is Xi Jinping  
The Head of State of Countries is 4  
The Head of State of Japan is Fumio Kishida
```

2.3.3 Practice exercise 3

The GDP per capita of USA for most years from 1960 to 2021 is given by the dictionary D given in the code cell below.

Find:

1. The GDP per capita in 2015
2. The GDP per capita of 2014 is missing. Update the dictionary to include the GDP per capita of 2014 as the average of the GDP per capita of 2013 and 2015.
3. Impute the GDP per capita of other missing years in the same manner as in (2), i.e., as the average GDP per capita of the previous year and the next year. Note that the GDP per capita is not missing for any two consecutive years.
4. Print the years and the imputed GDP per capita for the years having a missing value of GDP per capita in (3).

```
D = {'1960':3007,'1961':3067,'1962':3244,'1963':3375,'1964':3574,'1965':3828,'1966':4146,'
```

Solution:

```
print("GDP per capita in 2015 =", D['2015'])  
D['2014'] = (D['2013']+D['2015'])/2  
for i in range(1960,2021):  
    if str(i) not in D.keys():  
        D[str(i)] = (D[str(i-1)]+D[str(i+1)])/2  
        print("Imputed GDP per capita for the year",i,"is $",D[str(i)])
```

GDP per capita in 2015 = 56763
Imputed GDP per capita for the year 1969 is \$ 4965.0
Imputed GDP per capita for the year 1977 is \$ 9578.5
Imputed GDP per capita for the year 1999 is \$ 34592.0

2.4 Functions

If an algorithm or block of code is being used several times in a code, then it can be separately defined as a function. This makes the code more organized and readable. For example, let us define a function that prints prime numbers between *a* and *b*, and returns the number of prime numbers found.

```
#Function definition
def prime_numbers (a,b=100):
    num_prime_nos = 0

    #Iterating over all numbers between a and b
    for i in range(a,b):
        num_divisors=0

        #Checking if the ith number has any factors
        for j in range(2, i):
            if i%j == 0:
                num_divisors=1;break;

        #If there are no factors, then printing and counting the number as prime
        if num_divisors==0:
            print(i)
            num_prime_nos = num_prime_nos+1

    #Return count of the number of prime numbers
    return num_prime_nos
```

In the above function, the keyword `def` is used to define the function, `prime_numbers` is the name of the function, *a* and *b* are the arguments that the function uses to compute the output.

Let us use the defined function to print and count the prime numbers between 40 and 60.

```
#Printing prime numbers between 40 and 60
num_prime_nos_found = prime_numbers(40,60)
```


41
43
47
53
59

```
num_prime_nos_found
```

5

If the user calls the function without specifying the value of the argument `b`, then it will take the default value of 100, as mentioned in the function definition. However, for the argument `a`, the user will need to specify a value, as there is no value defined as a default value in the function definition.

2.4.1 Global and local variables with respect to a function

A variable defined within a function is local to that function, while a variable defined outside the function is global to that function. In case a variable with the same name is defined both outside and inside a function, it will refer to its global value outside the function and local value within the function.

The example below shows a variable with the name `var` referring to its local value when called within the function, and global value when called outside the function.

```
var = 5
def sample_function(var):
    print("Local value of 'var' within 'sample_function()' = ",var)

sample_function(4)
print("Global value of 'var' outside 'sample_function()' = ",var)
```

```
Local value of 'var' within 'sample_function()' = 4
Global value of 'var' outside 'sample_function()' = 5
```

2.4.2 Practice exercise 4

The object `deck` defined below corresponds to a deck of cards. Estimate the probability that a five card hand will be a [flush](#), as follows:

1. Write a function that accepts a hand of 5 cards as argument, and returns whether the hand is a flush or not.
2. Randomly pull a hand of 5 cards from the deck. Call the function developed in (1) to determine if the hand is a flush.
3. Repeat (2) 10,000 times.
4. Estimate the probability of the hand being a flush from the results of the 10,000 simulations.

You may use the function `shuffle()` from the `random` library to shuffle the deck everytime before pulling a hand of 5 cards.

```
deck = [{'value':i, 'suit':c}
for c in ['spades', 'clubs', 'hearts', 'diamonds']
for i in range(2,15)]
```

Solution:

```
import random as rm

#Function to check if a 5-card hand is a flush
def chck_flush(hands):

    #Assuming that the hand is a flush, before checking the cards
    yes_flush =1

    #Storing the suit of the first card in 'first_suit'
    first_suit = hands[0]['suit']

    #Iterating over the remaining 4 cards of the hand
    for j in range(1,len(hands)):

        #If the suit of any of the cards does not match the suit of the first card, the ha
        if first_suit!=hands[j]['suit']:
            yes_flush = 0;

            #As soon as a card with a different suit is found, the hand is not a flush and
            break;
    return yes_flush

flush=0
for i in range(10000):
```

```
#Shuffling the deck
rm.shuffle(deck)

#Picking out the first 5 cards of the deck as a hand and checking if they are a flush
#If the hand is a flush it is counted
flush=flush+chk_flush(deck[0:5])

print("Probability of obtaining a flush=", 100*(flush/10000),"%")
```

Probability of obtaining a flush= 0.18 %

2.5 Practice exercise 5

The code cell below defines an object having the nutrition information of drinks in starbucks. Assume that the manner in which the information is structured is consistent throughout the object.

```
, 'value': 1}, {'starbucks_type': 'Substitution={\"value\":\"Line 10\", \"starbucks_ref_desk_pos\": \"Beverage Nutrition Information: type\"
```

Use the object above to answer the following questions:

2.5.1

What is the datatype of the object?

```
print("Datatype=",type(starbucks_drinks_nutrition))
```

```
Datatype= <class 'dict'>
```

2.5.1.1

If the object in (1) is a dictionary, what is the datatype of the values of the dictionary?

```
print("Datatype=",type(starbucks_drinks_nutrition[list(starbucks_drinks_nutrition.keys())])
```

```
Datatype= <class 'list'>
```

2.5.1.2

If the object in (1) is a dictionary, what is the datatype of the elements within the values of the dictionary?

```
print("Datatype=",type(starbucks_drinks_nutrition[list(starbucks_drinks_nutrition.keys())])
```

```
Datatype= <class 'dict'>
```

2.5.1.3

How many calories are there in Iced Coffee?

```
print("Calories = ",starbucks_drinks_nutrition['Iced Coffee'][0]['value'])
```

```
Calories = 5
```

2.5.1.4

Which drink(s) have the highest amount of protein in them, and what is that protein amount?

```
#Defining an empty dictionary that will be used to store the protein of each drink
protein={}

for key,value in starbucks_drinks_nutrition.items():
    for nutrition in value:
        if nutrition['Nutrition_type']=='Protein':
            protein[key]=(nutrition['value'])

#Using dictionary comprehension to find the key-value pair having the maximum value in the
{key:value for key, value in protein.items() if value == max(protein.values())}
```

```
{'Starbucks® Doubleshot Protein Dark Chocolate': 20,
'Starbucks® Doubleshot Protein Vanilla': 20,
'Chocolate Smoothie': 20}
```

2.5.1.5

Which drink(s) have a fat content of more than 10g, and what is their fat content?

```
#Defining an empty dictionary that will be used to store the fat of each drink
fat={}
for key,value in starbucks_drinks_nutrition.items():
    for nutrition in value:
        if nutrition['Nutrition_type']=='Fat':
            fat[key]=(nutrition['value'])

#Using dictionary comprehension to find the key-value pair having the value more than 10
{key:value for key, value in fat.items() if value>=10}
```

```
{'Starbucks® Signature Hot Chocolate': 26.0, 'White Chocolate Mocha': 11.0}
```

Part II

Exploratory data analysis

3 Reading data

3.1 Types of data - structured and unstructured

Reading data is the first step to extract information from it. Data can exist broadly in two formats:

- (1) Structured data, and
- (2) Unstructured data.

Structured data is typically stored in a tabular form, where rows in the data correspond to “observations” and columns correspond to “variables”. For example, the following dataset contains 5 observations, where each observation (or row) consists of information about a movie. The variables (or columns) contain different pieces of information about a given movie. As all variables for a given row are related to the same movie, the data below is also called relational data.

| | Title | US Gross | Production Budget | Release Date | Major Genre |
|---|---------------------------------|-----------|-------------------|--------------|------------------|
| 0 | The Shawshank Redemption | 28241469 | 25000000 | Sep 23 1994 | Drama |
| 1 | Inception | 285630280 | 160000000 | Jul 16 2010 | Horror/Thriller |
| 2 | One Flew Over the Cuckoo's Nest | 108981275 | 4400000 | Nov 19 1975 | Comedy |
| 3 | The Dark Knight | 533345358 | 185000000 | Jul 18 2008 | Action/Adventure |
| 4 | Schindler's List | 96067179 | 25000000 | Dec 15 1993 | Drama |

Unstructured data is data that is not organized in any pre-defined manner. Examples of unstructured data can be text files, audio/video files, images, Internet of Things (IoT) data, etc. Unstructured data is relatively harder to analyze as most of the analytical methods and tools are oriented towards structured data. However, an unstructured data can be used to obtain structured data, which in turn can be analyzed. For example, an image can be converted to an array of pixels - which will be structured data. Machine learning algorithms can then be used on the array to classify the image as that of a dog or a cat.

In this course, we will focus on analyzing structured data.

3.2 Reading a *csv* file with *Pandas*

Structured data can be stored in a variety of formats. The most popular format is *data_file_name.csv*, where the extension *csv* stands for comma separated values. The variable values of each observation are separated by a comma in a *.csv* file. In other words, the **delimiter** is a comma in a *csv* file. However, the comma is not visible when a *.csv* file is opened with Microsoft Excel.

3.2.1 Using the *read_csv* function

We will use functions from the *Pandas* library of *Python* to read data. Let us import *Pandas* to use its functions.

```
import pandas as pd
```

Note that *pd* is the acronym that we will use to call a *Pandas* function. This acronym can be anything as desired by the user.

The function to read a *csv* file is `read_csv()`. It reads the dataset into an object of type *Pandas DataFrame*. Let us read the dataset *movie_ratings.csv* in Python.

```
movie_ratings = pd.read_csv('movie_ratings.csv')
```

The built-in python function `type` can be used to check the datatype of an object:

```
type(movie_ratings)
```

```
pandas.core.frame.DataFrame
```

Note that the file *movie_ratings.csv* is stored at the same location as the python script containing the above code. If that is not the case, we'll need to specify the location of the file as in the following code.

```
movie_ratings = pd.read_csv('D:/Books/DataScience_Intro_python/movie_ratings.csv')
```

Note that forward slash is used instead of backslash while specifying the path of the data file. Another option is to use two consecutive backslashes instead of a single forward slash.

3.2.2 Specifying the working directory

In case we need to read several datasets from a given location, it may be inconvenient to specify the path every time. In such a case we can change the current working directory to the location where the datasets are located.

We'll use the *os* library of *Python* to view and/or change the current working directory.

```
import os #Importing the 'os' library
os.getcwd() #Getting the path to the current working directory
```

C:\Users\username\STAT303-1\Quarto Book\DataScience_Intro_python

The function *getcwd()* stands for get current working directory.

Suppose the dataset to be read is located at 'D:\Books\DataScience_Intro_python\Datasets'. Then, we'll use the function *chdir* to change the current working directory to this location.

```
os.chdir('D:/Books/DataScience_Intro_python/Datasets')
```

Now we can read the dataset from this location without mentioning the entire path as shown below.

```
movie_ratings = pd.read_csv('movie_ratings.csv')
```

3.2.3 Data overview

Once the data has been read, we may want to see what the data looks like. We'll use another *Pandas* function *head()* to view the first few rows of the data.

```
movie_ratings.head()
```

| | Title | US Gross | Worldwide Gross | Production Budget | Release Date | MPAA Rating |
|---|--------------------|----------|-----------------|-------------------|--------------|-------------|
| 0 | Opal Dreams | 14443 | 14443 | 9000000 | Nov 22 2006 | PG/PG-13 |
| 1 | Major Dundee | 14873 | 14873 | 3800000 | Apr 07 1965 | PG/PG-13 |
| 2 | The Informers | 315000 | 315000 | 18000000 | Apr 24 2009 | R |
| 3 | Buffalo Soldiers | 353743 | 353743 | 15000000 | Jul 25 2003 | R |
| 4 | The Last Sin Eater | 388390 | 388390 | 2200000 | Feb 09 2007 | PG/PG-13 |

3.2.3.1 Row Indices and column names (axis labels)

The bold integers on the left are the indices of the DataFrame. Each index refers to a distinct row. For example, the index *2* corresponds to the row of the movie *The Informers*. By default, the indices are integers starting from 0. However, they can be changed (to even non-integer values) if desired by the user.

The bold text on top of the DataFrame refers to column names. For example, the column *US Gross* consists of the gross revenue of a movie in the US.

Collectively, the indices and column names are referred as **axis labels**.

3.2.3.2 Shape of DataFrame

For finding the number of rows and columns in the data, you may use the `shape()` function.

```
#Finding the shape of movie_ratings dataset
movie_ratings.shape
```

```
(2228, 11)
```

The *movie_ratings* dataset contains 2,228 observations (or rows) and 11 variables (or columns).

3.2.4 Summary statistics

3.2.4.1 Numeric columns summary

The Pandas function of the DataFrame class, `describe()` can be used very conveniently to print the summary statistics of numeric columns of the data.

```
#Finding summary statistics of movie_ratings dataset
movie_ratings.describe()
```

Table 3.3: Summary statistics of numeric variables

| | US Gross | Worldwide Gross | Production Budget | IMDB Rating | IMDB Votes | Release Year |
|-------|--------------|-----------------|-------------------|-------------|--------------|--------------|
| count | 2.228000e+03 | 2.228000e+03 | 2.228000e+03 | 2228.000000 | 2228.000000 | 2228.000000 |
| mean | 5.076370e+07 | 1.019370e+08 | 3.816055e+07 | 6.239004 | 33585.154847 | 2002.005386 |
| std | 6.643081e+07 | 1.648589e+08 | 3.782604e+07 | 1.243285 | 47325.651561 | 5.524324 |

| | US Gross | Worldwide Gross | Production Budget | IMDB Rating | IMDB Votes | Release Year |
|-----|--------------|-----------------|-------------------|-------------|---------------|--------------|
| min | 0.000000e+00 | 8.840000e+02 | 2.180000e+02 | 1.400000 | 18.000000 | 1953.000000 |
| 25% | 9.646188e+06 | 1.320737e+07 | 1.200000e+07 | 5.500000 | 6659.250000 | 1999.000000 |
| 50% | 2.838649e+07 | 4.266892e+07 | 2.600000e+07 | 6.400000 | 18169.000000 | 2002.000000 |
| 75% | 6.453140e+07 | 1.200000e+08 | 5.300000e+07 | 7.100000 | 40092.750000 | 2006.000000 |
| max | 7.601676e+08 | 2.767891e+09 | 3.000000e+08 | 9.200000 | 519541.000000 | 2039.000000 |

Answer the following questions based on the above table.

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

3.2.4.2 Summary statistics across rows/columns

The Pandas DataFrame class has functions such as `sum()` and `mean()` to compute sum over rows or columns of a DataFrame.

Let us compute the mean of all the numeric columns of the data:

```
movie_ratings.mean(axis = 0)
```

```
US Gross          5.076370e+07
Worldwide Gross   1.019370e+08
Production Budget  3.816055e+07
IMDB Rating       6.239004e+00
IMDB Votes        3.358515e+04
dtype: float64
```

The argument `axis=0` denotes that the mean is taken over all the rows of the DataFrame. For computing a statistic across column the argument `axis=1` will be used.

If mean over a subset of columns is desired, then those column names can be subset from the data. For example, let us compute the mean IMDB rating, and mean IMDB votes of all the movies:

```
movie_ratings[['IMDB Rating','IMDB Votes']].mean(axis = 0)
```

```
IMDB Rating      6.239004
IMDB Votes       33585.154847
dtype: float64
```

3.2.5 Practice exercise 1

Read the file *Top 10 Albums By Year.csv*. This file contains the top 10 albums for each year from 1990 to 2021. Each row corresponds to a unique album.

3.2.5.1

Print the first 5 rows of the data.

```
album_data = pd.read_csv('./Datasets/Top 10 Albums By Year.csv')
album_data.head()
```

| | Year | Ranking | Artist | Album | Worldwide Sales | Chart Position |
|---|------|---------|------------------|--|-----------------|----------------|
| 0 | 1990 | 8 | Phil Collins | Serious Hits... Live! | 9956520 | 1 |
| 1 | 1990 | 1 | Madonna | The Immaculate Collection | 30000000 | 1 |
| 2 | 1990 | 10 | The Three Tenors | Carreras Domingo Pavarotti In Concert 1990 | 8533000 | 1 |
| 3 | 1990 | 4 | MC Hammer | Please Hammer Don't Hurt Em | 18000000 | 1 |
| 4 | 1990 | 6 | Movie Soundtrack | Aashiqui | 15000000 | 1 |

3.2.5.2

How many rows and columns are there in the data?

```
album_data.shape
```

```
(320, 12)
```

There are 320 rows and 12 columns in the data

3.2.5.3

Print the summary statistics of the data, and answer the following questions:

1. What proportion of albums have 15 or lesser tracks? Mention a range for the proportion.
2. What is the mean length of a track (in minutes)?

```
album_data.describe()
```

| | Year | Ranking | CDs | Tracks | Hours | Minutes | Seconds |
|-------|-------------|-----------|------------|------------|------------|------------|--------------|
| count | 320.000000 | 320.00000 | 320.000000 | 320.000000 | 320.000000 | 320.000000 | 320.000000 |
| mean | 2005.500000 | 5.50000 | 1.043750 | 14.306250 | 0.941406 | 56.478500 | 3388.715625 |
| std | 9.247553 | 2.87678 | 0.246528 | 5.868995 | 0.382895 | 22.970109 | 1378.209812 |
| min | 1990.000000 | 1.00000 | 1.000000 | 6.000000 | 0.320000 | 19.430000 | 1166.000000 |
| 25% | 1997.750000 | 3.00000 | 1.000000 | 12.000000 | 0.740000 | 44.137500 | 2648.250000 |
| 50% | 2005.500000 | 5.50000 | 1.000000 | 13.000000 | 0.860000 | 51.555000 | 3093.500000 |
| 75% | 2013.250000 | 8.00000 | 1.000000 | 15.000000 | 1.090000 | 65.112500 | 3906.750000 |
| max | 2021.000000 | 10.00000 | 4.000000 | 67.000000 | 5.070000 | 304.030000 | 18242.000000 |

At least 75% of the albums have 15 tracks since the 75th percentile value of the number of tracks is 15. However, albums between those having 75th percentile value for the number of tracks and those having the maximum number of tracks can also have 15 tracks. Thus, the proportion of albums having 15 or lesser tracks = [75%-99.99%].

```
print("Mean length of a track =",56.478500/14.306250, "minutes")
```

Mean length of a track = 3.9478200087374398 minutes

3.2.6 Creating new columns from existing columns

New variables (or columns) can be created based on existing variables, or with external data (we'll see adding external data later). For example, let us create a new variable **ratio_wgross_by_budget**, which is the ratio of Worldwide Gross and Production Budget for each movie:

```
movie_ratings['ratio_wgross_by_budget'] = movie_ratings['Worldwide Gross']/movie_ratings['
```

The new variable can be seen at the right end of the updated DataFrame as shown below.

```
movie_ratings.head()
```

| | Title | US Gross | Worldwide Gross | Production Budget | Release Date | MPAA Rating |
|---|--------------------|----------|-----------------|-------------------|--------------|-------------|
| 0 | Opal Dreams | 14443 | 14443 | 9000000 | Nov 22 2006 | PG/PG-13 |
| 1 | Major Dundee | 14873 | 14873 | 3800000 | Apr 07 1965 | PG/PG-13 |
| 2 | The Informers | 315000 | 315000 | 18000000 | Apr 24 2009 | R |
| 3 | Buffalo Soldiers | 353743 | 353743 | 15000000 | Jul 25 2003 | R |
| 4 | The Last Sin Eater | 388390 | 388390 | 2200000 | Feb 09 2007 | PG/PG-13 |

3.2.7 Datatype of variables

Note that in Table 3.3 (summary statistics), we don't see **Release Date**. This is because the datatype of **Release Date** is not **numeric**.

The datatype of each variable can be seen using the `dtypes()` function of the `DataFrame` class.

```
#Checking the datatypes of the variables
movie_ratings.dtypes
```

```
Title           object
US Gross        int64
Worldwide Gross  int64
Production Budget int64
Release Date     object
MPAA Rating      object
Source          object
Major Genre      object
Creative Type    object
IMDB Rating      float64
IMDB Votes       int64
dtype: object
```

Often, we wish to convert the datatypes of some of the variables to make them suitable for analysis. For example, the datatype of **Release Date** in the `DataFrame` `movie_ratings` is `object`. To perform numerical computations on this variable, we'll need to convert it to a `datetime` format. We'll use the Pandas function `to_datetime()` to convert it to a `datetime` format. Similar functions such as `to_numeric()`, `to_string()` etc., can be used for other conversions.

```
pd.to_datetime(movie_ratings['Release Date'])
```

```
0      2006-11-22
1      1965-04-07
2      2009-04-24
3      2003-07-25
4      2007-02-09
...
2223   2004-07-07
2224   1998-06-19
2225   2010-05-14
2226   1991-06-14
2227   1998-01-23
Name: Release Date, Length: 2228, dtype: datetime64[ns]
```

We can see above that the function `to_datetime()` converts *Release Date* to a `datetime` format.

Now, we'll update the variable `Release Date` in the DataFrame to be in the `datetime` format:

```
movie_ratings['Release Date'] = pd.to_datetime(movie_ratings['Release Date'])
```

```
movie_ratings.dtypes
```

```
Title      object
US Gross    int64
Worldwide Gross    int64
Production Budget    int64
Release Date    datetime64[ns]
MPAA Rating    object
Source         object
Major Genre    object
Creative Type   object
IMDB Rating    float64
IMDB Votes     int64
dtype: object
```

We can see that the datatype of *Release Date* has changed to `datetime` in the updated DataFrame, *movie_ratings*. Now we can perform computations on `Release Date`. Suppose

we wish to create a new variable `Release_year` that consists of the year of release of the movie. We'll use the attribute `year` of the `datetime` module to extract the year from `Release Date`:

```
#Extracting year from Release Date
movie_ratings['Release Year'] = movie_ratings['Release Date'].dt.year

movie_ratings.head()
```

| | Title | US Gross | Worldwide Gross | Production Budget | Release Date | MPAA Rating |
|---|--------------------|----------|-----------------|-------------------|--------------|-------------|
| 0 | Opal Dreams | 14443 | 14443 | 9000000 | 2006-11-22 | PG/PG-13 |
| 1 | Major Dundee | 14873 | 14873 | 3800000 | 1965-04-07 | PG/PG-13 |
| 2 | The Informers | 315000 | 315000 | 18000000 | 2009-04-24 | R |
| 3 | Buffalo Soldiers | 353743 | 353743 | 15000000 | 2003-07-25 | R |
| 4 | The Last Sin Eater | 388390 | 388390 | 2200000 | 2007-02-09 | PG/PG-13 |

As `year` is a numeric variable, it will appear in the numeric summary statistics with the `describe()` function, as shown below.

```
movie_ratings.describe()
```

| | US Gross | Worldwide Gross | Production Budget | IMDB Rating | IMDB Votes | Release Year |
|-------|--------------|-----------------|-------------------|-------------|---------------|--------------|
| count | 2.228000e+03 | 2.228000e+03 | 2.228000e+03 | 2228.000000 | 2228.000000 | 2228.000000 |
| mean | 5.076370e+07 | 1.019370e+08 | 3.816055e+07 | 6.239004 | 33585.154847 | 2002.005386 |
| std | 6.643081e+07 | 1.648589e+08 | 3.782604e+07 | 1.243285 | 47325.651561 | 5.524324 |
| min | 0.000000e+00 | 8.840000e+02 | 2.180000e+02 | 1.400000 | 18.000000 | 1953.000000 |
| 25% | 9.646188e+06 | 1.320737e+07 | 1.200000e+07 | 5.500000 | 6659.250000 | 1999.000000 |
| 50% | 2.838649e+07 | 4.266892e+07 | 2.600000e+07 | 6.400000 | 18169.000000 | 2002.000000 |
| 75% | 6.453140e+07 | 1.200000e+08 | 5.300000e+07 | 7.100000 | 40092.750000 | 2006.000000 |
| max | 7.601676e+08 | 2.767891e+09 | 3.000000e+08 | 9.200000 | 519541.000000 | 2039.000000 |

3.2.8 Practice exercise 2

3.2.8.1

Why is `Worldwide Sales` not included in the summary statistics table printed in Practice exercise 1?

```
album_data.dtypes
```



```

Year                int64
Ranking             int64
Artist              object
Album               object
Worldwide Sales     object
CDs                 int64
Tracks              int64
Album Length        object
Hours               float64
Minutes             float64
Seconds             int64
Genre               object
dtype: object

```

`Worldwide Sales` is not included in the summary statistics table printed in Practice exercise 1 because its data type is `object` and not `int` or `float`

3.2.8.2

Update the `DataFrame` so that `Worldwide Sales` is included in the summary statistics table. Print the summary statistics table.

Hint: Sometimes it may not be possible to convert an object to `numeric()`. For example, the object `'hi'` cannot be converted to a `numeric()` by the python compiler. To avoid getting an error, use the `errors` argument of `to_numeric()` to force such conversions to `NaN` (missing value).

```

album_data['Worldwide Sales'] = pd.to_numeric(album_data['Worldwide Sales'], errors = 'coerce')
album_data.describe()

```

| | Year | Ranking | Worldwide Sales | CDs | Tracks | Hours | Minutes | Seconds |
|-------|-------------|-----------|-----------------|------------|------------|------------|------------|------------|
| count | 320.000000 | 320.00000 | 3.190000e+02 | 320.000000 | 320.000000 | 320.000000 | 320.000000 | 320.000000 |
| mean | 2005.500000 | 5.50000 | 1.071093e+07 | 1.043750 | 14.306250 | 0.941406 | 56.478500 | 338.000000 |
| std | 9.247553 | 2.87678 | 7.566796e+06 | 0.246528 | 5.868995 | 0.382895 | 22.970109 | 137.000000 |
| min | 1990.000000 | 1.00000 | 1.909009e+06 | 1.000000 | 6.000000 | 0.320000 | 19.430000 | 116.000000 |
| 25% | 1997.750000 | 3.00000 | 5.000000e+06 | 1.000000 | 12.000000 | 0.740000 | 44.137500 | 264.000000 |
| 50% | 2005.500000 | 5.50000 | 8.255866e+06 | 1.000000 | 13.000000 | 0.860000 | 51.555000 | 309.000000 |
| 75% | 2013.250000 | 8.00000 | 1.400000e+07 | 1.000000 | 15.000000 | 1.090000 | 65.112500 | 390.000000 |
| max | 2021.000000 | 10.00000 | 4.500000e+07 | 4.000000 | 67.000000 | 5.070000 | 304.030000 | 182.000000 |

3.2.8.3

Create a new column that computes the average worldwide sales per year for each album, assuming that the worldwide sales are as of 2022. Print the first 5 rows of the updated DataFrame.

```
album_data['mean_sales_per_year'] = album_data['Worldwide Sales']/(2022-album_data['Year'])
album_data.head()
```

| | Year | Ranking | Artist | Album | Worldwide Sales | Cl |
|---|------|---------|------------------|--|-----------------|----|
| 0 | 1990 | 8 | Phil Collins | Serious Hits... Live! | 9956520.0 | 1 |
| 1 | 1990 | 1 | Madonna | The Immaculate Collection | 30000000.0 | 1 |
| 2 | 1990 | 10 | The Three Tenors | Carreras Domingo Pavarotti In Concert 1990 | 8533000.0 | 1 |
| 3 | 1990 | 4 | MC Hammer | Please Hammer Don't Hurt Em | 18000000.0 | 1 |
| 4 | 1990 | 6 | Movie Soundtrack | Aashiqui | 15000000.0 | 1 |

3.2.9 Reading a sub-set of data: loc and iloc

Sometimes we may be interested in working with a subset of rows and columns of the data, instead of working with the entire dataset. The indexing operators `loc` and `iloc` provide a convenient way of selecting a subset of desired rows and columns. The operator `loc` uses axis labels (row indices and column names) to subset the data, while `iloc` uses the position of rows or columns, where position has values 0,1,2,3,...and so on, for rows from top to bottom and columns from left to right. In other words, the first row has position 0, the second row has position 1, the third row has position 2, and so on. Similarly, the first column from left has position 0, the second column from left has position 1, the third column from left has position 2, and so on.

Let us read the file *movie_IMDBratings_sorted.csv*, which has movies sorted in the descending order of their IMDB ratings.

```
movies_sorted = pd.read_csv('./Datasets/movie_IMDBratings_sorted.csv', index_col = 0)
```

The argument `index_col=0` assigns the first column of the file as the row indices of the DataFrame.

```
movies_sorted.head()
```

| | Title | US Gross | Worldwide Gross | Production Budget | Release Date | M |
|------|--------------------------|-----------|-----------------|-------------------|--------------|----|
| Rank | | | | | | |
| 1 | The Shawshank Redemption | 28241469 | 28241469 | 25000000 | Sep 23 1994 | R |
| 2 | Inception | 285630280 | 753830280 | 160000000 | Jul 16 2010 | PG |
| 3 | The Dark Knight | 533345358 | 1022345358 | 185000000 | Jul 18 2008 | PG |
| 4 | Schindler's List | 96067179 | 321200000 | 25000000 | Dec 15 1993 | R |
| 5 | Pulp Fiction | 107928762 | 212928762 | 8000000 | Oct 14 1994 | R |

Let us say, we wish to subset the title, worldwide gross, production budget, and IMDB rating of top 3 movies.

```
# Subsetting the DataFrame by loc - using axis labels
movies_subset = movies_sorted.loc[1:3,['Title','Worldwide Gross','Production Budget','IMDB Rating']]
movies_subset
```

| | Title | Worldwide Gross | Production Budget | IMDB Rating |
|------|--------------------------|-----------------|-------------------|-------------|
| Rank | | | | |
| 1 | The Shawshank Redemption | 28241469 | 25000000 | 9.2 |
| 2 | Inception | 753830280 | 160000000 | 9.1 |
| 3 | The Dark Knight | 1022345358 | 185000000 | 8.9 |

```
# Subsetting the DataFrame by iloc - using index of the position of rows and columns
movies_subset = movies_sorted.iloc[0:3,[0,2,3,9]]
movies_subset
```

| | Title | Worldwide Gross | Production Budget | IMDB Rating |
|------|--------------------------|-----------------|-------------------|-------------|
| Rank | | | | |
| 1 | The Shawshank Redemption | 28241469 | 25000000 | 9.2 |
| 2 | Inception | 753830280 | 160000000 | 9.1 |
| 3 | The Dark Knight | 1022345358 | 185000000 | 8.9 |

Let us find the movie with the maximum **Worldwide Gross**.

We will use the `argmax()` function of the Pandas Series class to find the position of the movie with the maximum worldwide gross, and then use the position to find the movie.

```
position_max_wgross = movies_sorted['Worldwide Gross'].argmax()
```

```
movies_sorted.iloc[position_max_wgross,:]
```

```
Title                Avatar
US Gross              760167650
Worldwide Gross       2767891499
Production Budget     237000000
Release Date          Dec 18 2009
MPAA Rating           PG/PG-13
Source                Original Screenplay
Major Genre           Action/Adventure
Creative Type         Fiction
IMDB Rating           8.3
IMDB Votes            261439
Name: 59, dtype: object
```

Avatar has the highest worldwide gross of all the movies. Note that the `:` indicates that all the columns of the DataFrame are selected.

3.2.10 Practice exercise 3

3.2.10.1

Find the album having the highest worldwide sales per year, and its artist.

```
album_data.iloc[album_data['mean_sales_per_year'].argmax(),:]
```

```
Year                2021
Ranking              1
Artist              Adele
Album               30
Worldwide Sales     4485025.0
CDs                  1
Tracks              12
Album Length        0:58:14
Hours                0.97
Minutes              58.23
Seconds              3494
Genre               Pop
mean_sales_per_year  4485025.0
Name: 312, dtype: object
```

'30' has the highest worldwide sales and its artist is Adele.

3.2.10.2

Subset the data to include only Hip-Hop albums. How many Hip_Hop albums are there?

```
hiphop_albums = album_data.loc[album_data['Genre']=='Hip Hop',:]
print("There are",hiphop_albums.shape[0], "hip-hop albums")
```

There are 42 hip-hop albums

3.2.10.3

Which album amongst hip-hop has the highest mean sales per year per track, and who is its artist?

```
hiphop_albums.loc[:, 'mean_sales_per_year_track'] = hiphop_albums.loc[:, 'Worldwide Sales']/
hiphop_albums.iloc[hiphop_albums['mean_sales_per_year_track'].argmax(),:]
```

| | |
|---------------------------|---------------|
| Year | 2021 |
| Ranking | 6 |
| Artist | Cai Xukun |
| Album | |
| Worldwide Sales | 3402981.0 |
| CDs | 1 |
| Tracks | 11 |
| Album Length | 0:24:16 |
| Hours | 0.4 |
| Minutes | 24.27 |
| Seconds | 1456 |
| Genre | Hip Hop |
| mean_sales_per_year | 3402981.0 |
| mean_sales_per_year_track | 309361.909091 |
| Name: 318, dtype: object | |

has the highest mean sales per year per track amongst hip-hop albums, and its artist is Cai Xukun.

3.3 Reading other data formats - txt, html, json

Although *csv* is a very popular format for structured data, data is found in several other formats as well. Some of the other data formats are *txt*, *html* and *json*.

3.3.1 Reading *txt* files

The *txt* format offers some additional flexibility as compared to the *csv* format. In the *csv* format, the delimiter is a comma (or the column values are separated by a comma). However, in a *txt* file, the delimiter can be anything as desired by the user. Let us read the file *movie_ratings.txt*, where the variable values are separated by a tab character.

```
movie_ratings_txt = pd.read_csv('movie_ratings.txt',sep='\t')
```

We use the function `read_csv` to read a *txt* file. However, we mention the tab character (`r"\t"`) as a separator of variable values.

Note that there is no need to remember the argument name - *sep* for specifying the delimiter. You can always refer to the [read_csv\(\)](#) documentation to find the relevant argument.

3.3.2 Practice exercise 4

Read the file *bestseller_books.txt*. It contains top 50 best-selling books on amazon from 2009 to 2019. Identify the delimiter without opening the file with Notepad or a text-editing software. How many rows and columns are there in the dataset?

Solution:

```
#Reading some lines with 'error_bad_lines=False' to identify the delimiter
bestseller_books = pd.read_csv('./Datasets/bestseller_books.txt',error_bad_lines=False)
bestseller_books.head()
```

```
b'Skipping line 6: expected 1 fields, saw 2\nSkipping line 10: expected 1 fields, saw 3\nSkip
```

| 0 | 0;0;10-Day Green Smoothie Cleanse;JJ Smith;4.7... |
|---|---|
| 1 | 1;1;11/22/63: A Novel;Stephen King;4.6;2052;22... |
| 2 | 2;2;12 Rules for Life: An Antidote to Chaos;Jo... |
| 3 | 3;3;1984 (Signet Classics);George Orwell;4.7;2... |
| 4 | 5;5;A Dance with Dragons (A Song of Ice and Fi... |

```
;Unnamed: 0;Name;Author;User Rating;Reviews;Price;Year;Genre
```

```
#The delimiter seems to be ';' based on the output of the above code
bestseller_books = pd.read_csv('./Datasets/bestseller_books.txt',sep=';')
bestseller_books.head()
```

| | Unnamed: 0 | Unnamed: 0.1 | Name | Author |
|---|------------|--------------|---|---------------------|
| 0 | 0 | 0 | 10-Day Green Smoothie Cleanse | JJ Smith |
| 1 | 1 | 1 | 11/22/63: A Novel | Stephen King |
| 2 | 2 | 2 | 12 Rules for Life: An Antidote to Chaos | Jordan B. Peterson |
| 3 | 3 | 3 | 1984 (Signet Classics) | George Orwell |
| 4 | 4 | 4 | 5,000 Awesome Facts (About Everything!) (Natio... | National Geographic |

```
#The file read with ';' as the delimited is correct
print("The file has",bestseller_books.shape[0],"rows and",bestseller_books.shape[1],"columns")
```

The file has 550 rows and 9 columns

Alternatively, you can use the argument `sep = None`, and `engine = 'python'`. The default engine is C. However, the ‘python’ engine has a ‘sniffer’ tool which may identify the delimiter automatically.

```
bestseller_books = pd.read_csv('./Datasets/bestseller_books.txt',sep=None, engine = 'python')
bestseller_books.head()
```

| | Unnamed: 0 | Unnamed: 0.1 | Name | Author |
|---|------------|--------------|---|---------------------|
| 0 | 0 | 0 | 10-Day Green Smoothie Cleanse | JJ Smith |
| 1 | 1 | 1 | 11/22/63: A Novel | Stephen King |
| 2 | 2 | 2 | 12 Rules for Life: An Antidote to Chaos | Jordan B. Peterson |
| 3 | 3 | 3 | 1984 (Signet Classics) | George Orwell |
| 4 | 4 | 4 | 5,000 Awesome Facts (About Everything!) (Natio... | National Geographic |

3.3.3 Reading HTML data

The *Pandas* function `read_html` searches for tabular data, i.e., data contained within the `<table>` tags of an html file. Let us read the tables in the GDP per capita [page](#) on Wikipedia.

```
#Reading all the tables from the Wikipedia page on GDP per capita
tables = pd.read_html('https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)_pe
```

All the tables will be read and stored in the variable named as *tables*. Let us find the datatype of the variable *tables*.

```
#Finidng datatype of the variable - tables
type(tables)
```

```
list
```

The variable - *tables* is a list of all the tables read from the HTML data.

```
#Number of tables read from the page
len(tables)
```

```
6
```

The in-built function *len* can be used to find the length of the list - *tables* or the number of tables read from the Wikipedia page. Let us check out the first table.

```
#Checking out the first table. Note that the index of the first table will be 0.
tables[0]
```

| | 0 | 1 | 2 |
|---|---|---|--------------------|
| 0 | .mw-parser-output .legend{page-break-inside:av... | \$20,000 - \$30,000 \$10,000 - \$20,000 \$5,000 - \$... | \$1,000 - \$20,000 |

The above table doesn't seem to be useful. Let us check out the second table.

```
#Checking out the second table. Note that the index of the first table will be 1.
tables[1]
```

| | Country/Territory | UN Region | IMF[4][5] | | United Nations[6] | | World Bank[7] | |
|---|-------------------|-----------|-----------|------|-------------------|------|---------------|------|
| | Country/Territory | UN Region | Estimate | Year | Estimate | Year | Estimate | Year |
| 0 | Liechtenstein * | Europe | — | — | 180227 | 2020 | 169049 | 2019 |

| | Country/Territory | UN Region | IMF[4][5] | | United Nations[6] | World Bank[7] | | |
|-----|----------------------------|-----------|-----------|------|-------------------|---------------|----------|------|
| | Country/Territory | UN Region | Estimate | Year | Estimate | Year | Estimate | Year |
| 1 | Monaco * | Europe | — | — | 173696 | 2020 | 173688 | 2020 |
| 2 | Luxembourg * | Europe | 135046 | 2022 | 117182 | 2020 | 135683 | 2021 |
| 3 | Bermuda * | Americas | — | — | 123945 | 2020 | 110870 | 2021 |
| 4 | Ireland * | Europe | 101509 | 2022 | 86251 | 2020 | 85268 | 2020 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 212 | Central African Republic * | Africa | 527 | 2022 | 481 | 2020 | 477 | 2020 |
| 213 | Sierra Leone * | Africa | 513 | 2022 | 475 | 2020 | 485 | 2020 |
| 214 | Madagascar * | Africa | 504 | 2022 | 470 | 2020 | 496 | 2020 |
| 215 | South Sudan * | Africa | 393 | 2022 | 1421 | 2020 | 1120 | 2015 |
| 216 | Burundi * | Africa | 272 | 2022 | 286 | 2020 | 274 | 2020 |

The above table contains the estimated GDP per capita of all countries. This is the table that is likely to be relevant to a user interested in analyzing GDP per capita of countries. Instead of reading all tables of an HTML file, we can focus the search to tables containing certain relevant keywords. Let us try searching all table containing the word ‘Country’.

```
#Reading all the tables from the Wikipedia page on GDP per capita, containing the word 'Country'
tables = pd.read_html('https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)_per_capita')
```

The *match* argument can be used to specify the keywords to be present in the table to be read.

```
len(tables)
```

```
1
```

Only one table contains the keyword - ‘Country’. Let us check out the table obtained.

```
#Table having the keyword - 'Country' from the HTML page
tables[0]
```

| | Country/Territory | UN Region | IMF[4][5] | | United Nations[6] | World Bank[7] | | |
|-----|----------------------------|-----------|-----------|------|-------------------|---------------|----------|------|
| | Country/Territory | UN Region | Estimate | Year | Estimate | Year | Estimate | Year |
| 0 | Liechtenstein * | Europe | — | — | 180227 | 2020 | 169049 | 2019 |
| 1 | Monaco * | Europe | — | — | 173696 | 2020 | 173688 | 2020 |
| 2 | Luxembourg * | Europe | 135046 | 2022 | 117182 | 2020 | 135683 | 2021 |
| 3 | Bermuda * | Americas | — | — | 123945 | 2020 | 110870 | 2021 |
| 4 | Ireland * | Europe | 101509 | 2022 | 86251 | 2020 | 85268 | 2020 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 212 | Central African Republic * | Africa | 527 | 2022 | 481 | 2020 | 477 | 2020 |
| 213 | Sierra Leone * | Africa | 513 | 2022 | 475 | 2020 | 485 | 2020 |
| 214 | Madagascar * | Africa | 504 | 2022 | 470 | 2020 | 496 | 2020 |
| 215 | South Sudan * | Africa | 393 | 2022 | 1421 | 2020 | 1120 | 2015 |
| 216 | Burundi * | Africa | 272 | 2022 | 286 | 2020 | 274 | 2020 |

The argument *match* helps with a more focussed search, and helps us discard irrelevant tables.

3.3.4 Practice exercise 5

Read the table(s) consisting of attendance of spectators in FIFA worlds cup from this [page](#). Read only those table(s) that have the word ‘attendance’ in them. How many rows and columns are there in the table(s)?

```
dfs = pd.read_html('https://en.wikipedia.org/wiki/FIFA_World_Cup',
                    match='attendance')

print(len(dfs))
data = dfs[0]
print("Number of rows =",data.shape[0], "and number of columns=",data.shape[1])
```

```
1
Number of rows = 22 and number of columns= 9
```

3.3.5 Reading JSON data

JSON stands for JavaScript Object Notation, in which the data is stored and transmitted as plain text. A couple of benefits of the JSON format are:

1. Since the format is text only, JSON data can easily be exchanged between web applications, and used by any programming language.
2. Unlike the *csv* format, JSON supports a hierarchical data structure, and is easier to integrate with APIs.

The JSON format can support a hierarchical data structure, as it is built on the following two data structures (*Source: [technical documentation](#)*):

- A collection of name/value pairs. In various languages, this is realized as an object, record, struct, dictionary, hash table, keyed list, or associative array.
- An ordered list of values. In most languages, this is realized as an array, vector, list, or sequence.

These are universal data structures. Virtually all modern programming languages support them in one form or another. It makes sense that a data format that is interchangeable with programming languages also be based on these structures.

The *Pandas* function `read_json` converts a JSON string to a *Pandas* DataFrame. The function `dumps()` of the *json* library converts a Python object to a JSON string.

Lets read the JSON data on Ted Talks.

```
tedtalks_data = pd.read_json('https://raw.githubusercontent.com/cwkenwaysun/TEDmap/master/da
tedtalks_data.head()
```

| | id | speaker | headline | URL | descripti |
|---|----|--------------|--------------------------------------|---|-----------|
| 0 | 7 | David Pogue | Simplicity sells | http://www.ted.com/talks/view/id/7 | New Yor |
| 1 | 6 | Craig Venter | Sampling the ocean's DNA | http://www.ted.com/talks/view/id/6 | Genomic |
| 2 | 4 | Burt Rutan | The real future of space exploration | http://www.ted.com/talks/view/id/4 | In this p |
| 3 | 3 | Ashraf Ghani | How to rebuild a broken state | http://www.ted.com/talks/view/id/3 | Ashraf C |
| 4 | 5 | Chris Bangle | Great cars are great art | http://www.ted.com/talks/view/id/5 | America |

3.3.6 Practice exercise 6

Read the movies dataset from [here](#). How many rows and columns are there in the data?

```
movies_data = pd.read_json('https://raw.githubusercontent.com/vega/vega-datasets/master/da
print("Number of rows =",movies_data.shape[0], "and number of columns=",movies_data.shape[
```

Number of rows = 3201 and number of columns= 16

3.3.7 Reading data from web APIs

[API](#), an acronym for Application programming interface, is a way of transferring information between systems. Many websites have public APIs that provide data via JSON or other formats. For example, the [IMDb-API](#) is a web service for receiving movies, serial, and cast information. API results are in the JSON format and include items such as movie specifications, ratings, Wikipedia page content, etc. One of these APIs contains ratings of the top 250 movies on IMDB. Let us read this data using the IMDB API.

We'll use the *get* function from the python library *requests* to request data from the API and obtain a response code. The response code will let us know if our request to pull data from this API was successful.

```
#Importing the requests library
import requests as rq

# Downloading imdb top 250 movie's data
url = 'https://imdb-api.com/en/API/Top250Movies/k_v6gf8ppf' #URL of the API containing top
response = rq.get(url) #Requesting data from the API
response
```

<Response [200]>

We have a response code of 200, which indicates that the request was successful.

The response object's *JSON* method will return a dictionary containing JSON parsed into native Python objects.

```
movie_data = response.json()
```

```
movie_data.keys()
```

```
dict_keys(['items', 'errorMessage'])
```

The *movie_data* contains only two keys. The *items* key seems likely to contain information about the top 250 movies. Let us convert the values of the *items* key (which is list of dictionaries) to a dataframe, so that we can view it in a tabular form.

```
#Converting a list of dictionaries to a dataframe
movie_data_df = pd.DataFrame(movie_data['items'])
```

```
#Checking the movie data pulled using the API
movie_data_df.head()
```

| | id | rank | title | fullTitle | year | image |
|---|-----------|------|--------------------------|---------------------------------|------|---------------------------------------|
| 0 | tt0111161 | 1 | The Shawshank Redemption | The Shawshank Redemption (1994) | 1994 | https://m.m |
| 1 | tt0068646 | 2 | The Godfather | The Godfather (1972) | 1972 | https://m.m |
| 2 | tt0468569 | 3 | The Dark Knight | The Dark Knight (2008) | 2008 | https://m.m |
| 3 | tt0071562 | 4 | The Godfather Part II | The Godfather Part II (1974) | 1974 | https://m.m |
| 4 | tt0050083 | 5 | 12 Angry Men | 12 Angry Men (1957) | 1957 | https://m.m |

```
#Rows and columns of the movie data
movie_data_df.shape
```

(250, 9)

This API provides the names of the top 250 movies along with the year of release, IMDB ratings, and cast information.

3.4 Writing data

The *Pandas* function `to_csv` can be used to write (or export) data to a *csv* or *txt* file. Below are some examples.

Example 1: Let us export the movies data of the top 250 movies to a *csv* file.

```
#Exporting the data of the top 250 movies to a csv file
movie_data_df.to_csv('movie_data_exported.csv')
```

The file `movie_data_exported.csv` will appear in the working directory.

Example 2: Let us export the movies data of the top 250 movies to a *txt* file with a semi-colon as the delimiter.

```
movie_data_df.to_csv('movie_data_exported.txt', sep=';')
```

Example 3: Let us export the movies data of the top 250 movies to a *JSON* file.

```
with open('movie_data.json', 'w') as f:
    json.dump(movie_data, f)
```

4 NumPy

<IPython.core.display.Image object>

NumPy, short for Numerical Python is used to analyze numeric data with Python. NumPy arrays are primarily used to create homogeneous n -dimensional arrays ($n = 1, \dots, n$). Let us import the NumPy library to use its methods and functions, and the NumPy function `array()` to define a NumPy array.

```
import numpy as np
```

```
#Using the NumPy function array() to define a NumPy array
numpy_array = np.array([[1,2],[3,4]])
numpy_array
```

```
array([[1, 2],
       [3, 4]])
```

```
type(numpy_array)
```

```
numpy.ndarray
```

The NumPy function `array()` creates an object of type `numpy.ndarray`.

4.1 Why do we need NumPy arrays?

NumPy arrays can store data just like other data structures such as lists, tuples, and Pandas DataFrame. Computations performed using NumPy arrays can also be performed with data stored in the other data structures. However, NumPy is preferred for its efficiency, especially when working with large arrays of data.

4.1.1 Numpy arrays are memory efficient

A NumPy array is a collection of homogeneous data-types that are stored in contiguous memory locations. On the other hand, data structures such as lists are a collection of heterogeneous data types stored in non-contiguous memory locations. Homogenous data elements let the NumPy array be densely packed resulting in lesser memory consumption. The following example illustrates the smaller size of NumPy arrays as compared to other data structures.

```
#Example showing NumPy arrays take less storage space than lists, tuples and Pandas DataFrame
tuple_ex = tuple(range(1000))
list_ex = list(range(1000))
numpy_ex = np.array([range(1000)])
pandas_df = pd.DataFrame(range(1000))
print("Space taken by tuple =",tuple_ex.__sizeof__()," bytes")
print("Space taken by list =",list_ex.__sizeof__()," bytes")
print("Space taken by Pandas DataFrame =",pandas_df.__sizeof__()," bytes")
print("Space taken by NumPy array =",numpy_ex.__sizeof__()," bytes")
```

```
Space taken by tuple = 8024  bytes
Space taken by list = 8040  bytes
Space taken by Pandas DataFrame = 8128  bytes
Space taken by NumPy array = 4120  bytes
```

Note that NumPy arrays are memory efficient as long as they are homogenous. They will lose the memory efficiency if they are used to store elements of multiple data types.

The example below compares the size of a homogenous NumPy array to that of a similar heterogenous NumPy array to illustrate the point.

```
numpy_homogenous = np.array([[1,2],[3,3]])
print("Size of a homogenous numpy array = ",numpy_homogenous.__sizeof__(), "bytes")
```

```
Size of homogenous numpy array = 136 bytes
```

Now let us convert an element of the above array to a string, and check the size of the array.

```
numpy_homogenous = np.array([[1,'2'],[3,3]])
print("Size of a heterogenous numpy array = ",numpy_homogenous.__sizeof__(), "bytes")
```

```
Size of a heterogenous numpy array = 296 bytes
```

The size of the homogenous NumPy array is much lesser than that of the one with heterogenous data. Thus, NumPy arrays are primarily used for storing homogenous data.

On the other hand, the size of other data structures, such as a list, does not depend on whether the elements in them are homogenous or heterogenous, as shown by the example below.

```
list_homogenous = list([1,2,3,4])
print("Size of a homogenous list = ",list_homogenous.__sizeof__(), "bytes")
list_heterogenous = list([1,'2',3,4])
print("Size of a heterogenous list = ",list_heterogenous.__sizeof__(), "bytes")
```

Size of a homogenous list = 72 bytes

Size of a heterogenous list = 72 bytes

Note that the memory efficiency of NumPy arrays does not come into play with a very small amount of data. Thus, a list with four elements - 1,2,3 and 4, has a lesser size than a NumPy array with the same elements. However, with larger datasets, such as the one shown earlier (sequence of integers from 0 to 999), the memory efficiency of NumPy arrays can be seen.

Unlike data structures such as lists, tuples, and dictionary, all elements of a NumPy array should be of same type to leverage the memory efficiency of NumPy arrays.

4.1.2 NumPy arrays are fast

With NumPy arrays, mathematical computations can be performed faster, as compared to other data structures, due to the following reasons:

1. As the NumPy array is **densely packed** with homogenous data, it helps retrieve the data faster as well, thereby making computations faster.
2. With NumPy, **vectorized computations** can replace the relatively more expensive python **for** loops. The NumPy package breaks down the vectorized computations into multiple fragments and then processes all the fragments parallelly. However, with a **for** loop, computations will be one at a time.
3. The NumPy package **integrates C**, and **C++** codes in Python. These programming languages have very little execution time as compared to Python.

We'll see the faster speed on NumPy computations in the example below.

Example: This example shows that computations using NumPy arrays are typically much faster than computations with other data structures.

Q: Multiply whole numbers upto 1 million by an integer, say 2. Compare the time taken for the computation if the numbers are stored in a NumPy array vs a list.

Use the numpy function `arange()` to define a one-dimensional NumPy array.

```
#Examples showing NumPy arrays are more efficient for numerical computation
import time as tm
start_time = tm.time()
list_ex = list(range(1000000)) #List containinig whole numbers upto 1 million
a=(list_ex*2)
print("Time take to multiply numbers in a list = ", tm.time()-start_time)

start_time = tm.time()
tuple_ex = tuple(range(1000000)) #Tuple containinig whole numbers upto 1 million
a=(tuple_ex*2)
print("Time take to multiply numbers in a tuple = ", tm.time()-start_time)

start_time = tm.time()
df_ex = pd.DataFrame(range(1000000)) #Pandas DataFrame containinig whole numbers upto 1 mi
a=(df_ex*2)
print("Time take to multiply numbers in a Pandas DataFrame = ", tm.time()-start_time)

start_time = tm.time()
numpy_ex = np.arange(1000000) #NumPy array containinig whole numbers upto 1 million
a=(numpy_ex*2)
print("Time take to multiply numbers in a NumPy array = ", tm.time()-start_time)
```

```
Time take to multiply numbers in a list = 0.023949384689331055
Time take to multiply numbers in a tuple = 0.03192734718322754
Time take to multiply numbers in a Pandas DataFrame = 0.047330617904663086
Time take to multiply numbers in a NumPy array = 0.0
```

4.2 NumPy array: Basic attributes

Let us define a NumPy array:

```
numpy_ex = np.array([[1,2,3],[4,5,6]])
numpy_ex
```

```
array([[1, 2, 3],
       [4, 5, 6]])
```

The attributes of `numpy_ex` can be seen by typing `numpy_ex` followed by a `.`, and then pressing the *tab* key.

Some of the basic attributes of a NumPy array are the following:

4.2.1 `ndim`

Shows the number of dimensions (or axes) of the array.

```
numpy_ex.ndim
```

2

4.2.2 `shape`

This is a tuple of integers indicating the size of the array in each dimension. For a matrix with n rows and m columns, the shape will be (n, m) . The length of the shape tuple is therefore the rank, or the number of dimensions, `ndim`.

```
numpy_ex.shape
```

(2, 3)

4.2.3 `size`

This is the total number of elements of the array, which is the product of the elements of shape.

```
numpy_ex.size
```

6

4.2.4 `dtype`

This is an object describing the type of the elements in the array. One can create or specify dtype's using standard Python types. NumPy provides many, for example `bool_`, `character`, `int_`, `int8`, `int16`, `int32`, `int64`, `float_`, `float8`, `float16`, `float32`, `float64`, `complex_`, `complex64`, `object_`.

```
numpy_ex.dtype
```

```
dtype('int32')
```

4.2.5 T

This attribute is used to transpose the NumPy array. This is often used to make matrices (2-dimensional arrays) compatible for multiplication.

For matrix multiplication, the columns of the first matrix must be equal to the rows of the second matrix. For example, consider the matrix below:

```
matrix_to_multiply = np.array([[1,2,1],[0,1,0]])
```

Suppose we wish to multiply this matrix with `numpy_ex`. Note the shape of both the matrices below.

```
matrix_to_multiply.shape
```

```
(2, 3)
```

```
numpy_ex.shape
```

```
(2, 3)
```

To multiply the above matrices the number of columns of the one of the matrices must be the same as the number of rows of the other matrix. With the current matrices, this is not true as the number of columns of the first matrix is 3, and the the number of rows of the second matrix is 2 (no matter which matrix is considered to be the first one).

However, if we transpose one of the matrices, their shapes will be compatible for multiplication. Let's transpose `matrix_to_multiply`:

```
matrix_to_multiply_transpose = matrix_to_multiply.T  
matrix_to_multiply_transpose
```

```
array([[1, 0],  
       [2, 1],  
       [1, 0]])
```

The shape of `matrix_to_multiply_transpose` is:

```
matrix_to_multiply_transpose.shape
```

(3, 2)

The matrices `matrix_to_multiply_transpose` and `numpy_ex` are compatible for matrix multiplication. However, the result will depend on the order in which the matrices are multiplied:

```
#Matrix multiplication with matrix_to_multiply_transpose before numpy_ex
matrix_to_multiply_transpose.dot(numpy_ex)
```

```
array([[ 1,  2,  3],
       [ 6,  9, 12],
       [ 1,  2,  3]])
```

```
#Matrix multiplication with numpy_ex before matrix_to_multiply_transpose
numpy_ex.dot(matrix_to_multiply_transpose)
```

```
array([[ 8,  2],
       [20,  5]])
```

The shape of the resulting matrix is equal to the rows of the first matrix and the columns of the second matrix. The order of matrices must be decided as per the requirements of the problem.

4.3 Arithmetic operations

Numpy arrays support arithmetic operators like `+`, `-`, `*`, etc. We can perform an arithmetic operation on an array either with a single number (also called scalar) or with another array of the same shape. However, we cannot perform an arithmetic operation on an array with an array of a different shape.

Below are some examples of arithmetic operations on arrays.

```
#Defining two arrays of the same shape
arr1 = np.array([[1, 2, 3, 4],
                 [5, 6, 7, 8],
```

```

        [9, 1, 2, 3]])
arr2 = np.array([[11, 12, 13, 14],
                 [15, 16, 17, 18],
                 [19, 11, 12, 13]])

#Element-wise summation of arrays
arr1 + arr2

array([[12, 14, 16, 18],
       [20, 22, 24, 26],
       [28, 12, 14, 16]])

# Element-wise subtraction
arr2 - arr1

array([[10, 10, 10, 10],
       [10, 10, 10, 10],
       [10, 10, 10, 10]])

# Adding a scalar to an array adds the scalar to each element of the array
arr1 + 3

array([[ 4,  5,  6,  7],
       [ 8,  9, 10, 11],
       [12,  4,  5,  6]])

# Dividing an array by a scalar divides all elements of the array by the scalar
arr1 / 2

array([[0.5, 1. , 1.5, 2. ],
       [2.5, 3. , 3.5, 4. ],
       [4.5, 0.5, 1. , 1.5]])

# Element-wise multiplication
arr1 * arr2

array([[ 11,  24,  39,  56],
       [ 75,  96, 119, 144],
       [171,  11,  24,  39]])

```

```
# Modulus operator with scalar
arr1 % 4
```

```
array([[1, 2, 3, 0],
       [1, 2, 3, 0],
       [1, 1, 2, 3]], dtype=int32)
```

4.4 Broadcasting

Broadcasting allows arithmetic operations between two arrays with different numbers of dimensions but compatible shapes.

The [Broadcasting documentation](#) succinctly explains it as the following:

“The term broadcasting describes how NumPy treats arrays with different shapes during arithmetic operations. Subject to certain constraints, the smaller array is *broadcast* across the larger array so that they have compatible shapes. Broadcasting provides a means of vectorizing array operations so that looping occurs in C instead of Python. It does this without making needless copies of data and usually leads to efficient algorithm implementations.”

The example below shows the broadcasting of two arrays.

```
arr1 = np.array([[1, 2, 3, 4],
                 [5, 6, 7, 8],
                 [9, 1, 2, 3]])
arr2 = np.array([4, 5, 6, 7])
```

```
arr1 + arr2
```

```
array([[ 5,  7,  9, 11],
       [ 9, 11, 13, 15],
       [13,  6,  8, 10]])
```

When the expression `arr1 + arr2` is evaluated, `arr2` (which has the shape `(4,)`) is replicated three times to match the shape `(3, 4)` of `arr1`. Numpy performs the replication without actually creating three copies of the smaller dimension array, thus improving performance and using lower memory.

In the above addition of arrays, `arr2` was *stretched* or *broadcast* to the shape of `arr1`. However, this broadcasting was possible only because the right dimension of both the arrays is 4, and the left dimension of one of the arrays is 1.

See the [broadcasting documentation](#) to understand the rules for broadcasting:

“When operating on two arrays, NumPy compares their shapes element-wise. It starts with the trailing (i.e. rightmost) dimensions and works its way left. Two dimensions are compatible when:

- they are equal, or
- one of them is 1”

If the rightmost dimension of `arr2` is 3, broadcasting will not occur, as it is not equal to the rightmost dimension of `arr1`:

```
#Defining arr2 as an array of shape (3,)
arr2 = np.array([4, 5, 6])

#Broadcasting will not happen when the broadcasting rules are violated
arr1 + arr2
```

ValueError: operands could not be broadcast together with shapes (3,4) (3,)

4.5 Comparison

Numpy arrays support comparison operations like `==`, `!=`, `>` etc. The result is an array of booleans.

```
arr1 = np.array([[1, 2, 3], [3, 4, 5]])
arr2 = np.array([[2, 2, 3], [1, 2, 5]])
```

```
arr1 == arr2
```

```
array([[False,  True,  True],
       [False, False,  True]])
```

```
arr1 != arr2
```

```
array([[ True, False, False],
       [ True,  True, False]])
```

```
arr1 >= arr2
```

```
array([[False,  True,  True],  
       [ True,  True,  True]])
```

```
arr1 < arr2
```

```
array([[ True, False, False],  
       [False, False, False]])
```

Array comparison is frequently used to count the number of equal elements in two arrays using the `sum` method. Remember that `True` evaluates to 1 and `False` evaluates to 0 when booleans are used in arithmetic operations.

```
(arr1 == arr2).sum()
```

3

4.6 Concatenating arrays

Arrays can be concatenated along an axis with NumPy's `concatenate` function. The `axis` argument specifies the dimension for concatenation. The arrays should have the same number of dimensions, and the same length along each axis except the axis used for concatenation.

The examples below show concatenation of arrays.

```
arr1 = np.array([[1, 2, 3], [3, 4, 5]])  
arr2 = np.array([[2, 2, 3], [1, 2, 5]])  
print("Array 1:\n",arr1)  
print("Array 2:\n",arr2)
```

Array 1:

```
[[1 2 3]  
 [3 4 5]]
```

Array 2:

```
[[2 2 3]  
 [1 2 5]]
```



```
#Concatenating the arrays along the default axis: axis=0
np.concatenate((arr1,arr2))
```

```
array([[1, 2, 3],
       [3, 4, 5],
       [2, 2, 3],
       [1, 2, 5]])
```

```
#Concatenating the arrays along axis = 1
np.concatenate((arr1,arr2),axis=1)
```

```
array([[1, 2, 3, 2, 2, 3],
       [3, 4, 5, 1, 2, 5]])
```

Since the arrays need to have the same dimension only along the axis of concatenation, let us try concatenate the array below (**arr3**) with **arr1**, along axis = 0.

```
arr3 = np.array([2, 2, 3])
```

```
np.concatenate((arr1,arr3),axis=0)
```

ValueError: all the input arrays must have same number of dimensions, but the array at index

Note the above error, which indicates that **arr3** has only one dimension. Let us check the shape of **arr3**.

```
arr3.shape
```

```
(3,)
```

We can reshape **arr3** to a shape of (1,3) to make it compatible for concatenation with **arr1** along axis = 0.

```
arr3_reshaped = arr3.reshape(1,3)
arr3_reshaped
```

```
array([[2, 2, 3]])
```

Now we can concatenate the reshaped **arr3** with **arr1** along axis = 0.

```
np.concatenate((arr1,arr3_reshaped),axis=0)
```

```
array([[1, 2, 3],
       [3, 4, 5],
       [2, 2, 3]])
```

4.7 Practice exercise 1

4.7.0.1

Read the coordinates of the capital cities of the world from <http://techslides.com/list-of-countries-and-capitals> . Use NumPy to print the name and coordinates of the capital city closest to the US capital - Washington DC.

Note that:

1. The *Country Name* for US is given as *United States* in the data.
2. The ‘closeness’ of capital cities from the US capital is based on the Euclidean distance of their coordinates to those of the US capital.

Hints:

1. Use `read_html()` from the *Pandas* library to read the table.
2. Use the `to_numpy()` function of the *Pandas DataFrame* class to convert a DataFrame to a Numpy array
3. Use *broadcasting* to compute the euclidean distance of capital cities from Washington DC.

Solution:

```
import pandas as pd
capital_cities = pd.read_html('http://techslides.com/list-of-countries-and-capitals',headers=[0])
coordinates_capital_cities = capital_cities.iloc[:,2:4].to_numpy()
us_coordinates = capital_cities.loc[capital_cities['Country Name']=='United States',['Capital Name','lat','lon']]

#Broadcasting
distance_from_DC = np.sqrt(np.sum((us_coordinates-coordinates_capital_cities)**2,axis=1))

#Assigning a high value of distance to DC, otherwise it will itself be selected as being closest
distance_from_DC[distance_from_DC==0]=9999
closest_capital_index = np.argmin(distance_from_DC)
print("Closest capital city is:" ,capital_cities.loc[closest_capital_index,'Capital Name'])
```

```
print("Coordinates of the closest capital city are:",coordinates_capital_cities[closest_ca
```

Closest capital city is: Ottawa

Coordinates of the closest capital city are: [45.41666667 -75.7]

4.7.0.2

Use NumPy to:

1. Print the names of the countries of the top 10 capital cities closest to the US capital - Washington DC.
2. Create and print a NumPy array containing the coordinates of the top 10 cities.

Hint: Use the *concatenate()* function from the *NumPy* library to stack the coordinates of the top 10 cities.

```
top10_cities_coordinates = coordinates_capital_cities[closest_capital_index,:].reshape(1,2)
print("Top 10 countries closest to Washington DC are:\n Canada")
for i in range(9):
    distance_from_DC[closest_capital_index]=9999
    closest_capital_index = np.argmin(distance_from_DC)
    print(capital_cities.loc[closest_capital_index,'Country Name'])
    top10_cities_coordinates=np.concatenate((top10_cities_coordinates,coordinates_capital_
print("Coordinates of the top 10 cities closest to US are: \n",top10_cities_coordinates)
```

Top 10 countries closest to Washington DC are:

Canada
Bahamas
Bermuda
Cuba
Turks and Caicos Islands
Cayman Islands
Haiti
Jamaica
Dominican Republic
Saint Pierre and Miquelon

Coordinates of the top 10 cities closest to US are:

```
[[ 45.41666667 -75.7            ]
 [ 25.08333333 -77.35          ]
 [ 32.28333333 -64.783333      ]
```

```
[ 23.11666667 -82.35      ]
[ 21.46666667 -71.133333 ]
[ 19.3         -81.383333 ]
[ 18.53333333 -72.333333 ]
[ 18.          -76.8      ]
[ 18.46666667 -69.9      ]
[ 46.76666667 -56.183333 ]]
```

4.8 Vectorized computation with NumPy

Several matrix algebra operations such as multiplications, decompositions, determinants, etc. can be performed conveniently with NumPy. However, we'll focus on matrix multiplication as it is very commonly used to avoid python for loops and make computations faster. The `dot` function is used to multiply matrices:

```
#Defining a 2x2 matrix
a = np.array([[0,1],[3,4]])
a
```

```
array([[0, 1],
       [3, 4]])
```

```
#Defining a 2x2 matrix
b = np.array([[6,-1],[2,1]])
b
```

```
array([[ 6, -1],
       [ 2,  1]])
```

```
#Multiplying matrices 'a' and 'b' using the dot function
a.dot(b)
```

```
array([[ 2,  1],
       [26,  1]])
```

```
#Note that * results in element-wise multiplication
a*b
```

```
array([[ 0, -1],
       [ 6,  4]])
```

Example 2: This example will show vectorized computations with NumPy. Vectorized computations help perform computations more efficiently, and also make the code concise.

Q: Read the (1) quantities of roll, bun, cake and bread required by 3 people - Ben, Barbara & Beth, from *food_quantity.csv*, (2) price of these food items in two shops - Target and Kroger, from *price.csv*. Find out which shop should each person go to minimize their expenses.

```
#Reading the datasets on food quantity and price
import pandas as pd
food_qty = pd.read_csv('./Datasets/food_quantity.csv')
price = pd.read_csv('./Datasets/price.csv')
```

food_qty

| | Person | roll | bun | cake | bread |
|---|---------|------|-----|------|-------|
| 0 | Ben | 6 | 5 | 3 | 1 |
| 1 | Barbara | 3 | 6 | 2 | 2 |
| 2 | Beth | 3 | 4 | 3 | 1 |

price

| | Item | Target | Kroger |
|---|-------|--------|--------|
| 0 | roll | 1.5 | 1.0 |
| 1 | bun | 2.0 | 2.5 |
| 2 | cake | 5.0 | 4.5 |
| 3 | bread | 16.0 | 17.0 |

First, let's start from a simple problem. We'll compute the expenses of Ben if he prefers to buy all food items from Target

```
#Method 1: Using loop
bens_target_expense = 0 #Initializing Ben's expenses to 0
for k in range(4):      #Iterating over all the four desired food items
    bens_target_expense += food_qty.iloc[0,k+1]*price.iloc[k,1] #Total expenses on the kth
bens_target_expense      #Total expenses for Ben if he goes to Target
```

50.0

```
#Method 2: Using NumPy array
food_num = food_qty.iloc[0,1:].to_numpy() #Converting food quantity (for Ben) dataframe to NumPy array
price_num = price.iloc[:,1].to_numpy()    #Converting price (for Target) dataframe to NumPy array
food_num.dot(price_num) #Matrix multiplication of the quantity vector with the price vector
```

50.0

Ben will spend \$50 if he goes to Target

Now, let's add another layer of complication. We'll compute Ben's expenses for both stores - Target and Kroger

```
#Method 1: Using loops

#Initializing a Series of length two to store the expenses in Target and Kroger for Ben
bens_store_expense = pd.Series(0.0,index=price.columns[1:3])
for j in range(2): #Iterating over both the stores - Target and Kroger
    for k in range(4): #Iterating over all the four desired food items
        bens_store_expense[j] += food_qty.iloc[0,k+1]*price.iloc[k,j+1]
bens_store_expense
```

```
Target    50.0
Kroger    49.0
dtype: float64
```

```
#Method 2: Using NumPy array
food_num = food_qty.iloc[0,1:].to_numpy() #Converting food quantity (for Ben) dataframe to NumPy array
price_num = price.iloc[:,1:].to_numpy()   #Converting price dataframe to NumPy array
food_num.dot(price_num) #Matrix multiplication of the quantity vector with the price vector
```

```
array([50.0, 49.0], dtype=object)
```

Ben will spend \$50 if he goes to Target, and \$49 if he goes to Kroger. Thus, he should choose Kroger.

Now, let's add the final layer of complication, and solve the problem. We'll compute everyone's expenses for both stores - Target and Kroger

```
#Method 1: Using loops
store_expense = pd.DataFrame(0.0,index=price.columns[1:3],columns = food_qty['Person'])
for i in range(3):    #Iterating over all the three people - Ben, Barbara, and Beth
    for j in range(2):    #Iterating over both the stores - Target and Kroger
        for k in range(4):    #Iterating over all the four desired food items
            store_expense.iloc[j,i] += food_qty.iloc[i,k+1]*price.iloc[k,j+1]
store_expense
```

| Person | Ben | Barbara | Beth |
|--------|------|---------|------|
| Target | 50.0 | 58.5 | 43.5 |
| Kroger | 49.0 | 61.0 | 43.5 |

```
#Method 2: Using NumPy array
food_num = food_qty.iloc[:,1:].to_numpy() #Converting food quantity dataframe to NumPy array
price_num = price.iloc[:,1:].to_numpy() #Converting price dataframe to NumPy array
food_num.dot(price_num) #Matrix multiplication of the quantity matrix with the price matrix
```

```
array([[50. , 49. ],
       [58.5, 61. ],
       [43.5, 43.5]])
```

Based on the above table, Ben should go to Kroger, Barbara to Target and Beth can go to either store.

Note that, with each layer of complication, the number of for loops keep increasing, thereby increasing the complexity of Method 1, while the method with NumPy array does not change much. Vectorized computations with arrays are much more efficient.

4.8.1 Practice exercise 2

Use matrix multiplication to find the average IMDB rating and average Rotten tomatoes rating for each genre - comedy, action, drama and horror. Use the data: *movies_cleaned.csv*. Which is the most preferred genre for IMDB users, and which is the least preferred genre for Rotten Tomatoes users?

Hint: 1. Create two matrices - one containing the IMDB and Rotten Tomatoes ratings, and the other containing the genre flags (comedy/action/drama/horror).

2. Multiply the two matrices created in 1.

3. Divide each row/column of the resulting matrix by a vector having the number of ratings in each genre to get the average rating for the genre.

Solution:

```
import pandas as pd
data = pd.read_csv('./Datasets/movies_cleaned.csv')
data.head()
```

| | Title | IMDB Rating | Rotten Tomatoes Rating | Running Time min | Release Date | US C |
|---|---------------------|-------------|------------------------|------------------|--------------|------|
| 0 | Broken Arrow | 5.8 | 55 | 108 | Feb 09 1996 | 7064 |
| 1 | Brazil | 8.0 | 98 | 136 | Dec 18 1985 | 9929 |
| 2 | The Cable Guy | 5.8 | 52 | 95 | Jun 14 1996 | 6024 |
| 3 | Chain Reaction | 5.2 | 13 | 106 | Aug 02 1996 | 2122 |
| 4 | Clash of the Titans | 5.9 | 65 | 108 | Jun 12 1981 | 3000 |

```
# Getting ratings of all movies
drating = data[['IMDB Rating','Rotten Tomatoes Rating']]
drating_num = drating.to_numpy() #Converting the data to NumPy array
drating_num
```

```
array([[ 5.8, 55. ],
       [ 8. , 98. ],
       [ 5.8, 52. ],
       ...,
       [ 7. , 65. ],
       [ 5.7, 26. ],
       [ 6.7, 82. ]])
```

```
# Getting the matrix indicating the genre of all movies
dgenre = data.iloc[:,8:12]
dgenre_num = dgenre.to_numpy() #Converting the data to NumPy array
dgenre_num
```

```
array([[0, 1, 0, 0],
       [1, 0, 0, 0],
       [1, 0, 0, 0],
       ...,
       [1, 0, 0, 0],
```



```
[0, 1, 0, 0],
[0, 1, 0, 0]], dtype=int64)
```

We'll first find the total IMDB and Rotten tomatoes ratings for all movies of each genre, and then divide them by the number of movies of the corresponding genre to find the average rating for the genre.

For finding the total IMDB and Rotten tomatoes ratings, we'll multiply `drating_num` with `dgenre_num`. However, before multiplying, we'll check if their shapes are compatible for matrix multiplication.

```
#Shape of drating_num
drating_num.shape
```

```
(980, 2)
```

```
#Shape of dgenre_num
dgenre_num.shape
```

```
(980, 4)
```

Note that the above shapes are not compatible for matrix multiplication. We'll transpose `dgenre_num` to make the shapes compatible.

```
#Total IMDB and Rotten tomatoes ratings for each genre
ratings_sum_genre = drating_num.T.dot(dgenre_num)
ratings_sum_genre
```

```
array([[ 1785.6,  1673.1,  1630.3,   946.2],
       [14119. , 13725. , 14535. ,  6533. ]])
```

```
#Number of movies in the data will be stored in 'rows', and number of columns stored in 'c
rows, cols = data.shape
```

```
#Getting number of movies in each genre
movies_count_genre = dgenre_num.T.dot(np.ones(rows))
movies_count_genre
```

```
array([302., 264., 239., 154.]
```

```
#Finding the average IMDB and average Rotten tomatoes ratings for each genre
ratings_sum_genre/movies_count_genre
```

```
array([[ 5.91258278,  6.3375      ,  6.82133891,  6.14415584],
       [46.75165563, 51.98863636, 60.81589958, 42.42207792]])
```

```
pd.DataFrame(ratings_sum_genre/movies_count_genre,columns = ['comedy','Action','drama','horror'],
             index = ['IMDB Rating','Rotten Tomatoes Rating'])
```

| | comedy | Action | drama | horror |
|------------------------|-----------|-----------|-----------|-----------|
| IMDB Rating | 5.912583 | 6.337500 | 6.821339 | 6.144156 |
| Rotten Tomatoes Rating | 46.751656 | 51.988636 | 60.815900 | 42.422078 |

IMDB users prefer *drama*, and are amused the least by *comedy* movies, on an average. However, Rotten tomatoes critics would rather watch *comedy* than *horror* movies, on an average.

4.9 Pseudorandom number generation

Random numbers often need to be generated to analyze processes or systems, especially in cases when these processes or systems are governed by known probability distributions. For example, the number of personnel required to answer calls at a call center can be analyzed by simulating occurrence and duration of calls.

NumPy's `random` module can be used to generate arrays of random numbers from several different probability distributions. For example, a 3x5 array of uniformly distributed random numbers can be generated using the `uniform` function of the `random` module.

```
np.random.uniform(size = (3,5))
```

```
array([[0.69256322, 0.69259973, 0.03515058, 0.45186048, 0.43513769],
       [0.07373366, 0.07465425, 0.92195975, 0.72915895, 0.8906299 ],
       [0.15816734, 0.88144978, 0.05954028, 0.81403832, 0.97725557]])
```

Random numbers can also be generated by Python's built-in `random` module. However, it generates one random number at a time, which makes it much slower than NumPy's `random` module.

Example: Suppose 500 people eat at Food cart 1, and another 500 eat at Food cart 2, everyday.

The waiting time at Food cart 2 has a normal distribution with mean 8 minutes and standard deviation 3 minutes, while the waiting time at Food cart 1 has a uniform distribution with minimum 5 minutes and maximum 25 minutes.

Simulate a dataset containing waiting times for 500 ppl for 30 days in each of the food joints. Assume that the waiting times are measured simultaneously at a certain time in both places, i.e., the observations are paired.

On how many days is the average waiting time at Food cart 2 higher than that at Food cart 1?

What percentage of times the waiting time at Food cart 2 was higher than the waiting time at Food cart 1?

Try both approaches: (1) Using loops to generate data, (2) numpy array to generate data. Compare the time taken in both approaches.

```
import time as tm

#Method 1: Using loops
start_time = tm.time() #Current system time

#Initializing waiting times for 500 ppl over 30 days
waiting_times_FoodCart1 = pd.DataFrame(0,index=range(500),columns=range(30)) #FoodCart1
waiting_times_FoodCart2 = pd.DataFrame(0,index=range(500),columns=range(30)) #FoodCart2
import random as rm
for i in range(500): #Iterating over 500 ppl
    for j in range(30): #Iterating over 30 days
        waiting_times_FoodCart2.iloc[i,j] = rm.gauss(8,3) #Simulating waiting time in Food
        waiting_times_FoodCart1.iloc[i,j] = rm.uniform(5,25) #Simulating waiting time in F
time_diff = waiting_times_FoodCart2-waiting_times_FoodCart1

print("On ",sum(time_diff.mean(>0))," days, the average waiting time at FoodCart2 higher t
print("Percentage of times waiting time at FoodCart2 was greater than that at FoodCart1 =
end_time = tm.time() #Current system time
print("Time taken = ", end_time-start_time)
```

On 0 days, the average waiting time at FoodCart2 higher than that at FoodCart1

Percentage of times waiting time at FoodCart2 was greater than that at FoodCart1 = 16.22666

Time taken = 4.521248817443848

```
#Method 2: Using NumPy arrays
start_time = tm.time()
waiting_time_FoodCart2 = np.random.normal(8,3,size = (500,30)) #Simultaneously generating
waiting_time_FoodCart1 = np.random.uniform(5,25,size = (500,30)) #Simultaneously generating
time_diff = waiting_time_FoodCart2-waiting_time_FoodCart1
print("On ",(time_diff.mean(>0).sum())," days, the average waiting time at FoodCart2 higher than that at FoodCart1 = ")
print("Percentage of times waiting time at FoodCart2 was greater than that at FoodCart1 = ")
end_time = tm.time()
print("Time taken = ", end_time-start_time)
```

```
On 0 days, the average waiting time at FoodCart2 higher than that at FoodCart1
Percentage of times waiting time at FoodCart2 was greater than that at FoodCart1 = 16.52 %
Time taken = 0.008000850677490234
```

The approach with NumPy is much faster than the one with loops.

4.9.1 Practice exercise 3

Bootstrapping: Find the 95% confidence interval of mean profit for ‘Action’ movies, using Bootstrapping.

Bootstrapping is a non-parametric method for obtaining confidence interval. Use the algorithm below to find the confidence interval:

1. Find the profit for each of the ‘Action’ movies. Suppose there are N such movies. We will have a *Profit* column with N values.
2. Randomly sample N values with replacement from the *Profit* column
3. Find the mean of the N values obtained in (b)
4. Repeat steps (b) and (c) $M=1000$ times
5. The 95% Confidence interval is the range between the 2.5% and 97.5% percentile values of the 1000 means obtained in (c)
Use the *movies_cleaned.csv* dataset.

Solution:

```
#Reading data
movies = pd.read_csv('./Datasets/movies_cleaned.csv')
```

```

#Filtering action movies
movies_action = movies.loc[movies['Action']==1,:]

#Computing profit of movies
movies_action.loc[:, 'Profit'] = movies_action.loc[:, 'Worldwide Gross'] - movies_action.loc[:, 'Worldwide Budget']

#Subsetting the profit column
profit_vec = movies_action['Profit']

#Creating a matrix of 1000 samples with replacement from the profit column
bootstrap_samples=np.random.choice(profit_vec,size = (1000,len(profit_vec)))

#Computing the mean of each of the 1000 samples
bootstrap_sample_means = bootstrap_samples.mean(axis=1)

#The confidence interval is the 2.5th and 97.5th percentile of the mean of the 1000 samples
print("Confidence interval = ["+str(np.round(np.percentile(bootstrap_sample_means,2.5)/1e6,2)+" million, "+str(np.round(np.percentile(bootstrap_sample_means,97.5)/1e6,2)+" million)"]

```

Confidence interval = [\$132.53 million, \$182.69 million]

5 Pandas

5.1 Introduction

The Pandas library contains several methods and functions for cleaning, manipulating and analyzing data. While NumPy is suited for working with homogenous numerical array data, Pandas is designed for working with tabular or heterogenous data.

Pandas is built on top of the NumPy package. Thus, there are some similarities between the two libraries. Like NumPy, Pandas provides the basic mathematical functionalities like addition, subtraction, conditional operations and broadcasting. However, unlike NumPy library which provides objects for multi-dimensional arrays, Pandas provides the 2D table object called DataFrame.

Data in pandas is often used to feed statistical analysis in SciPy, plotting functions from Matplotlib, and machine learning algorithms in Scikit-learn.

Typically, the Pandas library is used for:

- Cleaning the data by tasks such as removing missing values, filtering rows / columns, aggregating data, mutating data, etc.
- Computing summary statistics such as the mean, median, max, min, standard deviation, etc.
- Computing correlation among columns in the data
- Computing the data distribution
- Visualizing the data with help from the Matplotlib library
- Writing the cleaned and transformed data into a CSV file or other database formats

Let's import the Pandas library to use its methods and functions.

```
import pandas as pd
```

5.2 Pandas data structures - Series and DataFrame

There are two core components of the Pandas library - Series and DataFrame.

A DataFrame is a two-dimensional object - comprising of tabular data organized in rows and columns, where individual columns can be of different value types (numeric / string / boolean etc.). A DataFrame has row labels (also called row indices) which refer to individual rows, and column labels (also called column names) that refer to individual columns. By default, the row indices are integers starting from zero. However, both the row indices and column names can be customized by the user.

Let us read the spotify data - *spotify_data.csv*, using the Pandas function `read_csv()`.

```
spotify_data = pd.read_csv('./Datasets/spotify_data.csv')
spotify_data.head()
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|---|------------------|--------|-------------|-------------------|------------------------|------------------|
| 0 | 16996777 | rap | Juice WRLD | 96 | All Girls Are The Same | 0 |
| 1 | 16996777 | rap | Juice WRLD | 96 | Lucid Dreams | 0 |
| 2 | 16996777 | rap | Juice WRLD | 96 | Hear Me Calling | 0 |
| 3 | 16996777 | rap | Juice WRLD | 96 | Robbery | 0 |
| 4 | 5988689 | rap | Roddy Ricch | 88 | Big Stepper | 0 |

The object `spotify_data` is a pandas DataFrame:

```
type(spotify_data)
```

`pandas.core.frame.DataFrame`

A Series is a one-dimensional object, containing a sequence of values, where each value has an index. Each column of a DataFrame is Series as shown in the example below.

```
#Extracting movie titles from the movie_ratings DataFrame
spotify_songs = spotify_data['track_name']
spotify_songs
```

```
0           All Girls Are The Same
1           Lucid Dreams
2           Hear Me Calling
3           Robbery
4           Big Stepper
...
243185           Stardust
```

```

243186          Knockin' A Jug - 78 rpm Version
243187          When It's Sleepy Time Down South
243188    On The Sunny Side Of The Street - Part 2
243189          My Sweet
Name: track_name, Length: 243190, dtype: object

```

```

#The object movie_titles is a Series
type(spotify_songs)

```

```
pandas.core.series.Series
```

A Series is essentially a column, and a DataFrame is a two-dimensional table made up of a collection of Series

```
<IPython.core.display.Image object>
```

5.3 Creating a Pandas Series / DataFrame

5.3.1 Specifying data within the Series() / DataFrame() functions

A Pandas Series and DataFrame can be created by specifying the data within the [Series\(\)](#) / [DataFrame\(\)](#) function. Below are examples of defining a Pandas Series / DataFrame.

```

#Defining a Pandas Series
series_example = pd.Series(['these','are','english','words'])
series_example

```

```

0      these
1        are
2    english
3      words
dtype: object

```

Note that the default row indices are integers starting from 0. However, the index can be specified with the `index` argument if desired by the user:

```

#Defining a Pandas Series with custom row labels
series_example = pd.Series(['these','are','english','words'], index = range(101,105))

```



```
series_example
```

```
101     these
102     are
103     english
104     words
dtype: object
```

5.3.2 Transforming in-built data structures

A Pandas DataFrame can be created by converting the in-built python data structures such as lists, dictionaries, and list of dictionaries to DataFrame. See the examples below.

```
#List consisting of expected age to marry of students of the STAT303-1 Fall 2022 class
exp_marriage_age_list=['24','30','28','29','30','27','26','28','30+','26','28','30','30',
```

```
#Example 1: Creating a Pandas Series from a list
exp_marriage_age_series=pd.Series(exp_marriage_age_list,name = 'expected_marriage_age')
exp_marriage_age_series.head()
```

```
0    24
1    30
2    28
3    29
4    30
Name: expected_marriage_age, dtype: object
```

```
#Dictionary consisting of the GDP per capita of the US from 1960 to 2021 with some missing
GDP_per_capita_dict = {'1960':3007,'1961':3067,'1962':3244,'1963':3375,'1964':3574,'1965':
```

```
#Example 2: Creating a Pandas Series from a Dictionary
GDP_per_capita_series = pd.Series(GDP_per_capita_dict)
GDP_per_capita_series.head()
```

```
1960    3007
1961    3067
1962    3244
1963    3375
```

```
1964    3574
dtype: int64
```

```
#List of dictionary consisting of 52 playing cards of the deck
deck_list_of_dictionaries = [{'value':i, 'suit':c}
for c in ['spades', 'clubs', 'hearts', 'diamonds']
for i in range(2,15)]
```

```
#Example 3: Creating a Pandas DataFrame from a List of dictionaries
deck_df = pd.DataFrame(deck_list_of_dictionaries)
deck_df.head()
```

| | value | suit |
|---|-------|--------|
| 0 | 2 | spades |
| 1 | 3 | spades |
| 2 | 4 | spades |
| 3 | 5 | spades |
| 4 | 6 | spades |

5.3.3 Importing data from files

In the real world, a Pandas DataFrame will typically be created by loading the datasets from existing storage such as SQL Database, CSV file, Excel file, text files, HTML files, etc., as we learned in the third chapter of the book on Reading data.

5.4 Attributes and Methods of a Pandas DataFrame

All attributes and methods of a Pandas DataFrame object can be viewed with the python's built-in `dir()` function.

```
#List of attributes and methods of a Pandas DataFrame
#This code is not executed as the list is too long
dir(spotify_data)
```

Although we'll see examples of attributes and methods of a Pandas DataFrame, please note that most of these attributes and methods are also applicable to the Pandas Series object.

5.4.1 Attributes of a Pandas DataFrame

Some of the attributes of the Pandas DataFrame class are the following.

5.4.1.1 dtypes

This attribute is a Series consisting the datatypes of columns of a Pandas DataFrame.

```
spotify_data.dtypes
```

```
artist_followers    int64
genres              object
artist_name         object
artist_popularity   int64
track_name          object
track_popularity    int64
duration_ms         int64
explicit            int64
release_year        int64
danceability        float64
energy              float64
key                 int64
loudness            float64
mode                int64
speechiness         float64
acousticness        float64
instrumentalness     float64
liveness            float64
valence             float64
tempo               float64
time_signature      int64
dtype: object
```

The table below describes the datatypes of columns in a Pandas DataFrame.

| Pandas Type | Native Python Type | Description |
|---------------------------|--|--|
| object | string | The most general dtype. This datatype is assigned to a column if the column has mixed types (numbers and strings) |
| int64 | int | This datatype is for integers from -9,223,372,036,854,775,808 to 9,223,372,036,854,775,807 or for integers having a maximum size of 64 bits |
| float64 | float | This datatype is for real numbers. If a column contains integers and NaNs, Pandas will default to float64. This is because the missing values may be a real number |
| datetime64, timedelta[ns] | N/A (but see the datetime module in Python's standard library) | Values meant to hold time data. This datatype is useful for time series analysis |

5.4.1.2 [columns](#)

This attribute consists of the column labels (or column names) of a Pandas DataFrame.

```
spotify_data.columns
```

```
Index(['artist_followers', 'genres', 'artist_name', 'artist_popularity',
      'track_name', 'track_popularity', 'duration_ms', 'explicit',
      'release_year', 'danceability', 'energy', 'key', 'loudness', 'mode',
      'speechiness', 'acousticness', 'instrumentalness', 'liveness',
      'valence', 'tempo', 'time_signature'],
      dtype='object')
```

5.4.1.3 [index](#)

This attribute consists of the row labels (or row indices) of a Pandas DataFrame.

```
spotify_data.index
```

```
RangeIndex(start=0, stop=243190, step=1)
```

5.4.1.4 axes

This is a list of length two, where the first element is the row labels, and the second element is the columns labels. In other words, this attribute combines the information in the attributes - index and columns.

```
spotify_data.axes
```

```
[RangeIndex(start=0, stop=243190, step=1),  
 Index(['artist_followers', 'genres', 'artist_name', 'artist_popularity',  
        'track_name', 'track_popularity', 'duration_ms', 'explicit',  
        'release_year', 'danceability', 'energy', 'key', 'loudness', 'mode',  
        'speechiness', 'acousticness', 'instrumentalness', 'liveness',  
        'valence', 'tempo', 'time_signature'],  
       dtype='object')]
```

5.4.1.5 ndim

As in NumPy, this attribute specifies the number of dimensions. However, unlike NumPy, a Pandas DataFrame has a fixed dimension of 2, and a Pandas Series has a fixed dimension of 1.

```
spotify_data.ndim
```

```
2
```

5.4.1.6 size

This attribute specifies the number of elements in a DataFrame. Its value is the product of the number of rows and columns.

```
spotify_data.size
```

```
5106990
```

5.4.1.7 `shape`

This is a tuple consisting of the number of rows and columns in a Pandas DataFrame.

```
spotify_data.shape
```

```
(243190, 21)
```

5.4.1.8 `values`

This provides a NumPy representation of a Pandas DataFrame.

```
spotify_data.values
```

```
array([[16996777, 'rap', 'Juice WRLD', ..., 0.203, 161.991, 4],
       [16996777, 'rap', 'Juice WRLD', ..., 0.218, 83.903, 4],
       [16996777, 'rap', 'Juice WRLD', ..., 0.499, 88.933, 4],
       ...,
       [2256652, 'jazz', 'Louis Armstrong', ..., 0.37, 105.093, 4],
       [2256652, 'jazz', 'Louis Armstrong', ..., 0.576, 101.279, 4],
       [2256652, 'jazz', 'Louis Armstrong', ..., 0.816, 105.84, 4]],
      dtype=object)
```

5.4.2 Methods of a Pandas DataFrame

Some of the commonly used methods of the Pandas DataFrame class are the following.

5.4.2.1 `head()`

Prints the first n rows of a DataFrame.

```
spotify_data.head(2)
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|---|------------------|--------|-------------|-------------------|------------------------|------------------|
| 0 | 16996777 | rap | Juice WRLD | 96 | All Girls Are The Same | 0 |
| 1 | 16996777 | rap | Juice WRLD | 96 | Lucid Dreams | 0 |

5.4.2.2 `tail()`

Prints the last n rows of a DataFrame.

```
spotify_data.tail(3)
```

| | artist_followers | genres | artist_name | artist_popularity | track_name |
|--------|------------------|--------|-----------------|-------------------|----------------------------------|
| 243187 | 2256652 | jazz | Louis Armstrong | 74 | When It's Sleepy Time Down South |
| 243188 | 2256652 | jazz | Louis Armstrong | 74 | On The Sunny Side Of The Street |
| 243189 | 2256652 | jazz | Louis Armstrong | 74 | My Sweet |

5.4.2.3 `describe()`

Print summary statistics of a Pandas DataFrame, as seen in chapter 3 on Reading Data.

```
spotify_data.describe()
```

| | artist_followers | artist_popularity | track_popularity | duration_ms | explicit | release_year |
|-------|------------------|-------------------|------------------|--------------|---------------|---------------|
| count | 2.431900e+05 | 243190.000000 | 243190.000000 | 2.431900e+05 | 243190.000000 | 243190.000000 |
| mean | 1.960931e+06 | 65.342633 | 36.080772 | 2.263209e+05 | 0.050039 | 1992.475258 |
| std | 5.028746e+06 | 10.289182 | 16.476836 | 9.973214e+04 | 0.218026 | 18.481463 |
| min | 2.300000e+01 | 51.000000 | 0.000000 | 3.344000e+03 | 0.000000 | 1923.000000 |
| 25% | 1.832620e+05 | 57.000000 | 25.000000 | 1.776670e+05 | 0.000000 | 1980.000000 |
| 50% | 5.352520e+05 | 64.000000 | 36.000000 | 2.188670e+05 | 0.000000 | 1994.000000 |
| 75% | 1.587332e+06 | 72.000000 | 48.000000 | 2.645465e+05 | 0.000000 | 2008.000000 |
| max | 7.890023e+07 | 100.000000 | 99.000000 | 4.995083e+06 | 1.000000 | 2021.000000 |

5.4.2.4 `max()/min()`

Returns the max/min values of numeric columns. If the function is applied on non-numeric columns, it will return the maximum/minimum value based on the order of the alphabet.

```
#The max() method applied on a Series  
spotify_data['artist_popularity'].max()
```

```
#The max() method applied on a DataFrame
spotify_data.max()
```

```
artist_followers      78900234
genres                rock
artist_name           OSN
artist_popularity     100
track_name            days gone by
track_popularity      99
duration_ms          4995083
explicit              1
release_year          2021
danceability          0.988
energy                1.0
key                   11
loudness              3.744
mode                  1
speechiness           0.969
acousticness          0.996
instrumentalness      1.0
liveness              1.0
valence               1.0
tempo                 243.507
time_signature        5
dtype: object
```

5.4.2.5 `mean()`/`median()`

Returns the mean/median values of numeric columns.

```
spotify_data.median()
```

```
artist_followers      535252.000000
artist_popularity      64.000000
track_popularity       36.000000
duration_ms           218867.000000
explicit               0.000000
release_year           1994.000000
danceability           0.579000
energy                 0.591000
```


| | |
|------------------|------------|
| key | 5.000000 |
| loudness | -8.645000 |
| mode | 1.000000 |
| speechiness | 0.043100 |
| acousticness | 0.325000 |
| instrumentalness | 0.000011 |
| liveness | 0.141000 |
| valence | 0.560000 |
| tempo | 118.002000 |
| time_signature | 4.000000 |
| dtype: | float64 |

5.4.2.6 `std()`

Returns the standard deviation of numeric columns.

```
spotify_data.std()
```

| | |
|-------------------|--------------|
| artist_followers | 5.028746e+06 |
| artist_popularity | 1.028918e+01 |
| track_popularity | 1.647684e+01 |
| duration_ms | 9.973214e+04 |
| explicit | 2.180260e-01 |
| release_year | 1.848146e+01 |
| danceability | 1.594436e-01 |
| energy | 2.366309e-01 |
| key | 3.532546e+00 |
| loudness | 4.449731e+00 |
| mode | 4.698771e-01 |
| speechiness | 1.980684e-01 |
| acousticness | 3.211417e-01 |
| instrumentalness | 2.095551e-01 |
| liveness | 1.980759e-01 |
| valence | 2.500172e-01 |
| tempo | 2.986422e+01 |
| time_signature | 4.580822e-01 |
| dtype: | float64 |

5.4.2.7 `sample(n)`

Returns n random observations from a Pandas DataFrame.

```
spotify_data.sample(4)
```

| | artist_followers | genres | artist_name | artist_popularity | track_name |
|--------|------------------|---------|---------------|-------------------|-----------------------------------|
| 42809 | 385756 | rock | Saxon | 56 | Never Surrender - 2009 Remastered |
| 25730 | 810526 | hip hop | Froid | 68 | Pseudosocial |
| 147392 | 479209 | jazz | Sarah Vaughan | 59 | Love Dance |
| 233189 | 1201905 | rock | Grateful Dead | 72 | Cold Rain and Snow - 2013 Remast |

5.4.2.8 dropna()

Drops all observations with at least one missing value.

```
#This code is not executed to avoid prining a large table
spotify_data.dropna()
```

5.4.2.9 apply()

This method is used to apply a function over all columns or rows of a Pandas DataFrame. For example, let us find the range of values of `artist_followers`, `artist_popularity` and `release_year`.

```
#Defining the function to compute range of values of a columns
def range_of_values(x):
    return x.max()-x.min()

#Applying the function to three coluumns for which we wish to find the range of values
spotify_data[['artist_followers','artist_popularity','release_year']].apply(range_of_value
```

```
artist_followers      78900211
artist_popularity      49
release_year          98
dtype: int64
```

The `apply()` method is often used with the one line function known as `lambda` function in python. These functions do not require a name, and can be defined using the keyword `lambda`. The above block of code can be concisely written as:

```
spotify_data[['artist_followers','artist_popularity','release_year']].apply(lambda x:x.max-
```

```
artist_followers      78900211
artist_popularity      49
release_year          98
dtype: int64
```

Note that the Series object also has an `apply()` method associated with it. The method can be used to apply a function to each value of a Series.

5.4.2.10 `map()`

The function is used to map distinct values of a Pandas Series to another set of corresponding values.

For example, suppose we wish to create a new column in the spotify dataset which indicates the modality of the song - major (mode = 1) or minor (mode = 0). We'll map the values of the `mode` column to the categories *major* and *minor*:

```
#Creating a dictionary that maps the values 0 and 1 to minor and major respectively
map_mode = {0:'minor', 1:'major'}

#The map() function requires a dictionary object, and maps the 'values' of the 'keys' in t
spotify_data['modality'] = spotify_data['mode'].map(map_mode)
```

We can see the variable `modality` in the updated DataFrame.

```
spotify_data.head()
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|---|------------------|--------|-------------|-------------------|------------------------|------------------|
| 0 | 16996777 | rap | Juice WRLD | 96 | All Girls Are The Same | 0 |
| 1 | 16996777 | rap | Juice WRLD | 96 | Lucid Dreams | 0 |
| 2 | 16996777 | rap | Juice WRLD | 96 | Hear Me Calling | 0 |
| 3 | 16996777 | rap | Juice WRLD | 96 | Robbery | 0 |
| 4 | 5988689 | rap | Roddy Ricch | 88 | Big Stepper | 0 |

5.4.2.11 `drop()`

This function is used to drop rows/columns from a DataFrame.

For example, let us drop the columns `mode` from the spotify dataset:

```
#Dropping the column 'mode'
spotify_data_new = spotify_data.drop('mode',axis=1)
spotify_data_new.head()
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|---|------------------|--------|-------------|-------------------|------------------------|------------------|
| 0 | 16996777 | rap | Juice WRLD | 96 | All Girls Are The Same | 0 |
| 1 | 16996777 | rap | Juice WRLD | 96 | Lucid Dreams | 0 |
| 2 | 16996777 | rap | Juice WRLD | 96 | Hear Me Calling | 0 |
| 3 | 16996777 | rap | Juice WRLD | 96 | Robbery | 0 |
| 4 | 5988689 | rap | Roddy Ricch | 88 | Big Stepper | 0 |

Note that if multiple columns or rows are to be dropped, they must be enclosed in box brackets.

5.4.2.12 `unique()`

This functions provides the unique values of a Series. For example, let us find the number of unique genres of songs in the spotify dataset:

```
spotify_data.genres.unique()
```

```
array(['rap', 'pop', 'miscellaneous', 'metal', 'hip hop', 'rock',
      'pop & rock', 'hoerspiel', 'folk', 'electronic', 'jazz', 'country',
      'latin'], dtype=object)
```

5.4.2.13 `value_counts()`

This function provides the number of observations of each value of a Series. For example, let us find the number of songs of each genre in the spotify dataset:

```
spotify_data.genres.value_counts()
```

```
pop          70441
rock         49785
pop & rock   43437
miscellaneous 35848
jazz         13363
```

```

hoerspiel      12514
hip hop        7373
folk           2821
latin          2125
rap            1798
metal          1659
country        1236
electronic     790
Name: genres, dtype: int64

```

More than half the songs in the dataset are *pop*, *rock* or *pop & rock*.

5.4.2.14 `isin()`

This function provides a boolean Series indicating the position of certain values in a Series. The function is helpful in sub-setting data. For example, let us subset the songs that are either *latin*, *rap*, or *metal*:

```

latin_rap_metal_songs = spotify_data.loc[spotify_data.genres.isin(['latin','rap','metal'])]
latin_rap_metal_songs.head()

```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|---|------------------|--------|-------------|-------------------|------------------------|------------------|
| 0 | 16996777 | rap | Juice WRLD | 96 | All Girls Are The Same | 0 |
| 1 | 16996777 | rap | Juice WRLD | 96 | Lucid Dreams | 0 |
| 2 | 16996777 | rap | Juice WRLD | 96 | Hear Me Calling | 0 |
| 3 | 16996777 | rap | Juice WRLD | 96 | Robbery | 0 |
| 4 | 5988689 | rap | Roddy Ricch | 88 | Big Stepper | 0 |

5.5 Data manipulations with Pandas

5.5.1 Sub-setting data

5.5.1.1 `loc` and `iloc` with the original row / column index

Subsetting observations: In the chapter on reading data, we learned about operators `loc` and `iloc` that can be used to subset data based on axis labels and position of rows/columns respectively. However, usually we are not aware of the relevant row indices, and we may want to subset data based on some condition(s). For example, suppose we wish to analyze only those songs whose track popularity is higher than 50.

Q: Do we need to subset rows or columns in this case?

A: Rows, as songs correspond to rows, while features of songs correspond to columns.

As we need to subset rows, the filter must be applied at the starting index, i.e., the index before the `,`. As we don't need to subset any specific features of the songs, there is no subsetting to be done on the columns. `A :` at the ending index means that all columns need to be selected.

```
#Subsetting spotify songs that have track popularity score of more than 50
popular_songs = spotify_data.loc[spotify_data.track_popularity>=50,:]
popular_songs.head()
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|-----|------------------|------------|-----------------|-------------------|-------------------------|------------------|
| 181 | 1277325 | hip hop | Dave | 77 | Titanium | 69 |
| 191 | 1123869 | rap | Jay Wheeler | 85 | Viendo el Techo | 64 |
| 208 | 3657199 | rap | Polo G | 91 | RAPSTAR | 89 |
| 263 | 1461700 | pop & rock | Teoman | 67 | Gecenin Sonuna Yolculuk | 52 |
| 293 | 299746 | pop & rock | Lars Winnerbäck | 62 | Själ och hjärta | 55 |

Subsetting columns: Suppose we wish to analyze only *track_name*, *release_year* and *track_popularity* of songs. Then, we can subset the relevant columns:

```
relevant_columns = spotify_data.loc[:,['track_name','release_year','track_popularity']]
relevant_columns.head()
```

| | track_name | release_year | track_popularity |
|---|------------------------|--------------|------------------|
| 0 | All Girls Are The Same | 2021 | 0 |
| 1 | Lucid Dreams | 2021 | 0 |
| 2 | Hear Me Calling | 2021 | 0 |
| 3 | Robbery | 2021 | 0 |
| 4 | Big Stepper | 2021 | 0 |

Note that when multiple columns are subset with `loc` they are enclosed in a box bracket, unlike the case with a single column. Similarly if multiple observations are selected using the row labels, the row labels must be enclosed in box brackets.

5.5.1.2 Re-indexing rows followed by `loc` / `iloc`

Suppose we wish to subset data based on the **genres**. If we want to subset *hiphop* songs, we may subset as:

```
#Subsetting hiphop songs
hiphop_songs = spotify_data.loc[spotify_data['genres']=='hip hop',:]
hiphop_songs.head()
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|----|------------------|---------|--------------|-------------------|-------------------|------------------|
| 64 | 6485079 | hip hop | DaBaby | 93 | FIND MY WAY | 0 |
| 80 | 22831280 | hip hop | Daddy Yankee | 91 | Hula Hoop | 0 |
| 81 | 22831280 | hip hop | Daddy Yankee | 91 | Gasolina - Live | 0 |
| 87 | 22831280 | hip hop | Daddy Yankee | 91 | La Nueva Y La Ex | 0 |
| 88 | 22831280 | hip hop | Daddy Yankee | 91 | Que Tire Pa Lante | 0 |

However, if we need to subset data by **genres** frequently in our analysis, and we don't need the current row labels, we may replace the row labels as **genres** to shorten the code for filtering the observations based on **genres**.

We use the `set_index()` function to re-index the rows based on existing column(s) of the DataFrame.

```
#Defining row labels as the values of the column `genres`
spotify_data_reindexed = spotify_data.set_index(keys=spotify_data['genres'])
spotify_data_reindexed.head()
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|--------|------------------|--------|-------------|-------------------|------------------------|------------------|
| genres | | | | | | |
| rap | 16996777 | rap | Juice WRLD | 96 | All Girls Are The Same | 0 |
| rap | 16996777 | rap | Juice WRLD | 96 | Lucid Dreams | 0 |
| rap | 16996777 | rap | Juice WRLD | 96 | Hear Me Calling | 0 |
| rap | 16996777 | rap | Juice WRLD | 96 | Robbery | 0 |
| rap | 5988689 | rap | Roddy Ricch | 88 | Big Stepper | 0 |

Now, we can subset *hiphop* songs using the row label of the data:

```
#Subsetting hiphop songs using row labels
hiphop_songs = spotify_data_reindexed.loc['hip hop',:]
hiphop_songs.head()
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|---------|------------------|---------|--------------|-------------------|-------------------|------------------|
| genres | | | | | | |
| hip hop | 6485079 | hip hop | DaBaby | 93 | FIND MY WAY | 0 |
| hip hop | 22831280 | hip hop | Daddy Yankee | 91 | Hula Hoop | 0 |
| hip hop | 22831280 | hip hop | Daddy Yankee | 91 | Gasolina - Live | 0 |
| hip hop | 22831280 | hip hop | Daddy Yankee | 91 | La Nueva Y La Ex | 0 |
| hip hop | 22831280 | hip hop | Daddy Yankee | 91 | Que Tire Pa Lante | 0 |

5.5.2 Sorting data

Sorting dataset is a very common operation. The `sort_values()` function of Pandas can be used to sort a Pandas DataFrame or Series. Let us sort the spotify data in decreasing order of *track_popularity*:

```
spotify_sorted = spotify_data.sort_values(by = 'track_popularity', ascending = False)
spotify_sorted.head()
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|------|------------------|---------|----------------|-------------------|------------------------|------------------|
| 2398 | 1444702 | pop | Olivia Rodrigo | 88 | drivers license | 99 |
| 2442 | 177401 | hip hop | Masked Wolf | 85 | Astronaut In The Ocean | 98 |
| 3133 | 1698014 | pop | Kali Uchis | 88 | telepatía | 97 |
| 6702 | 31308207 | pop | The Weeknd | 96 | Save Your Tears | 97 |
| 6703 | 31308207 | pop | The Weeknd | 96 | Blinding Lights | 96 |

Drivers license is the most popular song!

<IPython.core.display.HTML object>

5.5.3 Ranking data

With the `rank()` function, we can rank the observations.

For example, let us add a new column to the spotify data that provides the rank of the *track_popularity* column:


```
spotify_ranked = spotify_data.copy()
spotify_ranked['track_popularity_rank']=spotify_sorted['track_popularity'].rank()
spotify_ranked.head()
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|---|------------------|--------|-------------|-------------------|------------------------|------------------|
| 0 | 16996777 | rap | Juice WRLD | 96 | All Girls Are The Same | 0 |
| 1 | 16996777 | rap | Juice WRLD | 96 | Lucid Dreams | 0 |
| 2 | 16996777 | rap | Juice WRLD | 96 | Hear Me Calling | 0 |
| 3 | 16996777 | rap | Juice WRLD | 96 | Robbery | 0 |
| 4 | 5988689 | rap | Roddy Ricch | 88 | Big Stepper | 0 |

Note the column `track_popularity_rank`. Why does it contain floating point numbers? Check the `rank()` documentation to find out!

5.5.4 Practice exercise 1

5.5.4.1

Read the file *STAT303-1 survey for data analysis.csv*.

```
survey_data = pd.read_csv('./Datasets/STAT303-1 survey for data analysis.csv')
```

5.5.4.2

How many observations and variables are there in the data?

```
print("The data has ",survey_data.shape[0],"observations, and", survey_data.shape[1], "col
```

The data has 192 observations, and 51 columns

5.5.4.3

Rename all the columns of the data, except the first two columns, with the shorter names in the list `new_col_names` given below. The order of column names in the list is the same as the order in which the columns are to be renamed starting with the third column from the left.

```
new_col_names = ['parties_per_month', 'do_you_smoke', 'weed', 'are_you_an_introvert_or_ext
```

```
survey_data.columns = list(survey_data.columns[0:2])+new_col_names
```

5.5.4.4

Rename the following columns again:

1. Rename `do_you_smoke` to `smoke`.
2. Rename `are_you_an_introvert_or_extrovert` to `introvert_extrovert`.

Hint: Use the function `rename()`

```
survey_data.rename(columns={'do_you_smoke':'smoke','are_you_an_introvert_or_extrovert':'introvert_extrovert'})
```

5.5.4.5

Find the proportion of people going to more than 4 parties per month. Use the variable `parties_per_month`.

```
survey_data['parties_per_month']=pd.to_numeric(survey_data.parties_per_month,errors='coerce')
survey_data.loc[survey_data['parties_per_month']>4,:].shape[0]/survey_data.shape[0]
```

0.3385416666666667

5.5.4.6

Among the people who go to more than 4 parties a month, what proportion of them are introverts?

```
survey_data.loc[((survey_data['parties_per_month']>4) & (survey_data.introvert_extrovert=='introvert')).shape[0]/survey_data.loc[survey_data['parties_per_month']>4,:].shape[0]
```

0.5076923076923077

5.5.4.7

Find the proportion of people in each category of the variable `how_happy`.

```
survey_data.how_happy.value_counts()/survey_data.shape[0]
```

```
Pretty happy    0.703125
Very happy      0.151042
Not too happy   0.088542
Don't know      0.057292
Name: how_happy, dtype: float64
```

5.5.4.8

Among the people who go to more than 4 parties a month, what proportion of them are either `Pretty happy` or `Very happy`?

```
survey_data.loc[((survey_data['parties_per_month']>4) & (survey_data.how_happy.isin(['Pretty happy', 'Very happy'])))
```

```
0.9076923076923077
```

5.5.4.9

Examine the column `num_insta_followers`. Some numbers in the column contain a comma(,) or a tilde(~). Remove both these characters from the numbers in the column.

Hint: You may use the function `str.replace()` of the Pandas Series class.

```
survey_data_insta = survey_data.copy()
survey_data_insta['num_insta_followers'] = survey_data_insta['num_insta_followers'].str.replace(',', '')
survey_data_insta['num_insta_followers'] = survey_data_insta['num_insta_followers'].str.replace('~', '')
```

5.5.4.10

Convert the column `num_insta_followers` to numeric. Coerce the errors.

```
survey_data_insta.num_insta_followers = pd.to_numeric(survey_data_insta.num_insta_followers, errors='coerce')
```

5.5.4.11

Drop the observations consisting of missing values for `num_insta_followers`. Report the number of observations dropped.

```
survey_data.num_insta_followers.isna().sum()
```

3

There are 3 missing values of `num_insta_followers`.

```
#Dropping observations with missing values of num_insta_followers
survey_data=survey_data[~survey_data.num_insta_followers.isna()]
```

5.5.4.12

What is the mean `internet_hours_per_day` for the top 46 people in terms of number of instagram followers?

```
survey_data_insta.sort_values(by = 'num_insta_followers',ascending=False, inplace=True)
top_insta = survey_data_insta.iloc[:46,:]
top_insta.internet_hours_per_day = pd.to_numeric(top_insta.internet_hours_per_day,errors =
top_insta.internet_hours_per_day.mean()
```

5.088888888888889

5.5.4.13

What is the mean `internet_hours_per_day` for the remaining people?

```
low_insta = survey_data_insta.iloc[46:,:]
low_insta.internet_hours_per_day = pd.to_numeric(low_insta.internet_hours_per_day,errors =
low_insta.internet_hours_per_day.mean()
```

13.118881118881118

5.6 Arithmetic operations

5.6.1 Arithmetic operations between DataFrames

Let us create two toy DataFrames:

```
#Creating two toy DataFrames
toy_df1 = pd.DataFrame([(1,2),(3,4),(5,6)], columns=['a','b'])
toy_df2 = pd.DataFrame([(100,200),(300,400),(500,600)], columns=['a','b'])
```

```
#DataFrame 1
toy_df1
```

| | a | b |
|---|---|---|
| 0 | 1 | 2 |
| 1 | 3 | 4 |
| 2 | 5 | 6 |

```
#DataFrame 2
toy_df2
```

| | a | b |
|---|-----|-----|
| 0 | 100 | 200 |
| 1 | 300 | 400 |
| 2 | 500 | 600 |

Element by element operations between two DataFrames can be performed with the operators `+`, `-`, `*`, `/`, `**`, and `%`. Below is an example of element-by-element addition of two DataFrames:

```
# Element-by-element arithmetic addition of the two DataFrames
toy_df1 + toy_df2
```

| | a | b |
|---|-----|-----|
| 0 | 101 | 202 |
| 1 | 303 | 404 |
| 2 | 505 | 606 |

Note that these operations create problems when the row indices and/or column names of the two DataFrames do not match. See the example below:

```
#Creating another toy example of a DataFrame
toy_df3 = pd.DataFrame([(100,200),(300,400),(500,600)], columns=['a','b'], index=[1,2,3])
toy_df3
```

| | a | b |
|---|-----|-----|
| 1 | 100 | 200 |
| 2 | 300 | 400 |
| 3 | 500 | 600 |

```
#Adding DataFrames with some unmatching row indices
toy_df1 + toy_df3
```

| | a | b |
|---|-------|-------|
| 0 | NaN | NaN |
| 1 | 103.0 | 204.0 |
| 2 | 305.0 | 406.0 |
| 3 | NaN | NaN |

Note that the rows whose indices match between the two DataFrames are added up. The rest of the values are missing (or NaN) because only one of the DataFrames has that index.

As in the case of row indices, missing values will also appear in the case of unmatching column names, as shown in the example below.

```
toy_df4 = pd.DataFrame([(100,200),(300,400),(500,600)], columns=['b','c'])
toy_df4
```

| | b | c |
|---|-----|-----|
| 0 | 100 | 200 |
| 1 | 300 | 400 |
| 2 | 500 | 600 |

```
#Adding DataFrames with some unmatching column names
toy_df1 + toy_df4
```

| | a | b | c |
|---|-----|-----|-----|
| 0 | NaN | 102 | NaN |
| 1 | NaN | 304 | NaN |
| 2 | NaN | 506 | NaN |

5.6.2 Arithmetic operations between a Series and a DataFrame

Broadcasting: As in NumPy, we can **broadcast** a Series to match the shape of another DataFrame:

```
# Broadcasting: The row [1,2] (a Series) is added on every row in df2
toy_df1.iloc[0,:] + toy_df2
```

| | a | b |
|---|-----|-----|
| 0 | 101 | 202 |
| 1 | 301 | 402 |
| 2 | 501 | 602 |

Note that the `+` operator is used to add values of a Series to a DataFrame based on column names. For adding a Series to a DataFrame based on row indices, we cannot use the `+` operator. Instead, we'll need to use the `add()` function as explained below.

Broadcasting based on row/column labels: We can use the `add()` function to broadcast a Series to a DataFrame. By default the Series adds based on column names, as in the case of the `+` operator.

```
# Add the first row of df1 (a Series) to every row in df2
toy_df2.add(toy_df1.iloc[0,:])
```

| | a | b |
|---|-----|-----|
| 0 | 101 | 202 |
| 1 | 301 | 402 |
| 2 | 501 | 602 |

For broadcasting based on row indices, we use the `axis` argument of the `add()` function.

```
# The second column of df1 (a Series) is added to every col in df2
toy_df2.add(toy_df1.iloc[:,1],axis='index')
```

| | a | b |
|---|-----|-----|
| 0 | 102 | 202 |
| 1 | 304 | 404 |
| 2 | 506 | 606 |

5.6.3 Case study

To see the application of arithmetic operations on DataFrames, let us see the case study below.

Song recommendation: Spotify recommends songs based on songs listened by the user. Suppose you have listened to the song *drivers license*. Spotify intends to recommend you 5 songs that are *similar* to *drivers license*. Which songs should it recommend?

Let us see the available song information that can help us identify songs similar to *drivers license*. The `columns` attribute of DataFrame will display all the columns names. The description of some of the column names relating to audio features is [here](#).

```
spotify_data.columns
```

```
Index(['artist_followers', 'genres', 'artist_name', 'artist_popularity',
      'track_name', 'track_popularity', 'duration_ms', 'explicit',
      'release_year', 'danceability', 'energy', 'key', 'loudness', 'mode',
      'speechiness', 'acousticness', 'instrumentalness', 'liveness',
      'valence', 'tempo', 'time_signature'],
      dtype='object')
```

Solution approach: We have several features of a song. Let us find songs similar to *drivers license* in terms of *danceability*, *energy*, *key*, *loudness*, *mode*, *speechiness*, *acousticness*, *instrumentalness*, *liveness*, *valence*, *time_signature* and *tempo*. Note that we are considering only audio features for simplicity.

To find the songs most similar to *drivers license*, we need to define a measure that quantifies the similarity. Let us define similarity of a song with *drivers license* as the Euclidean distance of the song from *drivers license*, where the coordinates of a song are: (danceability, energy, key, loudness, mode, speechiness, acousticness, instrumentalness, liveness, valence, time_signature, tempo). Thus, similarity can be formulated as:

$$Similarity_{DL-S} = \sqrt{(danceability_{DL} - danceability_S)^2 + (energy_{DL} - energy_S)^2 + \dots + (tempo_{DL} - tempo_S)^2}$$

where the subscript DL stands for *drivers license* and S stands for any song. The top 5 songs with the least value of $Similarity_{DL-S}$ will be the most similar to *drivers license* and should be recommended.

Let us subset the columns that we need to use to compute the Euclidean distance.

```
audio_features = spotify_data[['danceability', 'energy', 'key', 'loudness', 'mode', 'speechiness',
                              'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo']]

audio_features.head()
```

| | danceability | energy | key | loudness | mode | speechiness | acousticness | instrumentalness | liveness | valence | tempo |
|---|--------------|--------|-----|----------|------|-------------|--------------|------------------|----------|---------|--------|
| 0 | 0.673 | 0.529 | 0 | -7.226 | 1 | 0.3060 | 0.0769 | 0.000338 | 0.0856 | 0.5806 | 125.29 |
| 1 | 0.511 | 0.566 | 6 | -7.230 | 0 | 0.2000 | 0.3490 | 0.000000 | 0.3400 | 0.4378 | 127.95 |
| 2 | 0.699 | 0.687 | 7 | -3.997 | 0 | 0.1060 | 0.3080 | 0.000036 | 0.1210 | 0.6849 | 125.04 |
| 3 | 0.708 | 0.690 | 2 | -5.181 | 1 | 0.0442 | 0.3480 | 0.000000 | 0.2220 | 0.5504 | 125.04 |
| 4 | 0.753 | 0.597 | 8 | -8.469 | 1 | 0.2920 | 0.0477 | 0.000000 | 0.1970 | 0.4219 | 125.04 |

```
#Distribution of values of audio_features
audio_features.describe()
```

| | danceability | energy | key | loudness | mode | speechiness | acousticness | instrumentalness | liveness | valence | tempo |
|-------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|------------------|---------------|---------------|---------------|
| count | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 |
| mean | 0.568357 | 0.580633 | 5.240326 | -9.432548 | 0.670928 | 0.111984 | 0.198068 | 0.033200 | 0.431000 | 0.421900 | 125.040000 |
| std | 0.159444 | 0.236631 | 3.532546 | 4.449731 | 0.469877 | 0.198068 | 0.033200 | 0.043100 | 0.075300 | 0.282300 | 3.450000 |
| min | 0.000000 | 0.000000 | 0.000000 | -60.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 95.000000 |
| 25% | 0.462000 | 0.405000 | 2.000000 | -11.990000 | 0.000000 | 0.033200 | 0.043100 | 0.075300 | 0.282300 | 0.421900 | 125.040000 |
| 50% | 0.579000 | 0.591000 | 5.000000 | -8.645000 | 1.000000 | 0.043100 | 0.075300 | 0.282300 | 0.431000 | 0.421900 | 125.040000 |
| 75% | 0.685000 | 0.776000 | 8.000000 | -6.131000 | 1.000000 | 0.075300 | 0.282300 | 0.431000 | 0.421900 | 0.421900 | 125.040000 |
| max | 0.988000 | 1.000000 | 11.000000 | 3.744000 | 1.000000 | 0.969000 | 0.969000 | 0.969000 | 0.969000 | 0.969000 | 125.040000 |

Note that the audio features differ in terms of scale. Some features like *key* have a wide range of [0,11], while others like *danceability* have a very narrow range of [0,0.988]. If we use them directly, features like *danceability* will have a much higher influence on $Similarity_{DL-S}$ as compared to features like *key*. Assuming we wish all the features to have equal weight in

quantifying a song's similarity to *drivers license*, we should scale the features, so that their values are comparable.

Let us scale the value of each column to a standard uniform distribution: $U[0,1]$.

For scaling the values of a column to $U[0,1]$, we need to subtract the minimum value of the column from each value, and divide by the range of values of the column. For example, *danceability* can be standardized as follows:

```
#Scaling danceability to U[0,1]
danceability_value_range = audio_features.danceability.max()-audio_features.danceability.m
danceability_std = (audio_features.danceability-audio_features.danceability.min())/danceab
danceability_std
```

```
0          0.681174
1          0.517206
2          0.707490
3          0.716599
4          0.762146
...
243185     0.621457
243186     0.797571
243187     0.533401
243188     0.565789
243189     0.750000
Name: danceability, Length: 243190, dtype: float64
```

However, it will be cumbersome to repeat the above code for each audio feature. We can instead write a function that scales values of a column to $U[0,1]$, and apply the function on all the audio features.

```
#Function to scale a column to U[0,1]
def scale_uniform(x):
    return (x-x.min())/(x.max()-x.min())
```

We will use the Pandas function `apply()` to apply the above function to the DataFrame `audio_features`.

```
#Scaling all audio features to U[0,1]
audio_features_scaled = audio_features.apply(scale_uniform)
```

The above two blocks of code can be concisely written with the `lambda` function as:

```
audio_features_scaled = audio_features.apply(lambda x: (x-x.min())/(x.max()-x.min()))

#All the audio features are scaled to U[0,1]
audio_features_scaled.describe()
```

| | danceability | energy | key | loudness | mode | speechiness | acousticness |
|-------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
| count | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 | 243190.000000 |
| mean | 0.575260 | 0.580633 | 0.476393 | 0.793290 | 0.670928 | 0.115566 | 0.004479 |
| std | 0.161380 | 0.236631 | 0.321141 | 0.069806 | 0.469877 | 0.204405 | 0.004479 |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| 25% | 0.467611 | 0.405000 | 0.181818 | 0.753169 | 0.000000 | 0.034262 | 0.000000 |
| 50% | 0.586032 | 0.591000 | 0.454545 | 0.805644 | 1.000000 | 0.044479 | 0.000000 |
| 75% | 0.693320 | 0.776000 | 0.727273 | 0.845083 | 1.000000 | 0.077709 | 0.000000 |
| max | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 |

Since we need to find the Euclidean distance from the song *drivers license*, let us find the index of the row containing features of *drivers license*.

```
#Index of the row consisting of drivers license can be found with the index attribute
drivers_license_index = spotify_data[spotify_data.track_name=='drivers license'].index[0]
```

Note that the object returned by the `index` attribute is of type `pandas.core.indexes.numeric.Int64Index`. The elements of this object can be retrieved like the elements of a python list. That is why the object is sliced with `[0]` to return the first element of the object. As there is only one observation with the `track_name` as *drivers license*, we sliced the first element. If there were multiple observations with `track_name` as *drivers license*, we will obtain the indices of all those observations with the `index` attribute.

Now, we'll subtract the audio features of *drivers license* from all other songs:

```
#Audio features of drivers license are being subtracted from audio features of all songs b
songs_minus_DL = audio_features_scaled-audio_features_scaled.loc[drivers_license_index,:]
```

Now, let us square the difference computed above. We'll use the in-built python function `pow()` to square the difference:

```
songs_minus_DL_sq = songs_minus_DL.pow(2)
songs_minus_DL_sq.head()
```

| | danceability | energy | key | loudness | mode | speechiness | acousticness | instrumentalness | liveness |
|---|--------------|----------|----------|----------|------|-------------|--------------|------------------|----------|
| 0 | 0.007933 | 0.008649 | 0.826446 | 0.000580 | 0.0 | 0.064398 | 0.418204 | 1.055600e-07 | 0.000000 |
| 1 | 0.005610 | 0.016900 | 0.132231 | 0.000577 | 1.0 | 0.020844 | 0.139498 | 1.716100e-10 | 0.050000 |
| 2 | 0.013314 | 0.063001 | 0.074380 | 0.005586 | 1.0 | 0.002244 | 0.171942 | 5.382400e-10 | 0.000000 |
| 3 | 0.015499 | 0.064516 | 0.528926 | 0.003154 | 0.0 | 0.000269 | 0.140249 | 1.716100e-10 | 0.010000 |
| 4 | 0.028914 | 0.025921 | 0.033058 | 0.000021 | 0.0 | 0.057274 | 0.456981 | 1.716100e-10 | 0.000000 |

Now, we'll sum the squares of differences from all audio features to compute the similarity of all songs to *drivers license*.

```
distance_squared = songs_minus_DL_sq.sum(axis = 1)
distance_squared.head()
```

```
0    1.337163
1    1.438935
2    1.516317
3    1.004043
4    0.920316
dtype: float64
```

Now, we'll sort these distances to find the top 5 songs closest to drivers's license.

```
distances_sorted = distance_squared.sort_values()
distances_sorted.head()
```

```
2398    0.000000
81844    0.008633
4397    0.011160
130789    0.015018
143744    0.015058
dtype: float64
```

Using the indices of the top 5 distances, we will identify the top 5 songs most similar to *drivers license*:

```
spotify_data.loc[distances_sorted.index[0:6],:]
```

| | artist_followers | genres | artist_name | artist_popularity | track_name |
|--------|------------------|------------|----------------|-------------------|-----------------------------|
| 2398 | 1444702 | pop | Olivia Rodrigo | 88 | drivers license |
| 81844 | 2264501 | pop | Jay Chou | 74 | |
| 4397 | 25457 | pop | Terence Lam | 60 | in Bb major |
| 130789 | 176266 | pop | Alan Tam | 54 | |
| 143744 | 396326 | pop & rock | Laura Branigan | 64 | How Am I Supposed to Live W |
| 35627 | 1600562 | pop | Tiziano Ferro | 68 | Non Me Lo So Spiegare |

We can see the top 5 songs most similar to *drivers license* in the *track_name* column above. Interestingly, three of the five songs are Asian! These songs indeed sound similar to *drivers license*!

5.7 Correlation

Correlation may refer to any kind of association between two random variables. However, in this book, we will always consider correlation as the linear association between two random variables, or the Pearson's correlation coefficient. Note that correlation does not imply causality and vice-versa.

The Pandas function `corr()` provides the pairwise correlation between all columns of a DataFrame, or between two Series. The function `corrwith()` provides the pairwise correlation of a DataFrame with another DataFrame or Series.

```
#Pairwise correlation amongst all columns
spotify_data.corr()
```

| | artist_followers | artist_popularity | track_popularity | duration_ms | explicit | release_year |
|-------------------|------------------|-------------------|------------------|-------------|-----------|--------------|
| artist_followers | 1.000000 | 0.577861 | 0.197426 | 0.040435 | 0.082857 | 0.098589 |
| artist_popularity | 0.577861 | 1.000000 | 0.285565 | -0.097996 | 0.092147 | 0.062007 |
| track_popularity | 0.197426 | 0.285565 | 1.000000 | 0.060474 | 0.193685 | 0.568329 |
| duration_ms | 0.040435 | -0.097996 | 0.060474 | 1.000000 | -0.024226 | 0.067665 |
| explicit | 0.082857 | 0.092147 | 0.193685 | -0.024226 | 1.000000 | 0.215656 |
| release_year | 0.098589 | 0.062007 | 0.568329 | 0.067665 | 0.215656 | 1.000000 |
| danceability | -0.010120 | 0.038784 | 0.158507 | -0.145779 | 0.138522 | 0.204719 |
| energy | 0.080085 | 0.039583 | 0.217342 | 0.075990 | 0.104734 | 0.338008 |
| key | -0.000119 | -0.011005 | 0.013369 | 0.007710 | 0.011818 | 0.021404 |
| loudness | 0.123771 | 0.045165 | 0.296350 | 0.078586 | 0.124410 | 0.430000 |
| mode | 0.004313 | 0.018758 | -0.022486 | -0.034818 | -0.060350 | -0.071000 |
| speechiness | -0.059933 | 0.236942 | -0.056537 | -0.332585 | 0.077268 | -0.032000 |

| | artist_followers | artist_popularity | track_popularity | duration_ms | explicit | release_date |
|------------------|------------------|-------------------|------------------|-------------|-----------|--------------|
| acousticness | -0.107475 | -0.075715 | -0.284433 | -0.133960 | -0.129363 | -0.369 |
| instrumentalness | -0.033986 | -0.066679 | -0.124283 | 0.067055 | -0.039472 | -0.149 |
| liveness | 0.002425 | 0.099678 | -0.090479 | -0.034631 | -0.024283 | -0.045 |
| valence | -0.053317 | -0.034501 | -0.038859 | -0.155354 | -0.032549 | -0.070 |
| tempo | 0.016524 | -0.032036 | 0.058408 | 0.051046 | 0.006585 | 0.079 |
| time_signature | 0.030826 | -0.033423 | 0.071741 | 0.085015 | 0.043538 | 0.089 |

Q: Which audio feature is the most correlated with *track_popularity*?

```
spotify_data.corrwith(spotify_data.track_popularity).sort_values(ascending = False)
```

```
track_popularity    1.000000
release_year        0.568329
loudness            0.296350
artist_popularity   0.285565
energy              0.217342
artist_followers    0.197426
explicit            0.193685
danceability        0.158507
time_signature      0.071741
duration_ms         0.060474
tempo               0.058408
key                 0.013369
mode                -0.022486
valence             -0.038859
speechiness         -0.056537
liveness            -0.090479
instrumentalness    -0.124283
acousticness        -0.284433
dtype: float64
```

Loudness is the audio feature having the highest correlation with *track_popularity*.

Q: Which audio feature is the most weakly correlated with *track_popularity*?

5.7.1 Practice exercise 2

5.7.1.1

Use the updated dataset from Practice exercise 1.

The last four variables in the dataset are:

1. cant_change_math_ability
2. can_change_math_ability
3. math_is_genetic
4. much_effort_is_lack_of_talent

Each of the above variables has values - **Agree** / **Disagree**. Replace **Agree** with 1 and **Disagree** with 0.

Hint : You can do it with any one of the following methods:

1. Use the map() function
2. Use the apply() function with the lambda function
3. Use the replace() function
4. Use the applymap() function

Two of the above methods avoid a for-loop. Which ones?

Solution:

```
#Making a copy of data to avoid changing the original data.
survey_data_copy = survey_data.copy()

#Using the map function
for i in range(47,51):
    survey_data_copy.iloc[:,i] = survey_data_copy.iloc[:,i].map({'Agree':1,'Disagree':0})
survey_data_copy.iloc[:,47:51].head()
```

| | cant_change_math_ability | can_change_math_ability | math_is_genetic | much_effort_is_lack_of_talent |
|---|--------------------------|-------------------------|-----------------|-------------------------------|
| 0 | 0 | 1 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 |
| 2 | 0 | 1 | 0 | 0 |
| 3 | 0 | 1 | 0 | 0 |
| 4 | 1 | 0 | 0 | 0 |

```
#Making a copy of data to avoid changing the original data.
survey_data_copy = survey_data.copy()

#Using the lambda function with apply()
```

```

for i in range(47,51):
    survey_data_copy.iloc[:,i] = survey_data_copy.iloc[:,i].apply(lambda x: 1 if x=='Agree'
survey_data_copy.iloc[:,47:51].head()

```

| | cant_change_math_ability | can_change_math_ability | math_is_genetic | much_effort_is_lack_of_ta |
|---|--------------------------|-------------------------|-----------------|---------------------------|
| 0 | 0 | 1 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 |
| 2 | 0 | 1 | 0 | 0 |
| 3 | 0 | 1 | 0 | 0 |
| 4 | 1 | 0 | 0 | 0 |

```

#Making a copy of data to avoid changing the original data.
survey_data_copy = survey_data.copy()

```

```

#Using the replace() function
survey_data_copy.iloc[:,47:51] = survey_data_copy.iloc[:,47:51].replace('Agree','1')
survey_data_copy.iloc[:,47:51] = survey_data_copy.iloc[:,47:51].replace('Disagree','0')
survey_data_copy.iloc[:,47:51].head()

```

| | cant_change_math_ability | can_change_math_ability | math_is_genetic | much_effort_is_lack_of_ta |
|---|--------------------------|-------------------------|-----------------|---------------------------|
| 0 | 0 | 1 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 |
| 2 | 0 | 1 | 0 | 0 |
| 3 | 0 | 1 | 0 | 0 |
| 4 | 1 | 0 | 0 | 0 |

```

#Making a copy of data to avoid changing the original data.
survey_data_copy = survey_data.copy()

```

```

#Using the lambda function with applymap()
survey_data_copy.iloc[:,47:51] = survey_data_copy.iloc[:,47:51].applymap(lambda x: 1 if x=
survey_data_copy.iloc[:,47:51].head()

```

| | cant_change_math_ability | can_change_math_ability | math_is_genetic | much_effort_is_lack_of_ta |
|---|--------------------------|-------------------------|-----------------|---------------------------|
| 0 | 0 | 1 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 |
| 2 | 0 | 1 | 0 | 0 |

| | cant_change_math_ability | can_change_math_ability | math_is_genetic | much_effort_is_lack_of_talent |
|---|--------------------------|-------------------------|-----------------|-------------------------------|
| 3 | 0 | 1 | 0 | 0 |
| 4 | 1 | 0 | 0 | 0 |

5.7.1.2

Among the four variables, which one is the most negatively correlated with `math_is_genetic`?

```
#Computing correlation
survey_data_copy.iloc[:,47:51].corrwith(survey_data_copy.math_is_genetic)
```

```
cant_change_math_ability      0.294544
can_change_math_ability      -0.361546
math_is_genetic               1.000000
much_effort_is_lack_of_talent  0.154083
dtype: float64
```

The variable `can_change_math_ability` is the most negatively correlated with `math_is_genetic`.

6 Data visualization

<IPython.core.display.Image object>

“One picture is worth a thousand words” - Fred R. Barnard

Visual perception offers the highest bandwidth channel, as we acquire much more information through visual perception than with all of the other channels combined, as billions of our neurons are dedicated to this task. Moreover, the processing of visual information is, at its first stages, a highly parallel process. Thus, it is generally easier for humans to comprehend information with plots, diagrams and pictures, rather than with text and numbers. This makes data visualizations a vital part of data science. Some of the key purposes of data visualization are:

1. Data visualization is the first step towards exploratory data analysis (EDA), which reveals trends, patterns, insights, or even irregularities in data.
2. Data visualization can help explain the workings of complex mathematical models.
3. Data visualization are an elegant way to summarise the findings of a data analysis project.
4. Data visualizations (especially interactive ones such as those on Tableau) may be the end-product of data analytics project, where the stakeholders make decisions based on the visualizations.

We'll use a couple of libraries for making data visualizations - [matplotlib](#) and [seaborn](#). Matplotlib is mostly used for creating relatively simple two-dimensional plots. Its plotting interface that is similar to the `plot()` function in MATLAB, so those who have used MATLAB should find it familiar. Seaborn is a recently developed data visualization library based on matplotlib. It is more oriented towards visualizing data with Pandas DataFrame and NumPy arrays. While matplotlib may also be used to create complex plots, seaborn has some built-in themes that may make it more convenient to make complex plots. Seaborn also has color schemes and plot styles that improve the readability and aesthetics of matplotlib plots. However, preferences depend on the user and their coding style, and it is perfectly fine to use either library for making the same visualization.

6.1 Matplotlib

[Matplotlib](#) is:

- a low-level graph plotting library in python that strives to emulate MATLAB,
- can be used in Python scripts, Python and IPython shells, Jupyter notebooks and web application servers.
- is mostly written in python, a few segments are written in C, Objective-C and Javascript for Platform compatibility.

Conceptual model: Plotting requires action on a range of levels, ranging from the size of the figure to the text object in the plot. Matplotlib provides **object-oriented** interface in the hierarchical fashion to provide complete control over the plot. The user generates and keeps track of the figure and axes objects. These axes objects are then used for most plotting actions.

6.1.1 Matplotlib: Object hierarchy

A *hierarchy* means that there is a tree-like structure of matplotlib objects underlying each plot.

A *Figure* object is the outermost container for a matplotlib graphic, which can contain multiple *Axes* objects. Note that an *Axes* actually translates into what we think of as an individual plot or graph (rather than the plural of *axis* as we might expect).

The *Figure* object is a box-like container holding one or more *Axes* (actual plots), as shown in Figure 6.1. Below the *Axes* in the hierarchy are smaller objects such as *tick marks*, *individual lines*, *legends*, and *text boxes*. Almost every *element* of a chart is its own manipulable Python object, all the way down to the *ticks* and *labels*.

<IPython.core.display.Image object>

Figure 6.1: Matplotlib Object hierarchy

However, Matplotlib presents this as a figure anatomy, rather than an explicit hierarchy. Figure 6.2 shows the components of a figure that can be customized with Matplotlib. (*Source: <https://matplotlib.org/stable/gallery/showcase/anatomy.html>*).

<IPython.core.display.Image object>

Figure 6.2: Matplotlib anatomy of a figure

Let's visualize the life expectancy of different countries with GDP per capita. We'll read the data file *gdp_lifeExpectancy.csv*, which contains the GDP per capita and life expectancy of countries from 1952 to 2007.

```
import pandas as pd
import numpy as np
```

```
gdp_data = pd.read_csv('./Datasets/gdp_lifeExpectancy.csv')
gdp_data.head()
```

| | country | continent | year | lifeExp | pop | gdpPercap |
|---|-------------|-----------|------|---------|----------|------------|
| 0 | Afghanistan | Asia | 1952 | 28.801 | 8425333 | 779.445314 |
| 1 | Afghanistan | Asia | 1957 | 30.332 | 9240934 | 820.853030 |
| 2 | Afghanistan | Asia | 1962 | 31.997 | 10267083 | 853.100710 |
| 3 | Afghanistan | Asia | 1967 | 34.020 | 11537966 | 836.197138 |
| 4 | Afghanistan | Asia | 1972 | 36.088 | 13079460 | 739.981106 |

6.1.2 Scatterplots and trendline with Matplotlib

Purpose of scatterplots: Scatterplots (with or without a trendline) allow us to visualize the relationship between two numerical variables.

We'll import the `pyplot` module of matplotlib to make plots. We'll use the `plot()` function to make the scatter plot, and the functions `xlabel()` and `ylabel()` for labeling the plot axes.

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

Q: Make a scatterplot of Life expectancy vs GDP per capita.

There are two ways of plotting the figure:

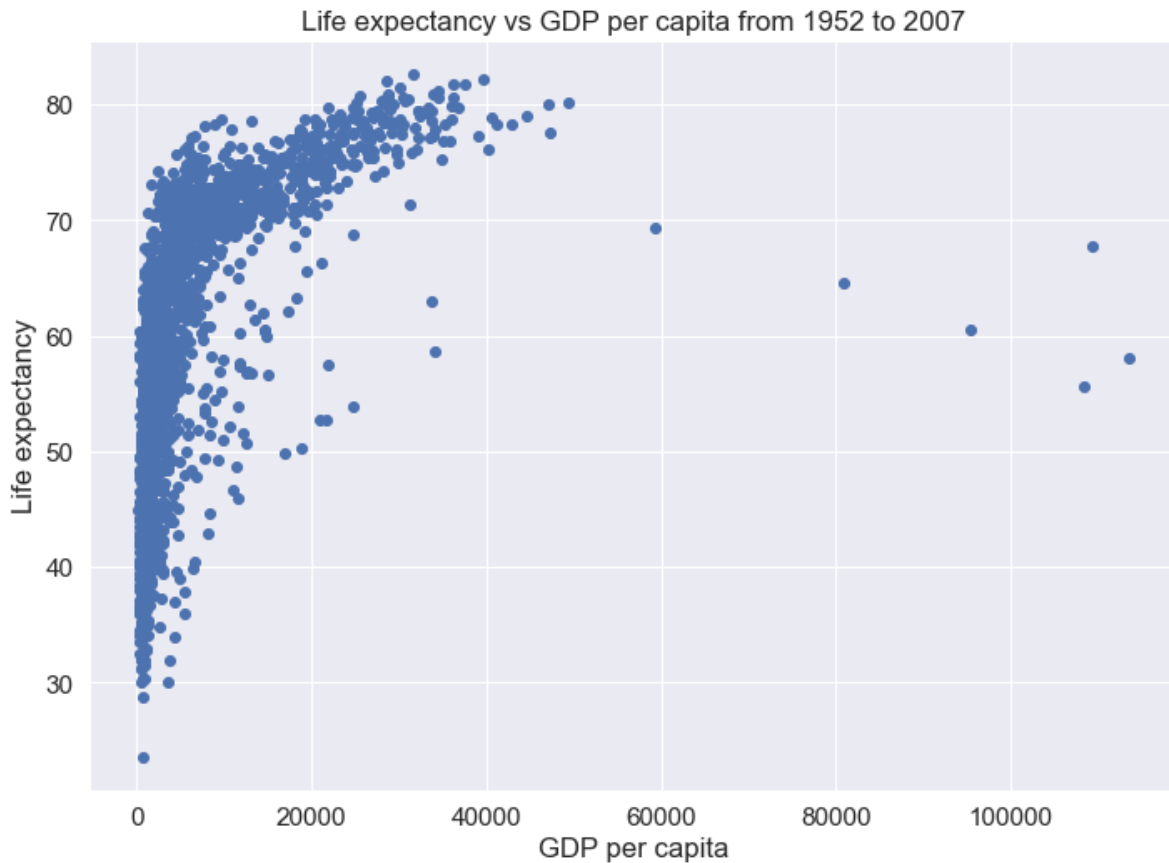
1. Explicitly creating figures and axes, and call methods on them (*object-oriented style*).
2. Letting pyplot implicitly track the plot that it wants to reference. Simple functions are used to add plot elements (lines, images, text, etc.) to the current axes in the current figure (*pyplot-style*).

We'll plot the figure in both ways.

```
#Method 1: Object-oriented style
fig, ax = plt.subplots() #Create a figure and an axes
x = gdp_data.gdpPercap
y = gdp_data.lifeExp
ax.plot(x,y,'o') #Plot data on the axes
ax.set_xlabel('GDP per capita') #Add an x-label to the axes
```

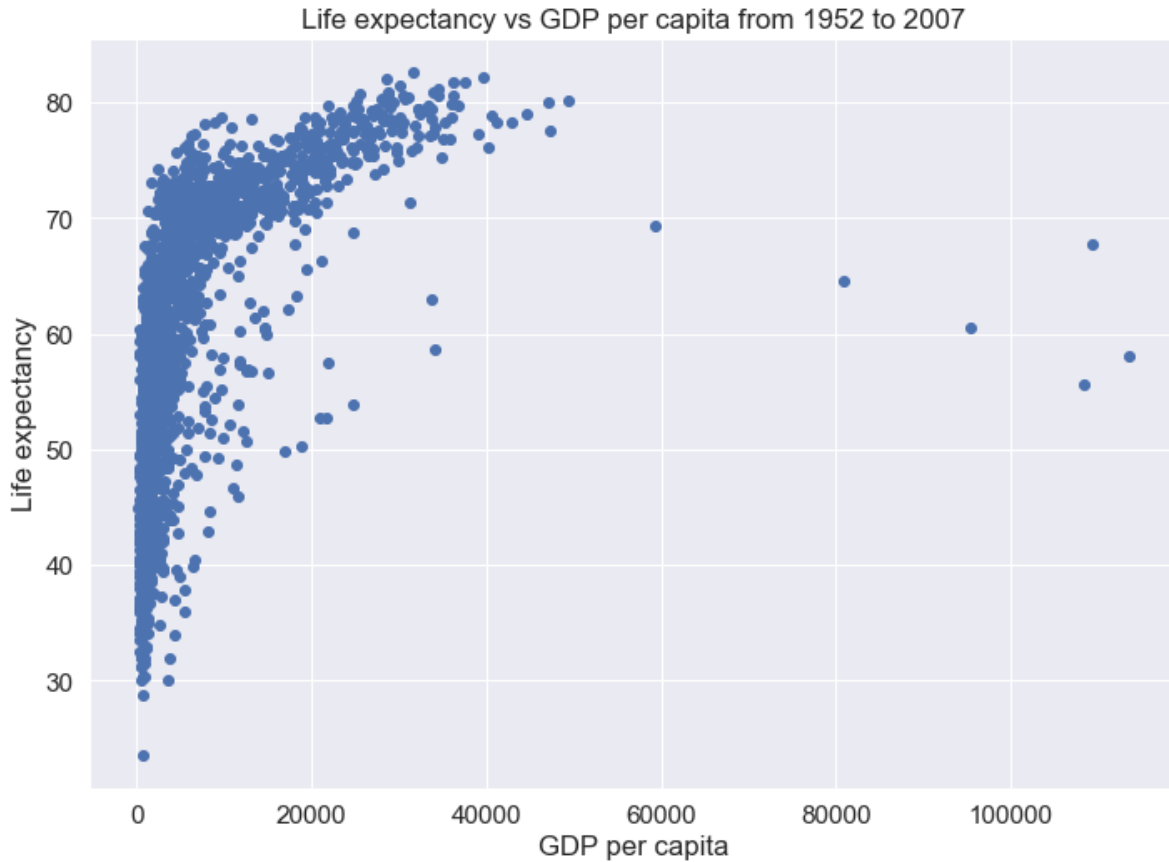
```
ax.set_ylabel('Life expectancy') #Add a y-label to the axes
ax.set_title('Life expectancy vs GDP per capita from 1952 to 2007')
```

Text(0.5, 1.0, 'Life expectancy vs GDP per capita from 1952 to 2007')



```
#Method 2: pyplot style
x = gdp_data.gdpPerCap
y = gdp_data.lifeExp
plt.plot(x,y,'o') #By default, the plot() function makes a lineplot. The 'o' arguments spe
plt.xlabel('GDP per capita') #Labelling the horizontal X-axis
plt.ylabel('Life expectancy') #Labelling the verical Y-axis
plt.title('Life expectancy vs GDP per capita from 1952 to 2007')
```

Text(0.5, 1.0, 'Life expectancy vs GDP per capita from 1952 to 2007')



Both the plotting styles - object-oriented style and the pyplot style are perfectly valid and have their pros and cons.

- Pyplot style is easier for simple plots
- Object-oriented style is slightly more complicated but more powerful as it allows for greater control over the axes in figure. This proves to be quite useful when we are dealing with a figure with multiple axes.

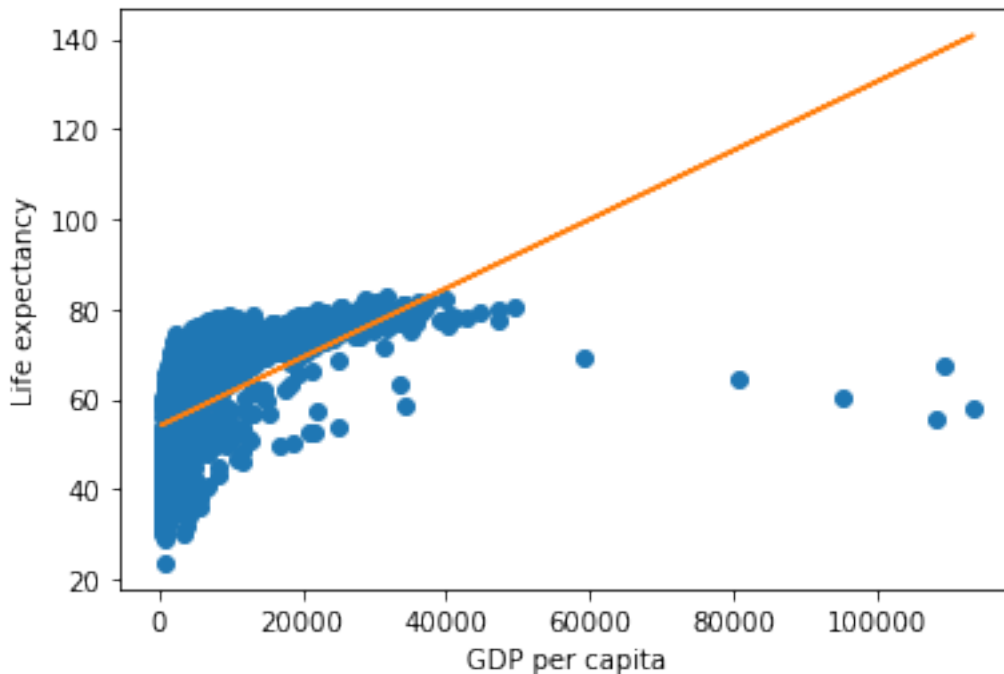
From the above plot, we observe that life expectancy seems to be positively correlated with the GDP per capita of the country, as one may expect. However, there are a few outliers in the data - which are countries having extremely high GDP per capita, but not a correspondingly high life expectancy.

Sometimes it is difficult to get an idea of the overall trend (positive or negative correlation). In such cases, it may help to add a trendline to the scatter plot. In the plot below we add a trendline over the scatterplot showing that the life expectancy on an average increases with increasing GDP per capita. The trendline is actually a linear regression of life expectancy on GDP per capita. However, we'll not discuss linear regression in this book.

Q: Add a trendline over the scatterplot of life expectancy vs GDP per capita.

```
#Making a scatterplot of Life expectancy vs GDP per capita
x = gdp_data.gdpPerCap
y = gdp_data.lifeExp
plt.plot(x,y,'o') #By default, the plot() function makes a lineplot. The 'o' arguments spe
plt.xlabel('GDP per capita') #Labelling the horizontal X-axis
plt.ylabel('Life expectancy') #Labelling the verical Y-axis

#Plotting a trendline (linear regression) on the scatterplot
slope_intercept_trendline = np.polyfit(x,y,1) #Finding the slope and intercept for the t
compute_y_given_x = np.poly1d(slope_intercept_trendline) #Defining a function that compute
plt.plot(x,compute_y_given_x(x)) #Plotting the trendline
```



The above plot shows that our earlier intuition of a positive correlation between Life expectancy and GDP per capita was correct.

We used the NumPy function `polyfit()` to compute the slope and intercept of the trendline. Then, we defined an object `compute_y_given_x` of `poly1d` class and used it to compute the trendline.

6.1.3 Subplots

There is often a need to make a few plots together to compare them. See the example below.

Q: Make scatterplots of life expectancy vs GDP per capita separately for each of the 4 continents of Asia, Europe, Africa and America. Arrange the plots in a 2 x 2 grid.

```
#Defining a 2x2 grid of subplots
fig, axes = plt.subplots(2,2,figsize=(16,10))
plt.subplots_adjust(wspace=0.2) #adjusting white space between individual plots

#Making a scatterplot of Life expectancy vs GDP per capita for each continent
continents = np.array(['Asia', 'Europe'], ['Africa', 'Americas']))

#Looping over the 2x2 grid
for i in range(2):
    for j in range(2):

        #Getting the GDP per capita and life expectancy of the countries of the (i,j)th co
        x = gdp_data.loc[gdp_data.continent==continents[i,j],:].gdpPercap
        y = gdp_data.loc[gdp_data.continent==continents[i,j],:].lifeExp

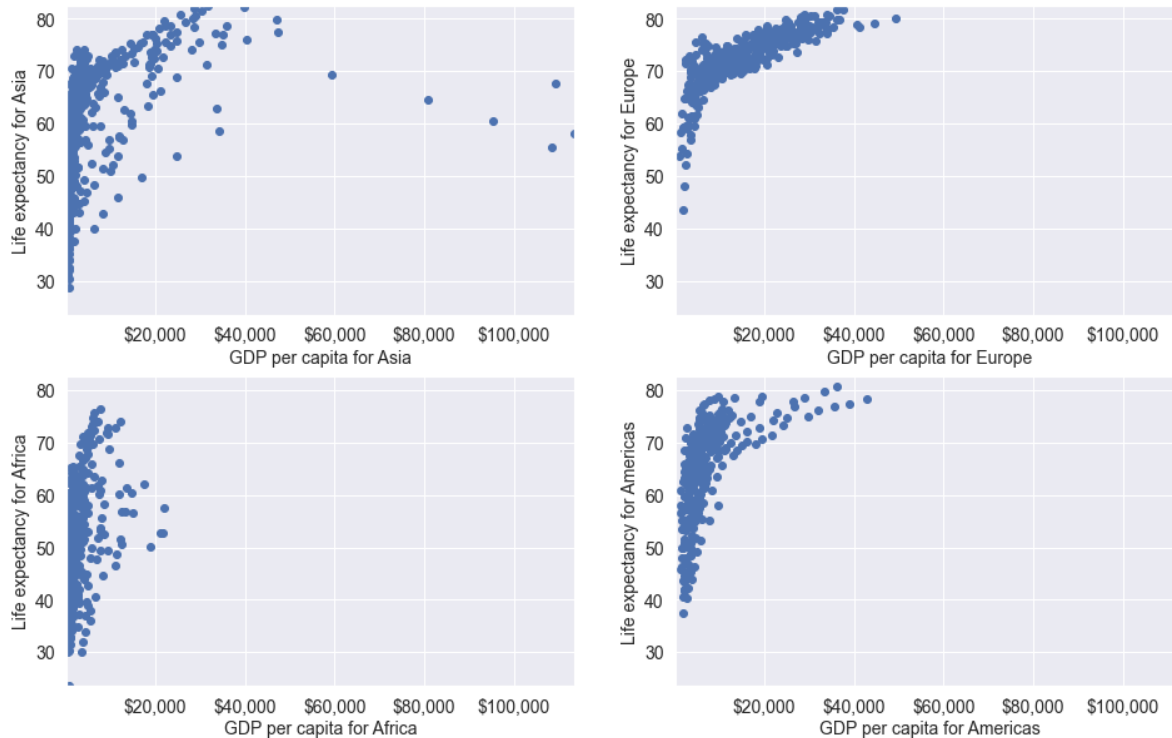
        #Making the scatterplot
        axes[i,j].plot(x,y,'o')

        #Setting limits on the 'x' and 'y' axes
        axes[i,j].set_xlim([gdp_data.gdpPercap.min(), gdp_data.gdpPercap.max()])
        axes[i,j].set_ylim([gdp_data.lifeExp.min(), gdp_data.lifeExp.max()])

        #Labelling the 'x' and 'y' axes
        axes[i,j].set_xlabel('GDP per capita for '+ continents[i,j],fontsize = 14)
        axes[i,j].set_ylabel('Life expectancy for '+ continents[i,j],fontsize = 14)

        #Putting a dollar sign, and thousand-comma separator on x-axis labels
        axes[i,j].xaxis.set_major_formatter('${x:,.0f}')

        #Increasing font size of axis labels
        axes[i,j].tick_params(axis = 'both',labelsize=14)
```

We observe that for each continent, except Africa, initially life expectancy increases rapidly with increasing GDP per capita. However, after a certain threshold of GDP per capita, life expectancy increases slowly. Several countries in Europe enjoy a relatively high GDP per capita as well as high life expectancy. Some countries in Asia have an extremely high GDP per capita, but a relatively low life expectancy. It will be interesting to see the proportion of GDP associated with healthcare for these outlying Asian countries, and European countries.

We used the `subplot` function of `matplotlib` to define the 2x2 grid of subplots. The function `subplots_adjust()` can be used to adjust white spaces around the plot. We used a `for` loop to iterate over each subplot. The `axes` object returned by the `subplot()` function was used to refer to individual subplots.

6.1.4 Practice problem 1

Is `NU_GPA` associated with `parties_per_month`? Analyze the association separately for *Sophomores*, *Juniors*, and *Seniors* (categories of the variable `school_year`).

Make scatterplots of `NU_GPA` vs `parties_per_month` in a 1 x 3 grid, where each grid is for a distinct `school_year`. Plot the trendline as well for each scatterplot. Use the file `survey_data_clean.csv`.

Solution:

```
survey_data = pd.read_csv('./Datasets/survey_data_clean.csv')

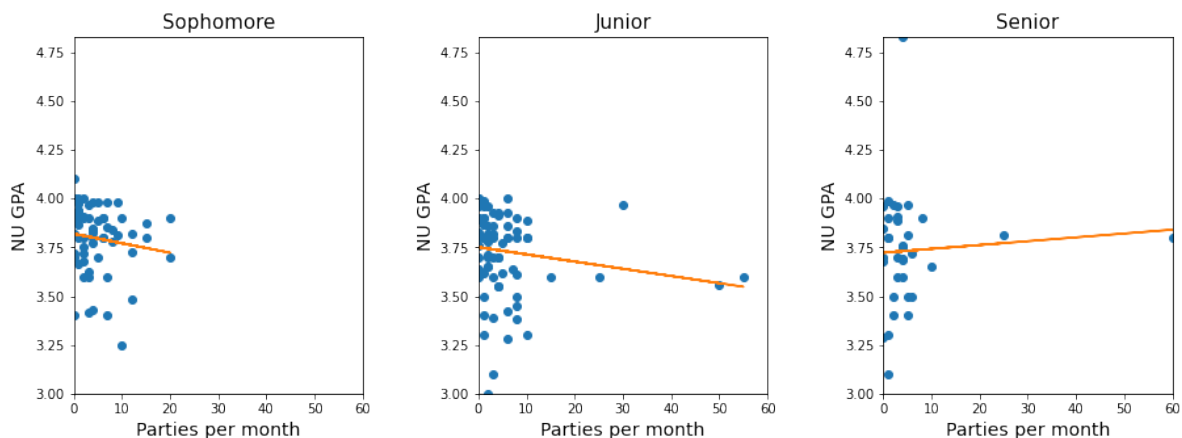
def NU_GPA_vs_parties_per_month(data):
    fig, axes = plt.subplots(1,3,figsize=(15,5))
    plt.subplots_adjust(wspace=0.4)

    school_years = np.array(['Sophomore', 'Junior','Senior'])
    for i in range(3):
        x = data.loc[data.school_year==school_years[i],:].parties_per_month
        y = data.loc[data.school_year==school_years[i],:].NU_GPA

        #The data has missing values. We can draw a trendline using only the non-missing v
        #`idx_non_missing` will have the indices of the non-missing value-pairs of NU_GPA
        idx_non_missing = np.isfinite(x) & np.isfinite(y)

        axes[i].plot(x,y,'o',label = school_years[i])
        axes[i].set_xlim([data.parties_per_month.min(), data.parties_per_month.max()])
        axes[i].set_ylim([data.NU_GPA.min(), data.NU_GPA.max()])
        axes[i].set_xlabel('Parties per month',fontsize = 14)
        axes[i].set_ylabel('NU GPA',fontsize = 14)
        axes[i].set_title(school_years[i],fontsize = 15)
        slope_intercept_trendline = np.polyfit(x[idx_non_missing],y[idx_non_missing],1)
        compute_y_given_x = np.poly1d(slope_intercept_trendline) #Defining a function that
        axes[i].plot(x,compute_y_given_x(x)) #Plotting the trendline

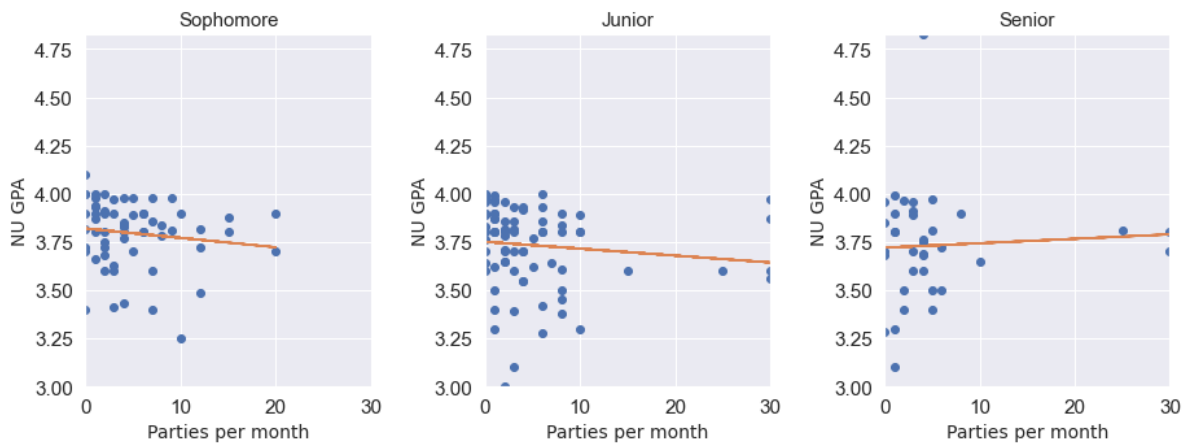
    NU_GPA_vs_parties_per_month(survey_data)
```



Note that the trendline in the above plots seems to be influenced by a few points having extreme values of `parties_per_month`. These points have a *high leverage* (a concept we'll learn in a future course on linear regression) in influencing the trendline. So, we should visualize the trend by removing or capping these *high-leverage* points, to avoid the distortion of the trend by a few points.

Let us cap the the values of `parties_per_month` to 30, and make the visualizations again.

```
survey_data_parties_capped = survey_data.copy()
survey_data_parties_capped.parties_per_month = survey_data.parties_per_month.apply(lambda
NU_GPA_vs_parties_per_month(survey_data_parties_capped)
```



We see that the trend didn't change much after removing the *high leverage* points. (Note that although the *high leverage* points have the leverage to influence the trendline, they need not necessarily influence it). From the visualization, `NU_GPA` doesn't seem to be associated with `parties_per_month` for students of any of the school years.

6.1.5 Overlapping plots with legend

We can also have the scatterplot of all the continents on the sample plot, with a distinct color for each continent. A legend will be required to identify the continent's color.

```
continents = np.array(['Asia', 'Europe'], ['Africa', 'Americas']))
plt.rcParams["figure.figsize"] = (9,6)
for i in range(2):
    for j in range(2):
        x = gdp_data.loc[gdp_data.continent==continents[i,j],:].gdpPercap
```

```

y = gdp_data.loc[gdp_data.continent==continents[i,j],:].lifeExp
plt.plot(x,y,'o',label = continents[i,j])
plt.xlim([gdp_data.gdpPercap.min(), gdp_data.gdpPercap.max()])
plt.ylim([gdp_data.lifeExp.min(), gdp_data.lifeExp.max()])
plt.xlabel('GDP per capita')
plt.ylabel('Life expectancy')
plt.legend()

```

<matplotlib.legend.Legend at 0x2320d6d70a0>



Note that a disadvantage of the above plot is overplotting. The data points corresponding to the *Americas* are hiding the data points of other continents. However, if the data points corresponding to different categories are spread apart, then it may be convenient to visualize all the categories on the same plot.

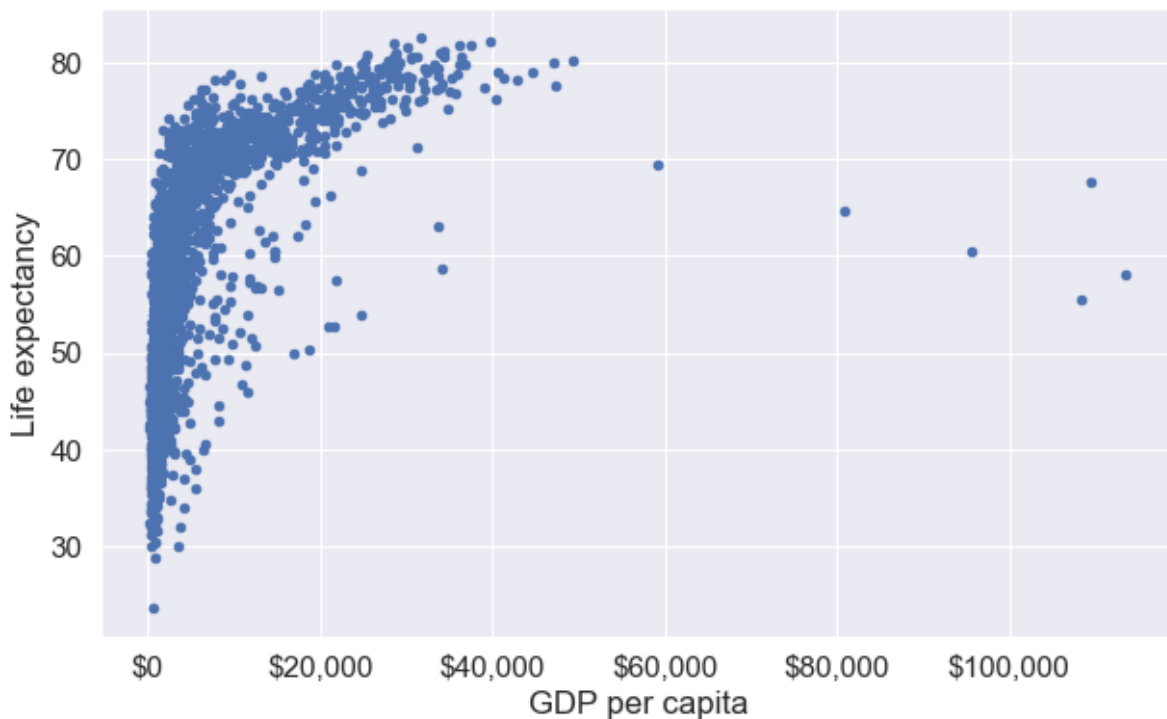
6.2 Pandas

Matplotlib is a low-level tool, in which different components of the plot, such as points, legend, axis titles, etc. need to be specified separately. The Pandas `plot()` function can be used directly with a DataFrame or Series to make plots.

6.2.1 Scatterplots with Pandas

```
#Plotting life expectancy vs GDP per capita using the Pandas plot() function
ax = gdp_data.plot(x = 'gdpPercap', y = 'lifeExp', kind = 'scatter',figsize=(10, 6),xlabel='GDP per capita',
                  ylabel = 'Life expectancy')
ax.xaxis.set_major_formatter('$x:,.0f')
```

c argument looks like a single numeric RGB or RGBA sequence, which should be avoided as va



In the above plot, note that:

- With matplotlib, it will take 3 lines to make the same plot - one for the scatterplot, and two for the axis titles.
- The object `ax` is of type `matplotlib.axes._subplots.AxesSubplot` (check the code below). This means we can use the attributes and methods associated with the `axes` object of Matplotlib. If you see the [documentation](#) of the Pandas `plot()` function, you will find that under the `kwargs**` argument, you have *Options to pass to matplotlib plotting method*. Thus, you get the convenience of using the Pandas `plot()` function, while also having the attributes and methods associated with Matplotlib.

```
type(ax)
```

```
matplotlib.axes._subplots.AxesSubplot
```

6.2.2 Lineplots with Pandas

Purpose of lineplots: Lineplots show the relationship between two numerical variables when the variable on the x-axis, also called the *explanatory variable*, is of a sequential nature; in other words there is an inherent ordering to the variable. The most common example of lineplots have some notion of time on the x-axis (or the horizontal axis): hours, days, weeks, years, etc. Since time is sequential, we connect consecutive observations of the variable on the y-axis with a line. Lineplots that have some notion of time on the x-axis are also called time series plots. Lineplots should be avoided when there is not a clear sequential ordering to the variable on the x-axis.

Let us re-arrange the data to show other benefits of the Pandas `plot()` function. Note that data reshaping is explained in Chapter 8 of the book, so you may ignore the code block below that uses the `pivot_table()` function.

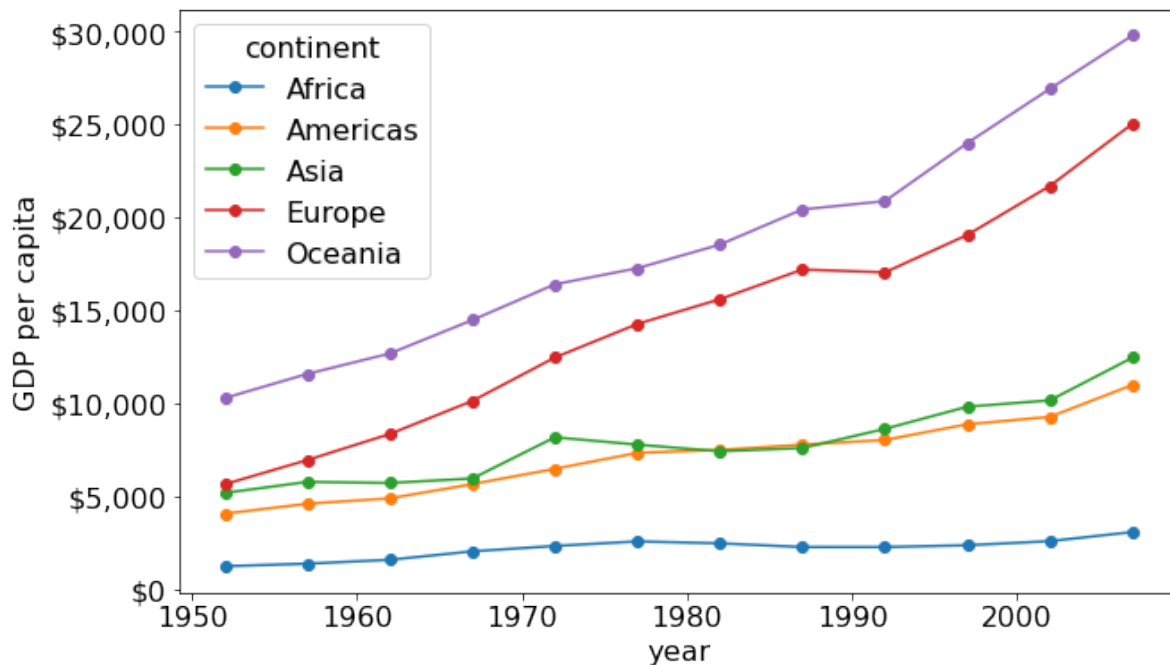
```
#You may ignore this code block until Chapter 8.
mean_gdp_per_capita = gdp_data.pivot_table(index = 'year', columns = 'continent', values =
mean_gdp_per_capita.head()
```

| continent | Africa | Americas | Asia | Europe | Oceania |
|-----------|-------------|-------------|-------------|--------------|--------------|
| year | | | | | |
| 1952 | 1252.572466 | 4079.062552 | 5195.484004 | 5661.057435 | 10298.085650 |
| 1957 | 1385.236062 | 4616.043733 | 5787.732940 | 6963.012816 | 11598.522455 |
| 1962 | 1598.078825 | 4901.541870 | 5729.369625 | 8365.486814 | 12696.452430 |
| 1967 | 2050.363801 | 5668.253496 | 5971.173374 | 10143.823757 | 14495.021790 |
| 1972 | 2339.615674 | 6491.334139 | 8187.468699 | 12479.575246 | 16417.333380 |

We have reshaped the data to obtain the mean GDP per capita of each continent for each year.

The pandas `plot()` function can be directly used with this DataFrame to create line plots showing mean GDP per capita of each continent with year.

```
ax = mean_gdp_per_capita.plot(ylabel = 'GDP per capita',figsize = (10,6),marker='o')
ax.yaxis.set_major_formatter('${x:,.0f}')
```



We observe that the mean GDP per capita of Europe and Oceania have increased rapidly, while that for Africa is increasing very slowly.

The above plot will take several lines of code if developed using only matplotlib. The pandas `plot()` function has a framework to conveniently make commonly used plots.

Note that argument `marker = 'o'` puts a solid circle at each of the data points.

6.2.3 Bar plots with Pandas

Purpose of bar plots: Barplots are used to visualize any aggregate statistics of a continuous variable with respect to the categories or levels of a categorical variable. For example, we may visualize the average IMDB rating (*aggregate statistics*) of movies based on their genre (*the categorical variable*).

Bar plots can be made using the pandas `bar` function with the DataFrame or Series, just like the line plots and scatterplots.

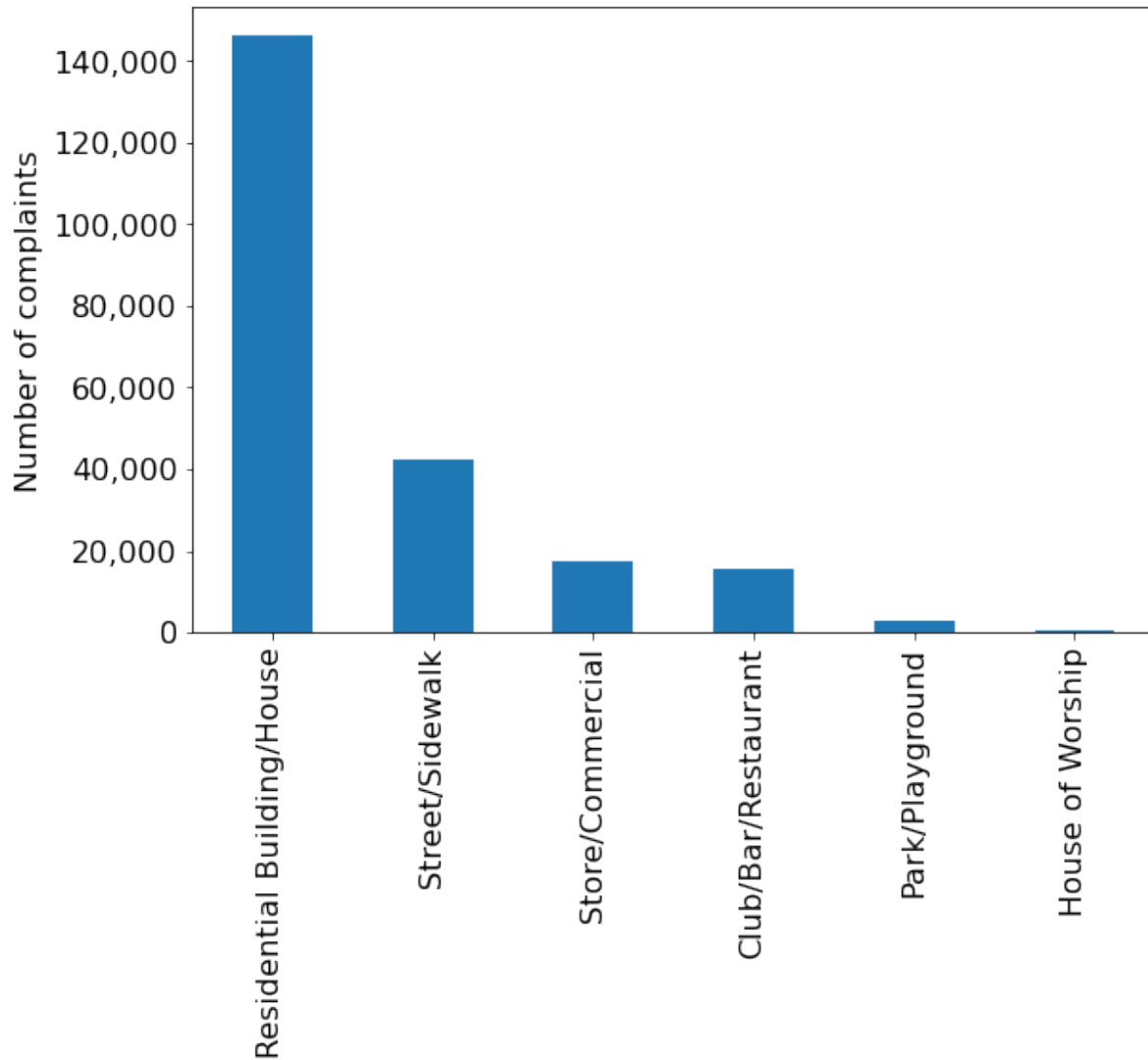
Below, we are reading the dataset of noise complaints of type *Loud music/Party* received the police in New York City in 2016.

```
nyc_party_complaints = pd.read_csv('./Datasets/party_nyc.csv')
nyc_party_complaints.head()
```

| | Created Date | Closed Date | Location Type | Incident Zip | City | Borough |
|---|-----------------|-----------------|----------------------------|--------------|----------|----------|
| 0 | 12/31/2015 0:01 | 12/31/2015 3:48 | Store/Commercial | 10034.0 | NEW YORK | MANHAT |
| 1 | 12/31/2015 0:02 | 12/31/2015 4:36 | Store/Commercial | 10040.0 | NEW YORK | MANHAT |
| 2 | 12/31/2015 0:03 | 12/31/2015 0:40 | Residential Building/House | 10026.0 | NEW YORK | MANHAT |
| 3 | 12/31/2015 0:03 | 12/31/2015 1:53 | Residential Building/House | 11231.0 | BROOKLYN | BROOKLYN |
| 4 | 12/31/2015 0:05 | 12/31/2015 3:49 | Residential Building/House | 10033.0 | NEW YORK | MANHAT |

Let us visualise the locations from where the the complaints are coming.

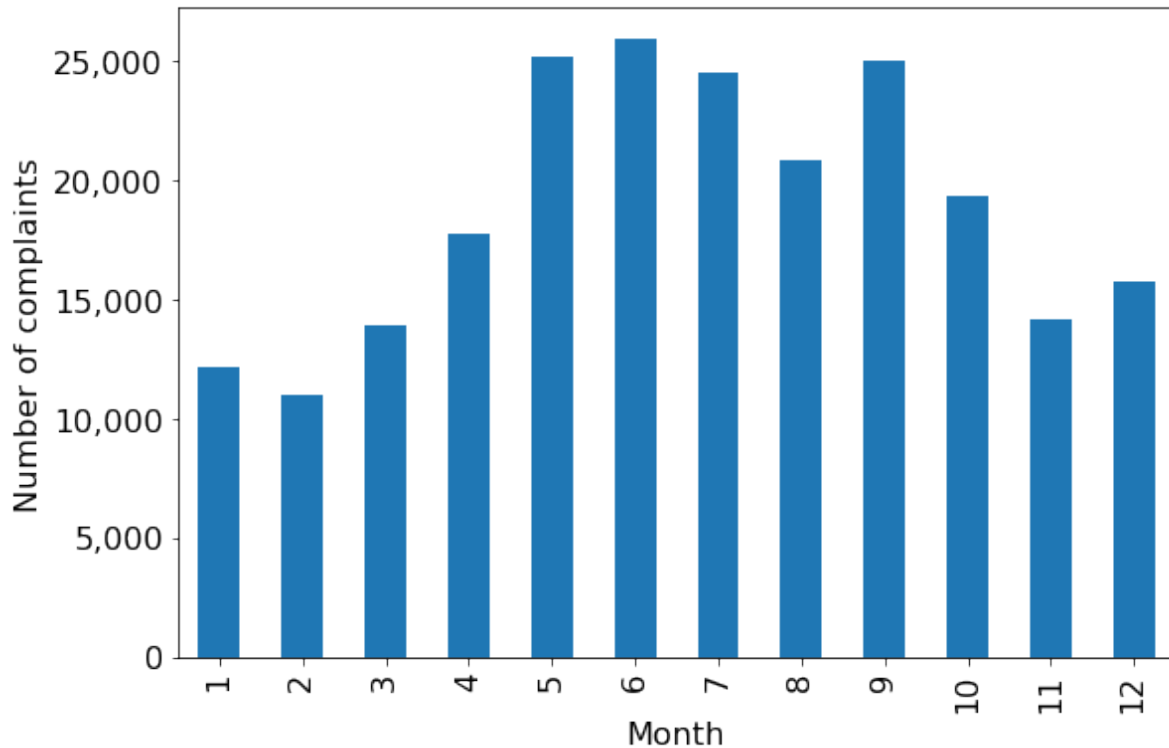
```
#Using the pandas function bar() to create bar plot
ax = nyc_party_complaints['Location Type'].value_counts().plot.bar(ylabel = 'Number of complaints')
ax.xaxis.set_major_formatter('{x:,.0f}')
```

From the above plot, we observe that most of the complaints come from residential buildings and houses, as one may expect.

Let us visualize the time of the year when most complaints occur.

```
#Using the pandas function bar() to create bar plot
ax = nyc_party_complaints['Month_of_the_year'].value_counts().sort_index().plot.bar(ylabel='Number of complaints', xlabel = 'Month of the year')
ax.yaxis.set_major_formatter('{x:,.0f}')
```



Try executing the code without `sort_index()` to figure out the purpose of using the function.

From the above plot, we observe that most of the complaints occur during summer and early Fall.

Let us create a stacked bar chart that combines both the above plots into a single plot. You may ignore the code used for re-shaping the data until Chapter 8. The purpose here is to show the utility of the pandas `bar()` function.

```
#Reshaping the data to make it suitable for a stacked barplot - ignore this code until chapter 8
complaints_location=pd.crosstab(nyc_party_complaints.Month_of_the_year, nyc_party_complaints.location_type)
complaints_location.head()
```

| Location Type Month_of_the_year | Club/Bar/Restaurant | House of Worship | Park/Playground | Residential Building/House |
|------------------------------------|---------------------|------------------|-----------------|----------------------------|
| 1 | 748 | 24 | 17 | 9393 |
| 2 | 570 | 29 | 16 | 8383 |
| 3 | 747 | 39 | 90 | 9689 |
| 4 | 848 | 53 | 129 | 11984 |
| 5 | 2091 | 72 | 322 | 15676 |

```
#Stacked bar plot showing number of complaints at different months of the year, and from d
ax = complaints_location.plot.bar(stacked=True,ylabel = 'Number of complaints',figsize=(15
ax.tick_params(axis = 'both',labelsize=15)
ax.yaxis.set_major_formatter('{x:,.0f}')
```

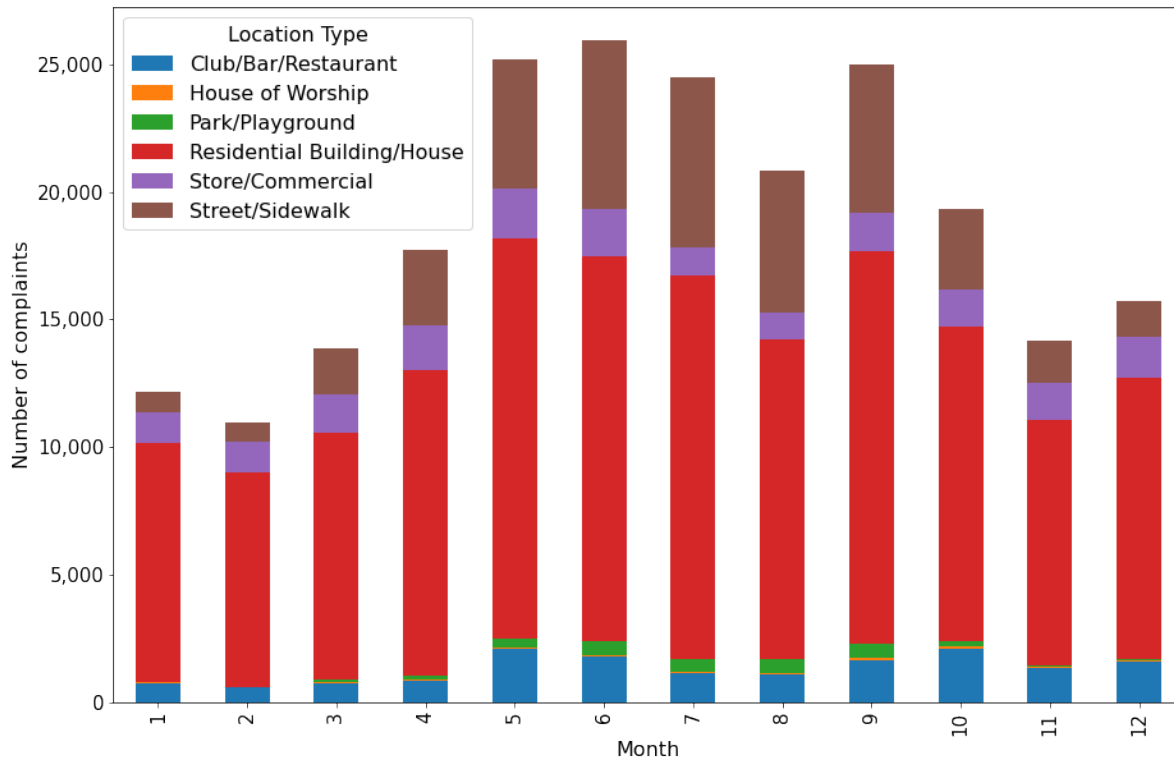
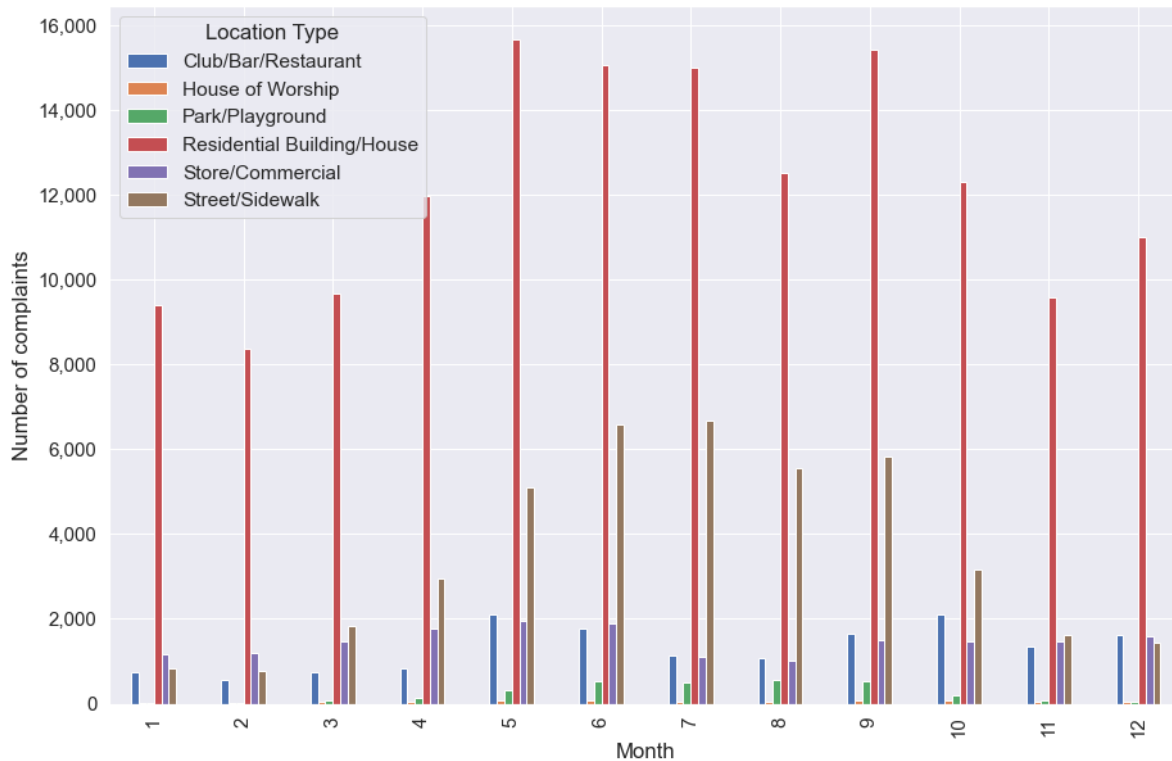


Figure 6.3: Stacked bar plot with Pandas

The above plots gives the insights about location and day of the year simultaneously that were previously separately obtained by the individual plots.

An alternative to stacked barplots are *side-by-side* barplots, as shown below.

```
#Side-by-side bar plot showing number of complaints at different months of the year, and f
ax = complaints_location.plot.bar(ylabel = 'Number of complaints',figsize=(15, 10), xlabel
ax.tick_params(axis = 'both',labelsize=15)
ax.yaxis.set_major_formatter('{x:,.0f}')
```



Q1 In which scenarios should we use a stacked barplot instead of a side-by-side barplot and vice-versa?

6.3 Seaborn

Seaborn offers the flexibility of simultaneously visualizing multiple variables in a single plot, and offers several themes to develop plots.

```
#Importing the seaborn library
import seaborn as sns
```

6.3.1 Bar plots with confidence intervals with Seaborn

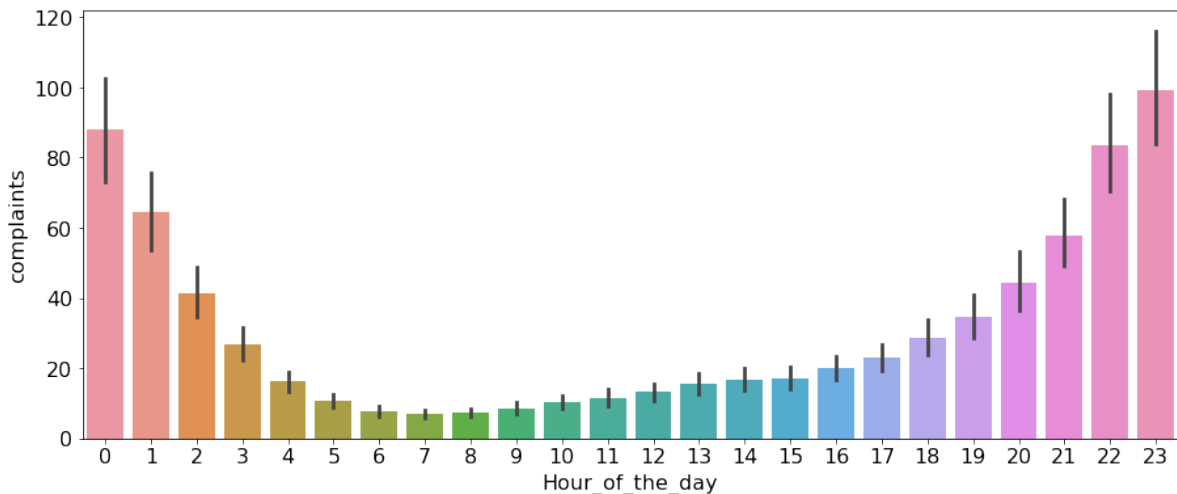
We'll group the data to obtain the total complaints for each *Location Type*, *Borough*, *Month_of_the_year*, and *Hour_of_the_day*. Note that you'll learn grouping data in Chapter 9, so you may ignore the next code block. The grouping is done to shape the data in a suitable form for visualization.

```
#Grouping the data to make it suitable for visualization using Seaborn. Ignore this code b
nyc_complaints_grouped = nyc_party_complaints[['Location Type', 'Borough', 'Month_of_the_yea
nyc_complaints_grouped.head()
```

| | Location Type | Borough | Month_of_the_year | Hour_of_the_day | complaints |
|---|---------------------|---------|-------------------|-----------------|------------|
| 0 | Club/Bar/Restaurant | BRONX | 1 | 0 | 10 |
| 1 | Club/Bar/Restaurant | BRONX | 1 | 1 | 10 |
| 2 | Club/Bar/Restaurant | BRONX | 1 | 2 | 6 |
| 3 | Club/Bar/Restaurant | BRONX | 1 | 3 | 6 |
| 4 | Club/Bar/Restaurant | BRONX | 1 | 4 | 3 |

Let us create a bar plot visualizing the average number of complaints with the time of the day.

```
ax = sns.barplot(x="Hour_of_the_day", y = 'complaints', data=nyc_complaints_grouped)
ax.figure.set_figwidth(15)
```



From the above plot, we observe that most of the complaints are made around midnight. However, interestingly, there are some complaints at each hour of the day.

Note that the above barplot shows the mean number of complaints in a month at each hour of the day. The black lines are the 95% confidence intervals of the mean number of complaints.

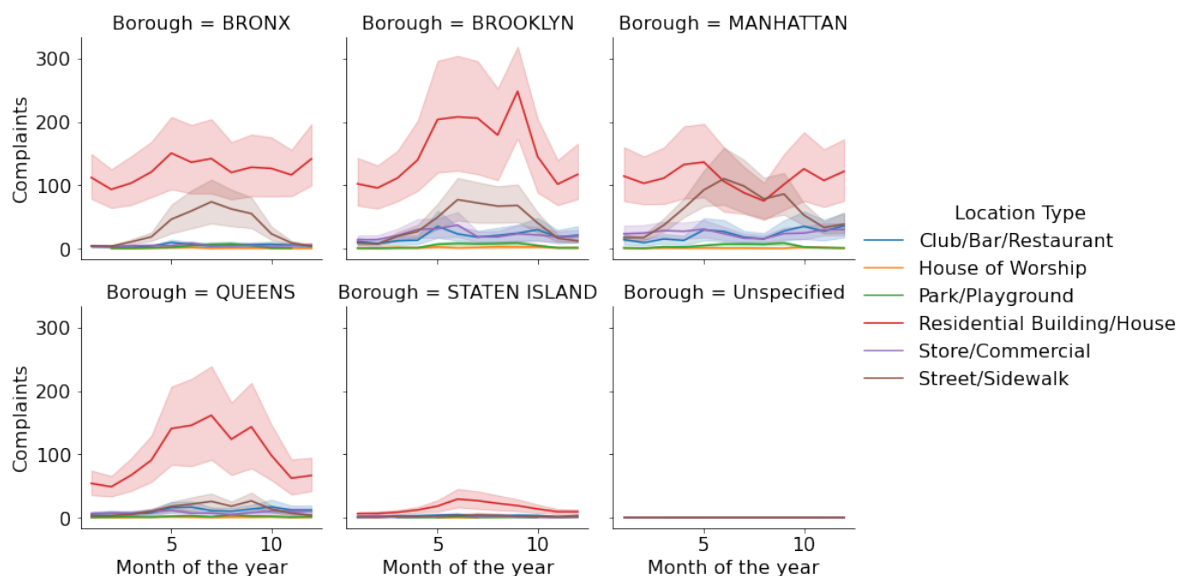
6.3.2 Facetgrid: Multi-plot grid for plotting conditional relationships

With pandas, we simultaneously visualized the number of complaints with month of the year and location type in Figure 6.3. We'll use Seaborn to add another variable - Borough to the visualization.

Q: Visualize the mean number of complaints with *Month_of_the_year*, *Location Type*, and *Borough*.

The seaborn class `FacetGrid` is used to design the plot, i.e., specify the way the data will be divided in mutually exclusive subsets for visualization. Then the `[map]` function of the `FacetGrid` class is used to apply a plotting function to each subset of the data.

```
#Visualizing the number of complaints with Month_of_the_year, Location Type, and Borough.
a = sns.FacetGrid(nyc_complaints_grouped, hue = 'Location Type', col = 'Borough',col_wrap=
a.map(sns.lineplot,'Month_of_the_year','complaints')
a.set_axis_labels("Month of the year", "Complaints")
a.add_legend()
```



From the above plot, we get a couple of interesting insights: 1. For Queens and Staten Island, most of the complaints occur in summer, for Manhattan and Bronx it is mostly during late spring, while Brooklyn has a spike of complaints in early Fall. 2. In most of the Boroughs, the majority complaints always occur in residential areas. However, for Manhattan, the number of street/sidewalk complaints in the summer are comparable to those from residential areas.

We have visualized 4 variables simultaneously in the above plot.

Let us consider another example, where we will visualize the weather in a few cities of Australia. The file *Australia_weather.csv* consists of weather details of Sydney, Canberra, and Melbourne from 2007 to 2017.

```
aussie_weather = pd.read_csv('./Datasets/Australia_weather.csv')
aussie_weather.head()
```

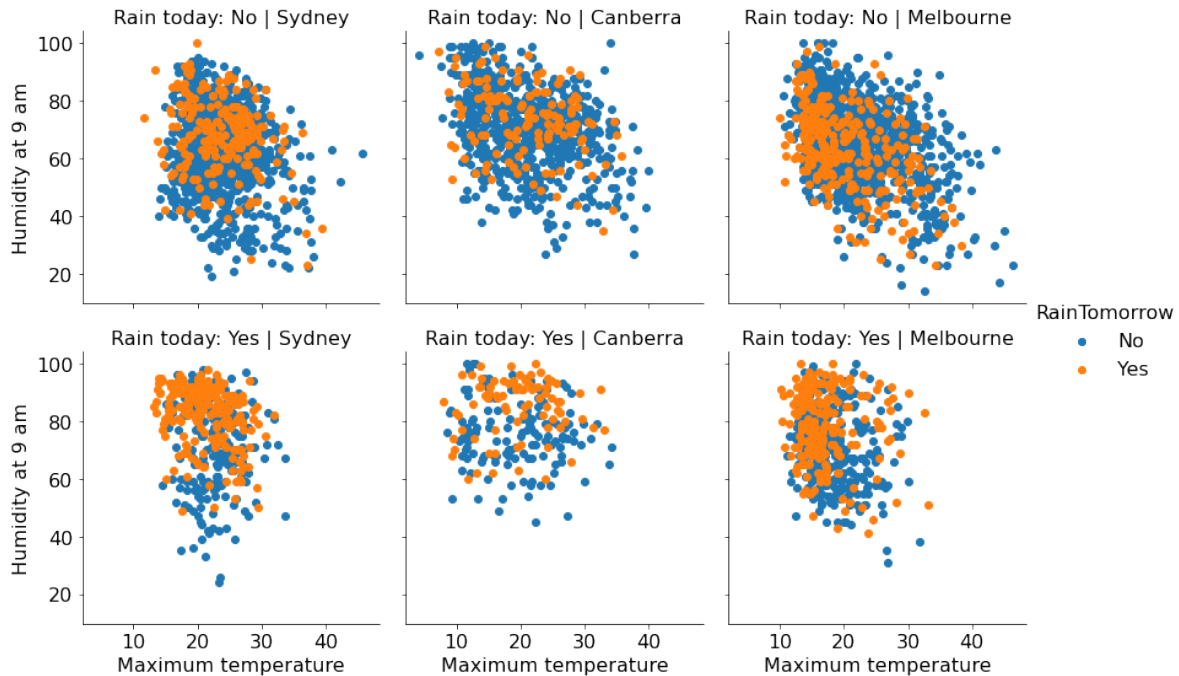
| | Date | Location | MinTemp | MaxTemp | Rainfall | Evaporation | Sunshine | WindGustDir | Wind |
|---|------------|----------|---------|---------|----------|-------------|----------|-------------|------|
| 0 | 10/20/2010 | Sydney | 12.9 | 20.3 | 0.2 | 3.0 | 10.9 | ENE | 37 |
| 1 | 10/21/2010 | Sydney | 13.3 | 21.5 | 0.0 | 6.6 | 11.0 | ENE | 41 |
| 2 | 10/22/2010 | Sydney | 15.3 | 23.0 | 0.0 | 5.6 | 11.0 | NNE | 41 |
| 3 | 10/26/2010 | Sydney | 12.9 | 26.7 | 0.2 | 3.8 | 12.1 | NE | 33 |
| 4 | 10/27/2010 | Sydney | 14.8 | 23.8 | 0.0 | 6.8 | 9.6 | SSE | 54 |

```
aussie_weather.shape
```

```
(4666, 24)
```

Q: Visualize if it rains the next day (*RainTomorrow*) given whether it has rained today (*RainToday*), the current day's humidity (*Humidity9am*), maximum temperature (*MaxTemp*) and the city (*Location*).

```
a = sns.FacetGrid(aussie_weather,col='Location',row='RainToday',height = 4,aspect = 1,hue
a.map(plt.scatter,'MaxTemp','Humidity9am')
a.set_axis_labels("Maximum temperature", "Humidity at 9 am")
a.set_titles(col_template="{col_name}", row_template="Rain today: {row_name}")
a.add_legend()
```



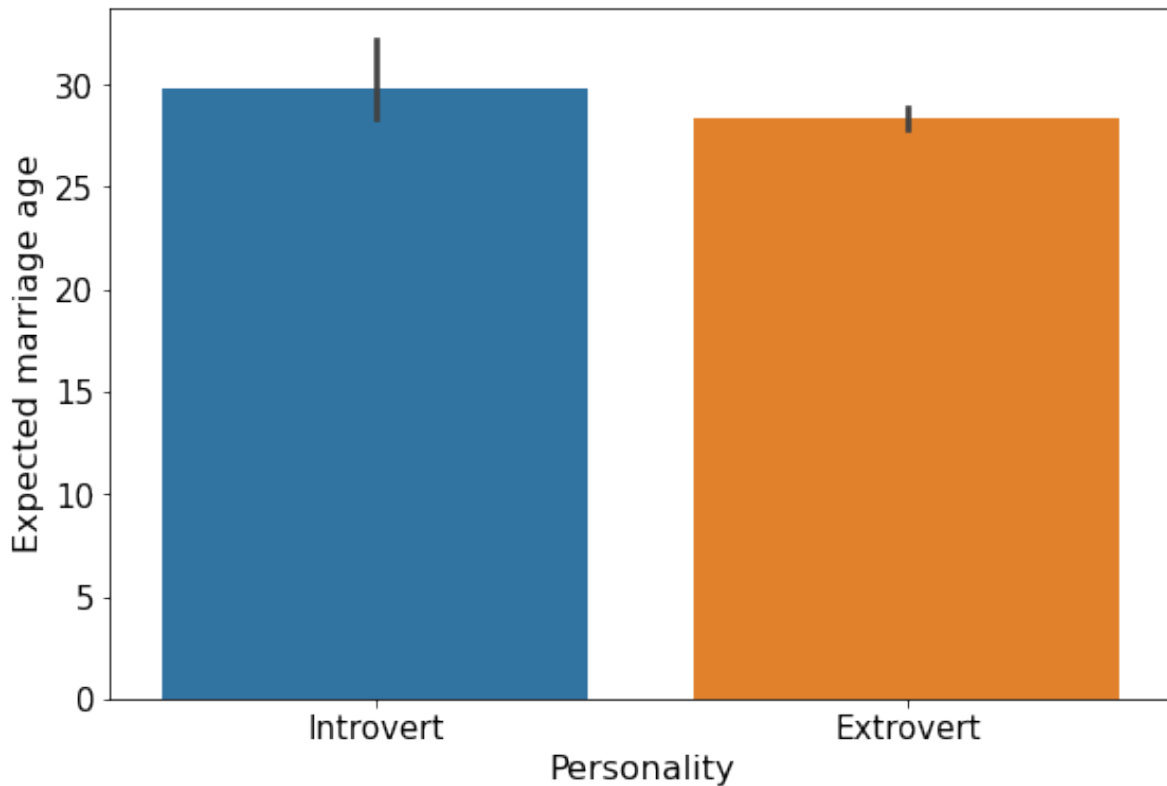
Humidity tends to be higher when it is going to rain the next day. However, the correlation is much more pronounced for Sydney. In case it is not raining on the current day, humidity seems to be slightly negatively correlated with temperature.

6.3.3 Practice exercise 2

How does the expected marriage age of the people of STAT303-1 depend on their characteristics? We'll use visualizations to answer this question. Use data from the file *survey_data_clean.csv*. Proceed as follows:

1. Make a visualization that compares the mean `expected_marriage_age` of introverts and extroverts (use the variable `introvert_extrovert`). What insights do you obtain?

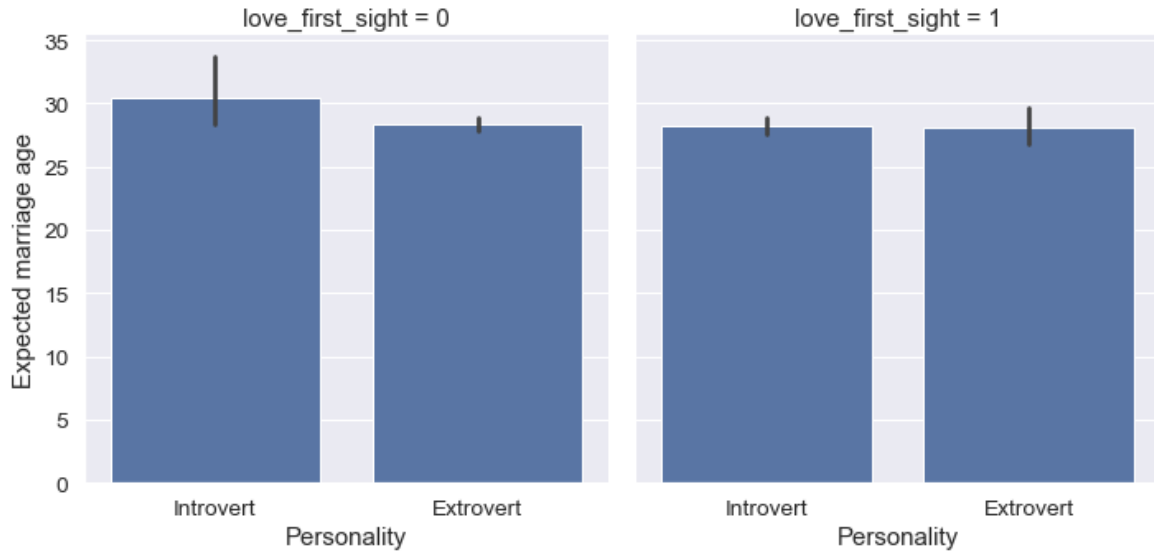
```
plt.rcParams["figure.figsize"] = (9,6)
sns.barplot(x = 'introvert_extrovert', y = 'expected_marriage_age', data = survey_data)
plt.xlabel('Personality', fontsize=16);
plt.ylabel('Expected marriage age', fontsize=16);
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
```

The mean expected marriage age for introverts is about 2 years higher than that for extroverts. Also, there is a higher variation in the expected marriage age of introverts as compared to extroverts.

2. Does the mean `expected_marriage_age` of introverts and extroverts depend on whether they believe in love in first sight (*variable name: `love_first_sight`*)? Update the previous visualization to answer the question.

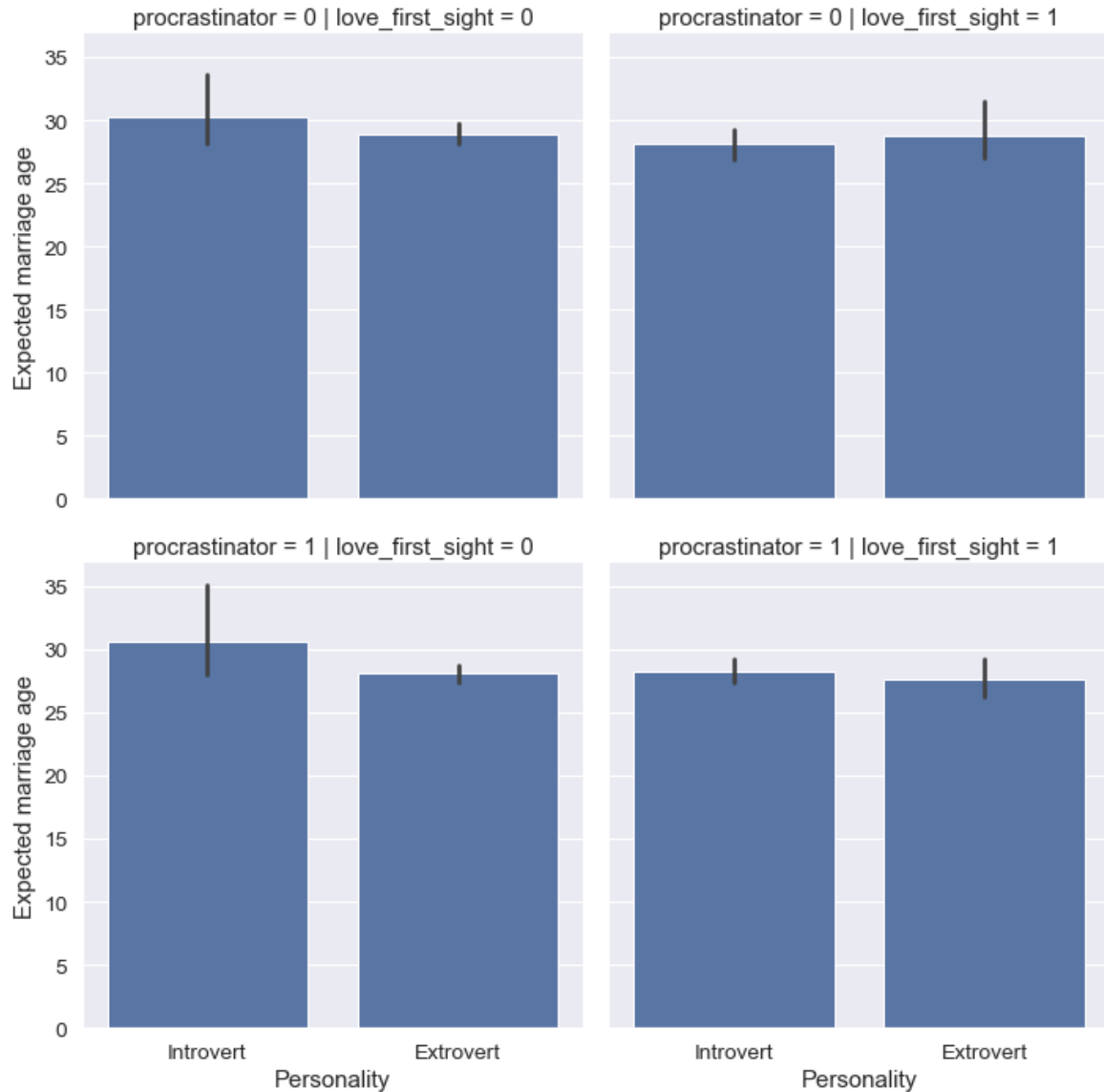
```
sns.set(font_scale=1.25)
a = sns.FacetGrid(survey_data,col='love_first_sight',height = 5,aspect = 1)
a.map(sns.barplot, 'introvert_extrovert' , 'expected_marriage_age' ,order = ['Introvert',
a.set_axis_labels("Personality", "Expected marriage age")
a.add_legend()
```



Yes, only those introverts who do not believe in love in first sight have a higher mean value of expected marriage age.

3. In addition to `love_first_sight`, does the mean `expected_marriage_age` of introverts and extroverts depend on whether they are a procrastinator (*variable name: `procrastinator`*)? Update the previous visualization to answer the question.

```
sns.set(font_scale=1.25)
a = sns.FacetGrid(survey_data,col='love_first_sight',height = 5,aspect = 1, row = 'procras
a.map(sns.barplot, 'introvert_extrovert' , 'expected_marriage_age' ,order = ['Introvert',
a.set_axis_labels("Personality", "Expected marriage age")
a.add_legend()
```



Procrastination does not seem to make much of a difference in the expected marriage age. The mean expected marriage age of procrastinating introverts seems to be only a little higher than the non-procrastinating introverts.

4. Is there any critical information missing in the above visualizations that, if revealed, may cast doubts on the patterns observed in them?

Yes, we don't know the number of observations corresponding to each bar of the bar plots. If there are a very few observations in any of the categories, then the trend shown by that category may not be reliable. For example, in the data (`survey_data`), there are only 8

introverts who are not procrastinators and believe in love in first sight, while there are 52 introverts who are procrastinators and do not believe in love in first sight.

If there are more introverts in the class of STAT303-1 who are not procrastinators and believe in love at first sight (may be they didn't fill the survey), then they are under-represented in the sample of people who filled the survey, and the trend observed for them may be less reliable than that for other people.

```
#Code for finding the number of people in each category - you will understand this code la
survey_data[['introvert_extrovert','love_first_sight','procrastinator','Timestamp']].group
'love_fi
```

| | | | Timestamp |
|---------------------|------------------|----------------|-----------|
| introvert_extrovert | love_first_sight | procrastinator | |
| Extrovert | 0 | 0 | 19 |
| | | 1 | 35 |
| | 1 | 0 | 10 |
| | | 1 | 15 |
| Introvert | 0 | 0 | 32 |
| | | 1 | 52 |
| | 1 | 0 | 8 |
| | | 1 | 21 |

6.3.4 Histogram and density plots with Seaborn

Purpose: Histogram and density plots visualize the distribution of a continuous variable.

A histogram plots the number of observations occurring within discrete, evenly spaced bins of a random variable, to visualize the distribution of the variable. It may be considered a special case of a bar plot as bars are used to plot the observation counts.

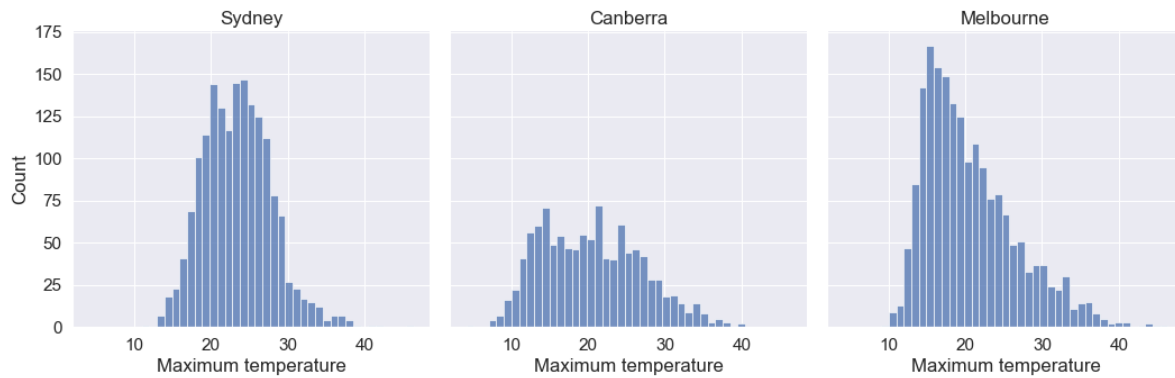
A density plot uses a kernel density estimate to approximate the distribution of random variable.

We can use the Seaborn `displot()` function to make both kinds of plots - histogram or density plot.

Example: Make a histogram showing the distributions of maximum temperature in Sydney, Canberra and Melbourne.

```
sns.set(font_scale = 1.4)
a = sns.displot(data = aussie_weather, x = 'MaxTemp', kind = 'hist', col='Location')
```

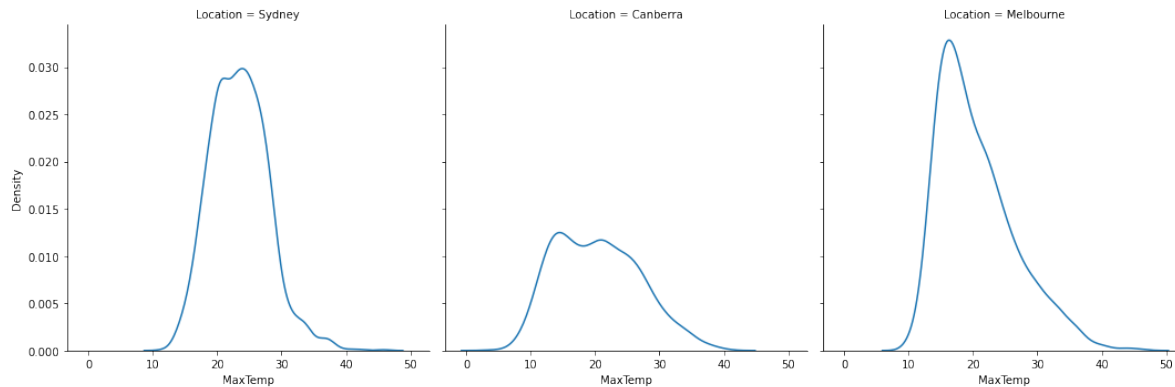
```
a.set_axis_labels("Maximum temperature", "Count")
a.set_titles("{col_name}")
```



From the above plot, we observe that: 1. Melbourne has a right skewed distribution with the median temperature being smaller than the mean. 2. Canberra seems to have the highest variation in the temperature.

Example: Make a density plot showing the distributions of maximum temperature in Sydney, Canberra and Melbourne.

```
sns.displot(data = aussie_weather, x = 'MaxTemp', kind = 'kde', col = 'Location')
```

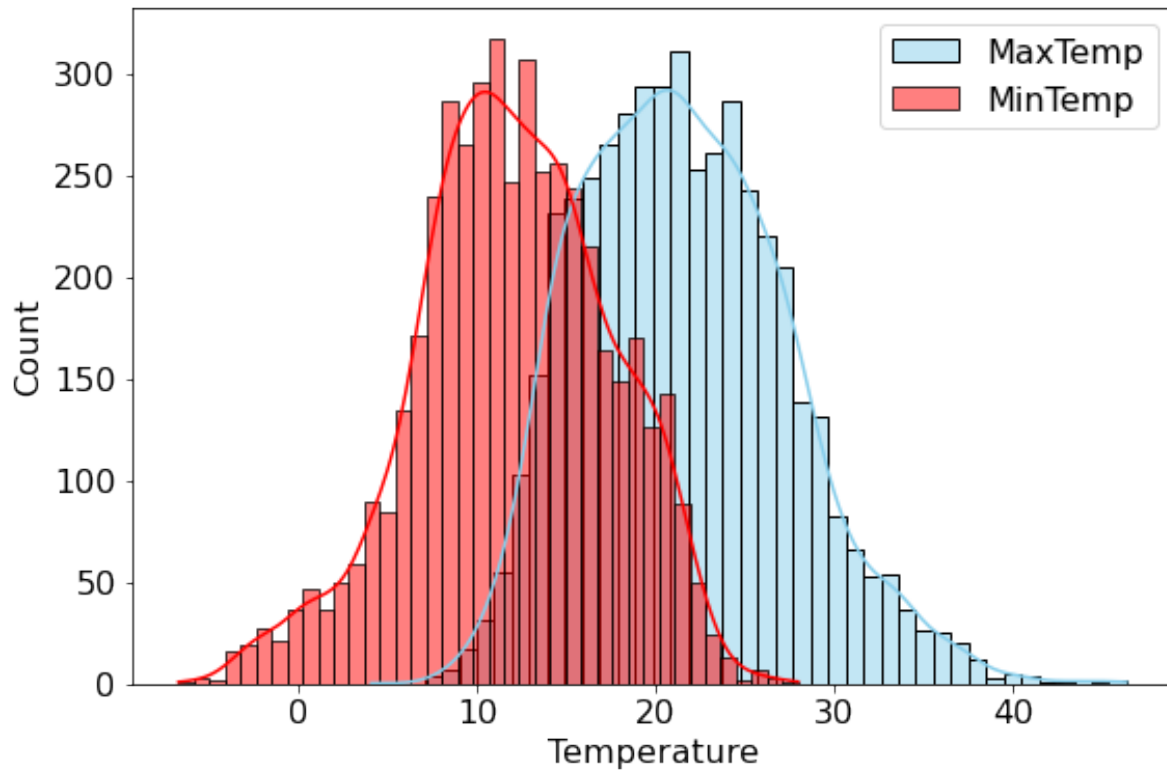


Example: Show the distributions of the maximum and minimum temperatures in a single plot.

```
sns.histplot(data=aussie_weather, x="MaxTemp", color="skyblue", label="MaxTemp", kde=True)
sns.histplot(data=aussie_weather, x="MinTemp", color="red", label="MinTemp", kde=True)
```

```
plt.legend()
plt.xlabel('Temperature')
```

```
Text(0.5, 0, 'Temperature')
```



The Seaborn function `histplot()` can be used to make a density plot overlapping on a histogram.

6.3.5 Boxplots with Seaborn

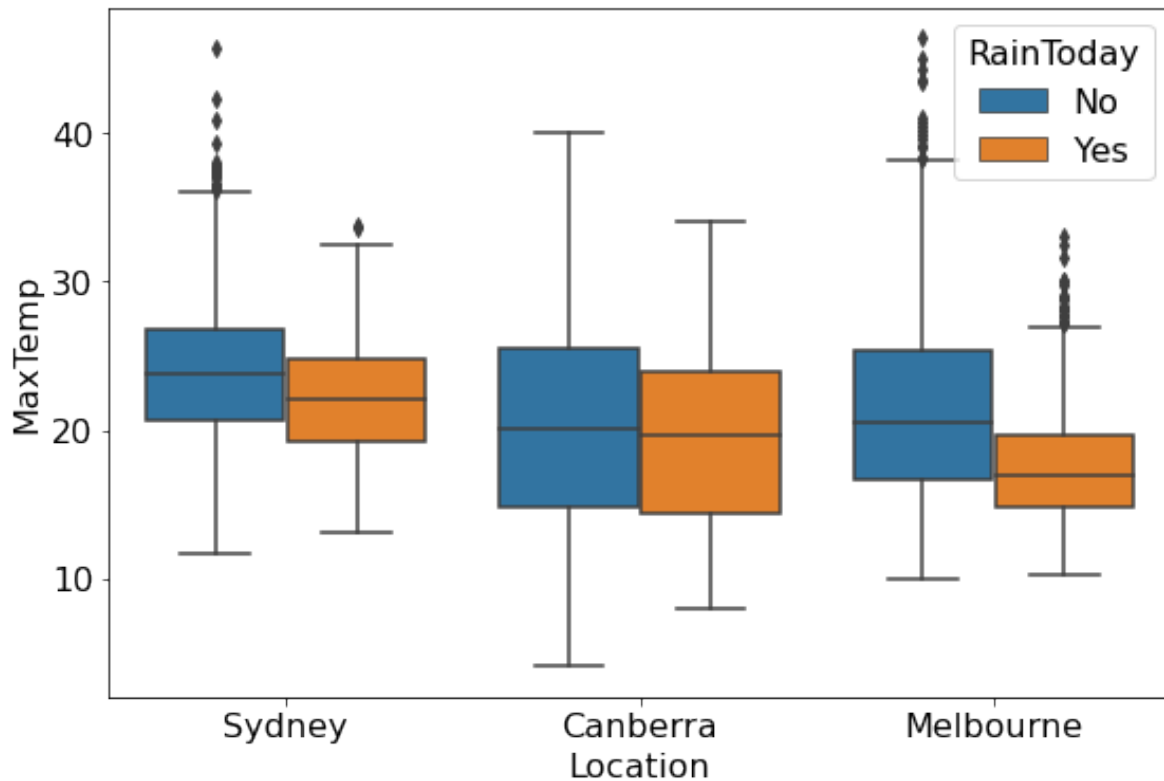
Purpose: Boxplots is a standardized way of visualizing the distribution of a continuous variable. They show five key metrics that describe the data distribution - median, 25th percentile value, 75th percentile value, minimum and maximum, as shown in the figure below. Note that the minimum and maximum exclude the outliers.

```
<IPython.core.display.Image object>
```

Example: Make a boxplot comparing the distributions of maximum temperatures of Sydney, Canberra and Melbourne, given whether or not it has rained on the day.

```
sns.boxplot(data = aussie_weather, x = 'Location', y = 'MaxTemp', hue = 'RainToday')
```

```
<AxesSubplot:xlabel='Location', ylabel='MaxTemp'>
```



From the above plot, we observe that: 1. The maximum temperature of the day, on an average, is lower if it rained on the day. 2. Sydney and Melbourne have some extremely high outlying values of maximum temperature.

We have used the Seaborn `boxplot()` function for the above plot.

6.3.6 Scatterplots with Seaborn

We made scatterplots with Matplotlib and Pandas earlier. With Seaborn, the `regplot()` function allows us to plot a trendline over the scatterplot, along with a 95% confidence interval for the trendline. Note that this is much easier than making a trendline with Matplotlib.

```
#Scatterplot and trendline with seaborn
plt.rcParams["figure.figsize"] = (9,6)
sns.set(font_scale=1.5)
ax=sns.regplot(x = 'gdpPercap', y = 'lifeExp', data = gdp_data,scatter_kws={"color": "orange", "alpha": 0.5})
ax.xaxis.set_major_formatter('${x:,.0f}')
ax.set_xlabel('GDP per capita')
ax.set_ylabel('Life expectancy')
```

```
Text(0, 0.5, 'Life expectancy')
```



Note that the confidence interval of the trendline broadens as we move farther away from most of the data points. In other words, there is more uncertainty about the trend as we move to a domain space farther away from the data.

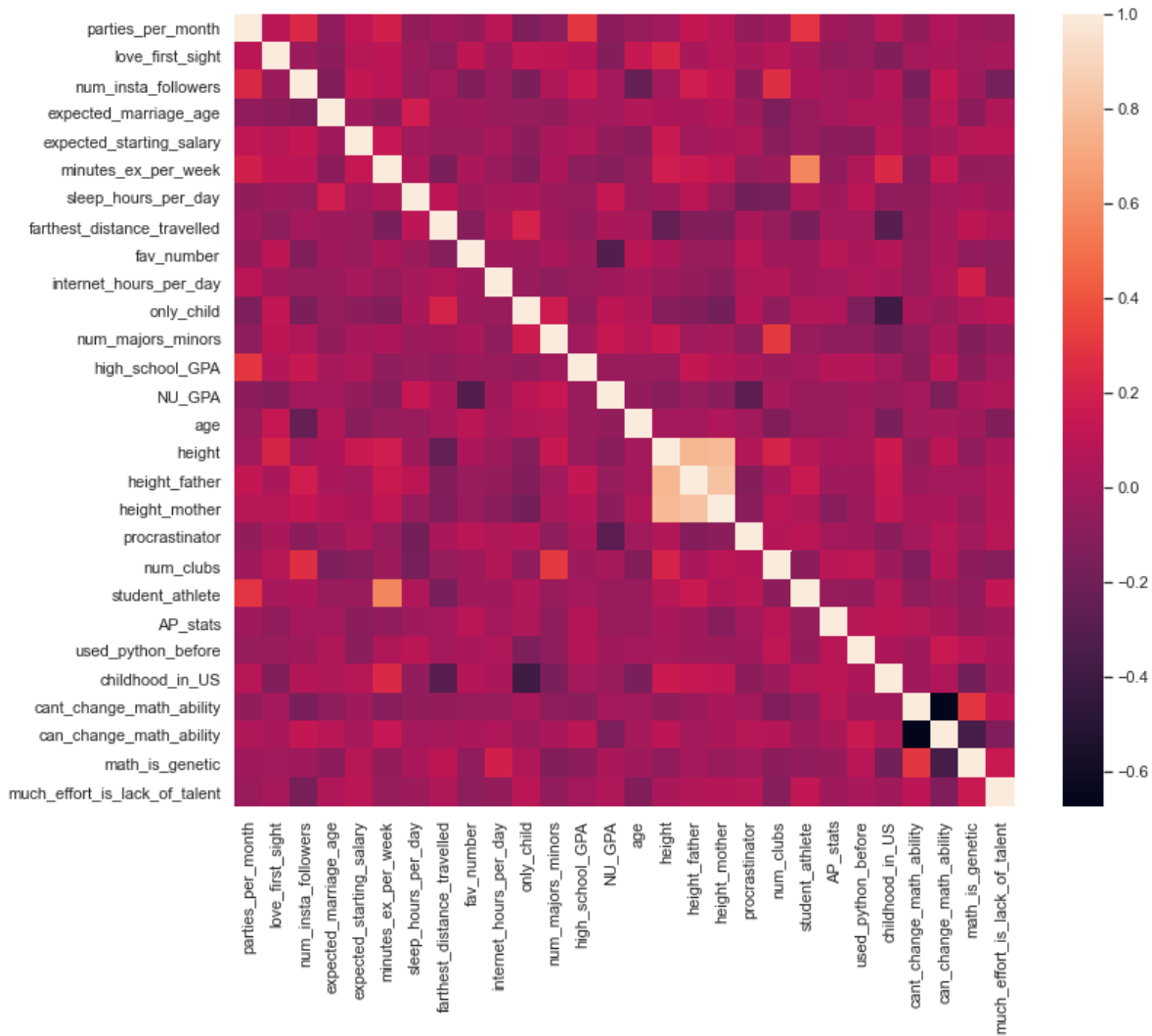
6.3.7 Heatmaps with Seaborn

Purpose: Heatmaps help us visualize the correlation between all variable-pairs.

Below is a heatmap visualizing the pairwise correlation of all the numerical variables of `survey_data_clean`. With a heatmap it becomes easier to see strongly correlated variables.

```
sns.set(rc={'figure.figsize':(12,10)})
sns.heatmap(survey_data.corr())
```

<AxesSubplot:>



From the above map, we can see that:

- `student_athlete` is strongly positively correlated with `minutes_ex_per_week`

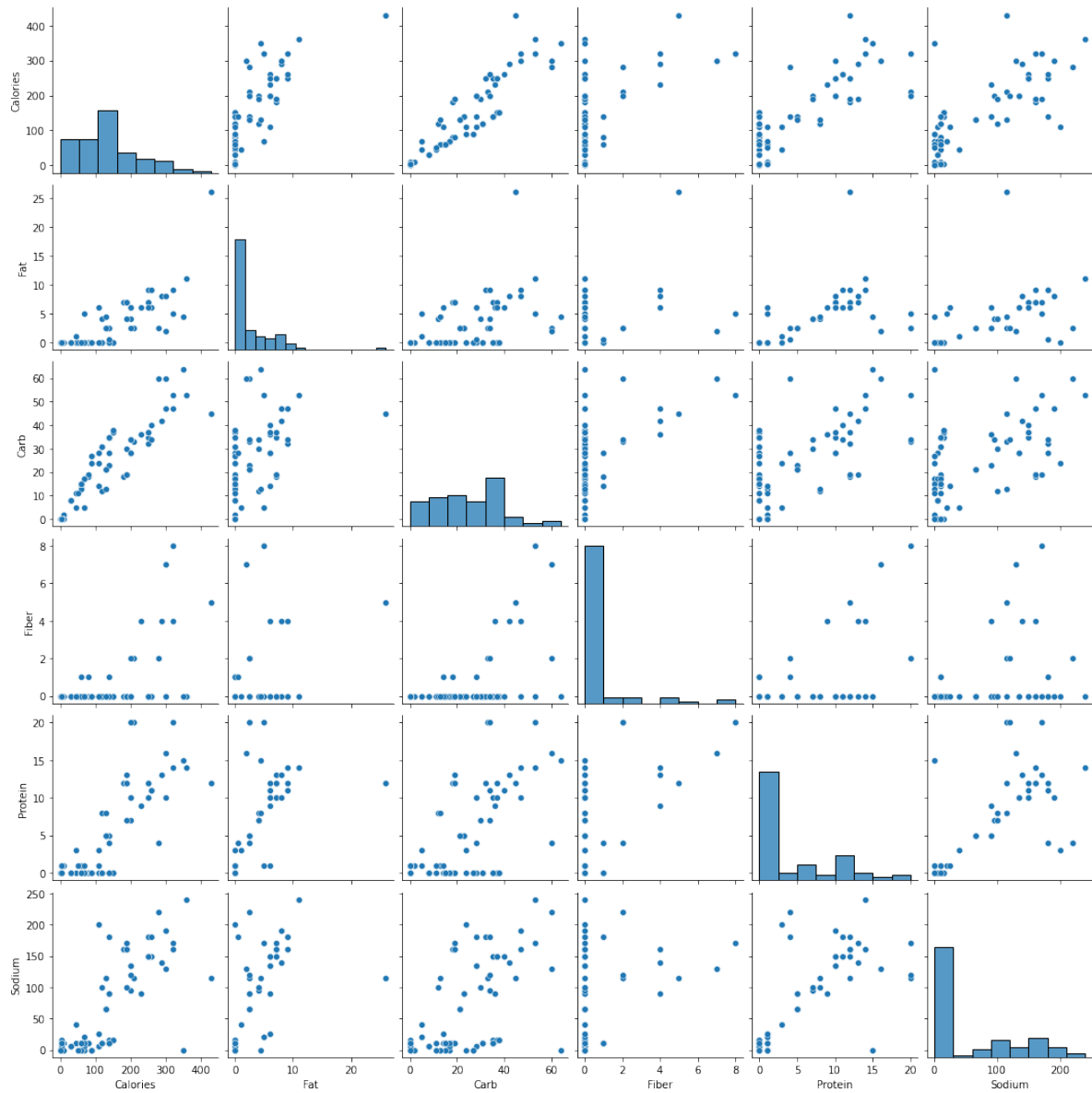
- `procrastinator` is strongly negatively correlated with `NU_GPA`

6.3.8 Pairplots with Seaborn

Purpose: Pairplots are used to visualize the association between all variable-pairs in the data. In other words, pairplots simultaneously visualize the scatterplots between all variable-pairs.

Let us visualize the pair-wise association of nutrition variables in the starbucks drinks data.

```
starbucks_drinks = pd.read_csv('./Datasets/starbucks-menu-nutrition-drinks.csv')
sns.pairplot(starbucks_drinks)
```



In the above pairplot, note that:

- The histograms on the diagonal of the grid show the distribution of each of the variables.
- Instead of a histogram, we can visualize the density plot with the argument `kde = True`.
- The scatterplots in the rest of the grid are the pair-wise plots of all the variables.

From the above plot, we observe that:

- Almost all the variable pairs have a positive correlation, i.e., if one of the nutrients increase in a drink, others also are likely to increase.
- The number of calories seem to be strongly positively correlated with the amount of carbs in the drink.
- From the density plots we can see that there is a lot of choice for consumers to buy a drink that has a zero value for any of the nutrients - fat, protein, fiber, or sodium.

7 Data cleaning and preparation

7.1 Handling missing data

Missing values in a dataset can occur due to several reasons such as breakdown of measuring equipment, accidental removal of observations, lack of response by respondents, error on the part of the researcher, etc.

Let us read the dataset *GDP_missing_data.csv*, in which we have randomly removed some values, or put missing values in some of the columns.

We'll also read *GDP_complete_data.csv*, in which we have not removed any values. We'll use this data later to assess the accuracy of our guess or estimate of missing values in *GDP_missing_data.csv*.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn as sk
import seaborn as sns
gdp_missing_values_data = pd.read_csv('./Datasets/GDP_missing_data.csv')
gdp_complete_data = pd.read_csv('./Datasets/GDP_complete_data.csv')
```

```
gdp_missing_values_data.head()
```

| | economicActivityFemale | country | lifeMale | infantMortality | gdpPerCapita | economicActivityMale |
|---|------------------------|-------------|----------|-----------------|--------------|----------------------|
| 0 | 7.2 | Afghanistan | 45.0 | 154.0 | 2474.0 | 87.5 |
| 1 | 7.8 | Algeria | 67.5 | 44.0 | 11433.0 | 76.4 |
| 2 | 41.3 | Argentina | 69.6 | 22.0 | NaN | 76.2 |
| 3 | 52.0 | Armenia | 67.2 | 25.0 | 13638.0 | 65.0 |
| 4 | 53.8 | Australia | NaN | 6.0 | 54891.0 | NaN |

Observe that the `gdp_missing_values_data` dataset consists of some missing values shown as NaN (Not a Number).

7.1.1 Identifying missing values (`isnull()`)

Missing values in a Pandas DataFrame can be identified with the `isnull()` method. The Pandas Series object also consists of the `isnull()` method. For finding the number of missing values in each column of `gdp_missing_values_data`, we will sum up the missing values in each column of the dataset:

```
gdp_missing_values_data.isnull().sum()
```

```
economicActivityFemale    10
country                   0
lifeMale                  10
infantMortality           10
gdpPerCapita              10
economicActivityMale      10
illiteracyMale            10
illiteracyFemale          10
lifeFemale                10
geographic_location       0
contraception             71
continent                 0
dtype: int64
```

Note that the descriptive statistics methods associated with Pandas objects ignore missing values by default. Consider the summary statistics of `gdp_missing_values_data`:

```
gdp_missing_values_data.describe()
```

| | economicActivityFemale | lifeMale | infantMortality | gdpPerCapita | economicActivityMale | illit |
|-------|------------------------|------------|-----------------|---------------|----------------------|------------|
| count | 145.000000 | 145.000000 | 145.000000 | 145.000000 | 145.000000 | 145.000000 |
| mean | 45.935172 | 65.491724 | 37.158621 | 24193.482759 | 76.563448 | 13.500000 |
| std | 16.875922 | 9.099256 | 34.465699 | 22748.764444 | 7.854730 | 16.400000 |
| min | 1.900000 | 36.000000 | 3.000000 | 772.000000 | 51.200000 | 0.000000 |
| 25% | 35.500000 | 62.900000 | 10.000000 | 6837.000000 | 72.000000 | 1.000000 |
| 50% | 47.600000 | 67.800000 | 24.000000 | 15184.000000 | 77.300000 | 6.600000 |
| 75% | 55.900000 | 72.400000 | 54.000000 | 35957.000000 | 81.600000 | 19.500000 |
| max | 90.600000 | 77.400000 | 169.000000 | 122740.000000 | 93.000000 | 70.000000 |

Observe that the `count` statistics report the number of non-missing values of each column in the data, as the number of rows in the data (see code below) is more than the number of non-

missing values of all the variables in the above table. Similarly, for the rest of the statistics, such as `mean`, `std`, etc., the missing values are ignored.

```
#The dataset gdp_missing_values_data has 155 rows
gdp_missing_values_data.shape[0]
```

155

7.1.2 Types of missing values

Now that we know how to identify missing values in the dataset, let us learn about the types of missing values that can be there. Rubin (1976) classified missing values in three categories.

7.1.2.1 Missing Completely at Random (MCAR)

If the probability of being missing is the same for all cases, then the data are said to be missing completely at random. An example of MCAR is a weighing scale that ran out of batteries. Some of the data will be missing simply because of bad luck.

7.1.2.2 Missing at Random (MAR)

If the probability of being missing is the same only within groups defined by the observed data, then the data are missing at random (MAR). MAR is a much broader class than MCAR. For example, when placed on a soft surface, a weighing scale may produce more missing values than when placed on a hard surface. Such data are thus not MCAR. If, however, we know surface type and if we can assume MCAR within the type of surface, then the data are MAR.

7.1.2.3 Missing Not at Random (MNAR)

MNAR means that the probability of being missing varies for reasons that are unknown to us. For example, the weighing scale mechanism may wear out over time, producing more missing data as time progresses, but we may fail to note this. If the heavier objects are measured later in time, then we obtain a distribution of the measurements that will be distorted. MNAR includes the possibility that the scale produces more missing values for the heavier objects (as above), a situation that might be difficult to recognize and handle.

Source: <https://stefvanbuuren.name/fimd/sec-MCAR.html>

7.1.3 Practice exercise 1

7.1.3.1

In which of the above scenarios can we ignore the observations corresponding to missing values without the risk of skewing the analysis/trends in the data?

7.1.3.2

In which of the above scenarios will it be the more risky to impute or estimate missing values?

7.1.3.3

For the dataset consisting of GDP per capita, think of hypothetical scenarios in which the missing values of GDP per capita can correspond to MCAR / MAR / MNAR.

7.1.4 Dropping observations with missing values (`dropna()`)

Sometimes our analysis requires that there should be no missing values in the dataset. For example, while building statistical models, we may require the values of all the predictor variables. The quickest way is to use the `dropna()` method, which drops the observations that even have a single missing value, and leaves only complete observations in the data.

Let us drop the rows containing even a single value from `gdp_missing_values_data`.

```
gdp_no_missing_data = gdp_missing_values_data.dropna()
```

```
#Shape of gdp_no_missing_data  
gdp_no_missing_data.shape
```

```
(42, 12)
```

Dropping rows with even a single missing value has reduced the number of rows from 155 to 42! However, earlier we saw that all the columns except `contraception` had at most 10 missing values. Removing all rows / columns with even a single missing value results in loss of data that is non-missing in the respective rows/columns. Thus, it is typically a bad idea to drop observations with even a single missing value, except in cases where we have a very small number of missing-value observations.

If a few values of a column are missing, we can possibly estimate them using the rest of the data, so that we can (hopefully) maximize the information that can be extracted from the data. However, if most of the values of a column are missing, it may be harder to estimate its values.

In this case, we see that around 50% values of the `contraception` column is missing. Thus, we'll drop the column as it may be hard to impute its values based on a relatively small number of non-missing values.

```
#Deleting column with missing values in almost half of the observations
gdp_missing_values_data.drop(['contraception'],axis=1,inplace=True)
gdp_missing_values_data.shape
```

```
(155, 11)
```

7.1.5 Some methods to impute missing values

There are an unlimited number of ways to impute missing values. Some imputation methods are provided in the [Pandas documentation](#).

The best way to impute them will depend on the problem, and the assumptions taken. Below are just a few examples.

7.1.5.1 Method 1: Naive Method

Filling the missing value of a column by copying the value of the previous non-missing observation.

```
#Filling missing values: Method 1- Naive way
gdp_imputed_data = gdp_missing_values_data.fillna(method = 'ffill')

#Checking if any missing values are remaining
gdp_imputed_data.isnull().sum()
```

```
economicActivityFemale    0
country                   0
lifeMale                  0
infantMortality           0
gdpPerCapita              0
economicActivityMale      0
```

```

illiteracyMale          1
illiteracyFemale        0
lifeFemale              0
geographic_location     0
continent               0
dtype: int64

```

After imputing missing values, note there is still one missing value for *illiteracyMale*. Can you guess why one missing value remained?

Let us check how good is this method in imputing missing values. We'll compare the imputed values of `gdpPerCapita` with the actual values. Recall that we had randomly put some missing values in `gdp_missing_values_data`, and we have the actual values in `gdp_complete_data`.

```

#Index of rows with missing values for GDP per capita
null_ind_gdpPC = gdp_missing_values_data.index[gdp_missing_values_data.gdpPerCapita.isnull()]

#Defining a function to plot the imputed values vs actual values
def plot_actual_vs_predicted():
    fig, ax = plt.subplots(figsize=(8, 6))
    plt.rc('xtick', labels=15)
    plt.rc('ytick', labels=15)
    x = gdp_complete_data.loc[null_ind_gdpPC, 'gdpPerCapita']
    y = gdp_imputed_data.loc[null_ind_gdpPC, 'gdpPerCapita']
    plt.scatter(x,y)
    z=np.polyfit(x,y,1)
    p=np.poly1d(z)
    plt.plot(x,x,color='orange')
    plt.xlabel('Actual GDP per capita',fontsize=20)
    plt.ylabel('Imputed GDP per capita',fontsize=20)
    ax.xaxis.set_major_formatter('${x:,.0f}')
    ax.yaxis.set_major_formatter('${x:,.0f}')
    rmse = np.sqrt(((x-y).pow(2)).mean())
    print("RMSE=",rmse)

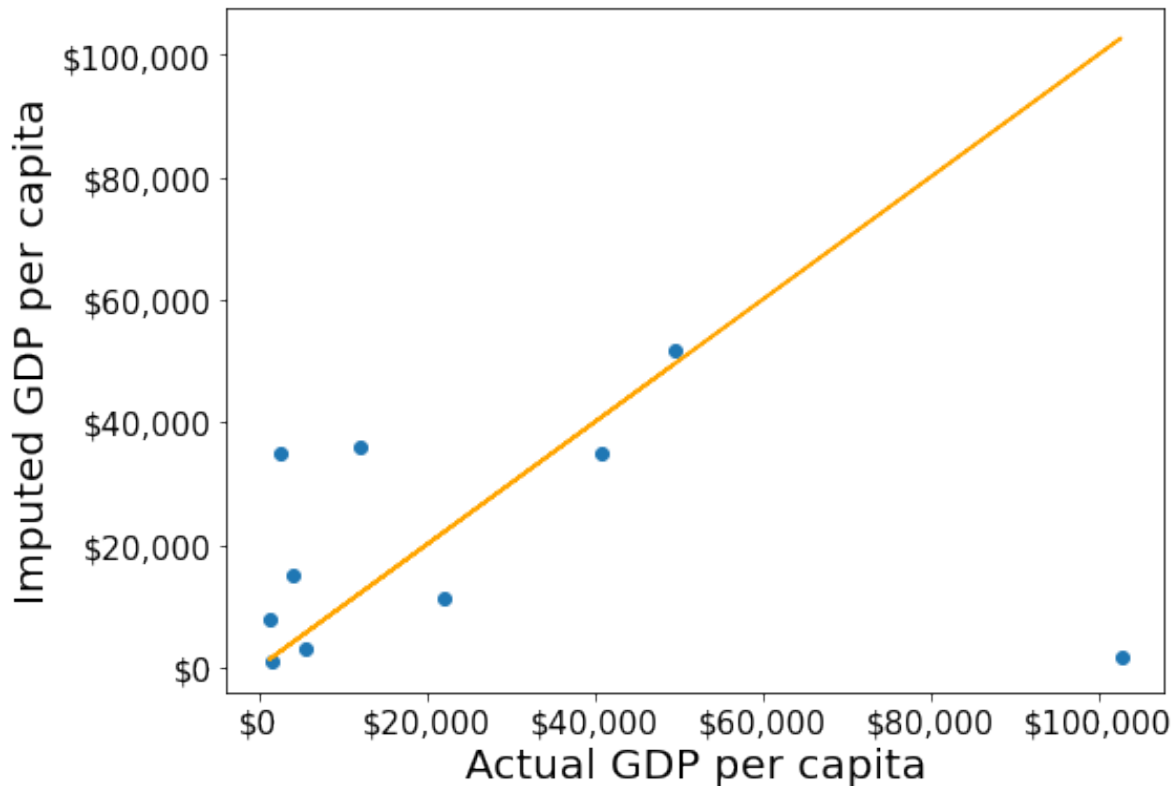
#Plot comparing imputed values with actual values, and computing the Root mean square error
plot_actual_vs_predicted()

```

```

RMSE= 34843.91091137732

```



We observe that the accuracy of imputation is poor as GDP per capita can vary a lot across countries, and the data is not sorted by GDP per capita. There is no reason why the GDP per capita of a country should be close to the GDP per capita of the country in the observation above it.

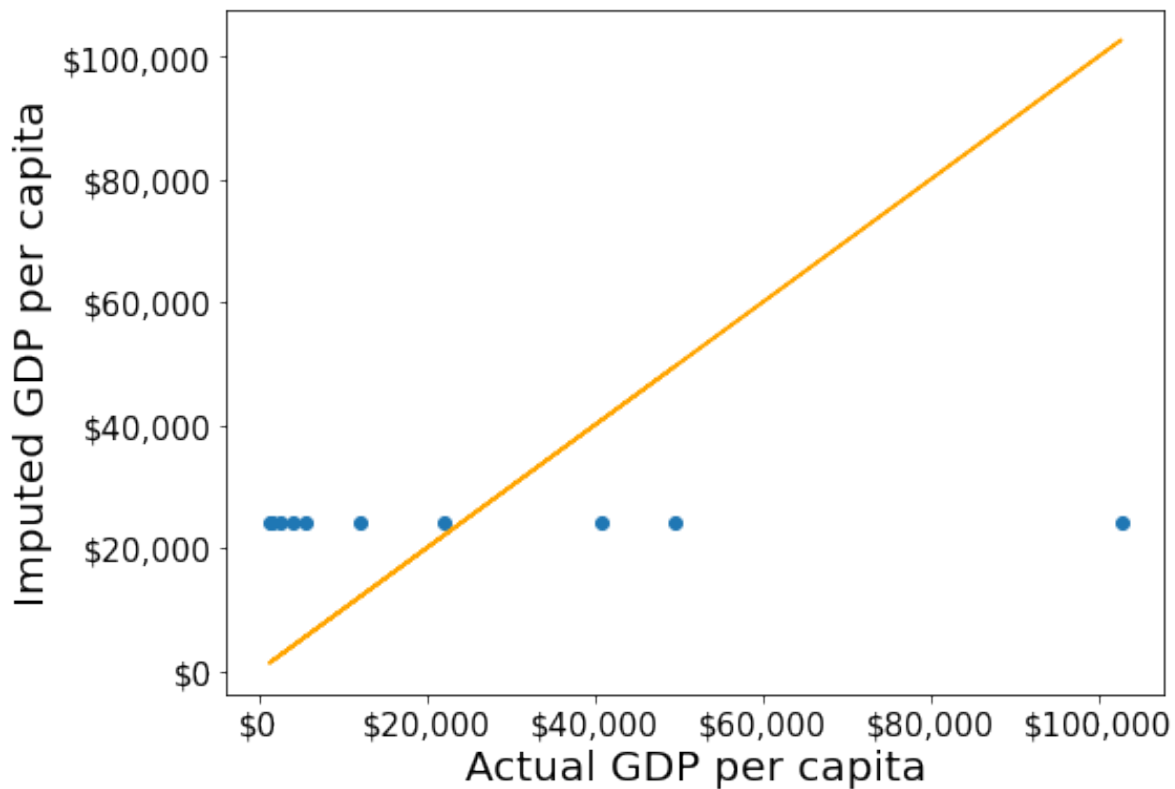
7.1.5.2 Method 2: Imputing missing values as the mean of non-missing values

Let us impute missing values in the column as the average of the non-missing values of the column. The sum of squared differences between actual values and the imputed values is likely to be smaller if we impute using the mean. However, this may not be true in cases other than MCAR (Missing completely at random).

```
#Filling missing values: Method 2
gdp_imputed_data = gdp_missing_values_data.fillna(gdp_missing_values_data.mean())

plot_actual_vs_predicted()
```

RMSE= 30793.549983587087



Although this method of imputation doesn't seem impressive, the RMSE of the estimates is lower than that of the naive method. Since we had introduced missing values randomly in `gdp_missing_values_data`, the mean GDP per capita will be the closest constant to the GDP per capita values, in terms of squared error.

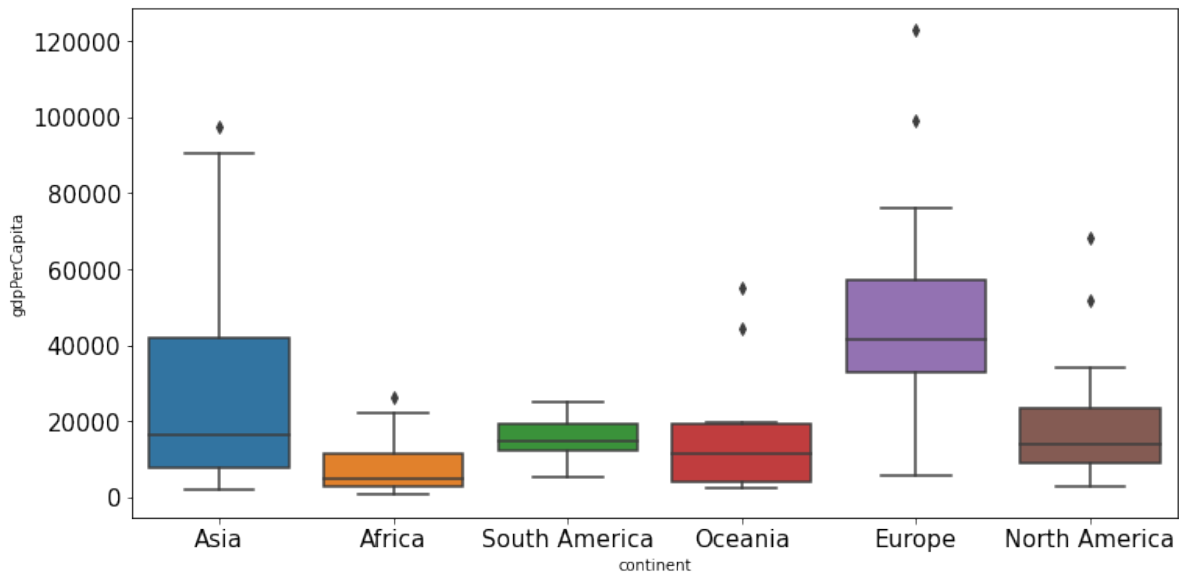
7.1.5.3 Method 3: Imputing missing values based on correlated variables in the data

If a variable is highly correlated with another variable in the dataset, we can approximate its missing values using the trendline with the highly correlated variable.

Let us visualize the distribution of GDP per capita for different continents.

```
plt.rcParams["figure.figsize"] = (12,6)
sns.boxplot(x = 'continent',y='gdpPerCapita',data = gdp_missing_values_data)
```

```
<AxesSubplot:xlabel='continent', ylabel='gdpPerCapita'>
```



We observe that there is a distinct difference between the GDPs per capita of some of the continents. Let us impute the missing GDP per capita of a country as the mean GDP per capita of the corresponding continent. This imputation should be better than imputing the missing GDP per capita as the mean of all the non-missing values, as the GDP per capita of a country is likely to be closer to the mean GDP per capita of the continent, rather than the mean GDP per capita of the whole world.

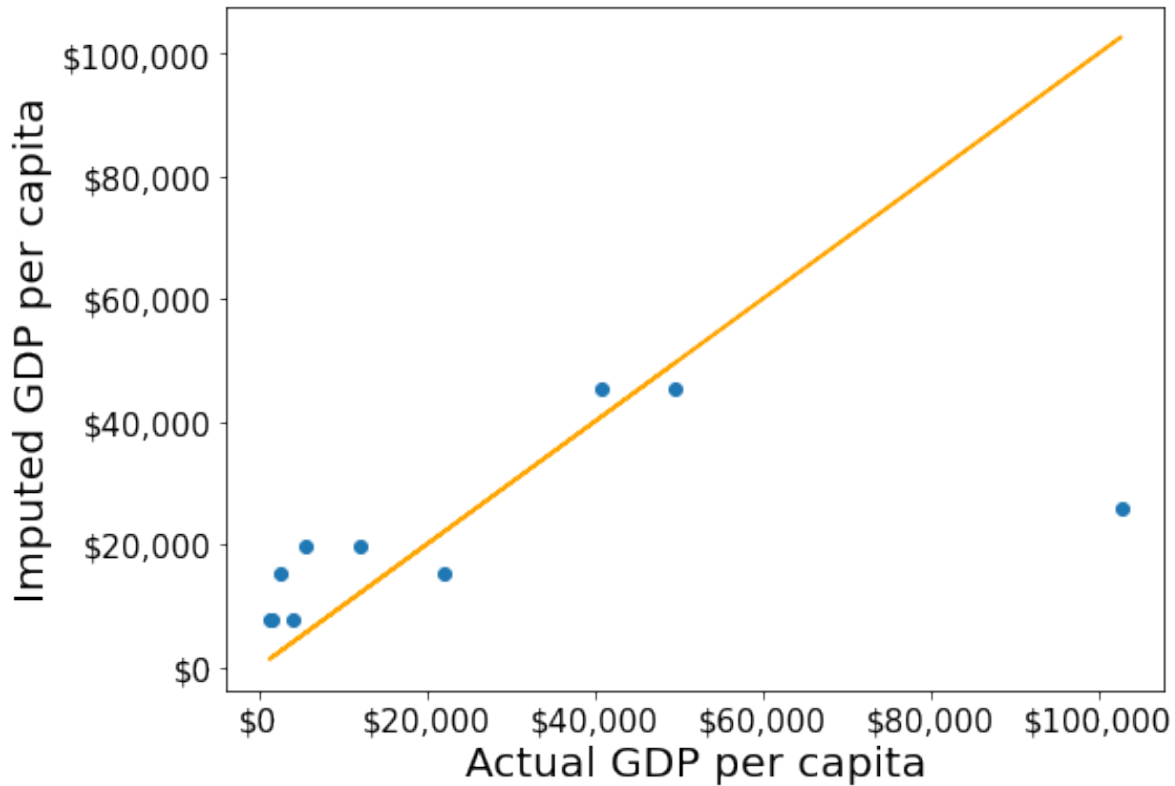
```
#Finding the mean GDP per capita of the continent - please defer the understanding of this
avg_gdpPerCapita = gdp_missing_values_data['gdpPerCapita'].groupby(gdp_missing_values_data
avg_gdpPerCapita
```

```
continent
Africa      7638.178571
Asia       25922.750000
Europe     45455.303030
North America 19625.210526
Oceania    15385.857143
South America 15360.909091
Name: gdpPerCapita, dtype: float64
```

```
#Creating a copy of missing data to impute missing values
gdp_imputed_data = gdp_missing_values_data.copy()
```

```
#Replacing missing GDP per capita with the mean GDP per capita for the corresponding conti
for cont in avg_gdpPerCapita.index:
    gdp_imputed_data.loc[(gdp_imputed_data.continent==cont) & (gdp_imputed_data.gdpPerCapi
                        'gdpPerCapita']=avg_gdpPerCapita[cont]
plot_actual_vs_predicted()
```

RMSE= 25473.20645170116



Note that the imputed values are closer to the actual values, and the RMSE has further reduced as expected.

7.1.5.4 Practice exercise 2

Find the numeric variable most strongly correlated with GDP per capita, and use it to impute its missing values. Find the RMSE of the imputed values.

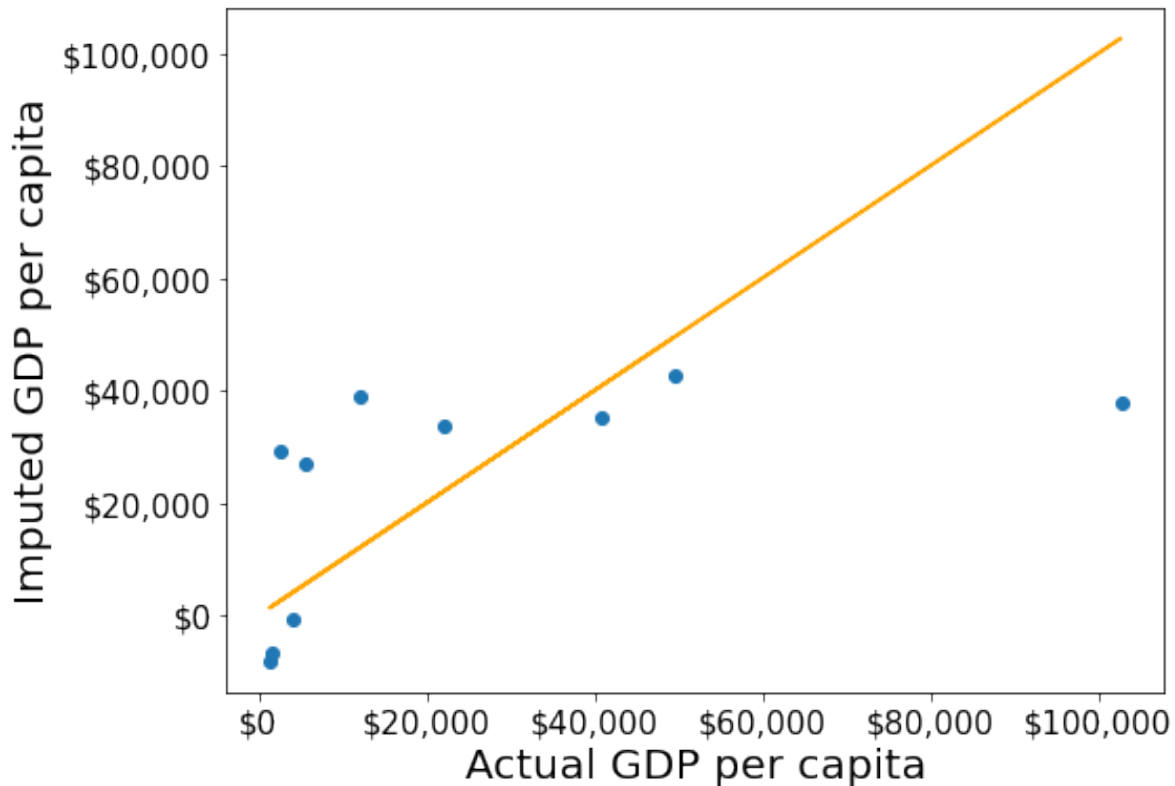
Solution:

```
#Let us identify the variable highly correlated with GDP per capita.
gdp_missing_values_data.corrwith(gdp_missing_values_data.gdpPerCapita)
```

```
economicActivityFemale    0.078332
lifeMale                  0.579850
infantMortality           -0.572201
gdpPerCapita              1.000000
economicActivityMale      -0.134108
illiteracyMale            -0.479143
illiteracyFemale          -0.448273
lifeFemale                0.615954
contraception             0.057923
dtype: float64
```

```
#The variable *lifeFemale* has the strongest correlation with GDP per capita. Let us use it
x = gdp_missing_values_data.lifeFemale
y = gdp_missing_values_data.gdpPerCapita
idx_non_missing = np.isfinite(x) & np.isfinite(y)
slope_intercept_trendline = np.polyfit(x[idx_non_missing],y[idx_non_missing],1) #Finding
compute_y_given_x = np.poly1d(slope_intercept_trendline)
#Creating a copy of missing data to impute missing values
gdp_imputed_data = gdp_missing_values_data.copy()
gdp_imputed_data.loc[null_ind_gdpPC,'gdpPerCapita']=compute_y_given_x(gdp_missing_values_data
plot_actual_vs_predicted())
```

```
RMSE= 25570.361516956993
```



7.1.5.5 Method 4: KNN: K-nearest neighbor

In this method, we'll impute the missing value of the variable as the mean value of the K -nearest neighbors having non-missing values for that variable. The neighbors to a data-point are identified based on their Euclidean distance to the point in terms of the standardized values of rest of the variables in the data.

Let's consider a toy example to understand missing value imputation by KNN. Suppose we have to impute missing values in a toy dataset, named as `toy_data` having 4 observations and 3 variables.

```
#Toy example - A 4x3 array with missing values
nan = np.nan
toy_data = np.array([[1, 2, nan], [3, 4, 3], [nan, 6, 5], [8, 8, 7]])
toy_data
```

```
array([[ 1.,  2., nan],
       [ 3.,  4.,  3.]
```



```
[nan, 6., 5.],
 [ 8., 8., 7.]])
```

We'll use some functions from the *sklearn* library to perform the KNN imputation. It is much easier to directly use the algorithm from *sklearn*, instead of coding it from scratch.

```
#Library to compute pair-wise Euclidean distance between all observations in the data
from sklearn import metrics

#Library to impute missing values with the KNN algorithm
from sklearn import impute
```

We'll use the *sklearn* function `nan_euclidean_distances()` to compute the Euclidean distance between all pairs of observations in the data.

```
#This is the distance matrix containing the distance of the ith observation from the jth o
metrics.pairwise.nan_euclidean_distances(toy_data,toy_data)
```

```
array([[ 0.          ,  3.46410162,  6.92820323, 11.29158979],
       [ 3.46410162,  0.          ,  3.46410162,  7.54983444],
       [ 6.92820323,  3.46410162,  0.          ,  3.46410162],
       [11.29158979,  7.54983444,  3.46410162,  0.          ]])
```

Note that the size of the above matrix is 4x4. This is because the $(i, j)^{th}$ element of the matrix is the distance of the i^{th} observation from the j^{th} observation. The matrix is symmetric because the distance of i^{th} observation to the j^{th} observation is the same as the distance of the j^{th} observation to the i^{th} observation.

We'll use the *sklearn* function `KNNImputer()` to impute the missing value of a column in `toy_data` as the mean of the values of the K nearest neighbors to the observation that have non-missing values for that column.

Let us impute the missing values in `toy_data` using the values of $K = 2$ nearest neighbors from the corresponding observation.

```
#imputing missing values with 2 nearest neighbors, where the neighbors have equal weights

#Define an object of type KNNImputer
imputer = impute.KNNImputer(n_neighbors=2)

#Use the object method 'fit_transform' to impute missing values
imputer.fit_transform(toy_data)
```

```
array([[1. , 2. , 4. ],
       [3. , 4. , 3. ],
       [5.5, 6. , 5. ],
       [8. , 8. , 7. ]])
```

The third observation was the closest to the 2nd and 4th observations based on the Euclidean distance matrix. Thus, the missing value in the 3rd row of the `toy_data` has been imputed as the mean of the values in the 2nd and 4th observations for the corresponding column. Similarly, the 1st observation is the closest to the 2nd and 3rd observations. Thus the missing value in the 1st row of `toy_data` has been imputed as the mean of the values in the 1st and 2nd observations for the corresponding column.

Let us use KNN to impute the missing values of `gdpPerCapita` in `gdp_missing_values_data`. We'll use only the numeric columns of the data in imputing the missing values. Also, we'll ignore `contraception` as it has a lot of missing values, and thus may not be useful.

```
#Considering numeric columns in the data to use KNN
num_cols = list(range(0,1))+list(range(2,9))
num_cols
```

```
[0, 2, 3, 4, 5, 6, 7, 8]
```

Before computing the pair-wise Euclidean distance of observations, we must standardize the data so that all columns are at the same scale. This will avoid columns with a higher magnitude of values having a higher weight in determining the Euclidean distance. Unless there is a reason to give a higher weight to a column, we assume all columns to have the same weight in the Euclidean distance computation.

We can use the code below to scale the data. However, after imputing the missing values, the data is to be scaled back to the original scale, so that each variable is in the same units as in the original dataset. However, if the code below is used, we'll lose the original scale of each of the columns.

```
#Scaling data to compute equally weighted distances from the 'k' nearest neighbors
scaled_data = gdp_missing_values_data.iloc[:,num_cols].apply(lambda x:(x-x.min()/(x.max()-x.min())))
```

To alleviate the problem of losing the original scale of the data, we'll use the [MinMaxScaler](#) object of the *sklearn* library. The object will store the original scale of the data, which will help transform the data back to the original scale once the missing values have been imputed in the standardized data.

```

# Scaling data - using sklearn

#Create an object of type MinMaxScaler
scaler = sk.preprocessing.MinMaxScaler()

#Use the object method 'fit_transform' to scale the values to a standard uniform distribution
scaled_data = pd.DataFrame(scaler.fit_transform(gdp_missing_values_data.iloc[:,num_cols]))

#Imputing missing values with KNNImputer

#Define an object of type KNNImputer
imputer = impute.KNNImputer(n_neighbors=3, weights="uniform")

#Use the object method 'fit_transform' to impute missing values
imputed_arr = imputer.fit_transform(scaled_data)

#Scaling back the scaled array to obtain the data at the original scale

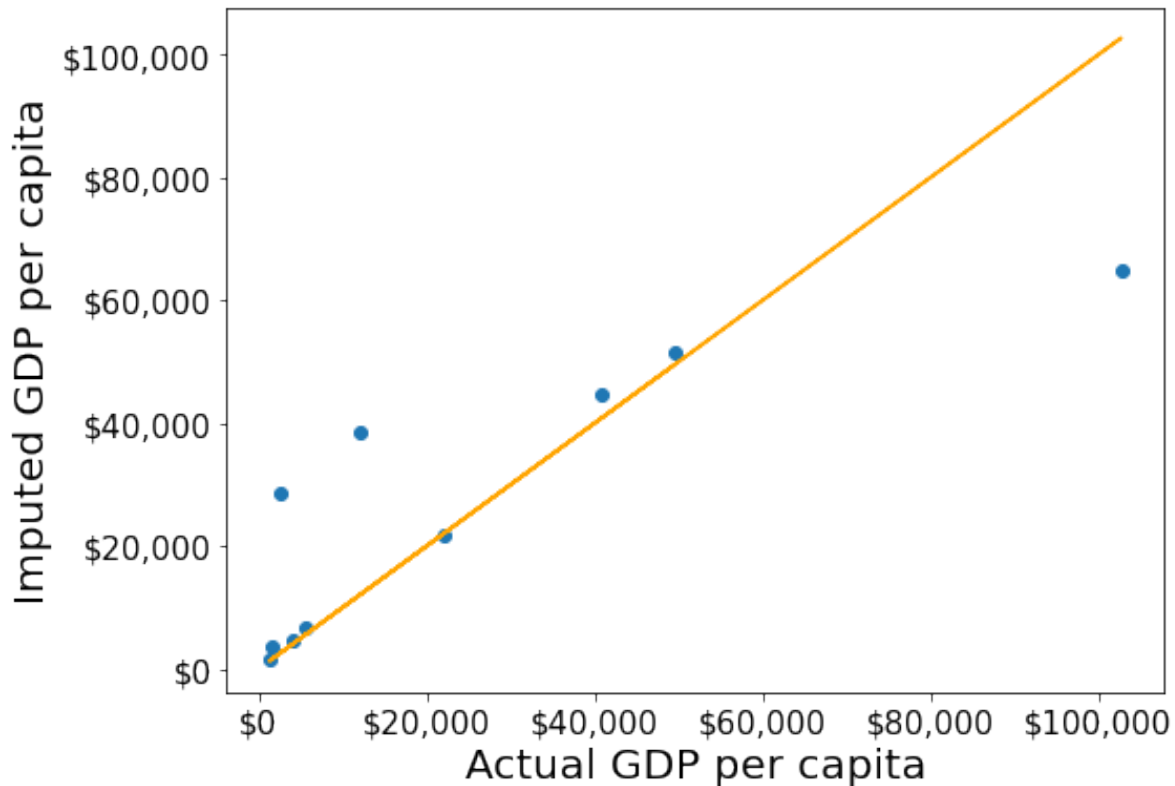
#Use the object method 'inverse_transform' to scale back the values to the original scale
unscaled_data = scaler.inverse_transform(imputed_arr)

#Note the method imputes the missing value of all the columns
#However, we are interested in imputing the missing values of only the 'gdpPerCapita' column
gdp_imputed_data = gdp_missing_values_data.copy()
gdp_imputed_data.loc[:, 'gdpPerCapita'] = unscaled_data[:,3]

#Visualizing the accuracy of missing value imputation with KNN
plot_actual_vs_predicted()

```

RMSE= 16804.195967740387



Note that the RMSE is the lowest in this method. It is because this method imputes missing values as the average of the values of “similar” observations, which is smarter and more robust than the previous methods.

We chose $K = 3$ in the missing value imputation for GDP per capita. However, the value of K is typically chosen using a method known as cross validation. We’ll learn about cross-validation in the next course of the sequence.

7.2 Data binning

Data binning is a method to group values of a continuous / categorical variable into bins (or categories). Binning may help with

- (i) Better interpretation of data
- (ii) Making better recommendations
- (iii) Smooth data, reduce noise

Examples:

Binning to better interpret data

1. The number of flu cases everyday may be binned to seasons such as fall, spring, winter and summer, to understand the effect of season on flu.

Binning to make recommendations:

2. A doctor may like to group patient age into bins. Grouping patient ages into categories such as Age ≤ 12 , $12 < \text{Age} \leq 18$, $18 < \text{Age} \leq 65$, Age > 65 may help recommend the kind/doses of covid vaccine a patient needs.
3. A credit card company may want to bin customers based on their spend, as “High spenders”, “Medium spenders” and “Low spenders”. Binning will help them design customized marketing campaigns for each bin, thereby increasing customer response (or revenue). On the other hand, they use the same campaign for customers withing the same bin, thus minimizng marketing costs.

Binning to smooth data, and reduce noise

4. A sales company may want to bin their total sales to a weekly / monthly / yearly level to reduce the noise in day-to-day sales.

Example: The dataset *College.csv* contains information about US universities. The description of variables of the dataset can be found on page 54 of this [book](#). Let’s see if we can apply binning to better interpret the association of instructional expenditure per student (**Expend**) with graduation rate (**Grad.Rate**) for US universities, and make recommendations.

```
college = pd.read_csv('./Datasets/College.csv')
college.head()
```

| | Unnamed: 0 | Private | Apps | Accept | Enroll | Top10perc | Top25perc | F.Undergrad |
|---|------------------------------|---------|------|--------|--------|-----------|-----------|-------------|
| 0 | Abilene Christian University | Yes | 1660 | 1232 | 721 | 23 | 52 | 2885 |
| 1 | Adelphi University | Yes | 2186 | 1924 | 512 | 16 | 29 | 2683 |
| 2 | Adrian College | Yes | 1428 | 1097 | 336 | 22 | 50 | 1036 |
| 3 | Agnes Scott College | Yes | 417 | 349 | 137 | 60 | 89 | 510 |
| 4 | Alaska Pacific University | Yes | 193 | 146 | 55 | 16 | 44 | 249 |

To visualize the association between two numeric variables, we typically make a scatterplot. Let us make a scatterplot of graduation rate with expenditure per student, with a trendline.

```
#Let's make a scatterplot of 'Grad.Rate' vs 'Expend' with a trendline, to visualize any tr
sns.set(font_scale=1.5)
ax=sns.regplot(data = college, x = "Expend", y = "Grad.Rate",scatter_kws={"color": "orange"
ax.xaxis.set_major_formatter('${x:,.0f}')
ax.set_xlabel('Expenditure per student')
ax.set_ylabel('Graduation rate')
```

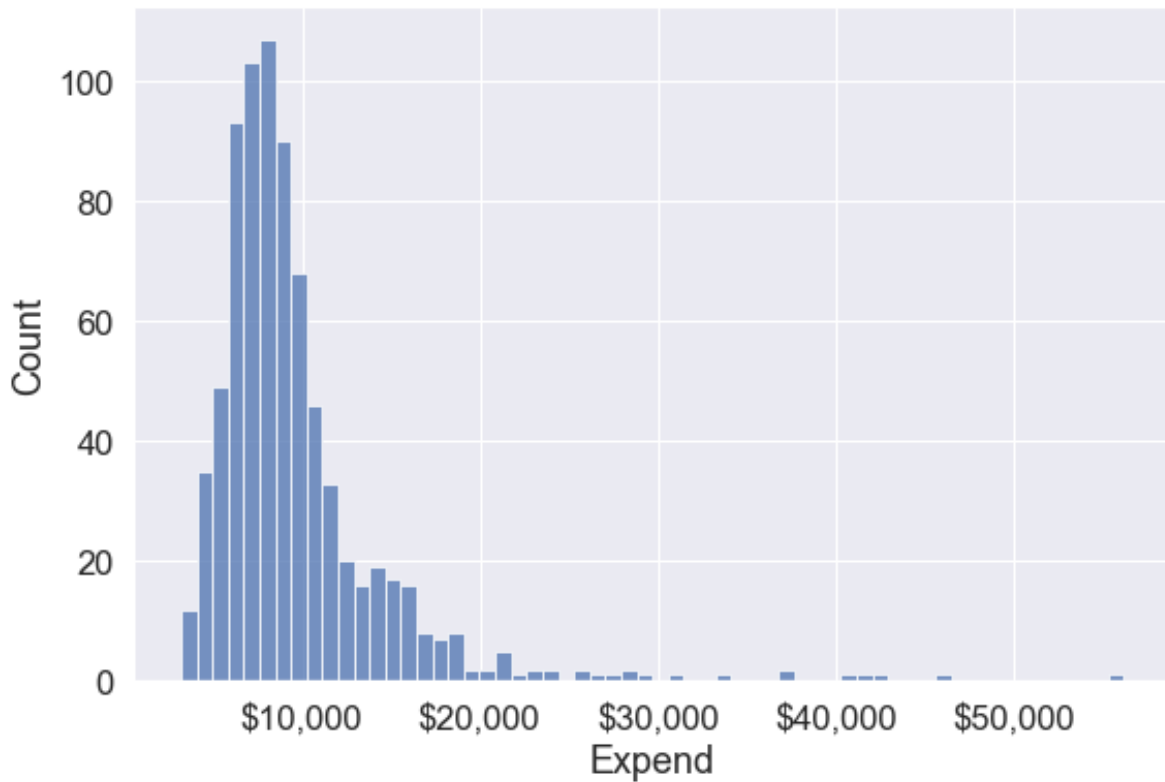
```
Text(0, 0.5, 'Graduation rate')
```



The trendline indicates a positive correlation between **Expend** and **Grad.Rate**. However, there seems to be a lot of noise and presence of outliers in the data, which makes it hard to interpret the overall trend.

We'll bin **Expend** to see if we can better analyze its association with **Grad.Rate**. However, let us first visualize the distribution of **Expend**.

```
#Visualizing the distribution of expend
ax=sns.histplot(data = college, x= 'Expend')
ax.xaxis.set_major_formatter('${x:,.0f}')
```



The distribution of `Expend` is right skewed with potentially some extremely high outlying values.

7.2.1 Binning with equal width bins

We'll use the Pandas function `cut()` to bin `Expend`. This function creates bins such that all bins have the same width.

```
#Using the cut() function in Pandas to bin "Expend"
Binned_expend = pd.cut(college['Expend'],3,retbins = True)
Binned_expend
```

```
(0      (3132.953, 20868.333]
```

```

1      (3132.953, 20868.333]
2      (3132.953, 20868.333]
3      (3132.953, 20868.333]
4      (3132.953, 20868.333]
...
772    (3132.953, 20868.333]
773    (3132.953, 20868.333]
774    (3132.953, 20868.333]
775    (38550.667, 56233.0]
776    (3132.953, 20868.333]
Name: Expend, Length: 777, dtype: category
Categories (3, interval[float64]): [(3132.953, 20868.333] < (20868.333, 38550.667] < (38550.667, 56233.0]]
array([ 3132.953      , 20868.33333333, 38550.66666667, 56233.0      ])

```

The `cut()` function returns a tuple of length 2. The first element of the tuple are the bins, while the second element is an array containing the cut-off values for the bins.

```
type(Binned_expend)
```

tuple

```
len(Binned_expend)
```

2

Once the bins are obtained, we'll add a column in the dataset that indicates the bin for `Expend`.

```

#Creating a categorical variable to store the level of expenditure on a student
college['Expend_bin'] = Binned_expend[0]
college.head()

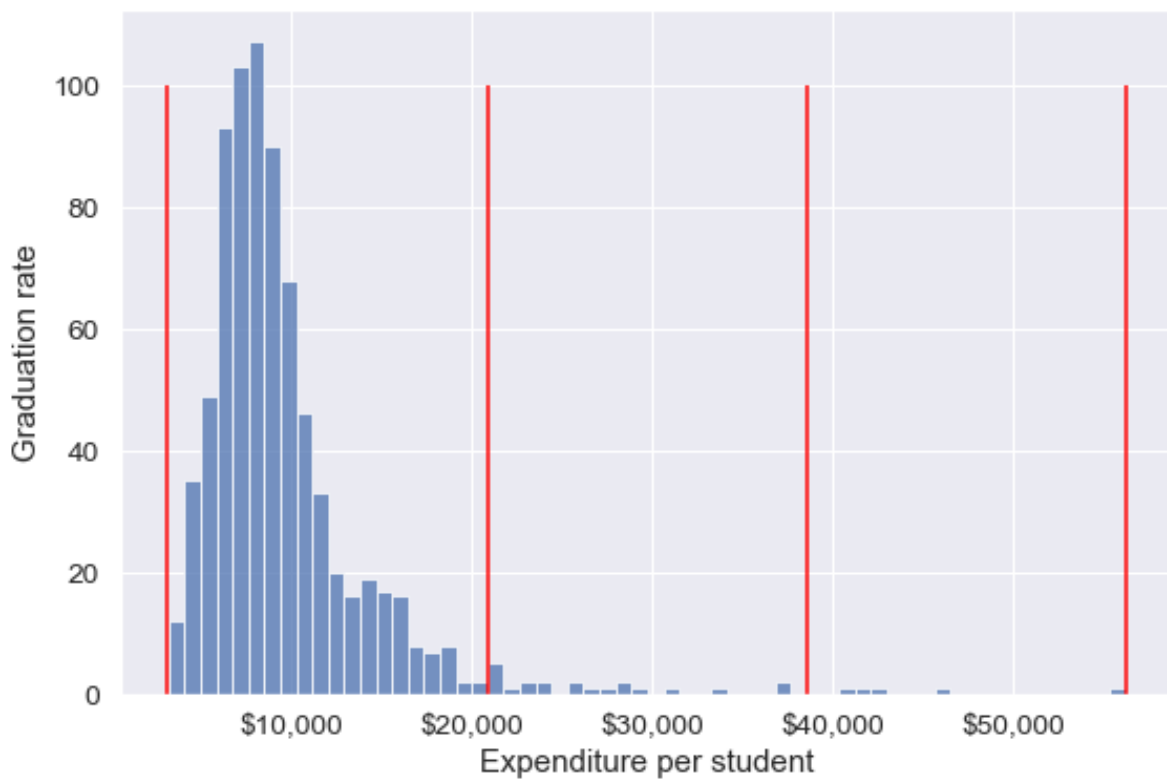
```

| | Unnamed: 0 | Private | Apps | Accept | Enroll | Top10perc | Top25perc | F.Undergrad |
|---|------------------------------|---------|------|--------|--------|-----------|-----------|-------------|
| 0 | Abilene Christian University | Yes | 1660 | 1232 | 721 | 23 | 52 | 2885 |
| 1 | Adelphi University | Yes | 2186 | 1924 | 512 | 16 | 29 | 2683 |
| 2 | Adrian College | Yes | 1428 | 1097 | 336 | 22 | 50 | 1036 |
| 3 | Agnes Scott College | Yes | 417 | 349 | 137 | 60 | 89 | 510 |
| 4 | Alaska Pacific University | Yes | 193 | 146 | 55 | 16 | 44 | 249 |

See the variable `Expend_bin` in the above dataset.

Let us visualize the `Expend` bins over the distribution of the `Expend` variable.

```
#Visualizing the bins for instructional expenditure on a student
sns.set(font_scale=1.25)
plt.rcParams["figure.figsize"] = (9,6)
ax=sns.histplot(data = college, x= 'Expend')
plt.vlines(Binned_expend[1], 0,100,color='red')
plt.xlabel('Expenditure per student');
plt.ylabel('Graduation rate');
ax.xaxis.set_major_formatter('${x:,.0f}')
```



By default, the bins created have equal width. They are created by dividing the range between the maximum and minimum value of `Expend` into the desired number of equal-width intervals. We can label the bins as well as follows.

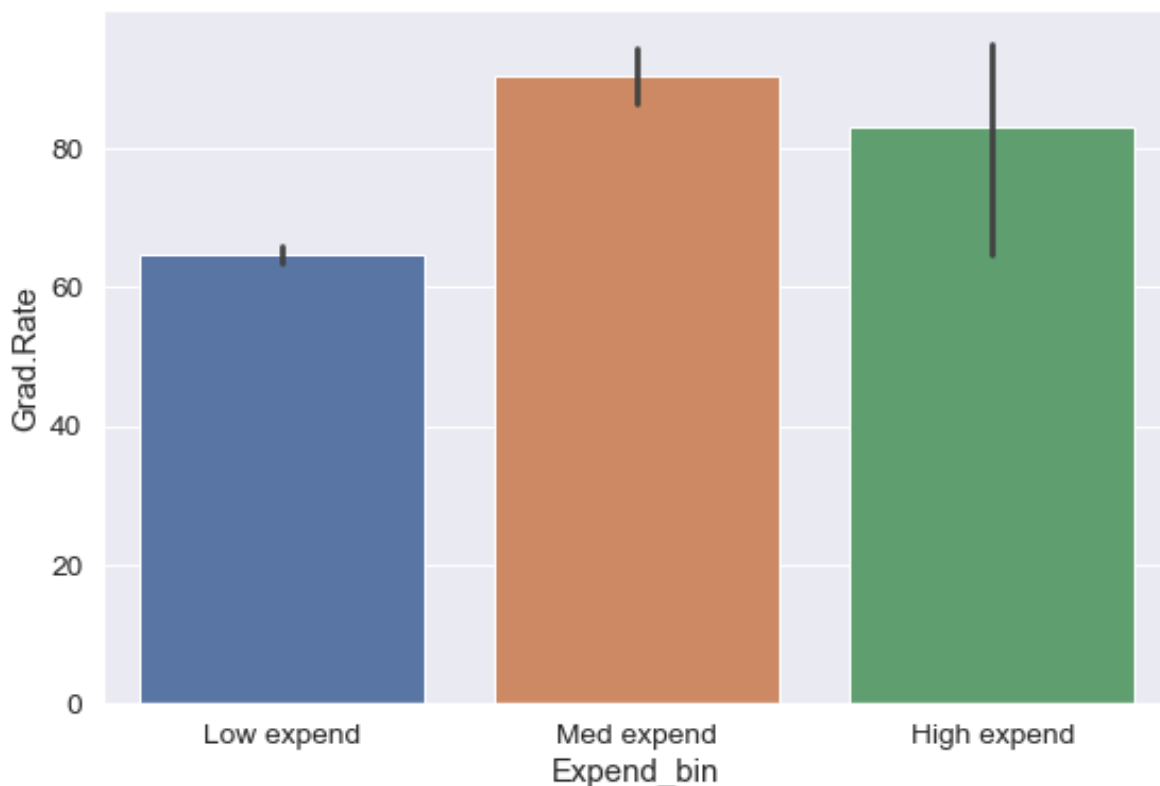
```
college['Expend_bin'] = pd.cut(college['Expend'],3,labels = ['Low expend','Med expend','Hi
college['Expend_bin']
```

```
0      Low expend
1      Low expend
2      Low expend
3      Low expend
4      Low expend
...
772    Low expend
773    Low expend
774    Low expend
775    High expend
776    Low expend
Name: Expend_bin, Length: 777, dtype: category
Categories (3, object): ['Low expend' < 'Med expend' < 'High expend']
```

Now that we have binned the variable `Expend`, let us see if we can better visualize the association of graduation rate with expenditure per student using `Expend_bin`.

```
#Visualizing average graduation rate vs categories of instructional expenditure per student
sns.barplot(x = 'Expend_bin', y = 'Grad.Rate', data = college)
```

```
<AxesSubplot:xlabel='Expend_bin', ylabel='Grad.Rate'>
```



It seems that the graduation rate is the highest for universities with medium level of expenditure per student. This is different from the trend we saw earlier in the scatter plot. Let us investigate.

Let us find the number of universities in each bin.

```
pd.value_counts(college['Expend_bin'])
```

```
Low expend    751
Med expend    21
High expend     5
Name: Expend_bin, dtype: int64
```

The bin **High expend** consists of only 5 universities, or 0.6% of all the universities in the dataset. These universities may be outliers that are skewing the trend (as also evident in the histogram above).

In such cases, we should bin observations such that all bins are of equal size, i.e., they have the same number of observations.

7.2.2 Binning with equal sized bins

Let us bin the variable `Expend` such that each bin consists of the same number of observations.

We'll use the Pandas function `qcut()` to make equal-sized bins (in contrast to equal-width bins in the previous section).

```
#Using the Pandas function qcut() to create bins with the same number of observations
Binned_expend = pd.qcut(college['Expend'],3,retbins = True)
college['Expend_bin'] = Binned_expend[0]
```

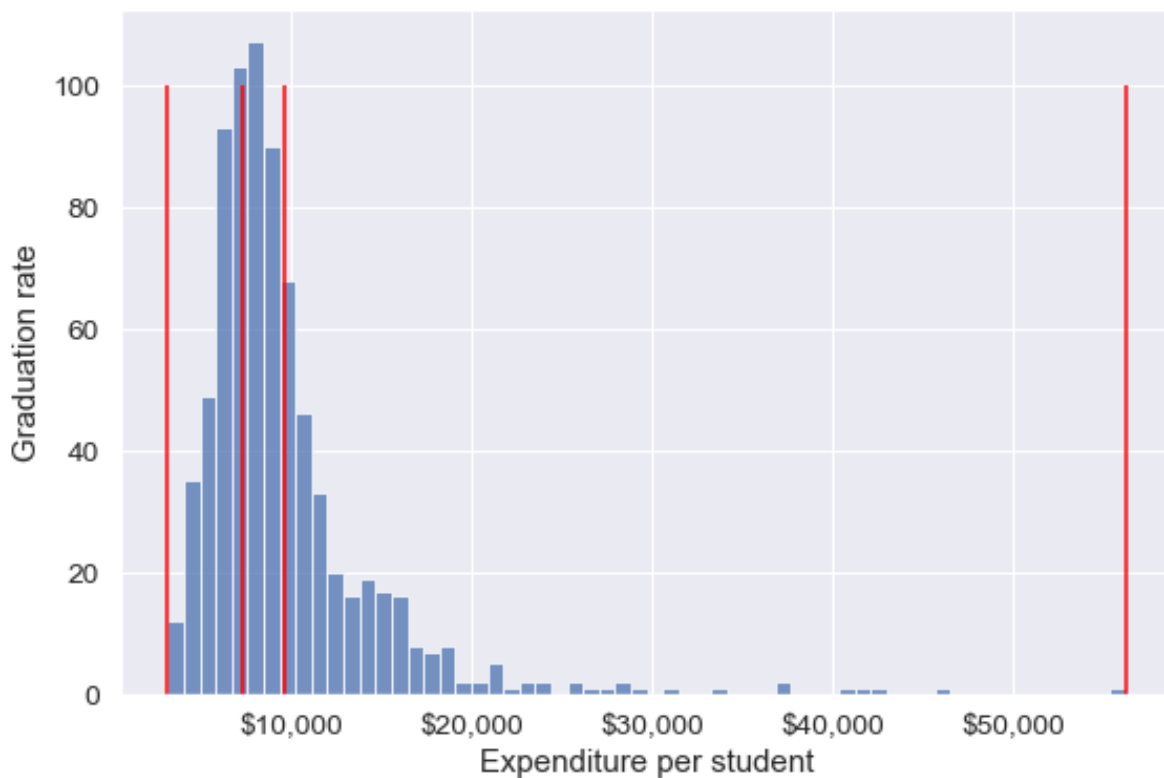
Each bin has the same number of observations with `qcut()`:

```
pd.value_counts(college['Expend_bin'])
```

```
(3185.999, 7334.333]    259
(7334.333, 9682.333]    259
(9682.333, 56233.0]     259
Name: Expend_bin, dtype: int64
```

Let us visualize the `Expend` bins over the distribution of the `Expend` variable.

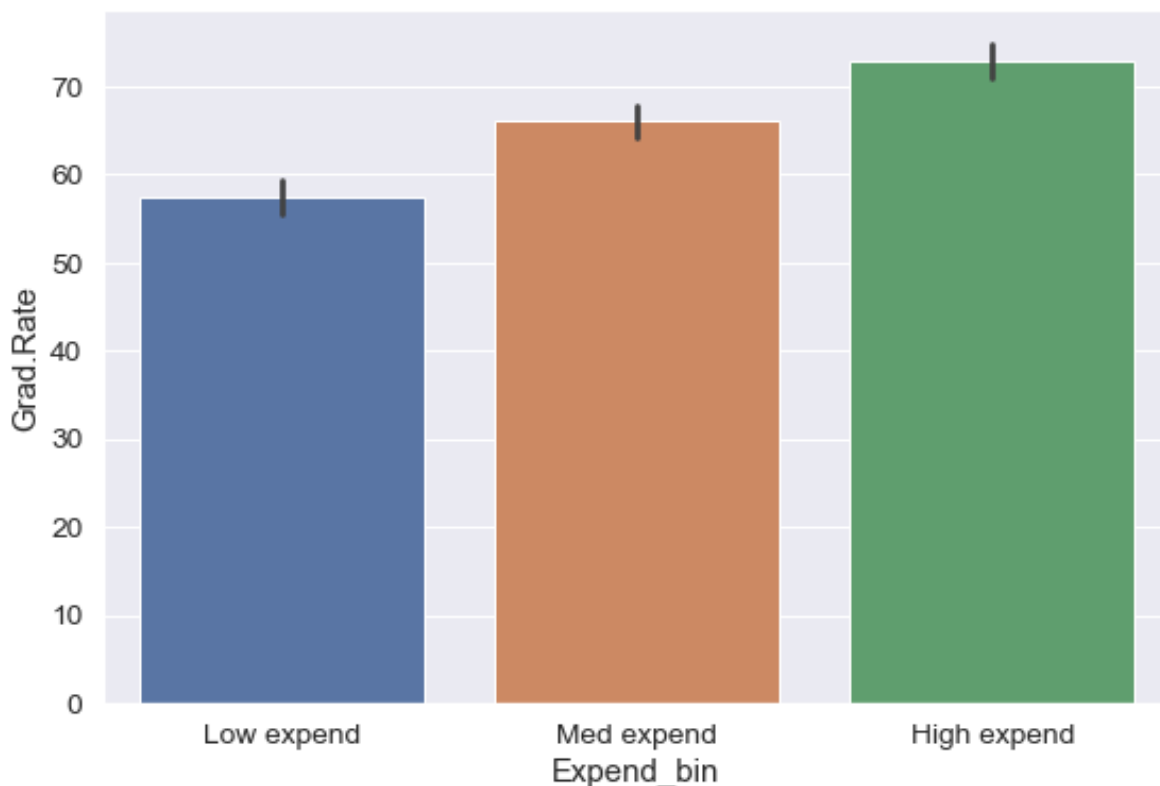
```
#Visualizing the bins for instructional expenditure on a student
sns.set(font_scale=1.25)
plt.rcParams["figure.figsize"] = (9,6)
ax=sns.histplot(data = college, x= 'Expend')
plt.vlines(Binned_expend[1], 0,100,color='red')
plt.xlabel('Expenditure per student');
plt.ylabel('Graduation rate');
ax.xaxis.set_major_formatter('${x:,.0f}')
```



Note that the bin-widths have been adjusted to have the same number of observations in each bin. The bins are narrower in domains of high density, and wider in domains of sparse density.

Let us again make the barplot visualizing the average graduate rate with level of instructional expenditure per student.

```
college['Expend_bin'] = pd.qcut(college['Expend'],3,labels = ['Low expend','Med expend','H
a=sns.barplot(x = 'Expend_bin', y = 'Grad.Rate', data = college)
```



Now we see the same trend that we saw in the scatterplot, but without the noise. We have smoothed the data. Note that making equal-sized bins helps reduce the effect of outliers in the overall trend.

Suppose this analysis was done to provide recommendations to universities for increasing their graduation rate. With binning, we can provide one recommendation to ‘*Low expend*’ universities, and another one to ‘*Med expend*’ universities. For example, the recommendations can be:

1. ‘*Low expend*’ universities can expect an increase of 9 percentage points in `Grad.Rate`, if they migrate to the ‘*Med expend*’ category.
2. ‘*Med expend*’ universities can expect an increase of 7 percentage points in `Grad.Rate`, if they migrate to the ‘*High expend*’ category.

The numbers in the above recommendations are based on the table below.

```
college['Grad.Rate'].groupby(college.Expend_bin).mean()
```

Expend_bin

```

Low expend      57.343629
Med expend      66.057915
High expend     72.988417
Name: Grad.Rate, dtype: float64

```

We can also make recommendations based on the confidence intervals of mean Grad.Rate. Confidence intervals are computed below. We are finding confidence intervals based on a method known as bootstrapping. Refer [https://en.wikipedia.org/wiki/Bootstrapping_\(statistics\)](https://en.wikipedia.org/wiki/Bootstrapping_(statistics)) for a detailed description of Bootstrapping.

```

#Bootstrapping to find 95% confidence intervals of Graduation Rate of US universities base
for expend_bin in college.Expend_bin.unique():
    data_sub = college.loc[college.Expend_bin==expend_bin,:]
    samples = np.random.choice(data_sub['Grad.Rate'], size=(10000,data_sub.shape[0]))
    print("95% Confidence interval of Grad.Rate for "+expend_bin+" univeristies = ["+str(n

```

```

95% Confidence interval of Grad.Rate for Low expend univeristies = [55.34,59.34]
95% Confidence interval of Grad.Rate for High expend univeristies = [71.01,74.92]
95% Confidence interval of Grad.Rate for Med expend univeristies = [64.22,67.93]

```

Apart from equal-width and equal-sized bins, custom bins can be created using the *bins* argument. Suppose, bins are to be created for **Expend** with cutoffs \$10,000, \$20,000, \$30,000...\$60,000. Then, we can use the *bins* argument as in the code below:

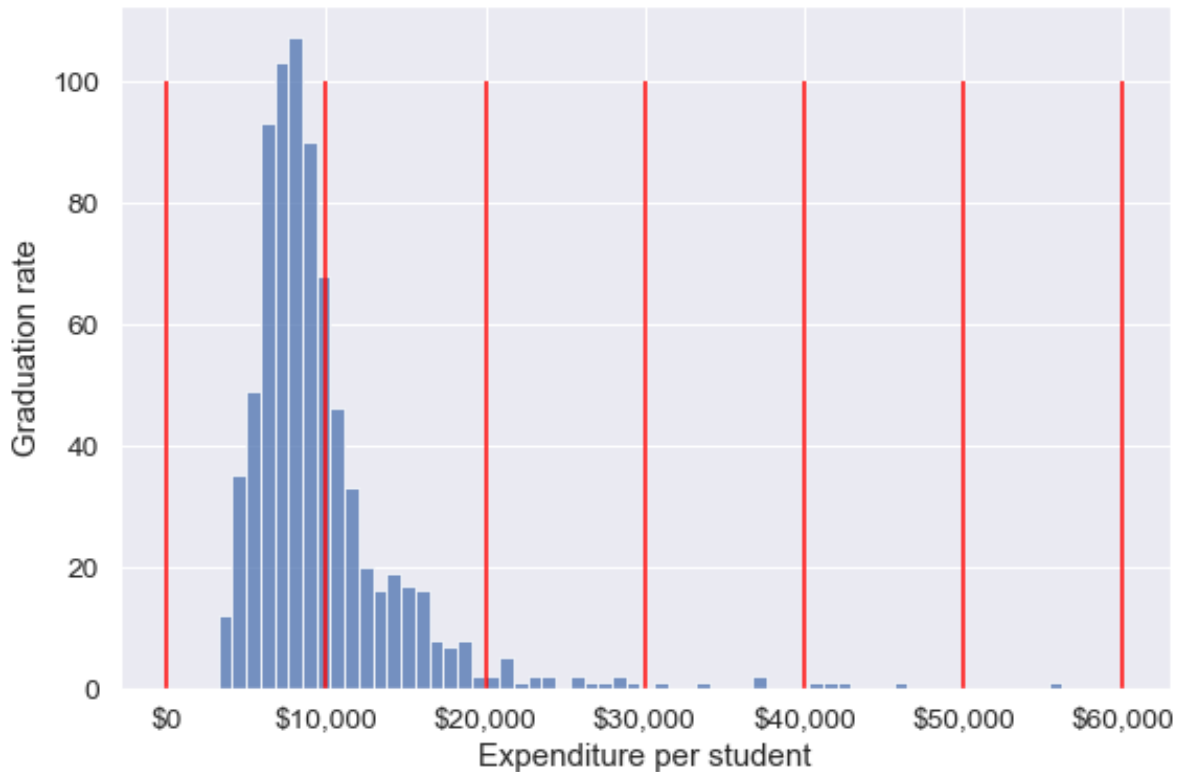
7.2.3 Binning with custom bins

```

Binned_expend = pd.cut(college.Expend,bins = list(range(0,70000,10000)),retbins=True)

#Visualizing the bins for instructional expenditure on a student
ax=sns.histplot(data = college, x= 'Expend')
plt.vlines(Binned_expend[1], 0,100,color='red')
plt.xlabel('Expenditure per student');
plt.ylabel('Graduation rate');
ax.xaxis.set_major_formatter('${x:,.0f}')

```



As custom bin-cutoffs can be specified with the `cut()` function, custom bin quantiles can be specified with the `qcut()` function.

7.3 Dummy / Indicator variables

Dummy variables (or indicator variables) take only the values of 0 and 1 to indicate the presence or absence of a categorical effect. They are particularly useful in regression modeling to help explain the dependent variable.

If a column in a DataFrame has k distinct values, we will get a DataFrame with k columns containing 0s and 1s with the Pandas `get_dummies()` function.

Let us make dummy variables with the equal-sized bins we created for the average instruction expenditure per student.

```
#Using the Pandas function qcut() to create bins with the same number of observations
Binned_expend = pd.qcut(college['Expend'],3,retbins = True,labels = ['Low_expend','Med_exp',
college['Expend_bin'] = Binned_expend[0]
```



```
#Making dummy variables based on the levels (categories) of the 'Expend_bin' variable
dummy_Expend = pd.get_dummies(college['Expend_bin'])
```

The dummy data `dummy_Expend` has a value of 1 if the observation corresponds to the category referenced by the column name.

```
dummy_Expend.head()
```

| | Low_expend | Med_expend | High_expend |
|---|------------|------------|-------------|
| 0 | 1 | 0 | 0 |
| 1 | 0 | 0 | 1 |
| 2 | 0 | 1 | 0 |
| 3 | 0 | 0 | 1 |
| 4 | 0 | 0 | 1 |

We can find the correlation between the dummy variables and graduation rate to identify if any of the dummy variables will be useful to estimate graduation rate (`Grad.Rate`).

```
#Finding if dummy variables will be useful to estimate 'Grad.Rate'
dummy_Expend.corrwith(college['Grad.Rate'])
```

```
Low_expend    -0.334456
Med_expend     0.024492
High_expend    0.309964
dtype: float64
```

The dummy variables `Low_expend` and `High_expend` may contribute in explaining `Grad.Rate` in a regression model.

7.3.1 Practice exercise 3

Read *survey_data_clean.csv*. Split the columns of the dataset, such that all columns with categorical values transform into dummy variables with each category corresponding to a column of 0s and 1s. Leave the *Timestamp* column.

As all categorical columns are transformed to dummy variables, all columns have numeric values.

What is the total number of columns in the transformed data? What is the total number of columns of the original data?

Find the:

1. Top 5 variables having the highest positive correlation with NU_GPA.
2. Top 5 variables having the highest negative correlation with NU_GPA.

Solution:

```
survey_data = pd.read_csv('./Datasets/survey_data_clean.csv')
survey_dummies=pd.get_dummies(survey_data.iloc[:,1:])
print("The total number of columns in the transformed data are", survey_dummies.shape[1])
print("The total number of columns in the original data are", survey_dummies.shape[0])
```

The total number of columns in the transformed data are 308

The total number of columns in the original data are 192

Below are the top 5 variables having the highest positive correlation with NU_GPA:

```
survey_dummies.corrwith(survey_dummies.NU_GPA).drop(index = 'NU_GPA').sort_values(ascending=False)
```

| | |
|--|----------|
| fav_letter_o | 0.307656 |
| fav_sport_Dance! | 0.269552 |
| major_Humanities / Communications;Physical Sciences / Natural Sciences / Engineering | 0.224237 |
| fav_alcohol_I don't drink | 0.222141 |
| learning_style_Reading/Writing (learn best through words often note-taking or reading) | 0.221099 |

dtype: float64

Below are the top 5 variables having the highest negative correlation with NU_GPA:

```
survey_dummies.corrwith(survey_dummies.NU_GPA).drop(index = 'NU_GPA').sort_values(ascending=False)
```

| | |
|--|-----------|
| fav_number | -0.307656 |
| procrastinator | -0.269552 |
| fav_sport_Underwater Basketweaving | -0.224237 |
| birth_month_February | -0.222141 |
| streaming_platforms_Netflix;Amazon Prime;HBO Max | -0.221099 |

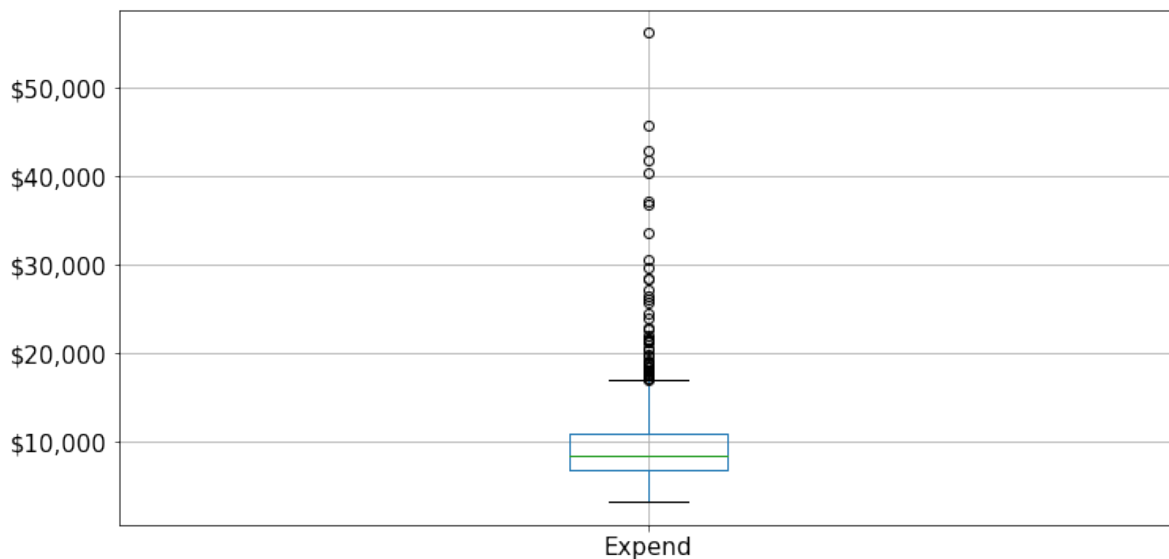
dtype: float64

7.4 Outlier detection

An outlier is an observation that is significantly different from the rest of the data. Detection of outliers is important as they may distort the general trends in data.

Let us visualize outliers in average instructional expenditure per student given by the variable Expend.

```
ax=college.boxplot(column = 'Expend')
ax.yaxis.set_major_formatter('${x:,.0f}')
```



There are several outliers (shown as circles in the above boxplot), which correspond to high values of average instructional expenditure per student. Boxplot identifies outliers based on the [Tukey's fences](#) criterion:

Tukey's fences: John Tukey proposed that observations outside the range $[Q1 - 1.5(Q3 - Q1), Q3 + 1.5(Q3 - Q1)]$ are outliers, where $Q1$ and $Q3$ are the lower (25%) and upper (75%) quartiles respectively. Let us detect outliers based on Tukey's fences.

```
#Finding upper and lower quartiles and interquartile range
q1 = np.percentile(college['Expend'],25)
q3 = np.percentile(college['Expend'],75)
intQ_range = q3-q1
```

```

#Tukey's fences
Lower_fence = q1 - 1.5*intQ_range
Upper_fence = q3 + 1.5*intQ_range

#These are the outlying observations - those outside of Tukey's fences
Outlying_obs = college[(college.Expend<Lower_fence) | (college.Expend>Upper_fence)]

#Data without outliers
college_data_without_outliers = college[((college.Expend>=Lower_fence) & (college.Expend<=

```

Earlier, the trend was distorted by outliers when we created bins of equal width. Let us see if we get the correct trend with the outliers removed from the data.

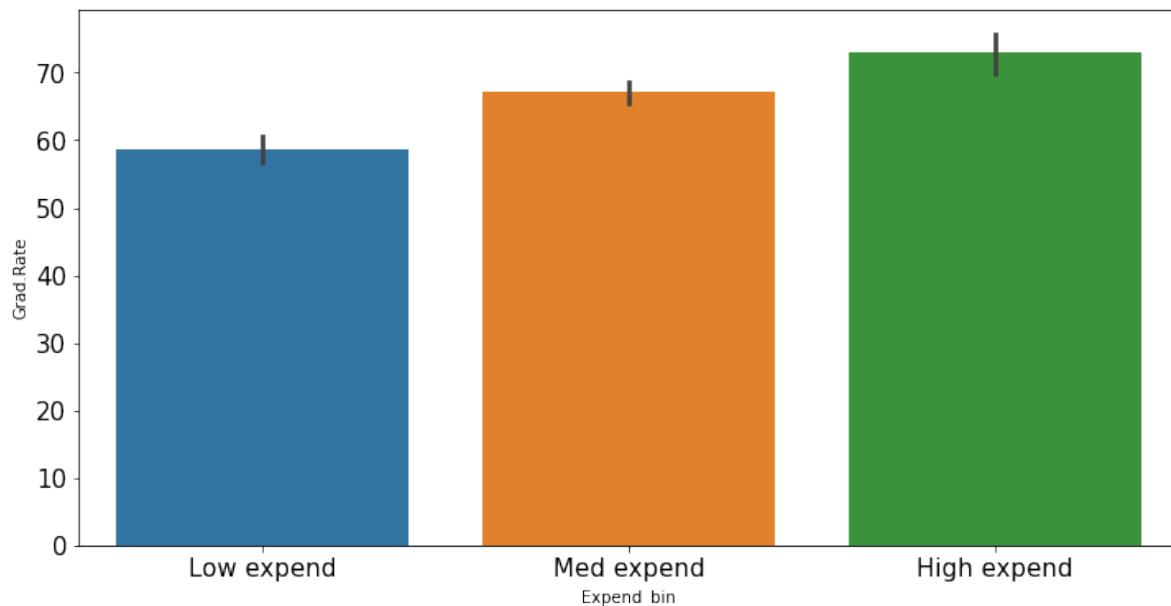
```

Binned_data = pd.cut(college_data_without_outliers['Expend'],3,labels = ['Low expend','Med
college_data_without_outliers.loc[:, 'Expend_bin'] = Binned_data[0]

sns.barplot(x = 'Expend_bin', y = 'Grad.Rate', data = college_data_without_outliers)

```

```
<AxesSubplot:xlabel='Expend_bin', ylabel='Grad.Rate'>
```

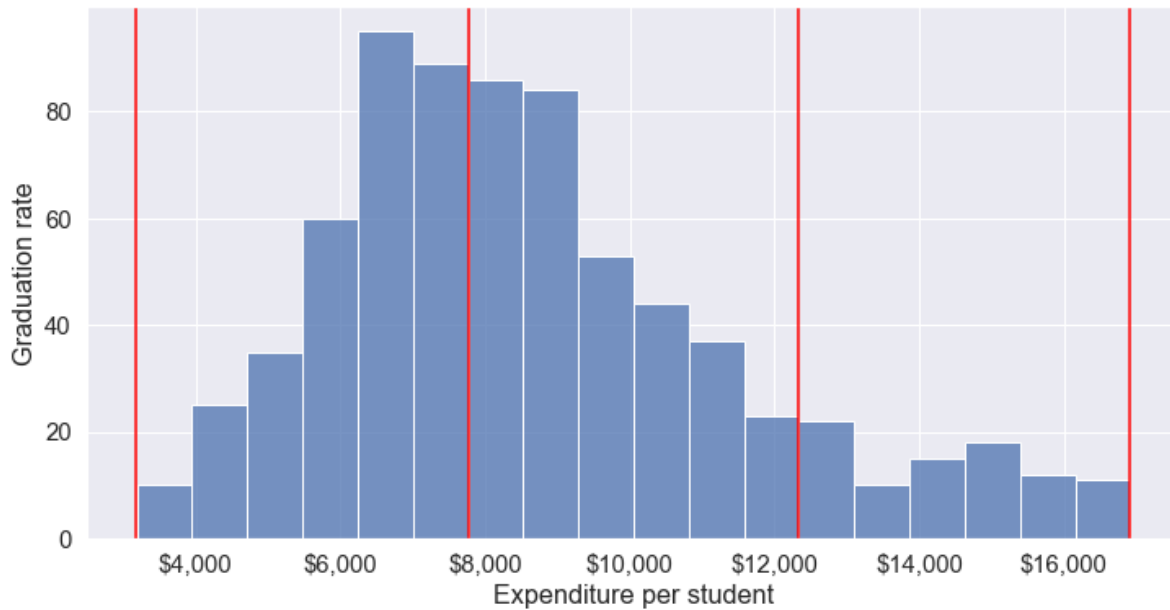


With the outliers removed, we obtain the correct overall trend, even in the case of equal-width bins. Note that these bins have unequal number of observations as shown below.

```

sns.set(font_scale=1.35)
ax=sns.histplot(data = college_data_without_outliers, x= 'Expend')
for i in range(4):
    plt.axvline(Binned_data[1][i], 0,100,color='red')
plt.xlabel('Expenditure per student');
plt.ylabel('Graduation rate');
ax.xaxis.set_major_formatter('${x:,.0f}')

```



Note that the right tail of the histogram has disappeared since we removed outliers.

```
college_data_without_outliers['Expend_bin'].value_counts()
```

```

Med expend      327
Low expend      314
High expend      88
Name: Expend_bin, dtype: int64

```

7.4.1 Practice exercise 4

Consider the dataset created for *survey_data_clean.csv* in [Practice exercise 3](#), which includes dummy variables for all the categorical variables. Find the number of outliers in each column of the dataset based on the Tukey's fences criterion. Do not use a `for` loop.

Which column(s) have the maximum number of outliers?

Do you think the outlying observations identified with the Tukey's fences criterion for those columns(s) should be considered as outliers? If not, then which type of columns should be considered when finding outliers?

Solution:

```
#Function to identify outliers based on Tukey's fences
def rem_outliers(x):
    q1 =x.quantile(0.25)
    q3 = x.quantile(0.75)
    intQ_range = q3-q1

    #Tukey's fences
    Lower_fence = q1 - 1.5*intQ_range
    Upper_fence = q3 + 1.5*intQ_range

    #The object returned will be a data frame with bool values - True or False. 'True' will
    return ((x<Lower_fence) | (x>Upper_fence))

survey_dummies.apply(rem_outliers).sum().sort_values(ascending=False)
```

```
learning_style_Reading/Writing (learn best through words often note-taking or reading)    48
much_effort_is_lack_of_talent                                                            48
left_right_brained_Left-brained (logic, science, critical thinking, numbers)             47
left_right_brained_Right-brained (creative, art, imaginative, intuitive)                47
fav_season_Spring                                                                       47
..                                                                                       ..
love_first_sight                                                                        0
birthdate_odd_even_Odd                                                                  0
procrastinator                                                                           0
birthdate_odd_even_Even                                                                  0
how_happy_Pretty happy                                                                  0
Length: 308, dtype: int64
```

Using Tukey's criterion, the variables `learning_style_Reading/Writing (learn best through words often note-taking or reading)` and `much_effort_is_lack_of_talent` have the most number of outliers.

However, these two variables only have 0s and 1s. For instance, let us consider `learning_style_Reading/Writing (learn best through words often note-taking or reading)`.

```
survey_dummies['learning_style_Reading/Writing (learn best through words often note-taking
```

```
0      144
```

```
1       48
```

```
Name: learning_style_Reading/Writing (learn best through words often note-taking or reading)
```

As the percentage of 1s are $\frac{48}{48+144} = 25\%$, the 75th percentile value is 0.25, and the upper Tukey's fence is $0.25 + 0.25 * 1.25 = 0.625$, which makes the value 1 an outlier. However, we should not consider this value as an outlier, as a considerable fraction of the data (25%) has the value 1 for this variable.

Furthermore, Tukey's fences are developed for continuous variables. However, the variable `learning_style_Reading/Writing (learn best through words often note-taking or reading)` is discrete with only two levels. Thus, while finding outliers we must consider only continuous variables.

```
#Finding continuous variables: Assuming numeric variables that have more than 2 distinct v
continuous_variables = [x for x in list(survey_data.apply(lambda x: x.name if ((len(x.valu
```

```
#Finding number of outliers for only continuous variables
survey_data.loc[:,continuous_variables].apply(rem_outliers).sum().sort_values(ascending=Fa
```

```
num_clubs                22
fav_number               19
parties_per_month        12
internet_hours_per_day   11
sleep_hours_per_day      10
expected_marriage_age     10
expected_starting_salary  8
high_school_GPA           8
height_mother            7
num_insta_followers       6
height_father            6
NU_GPA                   5
minutes_ex_per_week       4
height                   3
farthest_distance_travelled 2
age                      1
num_majors_minors         0
dtype: int64
```

The variable `num_clubs` has the maximum number of outliers.

```
#Finding how many clubs makes a person an outlier
q3_num_clubs = survey_data.num_clubs.quantile(0.75)
q1_num_clubs = survey_data.num_clubs.quantile(0.25)
print("Tukeys fences = [",q1_num_clubs-1.5*(q3_num_clubs-q1_num_clubs),q3_num_clubs+1.5*(q
```

Tukeys fences = [0.5 4.5]

People joining no club, or more than 4 clubs are outliers.

8 Data wrangling

Data wrangling refers to combining, transforming, and re-arranging data to make it suitable for further analysis. We'll use Pandas for all data wrangling operations.

```
import pandas as pd
import numpy as np
import seaborn as sns
```

8.1 Hierarchical indexing

Until now we have seen only a single level of indexing in the rows and columns of a Pandas DataFrame. Hierarchical indexing refers to having multiple index levels on an axis (row / column) of a Pandas DataFrame. It helps us to work with a higher dimensional data in a lower dimensional form.

8.1.1 Hierarchical indexing in Pandas Series

Let us define Pandas Series as we defined in Chapter 5:

```
#Defining a Pandas Series
series_example = pd.Series(['these', 'are', 'english', 'words', 'estas', 'son', 'palabras', 'en',
                             'ce', 'sont', 'des', 'françai', 'mots'])
series_example
```

```
0      these
1        are
2    english
3     words
4     estas
5       son
6  palabras
7        en
8   español
```

```

9         ce
10        sont
11         des
12    françai
13        mots
dtype: object

```

Let us use the attribute `nlevels` to find the number of levels of the row indices of this Series:

```

series_example.index.nlevels

```

```

1

```

The Series `series_example` has only one level of row indices.

Let us introduce another level of row indices while defining the Series:

```

#Defining a Pandas Series with multiple levels of row indices
series_example = pd.Series(['these','are','english','words','estas','son','palabras','en',
                             'ce','sont','des','françai','mots'],
                             index=[['English']*4+['Spanish']*5+['French']*5,list(range(1,5))])
series_example

```

```

English  1      these
          2       are
          3    english
          4     words
Spanish  1      estas
          2       son
          3    palabras
          4       en
          5    español
French   1       ce
          2     sont
          3      des
          4    françai
          5      mots
dtype: object

```

In the above Series, there are two levels of row indices:

```
series_example.index.nlevels
```

2

8.1.2 Hierarchical indexing in Pandas DataFrame

In a Pandas DataFrame, both the rows and the columns can have hierarchical indexing. For example, consider the DataFrame below:

```
data=np.array([[771517,2697000,815201,3849000],[4.2,5.6,2.8,4.6],
               [7.8,234.5,46.9,502],[6749, 597, 52, 305]])
df_example = pd.DataFrame(data,index = [['Demographics']*2+['Geography']*2,
                                       ['Population','Unemployment (%)','Area (mile-sq)','E
                                       columns = [['Illinois']*2+['California']*2,['Evanston','Chicago','San
df_example
```

| | | Illinois | | California | |
|--------------|------------------|----------|-----------|---------------|-------------|
| | | Evanston | Chicago | San Francisco | Los Angeles |
| Demographics | Population | 771517.0 | 2697000.0 | 815201.0 | 3849000.0 |
| | Unemployment (%) | 4.2 | 5.6 | 2.8 | 4.6 |
| Geography | Area (mile-sq) | 7.8 | 234.5 | 46.9 | 502.0 |
| | Elevation (feet) | 6749.0 | 597.0 | 52.0 | 305.0 |

In the above DataFrame, both the rows and columns have 2 levels of indexing. The number of levels of column indices can be found using the attribute `nlevels`:

```
df_example.columns.nlevels
```

2

The `columns` attribute will now have a *MultiIndex* datatype in contrast to the *Index* datatype with single level of indexing. The same holds for row indices.

```
type(df_example.columns)
```

```
pandas.core.indexes.multi.MultiIndex
```

```
df_example.columns
```

```
MultiIndex([( 'Illinois',      'Evanston'),
            ( 'Illinois',      'Chicago'),
            ('California', 'San Francisco'),
            ('California',   'Los Angeles')],
           )
```

The hierarchical levels can have names. Let us assign names to the each level of the row and column labels:

```
#Naming the row indices levels
df_example.index.names=['Information type', 'Statistic']

#Naming the column indices levels
df_example.columns.names=['State', 'City']

#Viewing the DataFrame
df_example
```

| | State | Illinois | California | | |
|------------------|------------------|----------|------------|---------------|-------------|
| | City | Evanston | Chicago | San Francisco | Los Angeles |
| Information type | Statistic | | | | |
| Demographics | Population | 771517.0 | 2697000.0 | 815201.0 | 3849000.0 |
| | Unemployment (%) | 4.2 | 5.6 | 2.8 | 4.6 |
| Geography | Area (mile-sq) | 7.8 | 234.5 | 46.9 | 502.0 |
| | Elevation (feet) | 6749.0 | 597.0 | 52.0 | 305.0 |

Observe that the names of the row and column labels appear when we view the DataFrame.

8.1.2.1 `get_level_values()`

The names of the column levels can be obtained using the function `get_level_values()`. The outer-most level corresponds to the *level* = 0, and it increases as we go to the inner levels.

```
#Column levels at level 0 (the outer level)
df_example.columns.get_level_values(0)
```

```
Index(['Illinois', 'Illinois', 'California', 'California'], dtype='object', name='State')
```

```
#Column levels at level 1 (the inner level)
df_example.columns.get_level_values(1)
```

```
Index(['Evanston', 'Chicago', 'San Francisco', 'Los Angeles'], dtype='object', name='City')
```

8.1.3 Subsetting data

We can use the indices at the outer levels to concisely subset a Series / DataFrame.

The first four observations of the Series `series_example` correspond to the outer row index `English`, while the last 5 rows correspond to the outer row index `Spanish`. Let us subset all the observations corresponding to the outer row index `English`:

```
#Subsetting data by row-index
series_example['English']
```

```
1      these
2        are
3    english
4      words
dtype: object
```

Just like in the case of single level indices, if we wish to subset corresponding to multiple outer-level indices, we put the indices within an additional box bracket `[]`. For example, let us subset all the observations corresponding to the row-indices `English` and `French`:

```
#Subsetting data by multiple row-indices
series_example[['English','French']]
```

```
English  1      these
         2        are
         3    english
         4      words
French   1         ce
        2      sont
        3      des
        4    françai
```

```

5      mots
dtype: object

```

We can also subset data using the inner row index. However, we will need to put a `:` sign to indicate that the row label at the inner level is being used.

```

#Subsetting data by row-index
series_example[:,2]

```

```

English      are
Spanish      son
French       sont
dtype: object

```

```

#Subsetting data by multiple row-indices
series_example.loc[:, [1,2]]

```

```

English  1      these
Spanish  1      estas
French   1         ce
English  2       are
Spanish  2       son
French   2      sont
dtype: object

```

As in Series, we can concisely subset rows / columns in a DataFrame based on the index at the outer levels.

```

df_example['Illinois']

```

| | City | Evanston | Chicago |
|------------------|------------------|----------|-----------|
| Information type | Statistic | | |
| Demographics | Population | 771517.0 | 2697000.0 |
| | Unemployment (%) | 4.2 | 5.6 |
| Geography | Area (mile-sq) | 7.8 | 234.5 |
| | Elevation (feet) | 6749.0 | 597.0 |

Note that the datatype of each column name is a tuple. For example, let us find the datatype of the 1st column name:

```
#First column name
df_example.columns[0]
```

```
('Illinois', 'Evanston')
```

```
#Datatype of first column name
type(df_example.columns[0])
```

tuple

Thus columns at the inner levels can be accessed by specifying the name as a tuple. For example, let us subset the column **Evanston**:

```
#Subsetting the column 'Evanston'
df_example[('Illinois','Evanston')]
```

```
Information type  Statistic
Demographics      Population      771517.0
                  Unemployment (%)    4.2
Geography         Area (mile-sq)     7.8
                  Elevation (feet)   6749.0
Name: (Illinois, Evanston), dtype: float64
```

```
#Subsetting the columns 'Evanston' and 'Chicago' of the outer column level 'Illinois'
df_example.loc[:,('Illinois',['Evanston','Chicago'])]
```

| Information type | State | Illinois | |
|------------------|------------------|----------|-----------|
| | City | Evanston | Chicago |
| Information type | Statistic | | |
| Demographics | Population | 771517.0 | 2697000.0 |
| | Unemployment (%) | 4.2 | 5.6 |
| Geography | Area (mile-sq) | 7.8 | 234.5 |
| | Elevation (feet) | 6749.0 | 597.0 |

8.1.4 Practice exercise 1

Read the table consisting of GDP per capita of countries from the webpage: [https://en.wikipedia.org/wiki/List_of_countries_by_GDP_\(nominal\)_per_capita](https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)_per_capita).

To only read the relevant table, read the tables that contain the word ‘*Country*’.

8.1.4.1

How many levels of indexing are there in the rows and columns?

```
dfs = pd.read_html('https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)_per_capita')
gdp_per_capita = dfs[0]
gdp_per_capita.head()
```

| | Country/Territory | UN Region | IMF[4] | | World Bank[5] | | United Nations[6] | |
|---|-------------------|-----------|----------|------|---------------|------|-------------------|------|
| | Country/Territory | UN Region | Estimate | Year | Estimate | Year | Estimate | Year |
| 0 | Liechtenstein * | Europe | — | — | 169049 | 2019 | 180227 | 2020 |
| 1 | Monaco * | Europe | — | — | 173688 | 2020 | 173696 | 2020 |
| 2 | Luxembourg * | Europe | 127673 | 2022 | 135683 | 2021 | 117182 | 2020 |
| 3 | Bermuda * | Americas | — | — | 110870 | 2021 | 123945 | 2020 |
| 4 | Ireland * | Europe | 102217 | 2022 | 99152 | 2021 | 86251 | 2020 |

Just by looking at the DataFrame, it seems as if there are two levels of indexing for columns and one level of indexing for rows. However, let us confirm it with the `nlevels` attribute.

```
gdp_per_capita.columns.nlevels
```

2

Yes, there are 2 levels of indexing for columns.

```
gdp_per_capita.index.nlevels
```

1

There is one level of indexing for rows.

8.1.4.2

Subset a DataFrame that selects the country, and the United Nations' estimates of GDP per capita with the corresponding year.

```
gdp_per_capita.loc[:,['Country/Territory','United Nations[6]']]
```

| Country/Territory | | United Nations[6] | |
|-------------------|----------------------------|-------------------|------|
| Country/Territory | | Estimate | Year |
| 0 | Liechtenstein * | 180227 | 2020 |
| 1 | Monaco * | 173696 | 2020 |
| 2 | Luxembourg * | 117182 | 2020 |
| 3 | Bermuda * | 123945 | 2020 |
| 4 | Ireland * | 86251 | 2020 |
| ... | ... | ... | ... |
| 217 | Madagascar * | 470 | 2020 |
| 218 | Central African Republic * | 481 | 2020 |
| 219 | Sierra Leone * | 475 | 2020 |
| 220 | South Sudan * | 1421 | 2020 |
| 221 | Burundi * | 286 | 2020 |

8.1.4.3

Subset a DataFrame that selects only the World Bank and United Nations' estimates of GDP per capita without the corresponding year or country.

```
gdp_per_capita.loc[:,(['World Bank[5]','United Nations[6]'],'Estimate')]
```

| World Bank[5] | | United Nations[6] |
|---------------|--------|-------------------|
| Estimate | | Estimate |
| 0 | 169049 | 180227 |
| 1 | 173688 | 173696 |
| 2 | 135683 | 117182 |
| 3 | 110870 | 123945 |
| 4 | 99152 | 86251 |
| ... | ... | ... |
| 217 | 515 | 470 |

| | World Bank[5] Estimate | United Nations[6] Estimate |
|-----|---------------------------|-------------------------------|
| 218 | 512 | 481 |
| 219 | 516 | 475 |
| 220 | 1120 | 1421 |
| 221 | 237 | 286 |

8.1.4.4

Subset a DataFrame that selects the country and only the World Bank and United Nations' estimates of GDP per capita without the corresponding year or country.

```
gdp_per_capita.loc[:, [('Country/Territory', 'Country/Territory'), ('United Nations[6]', 'Estimate')]]
```

| | Country/Territory Country/Territory | United Nations[6] Estimate | World Bank[5] Estimate |
|-----|--|-------------------------------|---------------------------|
| 0 | Liechtenstein * | 180227 | 169049 |
| 1 | Monaco * | 173696 | 173688 |
| 2 | Luxembourg * | 117182 | 135683 |
| 3 | Bermuda * | 123945 | 110870 |
| 4 | Ireland * | 86251 | 99152 |
| ... | ... | ... | ... |
| 217 | Madagascar * | 470 | 515 |
| 218 | Central African Republic * | 481 | 512 |
| 219 | Sierra Leone * | 475 | 516 |
| 220 | South Sudan * | 1421 | 1120 |
| 221 | Burundi * | 286 | 237 |

8.1.4.5

Drop all columns consisting of years. Use the `level` argument of the `drop()` method.

```
gdp_per_capita = gdp_per_capita.drop(columns='Year', level=1)
gdp_per_capita
```

| | Country/Territory Country/Territory | UN Region UN Region | IMF[4] Estimate | World Bank[5] Estimate | United Nations[6] Estimate |
|-----|--|------------------------|--------------------|---------------------------|-------------------------------|
| 0 | Liechtenstein * | Europe | — | 169049 | 180227 |
| 1 | Monaco * | Europe | — | 173688 | 173696 |
| 2 | Luxembourg * | Europe | 127673 | 135683 | 117182 |
| 3 | Bermuda * | Americas | — | 110870 | 123945 |
| 4 | Ireland * | Europe | 102217 | 99152 | 86251 |
| ... | ... | ... | ... | ... | ... |
| 217 | Madagascar * | Africa | 522 | 515 | 470 |
| 218 | Central African Republic * | Africa | 496 | 512 | 481 |
| 219 | Sierra Leone * | Africa | 494 | 516 | 475 |
| 220 | South Sudan * | Africa | 328 | 1120 | 1421 |
| 221 | Burundi * | Africa | 293 | 237 | 286 |

8.1.4.6

In the dataset obtained above, drop the inner level of the column labels. Use the `droplevel()` method.

```
gdp_per_capita = gdp_per_capita.droplevel(1,axis=1)
gdp_per_capita
```

| | Country/Territory | UN Region | IMF[4] | World Bank[5] | United Nations[6] |
|-----|----------------------------|-----------|--------|---------------|-------------------|
| 0 | Liechtenstein * | Europe | — | 169049 | 180227 |
| 1 | Monaco * | Europe | — | 173688 | 173696 |
| 2 | Luxembourg * | Europe | 127673 | 135683 | 117182 |
| 3 | Bermuda * | Americas | — | 110870 | 123945 |
| 4 | Ireland * | Europe | 102217 | 99152 | 86251 |
| ... | ... | ... | ... | ... | ... |
| 217 | Madagascar * | Africa | 522 | 515 | 470 |
| 218 | Central African Republic * | Africa | 496 | 512 | 481 |
| 219 | Sierra Leone * | Africa | 494 | 516 | 475 |
| 220 | South Sudan * | Africa | 328 | 1120 | 1421 |
| 221 | Burundi * | Africa | 293 | 237 | 286 |

8.1.5 Practice exercise 2

Recall problem 2(e) from assignment 3 on Pandas, where we needed to find the African country that is the closest to country *G* (Luxembourg) with regard to social indicators.

We will solve the question with the regular way in which we use single level of indexing (as you probably did during this assignment), and see if it is easier to do with hierarchical indexing.

Execute the code below that we used to pre-process data to make it suitable for answering this question.

```
#Pre-processing data - execute this code
social_indicator = pd.read_csv("./Datasets/social_indicator.txt",sep="\t",index_col = 0)
social_indicator.geographic_location = social_indicator.geographic_location.apply(lambda x:
social_indicator.rename(columns={'geographic_location':'continent'},inplace=True)
social_indicator = social_indicator.sort_index(axis=1)
social_indicator.drop(columns=['region','contraception'],inplace=True)
```

Below is the code to find the African country that is the closest to country *G* (Luxembourg) using single level of indexing. Your code in the assignment is probably similar to the one below:

```
#Finding the index of the country G (Luxembourg) that has the maximum GDP per capita
country_max_gdp_position = social_indicator.gdpPerCapita.argmax()

#Scaling the social indicator dataset
social_indicator_scaled = social_indicator.iloc[:,2:].apply(lambda x: (x-x.mean())/(x.std()

#Computing the Manhattan distances of all countries from country G (Luxembourg)
manhattan_distances = (social_indicator_scaled-social_indicator_scaled.iloc[country_max_gdp_posi

#Finding the indices of African countries
african_countries_indices = social_indicator.loc[social_indicator.continent=='Africa',:].i

#Filtering the Manhattan distances of African countries from country G (Luxembourg)
manhattan_distances_African = manhattan_distances[african_countries_indices]

#Finding the country among African countries that has the least Manhattan distance to coun
social_indicator.loc[manhattan_distances_African.idxmin(),'country']
```

'Reunion'

8.1.5.1

Use the method `set_index()` to set `continent` and `country` as hierarchical indices of rows. Find the African country that is the closest to country *G* (Luxembourg) using this hierarchi-

cally indexed data. How many lines will be eliminated from the code above? Which lines will be eliminated?

Hint: Since `continent` and `country` are row indices, you don't need to explicitly find:

1. The row index of country *G* (Luxembourg),
2. The row indices of African countries.
3. The Manhattan distances for African countries.

```
social_indicator.set_index(['continent','country'],inplace = True)
social_indicator_scaled = social_indicator.apply(lambda x: (x-x.mean())/(x.std()))
manhattan_distances = (social_indicator_scaled-social_indicator_scaled.loc(['Europe','Luxembourg'],
manhattan_distances['Africa'].idxmin()
```

'Reunion'

As we have converted the columns `continent` and `country` to row indices, all the lines of code where we were keeping track of the index of country *G*, African countries, and Manhattan distances of African countries are eliminated. Three lines of code are eliminated.

Hierarchical indexing relieves us from keeping track of indices, if we set indices that are relative to our analysis.

8.1.5.2

Use the Pandas DataFrame method `mean()` with the *level* argument to find the mean value of all social indicators for each continent.

```
social_indicator.mean(level=0)
```

| | economicActivityFemale | economicActivityMale | gdpPerCapita | illiteracyFemale | illiteracyMale |
|---------------|------------------------|----------------------|--------------|------------------|----------------|
| continent | | | | | |
| Asia | 41.592683 | 79.282927 | 27796.390244 | 23.635951 | 13.7808 |
| Africa | 46.732258 | 79.445161 | 7127.483871 | 52.907226 | 33.6735 |
| Oceania | 51.280000 | 77.953333 | 14525.666667 | 9.666667 | 6.58520 |
| North America | 45.238095 | 77.166667 | 18609.047619 | 17.390286 | 14.6099 |
| South America | 42.008333 | 75.575000 | 15925.916667 | 9.991667 | 6.75000 |
| Europe | 52.060000 | 70.291429 | 45438.200000 | 2.308343 | 1.41354 |

8.1.6 Practice exercise 3

Let us try to find the areas where NU students lack in diversity. Read *survey_data_clean.csv*. Use hierarchical indexing to classify the columns as follows:

Classify the following variables as *lifestyle*:

```
lifestyle = ['fav_alcohol', 'parties_per_month', 'smoke', 'weed', 'streaming_platforms', 'm',  
            'sleep_hours_per_day', 'internet_hours_per_day', 'procrastinator', 'num_clubs', 'stu
```

Classify the following variables as *personality*:

```
personality = ['introvert_extrovert', 'left_right_brained', 'personality_type',  
              'num_insta_followers', 'fav_sport', 'learning_style', 'dominant_hand']
```

Classify the following variables as *opinion*:

```
opinion = ['love_first_sight', 'expected_marriage_age', 'expected_starting_salary', 'how_  
          'fav_number', 'fav_letter', 'fav_season', 'political_affiliation', 'cant_change_ma  
          'can_change_math_ability', 'math_is_genetic', 'much_effort_is_lack_of_talent']
```

Classify the following variables as *academic information*:

```
academic_info = ['major', 'num_majors_minors',  
                'high_school_GPA', 'NU_GPA', 'school_year', 'AP_stats', 'used_python_before']
```

Classify the following variables as *demographics*:

```
demographics = [ 'only_child', 'birth_month',  
                'living_location_on_campus', 'age', 'height', 'height_father',  
                'height_mother', 'childhood_in_US', 'gender', 'region_of_residence']
```

Write a function that finds the number of variables having outliers in a dataset. Apply the function to each of the 5 categories of variables in the dataset. Our hypothesis is that the category that has the maximum number of variables with outliers has the least amount of diversity. For continuous variables, use Tukey's fences criterion to identify outliers. For categorical variables, consider levels having less than 1% observations as outliers. Assume that numeric variables that have more than 2 distinct values are continuous.

Solution:

```

#Using hierarchical indexing to classify columns

#Reading data
survey_data = pd.read_csv('./Datasets/survey_data_clean.csv')

#Arranging columns in the order of categories
survey_data_HI = survey_data[lifestyle+personality+opinion+academic_info+demographics]

#Creating hierarchical indexing to classify columns
survey_data_HI.columns=[['lifestyle']*len(lifestyle)+['personality']*len(personality)+['opinion']*len(opinion)+
                        ['academic_info']*len(academic_info)+['demographics']*len(demographics)+
                        lifestyle+opinion+academic_info+demographics]

#Function to identify outliers based on Tukey's fences for continuous variables and 1% critical value
def rem_outliers(x):
    if ((len(x.value_counts())>2) & (x.dtype!='O')):#continuous variable
        q1 =x.quantile(0.25)
        q3 = x.quantile(0.75)
        intQ_range = q3-q1

        #Tukey's fences
        Lower_fence = q1 - 1.5*intQ_range
        Upper_fence = q3 + 1.5*intQ_range

        num_outliers = ((x<Lower_fence) | (x>Upper_fence)).sum()
        if num_outliers>0:
            return True
        return False
    else:
        #categorical variable
        if np.min(x.value_counts()/len(x))<0.01:
            return True
        return False

#Number of variables containing outlier(s) in each category
for category in survey_data_HI.columns.get_level_values(0).unique():
    print("Number of missing values for category ",category," = ",survey_data_HI[category].isnull().sum())

Number of missing values for category lifestyle = 7
Number of missing values for category personality = 2
Number of missing values for category opinion = 4
Number of missing values for category academic_info = 3

```

Number of missing values for category demographics = 4

The *lifestyle* category has the highest number of variables containing outlier(s). If the hypothesis is true, then NU students have the least diversity in their lifestyle, among all the categories.

Although one may say that the *lifestyle* category has the the highest number of columns (as shown below), the proportion of columns having outlier(s) is also the highest for this category.

```
for category in survey_data_HI.columns.get_level_values(0).unique():
    print("Number of columns in category ",category," = ",survey_data_HI[category].shape[1])
```

```
Number of columns in category lifestyle = 12
Number of columns in category personality = 7
Number of columns in category opinion = 12
Number of columns in category academic_info = 7
Number of columns in category demographics = 10
```

8.1.7 Reshaping data

Apart from ease in subsetting data, hierarchical indexing also plays a role in reshaping data.

8.1.7.1 `unstack()` (Pandas Series method)

The Pandas Series method `unstack()` pivots the desired level of row indices to columns, thereby creating a DataFrame. By default, the inner-most level of the row labels is pivoted.

```
#Pivoting the inner-most Series row index to column labels
series_example_unstack = series_example.unstack()
series_example_unstack
```

| | 1 | 2 | 3 | 4 | 5 |
|---------|-------|------|----------|---------|---------|
| English | these | are | english | words | NaN |
| French | ce | sont | des | françai | mots |
| Spanish | estas | son | palabras | en | español |

We can pivot the outer level of the row labels by specifying it in the `level` argument:


```
#Pivoting the outer row indices to column labels
series_example_unstack = series_example.unstack(level=0)
series_example_unstack
```

| | English | French | Spanish |
|---|---------|---------|----------|
| 1 | these | ce | estas |
| 2 | are | sont | son |
| 3 | english | des | palabras |
| 4 | words | françai | en |
| 5 | NaN | mots | español |

8.1.7.2 `unstack()` (Pandas DataFrame method)

The Pandas DataFrame method `unstack()` pivots the specified level of row indices to the new inner-most level of column labels. By default, the inner-most level of the row labels is pivoted.

```
#Pivoting the inner level of row labels to the inner-most level of column labels
df_example.unstack()
```

| | | | | | | |
|------------------|----------------|------------------|------------|------------------|----------------|-----|
| State | Illinois | | | | | |
| City | Evanston | | Chicago | | | |
| Statistic | Area (mile-sq) | Elevation (feet) | Population | Unemployment (%) | Area (mile-sq) | Ele |
| Information type | | | | | | |
| Demographics | NaN | NaN | 771517.0 | 4.2 | NaN | Na |
| Geography | 7.8 | 6749.0 | NaN | NaN | 234.5 | 597 |

As with Series, we can pivot the outer level of the row labels by specifying it in the `level` argument:

```
#Pivoting the outer level (level = 0) of row labels to the inner-most level of column labels
df_example.unstack(level=0)
```

| State City | Illinois Evanston | | Chicago | | California San Fran- cisco | |
|-------------------------------|----------------------|-----------|--------------|-----------|-------------------------------------|-----------|
| Information type Statistic | Demographics | Geography | Demographics | Geography | Demographics | Geography |
| Area (mile-sq) | NaN | 7.8 | NaN | 234.5 | NaN | 46.9 |
| Elevation (feet) | NaN | 6749.0 | NaN | 597.0 | NaN | 52.0 |
| Population | 771517.0 | NaN | 2697000.0 | NaN | 815201.0 | NaN |
| Unemployment (%) | 4.2 | NaN | 5.6 | NaN | 2.8 | NaN |

8.1.7.3 `stack()`

The inverse of `unstack()` is the `stack()` method, which creates the inner-most level of row indices by pivoting the column labels of the prescribed level.

Note that if the column labels have only one level, we don't need to specify a level.

```
#Stacking the columns of a DataFrame
series_example_unstack.stack()
```

```
English  1      these
          2      are
          3  english
          4    words
French    1      ce
          2    sont
          3    des
          4  françai
          5    mots
Spanish   1    estas
          2    son
          3  palabras
          4      en
          5  español
dtype: object
```

However, if the columns have multiple levels, we can specify the level to stack as the inner-most row level. By default, the inner-most column level is stacked.

```
#Stacking the inner-most column labels inner-most row indices
df_example.stack()
```

| Information type | Statistic | State City | California | Illinois |
|------------------|------------------|---------------|------------|-----------|
| Demographics | Population | Chicago | NaN | 2697000.0 |
| | | Evanston | NaN | 771517.0 |
| | | Los Angeles | 3849000.0 | NaN |
| | | San Francisco | 815201.0 | NaN |
| | Unemployment (%) | Chicago | NaN | 5.6 |
| | | Evanston | NaN | 4.2 |
| | | Los Angeles | 4.6 | NaN |
| | | San Francisco | 2.8 | NaN |
| Geography | Area (mile-sq) | Chicago | NaN | 234.5 |
| | | Evanston | NaN | 7.8 |
| | | Los Angeles | 502.0 | NaN |
| | | San Francisco | 46.9 | NaN |
| | Elevation (feet) | Chicago | NaN | 597.0 |
| | | Evanston | NaN | 6749.0 |
| | | Los Angeles | 305.0 | NaN |
| | | San Francisco | 52.0 | NaN |

```
#Stacking the outer column labels inner-most row indices
df_example.stack(level=0)
```

| Information type | Statistic | City State | Chicago | Evanston | Los Angeles | San Francisco |
|------------------|------------------|---------------|-----------|----------|-------------|---------------|
| Demographics | Population | California | NaN | NaN | 3849000.0 | 815201.0 |
| | | Illinois | 2697000.0 | 771517.0 | NaN | NaN |
| | Unemployment (%) | California | NaN | NaN | 4.6 | 2.8 |
| | | Illinois | 5.6 | 4.2 | NaN | NaN |
| Geography | Area (mile-sq) | California | NaN | NaN | 502.0 | 46.9 |
| | | Illinois | 234.5 | 7.8 | NaN | NaN |
| | Elevation (feet) | California | NaN | NaN | 305.0 | 52.0 |
| | | Illinois | 597.0 | 6749.0 | NaN | NaN |

8.2 Merging data

The Pandas DataFrame method `merge()` uses columns defined as *key* column(s) to merge two datasets. In case the *key* column(s) are not defined, the overlapping column(s) are considered as the *key* columns.

8.2.1 Join types

When a dataset is merged with another based on *key* column(s), one of the following four types of join will occur depending on the repetition of the values of the key(s) in the datasets.

- (i) One-to-one, (ii) Many-to-one, (iii) One-to-Many, and (iv) Many-to-many

The type of join may sometimes determine the number of rows to be obtained in the merged dataset. If we don't get the expected number of rows in the merged dataset, an investigation of the datasets may be necessary to identify and resolve the issue. There may be several possible issues, for example, the dataset may not be arranged in a way that we have assumed it to be arranged.

We'll use toy datasets to understand the above types of joins. The *.csv* files with the prefix *student* consist of the names of a few students along with their majors, and the files with the prefix *skills* consist of the names of majors along with the skills imparted by the respective majors.

```
data_student = pd.read_csv('./Datasets/student_one.csv')
data_skill = pd.read_csv('./Datasets/skills_one.csv')
```

8.2.1.1 One-to-one join

Each row in one dataset is linked (or related) to a single row in another dataset based on the key column(s).

```
data_student
```

| | Student | Major |
|---|---------|------------------|
| 0 | Kitana | Statistics |
| 1 | Jax | Computer Science |
| 2 | Sonya | Material Science |
| 3 | Johnny | Music |

```
data_skill
```

| | Major | Skills |
|---|------------------|----------------------|
| 0 | Statistics | Inference |
| 1 | Computer Science | Machine learning |
| 2 | Material Science | Structure prediction |
| 3 | Music | Opera |

```
pd.merge(data_student,data_skill)
```

| | Student | Major | Skills |
|---|---------|------------------|----------------------|
| 0 | Kitana | Statistics | Inference |
| 1 | Jax | Computer Science | Machine learning |
| 2 | Sonya | Material Science | Structure prediction |
| 3 | Johnny | Music | Opera |

8.2.1.2 Many-to-one join

One or more rows in one dataset is linked (or related) to a single row in another dataset based on the key column(s).

```
data_student = pd.read_csv('./Datasets/student_many.csv')
data_skill = pd.read_csv('./Datasets/skills_one.csv')
```

```
data_student
```

| | Student | Major |
|---|---------|------------------|
| 0 | Kitana | Statistics |
| 1 | Kitana | Computer Science |
| 2 | Jax | Computer Science |
| 3 | Sonya | Material Science |
| 4 | Johnny | Music |
| 5 | Johnny | Statistics |

```
data_skill
```

| | Major | Skills |
|---|------------------|----------------------|
| 0 | Statistics | Inference |
| 1 | Computer Science | Machine learning |
| 2 | Material Science | Structure prediction |
| 3 | Music | Opera |

```
pd.merge(data_student,data_skill)
```

| | Student | Major | Skills |
|---|---------|------------------|----------------------|
| 0 | Kitana | Statistics | Inference |
| 1 | Johnny | Statistics | Inference |
| 2 | Kitana | Computer Science | Machine learning |
| 3 | Jax | Computer Science | Machine learning |
| 4 | Sonya | Material Science | Structure prediction |
| 5 | Johnny | Music | Opera |

8.2.1.3 One-to-many join

Each row in one dataset is linked (or related) to one, or more rows in another dataset based on the key column(s).

```
data_student = pd.read_csv('./Datasets/student_one.csv')
data_skill = pd.read_csv('./Datasets/skills_many.csv')
```

```
data_student
```

| | Student | Major |
|---|---------|------------------|
| 0 | Kitana | Statistics |
| 1 | Jax | Computer Science |
| 2 | Sonya | Material Science |
| 3 | Johnny | Music |

```
data_skill
```

| | Major | Skills |
|---|------------------|----------------------|
| 0 | Statistics | Inference |
| 1 | Statistics | Modeling |
| 2 | Computer Science | Machine learning |
| 3 | Computer Science | Computing |
| 4 | Material Science | Structure prediction |
| 5 | Music | Opera |
| 6 | Music | Pop |
| 7 | Music | Classical |

```
pd.merge(data_student,data_skill)
```

| | Student | Major | Skills |
|---|---------|------------------|----------------------|
| 0 | Kitana | Statistics | Inference |
| 1 | Kitana | Statistics | Modeling |
| 2 | Jax | Computer Science | Machine learning |
| 3 | Jax | Computer Science | Computing |
| 4 | Sonya | Material Science | Structure prediction |
| 5 | Johnny | Music | Opera |
| 6 | Johnny | Music | Pop |
| 7 | Johnny | Music | Classical |

8.2.1.4 Many-to-many join

One, or more, rows in one dataset is linked (or related) to one, or more, rows in another dataset using the key column(s).

```
data_student = pd.read_csv('./Datasets/student_many.csv')
data_skill = pd.read_csv('./Datasets/skills_many.csv')
```

```
data_student
```

| | Student | Major |
|---|---------|------------------|
| 0 | Kitana | Statistics |
| 1 | Kitana | Computer Science |
| 2 | Jax | Computer Science |
| 3 | Sonya | Material Science |

| | Student | Major |
|---|---------|------------|
| 4 | Johnny | Music |
| 5 | Johnny | Statistics |

```
data_skill
```

| | Major | Skills |
|---|------------------|----------------------|
| 0 | Statistics | Inference |
| 1 | Statistics | Modeling |
| 2 | Computer Science | Machine learning |
| 3 | Computer Science | Computing |
| 4 | Material Science | Structure prediction |
| 5 | Music | Opera |
| 6 | Music | Pop |
| 7 | Music | Classical |

```
pd.merge(data_student,data_skill)
```

| | Student | Major | Skills |
|----|---------|------------------|----------------------|
| 0 | Kitana | Statistics | Inference |
| 1 | Kitana | Statistics | Modeling |
| 2 | Johnny | Statistics | Inference |
| 3 | Johnny | Statistics | Modeling |
| 4 | Kitana | Computer Science | Machine learning |
| 5 | Kitana | Computer Science | Computing |
| 6 | Jax | Computer Science | Machine learning |
| 7 | Jax | Computer Science | Computing |
| 8 | Sonya | Material Science | Structure prediction |
| 9 | Johnny | Music | Opera |
| 10 | Johnny | Music | Pop |
| 11 | Johnny | Music | Classical |

Note that there are two ‘*Statistics*’ rows in `data_student`, and two ‘*Statistics*’ rows in `data_skill`, resulting in $2 \times 2 = 4$ ‘*Statistics*’ rows in the merged data. The same is true for the ‘*Computer Science*’ Major.

8.2.2 Join types with how argument

The above mentioned types of join (one-to-one, many-to-one, etc.) occur depending on the structure of the datasets being merged. We don't have control over the type of join. However, we can control **how** the joins are occurring. We can merge (or *join*) two datasets in one of the following four ways:

- (i) **inner** join, (ii) **left** join, (iii) **right** join, (iv) **outer** join

8.2.2.1 inner join

This is the join that occurs by default, i.e., without specifying the **how** argument in the `merge()` function. In **inner** join, only those observations are merged that have the same value(s) in the *key* column(s) of both the datasets.

```
data_student = pd.read_csv('./Datasets/student_how.csv')
data_skill = pd.read_csv('./Datasets/skills_how.csv')
```

```
data_student
```

| | Student | Major |
|---|---------|------------------|
| 0 | Kitana | Statistics |
| 1 | Jax | Computer Science |
| 2 | Sonya | Material Science |

```
data_skill
```

| | Major | Skills |
|---|------------------|------------------|
| 0 | Statistics | Inference |
| 1 | Computer Science | Machine learning |
| 2 | Music | Opera |

```
pd.merge(data_student,data_skill)
```

| | Student | Major | Skills |
|---|---------|------------|-----------|
| 0 | Kitana | Statistics | Inference |

| | Student | Major | Skills |
|---|---------|------------------|------------------|
| 1 | Jax | Computer Science | Machine learning |

When you may use inner join? You should use inner join when you cannot carry out the analysis unless the observation corresponding to the *key column(s)* is present in both the tables.

Example: Suppose you wish to analyze the association between vaccinations and covid infection rate based on country-level data. In one of the datasets, you have the infection rate for each country, while in the other one you have the number of vaccinations in each country. The countries which have either the vaccination or the infection rate missing, cannot help analyze the association. In such as case you may be interested only in countries that have values for both the variables. Thus, you will use inner join to discard the countries with either value missing.

8.2.2.2 left join

In **left** join, the merged dataset will have all the rows of the dataset that is specified first in the `merge()` function. Only those observations of the other dataset will be merged whose value(s) in the *key* column(s) exist in the dataset specified first in the `merge()` function.

```
pd.merge(data_student,data_skill,how='left')
```

| | Student | Major | Skills |
|---|---------|------------------|------------------|
| 0 | Kitana | Statistics | Inference |
| 1 | Jax | Computer Science | Machine learning |
| 2 | Sonya | Material Science | NaN |

When you may use left join? You should use left join when the primary variable(s) of interest are present in the one of the datasets, and whose missing values cannot be imputed. The variable(s) in the other dataset may not be as important or it may be possible to reasonably impute their values, if missing corresponding to the observation in the primary dataset.

Examples:

- 1) Suppose you wish to analyze the association between the covid infection rate and the government effectiveness score (a metric used to determine the effectiveness of the government in implementing policies, upholding law and order etc.) based on the data of all countries. Let us say that one of the datasets contains the covid infection rate, while the other one contains the government effectiveness score for each country. If the infection

rate for a country is missing, it might be hard to impute. However, the government effectiveness score may be easier to impute based on GDP per capita, crime rate etc. - information that is easily available online. In such a case, you may wish to use a left join where you keep all the countries for which the infection rate is known.

- 2) Suppose you wish to analyze the association between demographics such as age, income etc. and the amount of credit card spend. Let us say one of the datasets contains the demographic information of each customer, while the other one contains the credit card spend for the customers who made at least one purchase. In such a case, you may want to do a left join as customers not making any purchase might be absent in the card spend data. Their spend can be imputed as zero after merging the datasets.

8.2.2.3 right join

In **right** join, the merged dataset will have all the rows of the dataset that is specified second in the `merge()` function. Only those observations of the other dataset will be merged whose value(s) in the *key* column(s) exist in the dataset specified second in the `merge()` function.

```
pd.merge(data_student, data_skill, how='right')
```

| | Student | Major | Skills |
|---|---------|------------------|------------------|
| 0 | Kitana | Statistics | Inference |
| 1 | Jax | Computer Science | Machine learning |
| 2 | NaN | Music | Opera |

When you may use right join? You can always use a left join instead of a right join. Their purpose is the same.

8.2.2.4 outer join

In **outer** join, the merged dataset will have all the rows of both the datasets being merged.

```
pd.merge(data_student, data_skill, how='outer')
```

| | Student | Major | Skills |
|---|---------|------------------|------------------|
| 0 | Kitana | Statistics | Inference |
| 1 | Jax | Computer Science | Machine learning |
| 2 | Sonya | Material Science | NaN |
| 3 | NaN | Music | Opera |

| Student | Major | Skills |
|---------|-------|--------|
|---------|-------|--------|

When you may use outer join? You should use an outer join when you cannot afford to lose data present in either of the tables. All the other joins may result in loss of data.

Example: Suppose I took two course surveys for this course. If I need to analyze student sentiment during the course, I will take an outer join of both the surveys. Assume that each survey is a dataset, where each row corresponds to a unique student. Even if a student has answered one of the two surveys, it will be indicative of the sentiment, and will be useful to keep in the merged dataset.

8.3 Concatenating datasets

The Pandas DataFrame method `concat()` is used to stack datasets along an axis. The method is similar to NumPy's `concatenate()` method.

Example: You are given the life expectancy data of each continent as a separate *.csv file. Visualize the change of life expectancy over time for different continents.

```
data_asia = pd.read_csv('./Datasets/gdp_lifeExpec_Asia.csv')
data_europe = pd.read_csv('./Datasets/gdp_lifeExpec_Europe.csv')
data_africa = pd.read_csv('./Datasets/gdp_lifeExpec_Africa.csv')
data_oceania = pd.read_csv('./Datasets/gdp_lifeExpec_Oceania.csv')
data_americas = pd.read_csv('./Datasets/gdp_lifeExpec_Americas.csv')
```

```
#Appending all the data files, i.e., stacking them on top of each other
```

```
data_all_continents = pd.concat([data_asia,data_europe,data_africa,data_oceania,data_ameri
data_all_continents
```

| | | country | year | lifeExp | pop | gdpPercap |
|----------|-----|-------------|------|---------|----------|--------------|
| Asia | 0 | Afghanistan | 1952 | 28.801 | 8425333 | 779.445314 |
| | 1 | Afghanistan | 1957 | 30.332 | 9240934 | 820.853030 |
| | 2 | Afghanistan | 1962 | 31.997 | 10267083 | 853.100710 |
| | 3 | Afghanistan | 1967 | 34.020 | 11537966 | 836.197138 |
| | 4 | Afghanistan | 1972 | 36.088 | 13079460 | 739.981106 |
| ... | ... | ... | ... | ... | ... | ... |
| Americas | 295 | Venezuela | 1987 | 70.190 | 17910182 | 9883.584648 |
| | 296 | Venezuela | 1992 | 71.150 | 20265563 | 10733.926310 |
| | 297 | Venezuela | 1997 | 72.146 | 22374398 | 10165.495180 |

| | | country | year | lifeExp | pop | gdpPercap |
|--|-----|-----------|------|---------|----------|--------------|
| | 298 | Venezuela | 2002 | 72.766 | 24287670 | 8605.047831 |
| | 299 | Venezuela | 2007 | 73.747 | 26084662 | 11415.805690 |

Let's have the continent as a column as we need to use that in the visualization.

```
data_all_continents.reset_index(inplace = True)
```

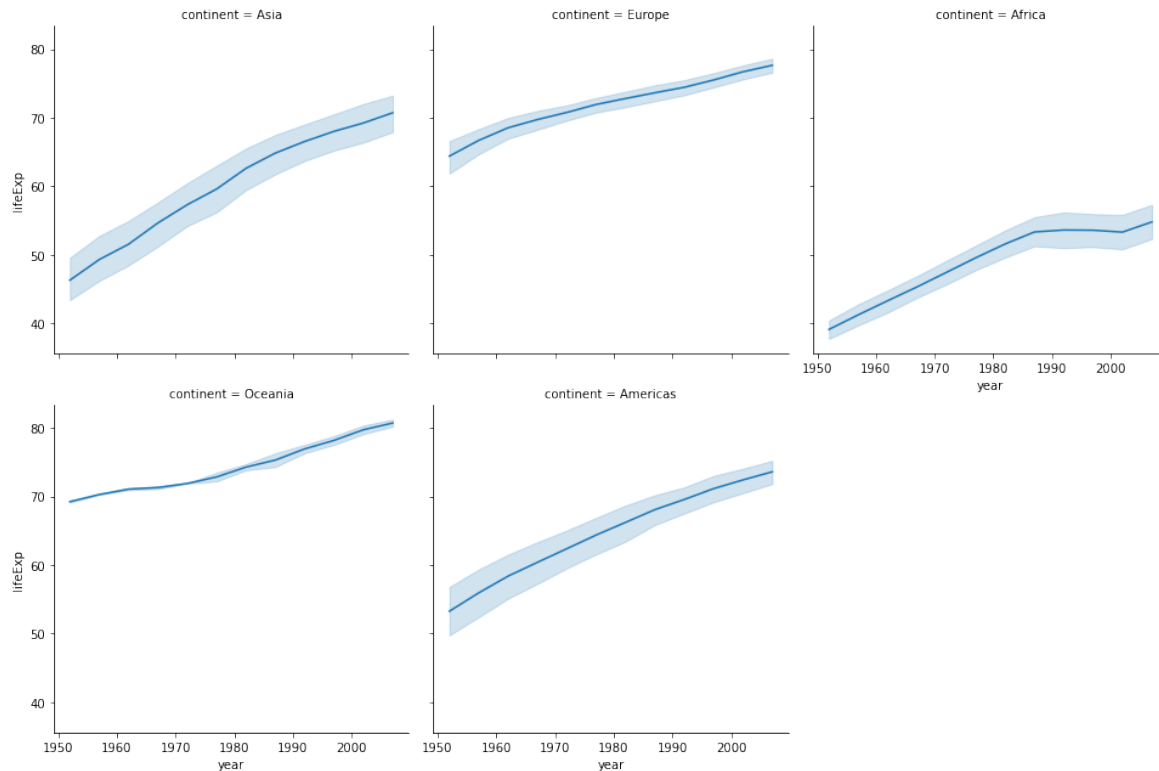
```
data_all_continents.head()
```

| | level_0 | level_1 | country | year | lifeExp | pop | gdpPercap |
|---|---------|---------|-------------|------|---------|----------|------------|
| 0 | Asia | 0 | Afghanistan | 1952 | 28.801 | 8425333 | 779.445314 |
| 1 | Asia | 1 | Afghanistan | 1957 | 30.332 | 9240934 | 820.853030 |
| 2 | Asia | 2 | Afghanistan | 1962 | 31.997 | 10267083 | 853.100710 |
| 3 | Asia | 3 | Afghanistan | 1967 | 34.020 | 11537966 | 836.197138 |
| 4 | Asia | 4 | Afghanistan | 1972 | 36.088 | 13079460 | 739.981106 |

```
data_all_continents.drop(columns = 'level_1',inplace = True)
data_all_continents.rename(columns = {'level_0':'continent'},inplace = True)
data_all_continents.head()
```

| | continent | country | year | lifeExp | pop | gdpPercap |
|---|-----------|-------------|------|---------|----------|------------|
| 0 | Asia | Afghanistan | 1952 | 28.801 | 8425333 | 779.445314 |
| 1 | Asia | Afghanistan | 1957 | 30.332 | 9240934 | 820.853030 |
| 2 | Asia | Afghanistan | 1962 | 31.997 | 10267083 | 853.100710 |
| 3 | Asia | Afghanistan | 1967 | 34.020 | 11537966 | 836.197138 |
| 4 | Asia | Afghanistan | 1972 | 36.088 | 13079460 | 739.981106 |

```
#change of life expectancy over time for different continents
a = sns.FacetGrid(data_all_continents,col = 'continent',col_wrap = 3,height = 4.5,aspect = 
a.map(sns.lineplot,'year','lifeExp')
a.add_legend()
```



In the above example, datasets were appended (or stacked on top of each other).

Datasets can also be concatenated side-by-side (by providing the argument `axis = 1` with the `concat()` function) as we saw with the `merge` function.

8.3.1 Practice exercise 4

Read the documentations of the Pandas DataFrame methods `merge()` and `concat()`, and identify the differences. Mention examples when you can use (i) either, (ii) only `concat()`, (iii) only `merge()`

Solution:

- (i) If we need to merge datasets using row indices, we can use either function.
- (ii) If we need to stack datasets one on top of the other, we can only use `concat()`
- (iii) If we need to merge datasets using overlapping columns we can only use `merge()`

8.4 Reshaping data

Data often needs to be re-arranged to ease analysis.

8.4.1 Pivoting “long” to “wide” format

`pivot()`

This function helps re-arrange data from the ‘*long*’ form to a ‘*wide*’ form.

Example: Let us consider the dataset `data_all_continents` obtained in the previous section after concatenating the data of all the continents.

```
data_all_continents.head()
```

| | continent | country | year | lifeExp | pop | gdpPercap |
|---|-----------|-------------|------|---------|----------|------------|
| 0 | Asia | Afghanistan | 1952 | 28.801 | 8425333 | 779.445314 |
| 1 | Asia | Afghanistan | 1957 | 30.332 | 9240934 | 820.853030 |
| 2 | Asia | Afghanistan | 1962 | 31.997 | 10267083 | 853.100710 |
| 3 | Asia | Afghanistan | 1967 | 34.020 | 11537966 | 836.197138 |
| 4 | Asia | Afghanistan | 1972 | 36.088 | 13079460 | 739.981106 |

8.4.1.1 Pivoting a single column

For visualizing life expectancy in 2007 against life expectancy in 1957, we will need to filter the data, and then make the plot. Everytime that we need to compare a metric for a year against another year, we will need to filter the data.

If we need to often compare metrics of a year against another year, it will be easier to have each year as a separate column, instead of having all years in a single column.

As we are increasing the number of columns and decreasing the number of rows, we are re-arranging the data from *long*-form to *wide*-form.

```
data_wide = data_all_continents.pivot(index = ['continent','country'],columns = 'year',val
```

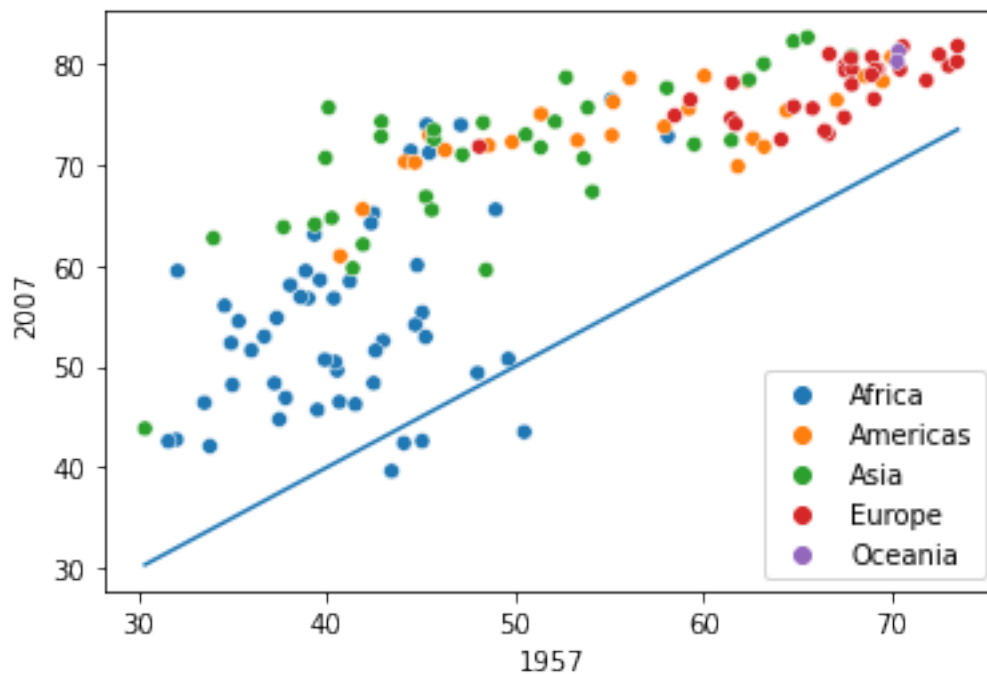
```
data_wide.head()
```

| | year | 1952 | 1957 | 1962 | 1967 | 1972 | 1977 | 1982 | 1987 | 1992 | 1997 |
|-----------|--------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| continent | country | | | | | | | | | | |
| Africa | Algeria | 43.077 | 45.685 | 48.303 | 51.407 | 54.518 | 58.014 | 61.368 | 65.799 | 67.744 | 69.100 |
| | Angola | 30.015 | 31.999 | 34.000 | 35.985 | 37.928 | 39.483 | 39.942 | 39.906 | 40.647 | 40.900 |
| | Benin | 38.223 | 40.358 | 42.618 | 44.885 | 47.014 | 49.190 | 50.904 | 52.337 | 53.919 | 54.700 |
| | Botswana | 47.622 | 49.618 | 51.520 | 53.298 | 56.024 | 59.319 | 61.484 | 63.622 | 62.745 | 52.500 |
| | Burkina Faso | 31.975 | 34.906 | 37.814 | 40.697 | 43.591 | 46.137 | 48.122 | 49.557 | 50.260 | 50.300 |

With values of `year` as columns, it is easy to compare any metric for different years.

```
#visualizing the change in life expectancy of all countries in 2007 as compared to that in 1957
sns.scatterplot(data = data_wide, x = 1957,y=2007,hue = 'continent')
sns.lineplot(data = data_wide, x = 1957,y = 1957)
```

<AxesSubplot:xlabel='1957', ylabel='2007'>



Observe that for some African countries, the life expectancy has decreased after 50 years. It is worth investigating these countries to identify factors associated with the decrease.

8.4.1.2 Pivoting multiple columns

In the above transformation, we retained only `lifeExp` in the *‘wide’* dataset. Suppose, we are also interested in visualizing GDP per capita of countries in one year against another year. In that case, we must have `gdpPercap` in the *‘wide’*-form data as well.

Let us create a dataset named as `data_wide_lifeExp_gdpPercap` that will contain both `lifeExp` and `gdpPercap` for each year in a separate column. We will specify the columns to pivot in the *values* argument of the `pivot()` function.

```
data_wide_lifeExp_gdpPercap = data_all_continents.pivot(index = ['continent', 'country'], values = ['lifeExp', 'gdpPercap'], columns = years)
data_wide_lifeExp_gdpPercap.head()
```

| continent | country | lifeExp | | | | | | | | | |
|-----------|--------------|---------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| | | 1952 | 1957 | 1962 | 1967 | 1972 | 1977 | 1982 | 1987 | 1992 | 1997 |
| Africa | Algeria | 43.077 | 45.685 | 48.303 | 51.407 | 54.518 | 58.014 | 61.368 | 65.799 | 67.744 | 69.146 |
| | Angola | 30.015 | 31.999 | 34.000 | 35.985 | 37.928 | 39.483 | 39.942 | 39.906 | 40.647 | 40.914 |
| | Benin | 38.223 | 40.358 | 42.618 | 44.885 | 47.014 | 49.190 | 50.904 | 52.337 | 53.919 | 54.753 |
| | Botswana | 47.622 | 49.618 | 51.520 | 53.298 | 56.024 | 59.319 | 61.484 | 63.622 | 62.745 | 52.514 |
| | Burkina Faso | 31.975 | 34.906 | 37.814 | 40.697 | 43.591 | 46.137 | 48.122 | 49.557 | 50.260 | 50.314 |

The metric for each year is now in a separate column, and can be visualized directly. Note that re-arranging the dataset from the *‘long’*-form to *‘wide-form’* leads to hierarchical indexing of columns when multiple *‘values’* need to be re-arranged. In this case, the multiple *‘values’* that need to be re-arranged are `lifeExp` and `gdpPercap`.

8.4.2 Melting “wide” to “long” format

`melt()`

This function is used to re-arrange the dataset from the *‘wide’* form to the *‘long’* form.

8.4.2.1 Melting columns with a single type of value

Let us consider `data_wide` created in the previous section.

```
data_wide.head()
```

| | year | 1952 | 1957 | 1962 | 1967 | 1972 | 1977 | 1982 | 1987 | 1992 | 1997 |
|-----------|--------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| continent | country | | | | | | | | | | |
| Africa | Algeria | 43.077 | 45.685 | 48.303 | 51.407 | 54.518 | 58.014 | 61.368 | 65.799 | 67.744 | 69.122 |
| | Angola | 30.015 | 31.999 | 34.000 | 35.985 | 37.928 | 39.483 | 39.942 | 39.906 | 40.647 | 40.915 |
| | Benin | 38.223 | 40.358 | 42.618 | 44.885 | 47.014 | 49.190 | 50.904 | 52.337 | 53.919 | 54.745 |
| | Botswana | 47.622 | 49.618 | 51.520 | 53.298 | 56.024 | 59.319 | 61.484 | 63.622 | 62.745 | 52.515 |
| | Burkina Faso | 31.975 | 34.906 | 37.814 | 40.697 | 43.591 | 46.137 | 48.122 | 49.557 | 50.260 | 50.515 |

Suppose, we wish to visualize the change of life expectancy over time for different continents, as we did in section 8.3. For plotting `lifeExp` against `year`, all the years must be in a single column. Thus, we need to *melt* the columns of `data_wide` to a single column and call it `year`.

But before melting the columns in the above dataset, we will convert `continent` to a column, as we need to make subplots based on continent.

The Pandas DataFrame method `reset_index()` can be used to remove one or more levels of indexing from the DataFrame.

```
#Making 'continent' a column instead of row-index at level 0
data_wide.reset_index(inplace=True,level=0)
data_wide.head()
```

| year | continent | 1952 | 1957 | 1962 | 1967 | 1972 | 1977 | 1982 | 1987 | 1992 | 1997 |
|--------------|-----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| country | | | | | | | | | | | |
| Algeria | Africa | 43.077 | 45.685 | 48.303 | 51.407 | 54.518 | 58.014 | 61.368 | 65.799 | 67.744 | 69.122 |
| Angola | Africa | 30.015 | 31.999 | 34.000 | 35.985 | 37.928 | 39.483 | 39.942 | 39.906 | 40.647 | 40.915 |
| Benin | Africa | 38.223 | 40.358 | 42.618 | 44.885 | 47.014 | 49.190 | 50.904 | 52.337 | 53.919 | 54.745 |
| Botswana | Africa | 47.622 | 49.618 | 51.520 | 53.298 | 56.024 | 59.319 | 61.484 | 63.622 | 62.745 | 52.515 |
| Burkina Faso | Africa | 31.975 | 34.906 | 37.814 | 40.697 | 43.591 | 46.137 | 48.122 | 49.557 | 50.260 | 50.515 |

```
data_melted=pd.melt(data_wide,id_vars = ['continent'],var_name = 'Year',value_name = 'LifeExp')
data_melted.head()
```

| | continent | Year | LifeExp |
|---|-----------|------|---------|
| 0 | Africa | 1952 | 43.077 |
| 1 | Africa | 1952 | 30.015 |
| 2 | Africa | 1952 | 38.223 |
| 3 | Africa | 1952 | 47.622 |

| | continent | Year | LifeExp |
|---|-----------|------|---------|
| 4 | Africa | 1952 | 31.975 |

With the above DataFrame, we can visualize the mean life expectancy against year separately for each continent.

If we wish to have country also in the above data, we can keep it while resetting the index:

```
#Creating 'data_wide' again
data_wide = data_all_continents.pivot(index = ['continent','country'],columns = 'year',values = 'LifeExp')

#Resetting the row-indices to default values
data_wide.reset_index(inplace=True)
data_wide.head()
```

| year | continent | country | 1952 | 1957 | 1962 | 1967 | 1972 | 1977 | 1982 | 1987 | 1992 |
|------|-----------|--------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| 0 | Africa | Algeria | 43.077 | 45.685 | 48.303 | 51.407 | 54.518 | 58.014 | 61.368 | 65.799 | 67.744 |
| 1 | Africa | Angola | 30.015 | 31.999 | 34.000 | 35.985 | 37.928 | 39.483 | 39.942 | 39.906 | 40.644 |
| 2 | Africa | Benin | 38.223 | 40.358 | 42.618 | 44.885 | 47.014 | 49.190 | 50.904 | 52.337 | 53.919 |
| 3 | Africa | Botswana | 47.622 | 49.618 | 51.520 | 53.298 | 56.024 | 59.319 | 61.484 | 63.622 | 62.744 |
| 4 | Africa | Burkina Faso | 31.975 | 34.906 | 37.814 | 40.697 | 43.591 | 46.137 | 48.122 | 49.557 | 50.260 |

```
#Melting the 'year' column
data_melted=pd.melt(data_wide,id_vars = ['continent','country'],var_name = 'Year',value_name = 'LifeExp')
data_melted.head()
```

| | continent | country | Year | LifeExp |
|---|-----------|--------------|------|---------|
| 0 | Africa | Algeria | 1952 | 43.077 |
| 1 | Africa | Angola | 1952 | 30.015 |
| 2 | Africa | Benin | 1952 | 38.223 |
| 3 | Africa | Botswana | 1952 | 47.622 |
| 4 | Africa | Burkina Faso | 1952 | 31.975 |

8.4.2.2 Melting columns with multiple types of values

Consider the dataset created in Section 8.4.1.2. It has two types of values - `lifeExp` and `gdpPercapita`, which are the column labels at the outer level. The `melt()` function will melt all the years of data into a single column. However, it will create another column based on

the outer level column labels - `lifeExp` and `gdpPercapita` to distinguish between these two types of values. Here, we see that the function `melt()` internally uses hierarchical indexing to handle the transformation of multiple types of columns.

```
data_melt = pd.melt(data_wide_lifeExp_gdpPercap.reset_index(),id_vars = ['continent','country'],value_vars = ['lifeExp','gdpPercap'])
data_melt.head()
```

| | continent | country | Metric | year | value |
|---|-----------|--------------|---------|------|--------|
| 0 | Africa | Algeria | lifeExp | 1952 | 43.077 |
| 1 | Africa | Angola | lifeExp | 1952 | 30.015 |
| 2 | Africa | Benin | lifeExp | 1952 | 38.223 |
| 3 | Africa | Botswana | lifeExp | 1952 | 47.622 |
| 4 | Africa | Burkina Faso | lifeExp | 1952 | 31.975 |

Although the data above is in ‘*long*’-form, it is not quiet in its original format, as in `data_all_continents`. We need to pivot again by `Metric` to have two separate columns of `gdpPercap` and `lifeExp`.

```
data_restore = data_melt.pivot(index = ['continent','country','year'],columns = 'Metric')
data_restore.head()
```

| continent | country | year | value | |
|-----------|---------|------|-------------|---------|
| | | | gdpPercap | lifeExp |
| Africa | Algeria | 1952 | 2449.008185 | 43.077 |
| | | 1957 | 3013.976023 | 45.685 |
| | | 1962 | 2550.816880 | 48.303 |
| | | 1967 | 3246.991771 | 51.407 |
| | | 1972 | 4182.663766 | 54.518 |

Now, we can convert the row indices of `continent` and `country` to columns to restore the dataset to the same form as `data_all_continents`.

```
data_restore.reset_index(inplace = True)
data_restore.head()
```

| | continent | country | year | value | |
|--------|-----------|---------|------|-------------|---------|
| Metric | | | | gdpPercap | lifeExp |
| 0 | Africa | Algeria | 1952 | 2449.008185 | 43.077 |
| 1 | Africa | Algeria | 1957 | 3013.976023 | 45.685 |
| 2 | Africa | Algeria | 1962 | 2550.816880 | 48.303 |
| 3 | Africa | Algeria | 1967 | 3246.991771 | 51.407 |
| 4 | Africa | Algeria | 1972 | 4182.663766 | 54.518 |

8.4.3 Practice exercise 5

8.4.3.1

Both `unstack()` and `pivot()` seem to transform the data from the *‘long’* form to the *‘wide’* form. Is there a difference between the two functions?

Solution:

Yes, both the functions transform the data from the *‘long’* form to the *‘wide’* form. However, `unstack()` pivots the row indices, while `pivot()` pivots the columns of the DataFrame.

Even though both functions are a bit different, it is possible to just use one of them to perform a reshaping operation. If we wish to pivot a column, we can either use `pivot()` directly on the column, or we can convert the column to row indices and then use `unstack()`. If we wish to pivot row indices, we can either use `unstack()` directly on the row indices, or we can convert row indices to a column and then use `pivot()`.

To summarise, using one function may be more straightforward than using the other one, but either can be used for reshaping data from the *‘long’* form to the *‘wide’* form.

Below is an example where we perform the same reshaping operation with either function.

Consider the data `data_all_continent`. Suppose we wish to transform it to `data_wide` as we did using `pivot()` in Section 8.4.1.1. Let us do it using `unstack()`, instead of `pivot()`.

The first step will be to reindex data to set `year` as row indices, and also `continent` and `country` as row indices because these two column were set as indices with the `pivot()` function in Section 8.4.1.1.

```
#Reindexing data to make 'continent', 'country', and 'year' as hierarchical row indices
data_reindexed=data_all_continents.set_index(['continent','country','year'])
data_reindexed
```

| continent | country | year | lifeExp | pop | gdpPercap |
|-----------|-------------|------|---------|----------|--------------|
| Asia | Afghanistan | 1952 | 28.801 | 8425333 | 779.445314 |
| | | 1957 | 30.332 | 9240934 | 820.853030 |
| | | 1962 | 31.997 | 10267083 | 853.100710 |
| | | 1967 | 34.020 | 11537966 | 836.197138 |
| | | 1972 | 36.088 | 13079460 | 739.981106 |
| ... | ... | ... | ... | ... | ... |
| Americas | Venezuela | 1987 | 70.190 | 17910182 | 9883.584648 |
| | | 1992 | 71.150 | 20265563 | 10733.926310 |
| | | 1997 | 72.146 | 22374398 | 10165.495180 |
| | | 2002 | 72.766 | 24287670 | 8605.047831 |
| | | 2007 | 73.747 | 26084662 | 11415.805690 |

Now we can use `unstack()` to pivot the desired row index, i.e., `year`. Also, since we are only interested in pivoting the values of `lifeExp` (as in the example in Section 8.4.1.1), we will filter the pivoted data with the `lifeExp` column label.

```
data_wide_with_unstack=data_reindexed.unstack('year')['lifeExp']
data_wide_with_unstack
```

| | year | 1952 | 1957 | 1962 | 1967 | 1972 | 1977 | 1982 | 1987 | 1992 |
|-----------|----------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| continent | country | | | | | | | | | |
| Africa | Algeria | 43.077 | 45.685 | 48.303 | 51.407 | 54.518 | 58.014 | 61.368 | 65.799 | 67.744 |
| | Angola | 30.015 | 31.999 | 34.000 | 35.985 | 37.928 | 39.483 | 39.942 | 39.906 | 40.647 |
| | Benin | 38.223 | 40.358 | 42.618 | 44.885 | 47.014 | 49.190 | 50.904 | 52.337 | 53.919 |
| | Botswana | 47.622 | 49.618 | 51.520 | 53.298 | 56.024 | 59.319 | 61.484 | 63.622 | 62.745 |
| | Burkina Faso | 31.975 | 34.906 | 37.814 | 40.697 | 43.591 | 46.137 | 48.122 | 49.557 | 50.260 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| Europe | Switzerland | 69.620 | 70.560 | 71.320 | 72.770 | 73.780 | 75.390 | 76.210 | 77.410 | 78.030 |
| | Turkey | 43.585 | 48.079 | 52.098 | 54.336 | 57.005 | 59.507 | 61.036 | 63.108 | 66.146 |
| | United Kingdom | 69.180 | 70.420 | 70.760 | 71.360 | 72.010 | 72.760 | 74.040 | 75.007 | 76.420 |
| Oceania | Australia | 69.120 | 70.330 | 70.930 | 71.100 | 71.930 | 73.490 | 74.740 | 76.320 | 77.560 |
| | New Zealand | 69.390 | 70.260 | 71.240 | 71.520 | 71.890 | 72.220 | 73.840 | 74.320 | 76.330 |

The above dataset is the same as that obtained using the `pivot()` function in Section 8.4.1.1.

8.4.3.2

Both `stack()` and `melt()` seem to transform the data from the *'wide'* form to the *'long'* form. Is there a difference between the two functions?

Solution:

Following the trend of the previous question, we can always use `stack()` instead of `melt()` and vice-versa. The main difference is that `melt()` lets us choose the identifier columns with the argument `id_vars`. However, if we use `stack()`, we will need to set the relevant melted row indices as columns. On the other hand, if we wished to have the melted columns as row indices, we can either directly use `stack()` or use `melt()` and then set the desired columns as row indices.

To summarise, using one function may be more straightforward than using the other one, but either can be used for reshaping data from the *'wide'* form to the *'long'* form.

Let us melt the data `data_wide_with_unstack` using the `stack()` function to obtain the same dataset as obtained with the `melt()` function in Section [8.4.1.2](#).

```
#Stacking the data
data_stacked = data_wide_with_unstack.stack()
data_stacked
```

| continent | country | year | |
|-----------|-------------|------|--------|
| Africa | Algeria | 1952 | 43.077 |
| | | 1957 | 45.685 |
| | | 1962 | 48.303 |
| | | 1967 | 51.407 |
| | | 1972 | 54.518 |
| Oceania | New Zealand | ... | |
| | | 1987 | 74.320 |
| | | 1992 | 76.330 |
| | | 1997 | 77.550 |
| | | 2002 | 79.110 |
| | | 2007 | 80.204 |

Length: 1704, dtype: float64

Now we need to convert the row indices `continent` and `country` to columns as in the melted data in Section [8.4.1.2](#).

```
#Putting 'continent' and 'country' as columns
data_long_with_stack = data_stacked.reset_index()
```

```
data_long_with_stack
```

| | continent | country | year | 0 |
|------|-----------|-------------|------|--------|
| 0 | Africa | Algeria | 1952 | 43.077 |
| 1 | Africa | Algeria | 1957 | 45.685 |
| 2 | Africa | Algeria | 1962 | 48.303 |
| 3 | Africa | Algeria | 1967 | 51.407 |
| 4 | Africa | Algeria | 1972 | 54.518 |
| ... | ... | ... | ... | ... |
| 1699 | Oceania | New Zealand | 1987 | 74.320 |
| 1700 | Oceania | New Zealand | 1992 | 76.330 |
| 1701 | Oceania | New Zealand | 1997 | 77.550 |
| 1702 | Oceania | New Zealand | 2002 | 79.110 |
| 1703 | Oceania | New Zealand | 2007 | 80.204 |

Finally, we need to rename the column named as 0 to `LifeExp` to obtain the same dataset as in Section [8.4.1.2](#).

```
#Renaming column 0 to 'LifeExp'  
data_long_with_stack.rename(columns = {0:'LifeExp'},inplace=True)  
data_long_with_stack
```

| | continent | country | year | LifeExp |
|------|-----------|-------------|------|---------|
| 0 | Africa | Algeria | 1952 | 43.077 |
| 1 | Africa | Algeria | 1957 | 45.685 |
| 2 | Africa | Algeria | 1962 | 48.303 |
| 3 | Africa | Algeria | 1967 | 51.407 |
| 4 | Africa | Algeria | 1972 | 54.518 |
| ... | ... | ... | ... | ... |
| 1699 | Oceania | New Zealand | 1987 | 74.320 |
| 1700 | Oceania | New Zealand | 1992 | 76.330 |
| 1701 | Oceania | New Zealand | 1997 | 77.550 |
| 1702 | Oceania | New Zealand | 2002 | 79.110 |
| 1703 | Oceania | New Zealand | 2007 | 80.204 |

9 Data aggregation

Data aggregation refers to summarizing data with statistics such as sum, count, average, maximum, minimum, etc. to provide a high level view of the data. Often there are mutually exclusive groups in the data that are of interest. In such cases, we may be interested in finding these statistics separately for each group. The Pandas DataFrame method `groupby()` is used to split the data into groups, and then the desired function(s) are applied on each of these groups for groupwise data aggregation. However, the `groupby()` method is not limited to groupwise data aggregation, but can also be used for several other kinds of groupwise operations.

Groupby mechanics: (Source: https://pandas.pydata.org/docs/user_guide/groupby.html)

Group by: split-apply-combine By ‘group by’ we are referring to a process involving one or more of the following steps:

1. Splitting the data into groups based on some criteria.
2. Applying a function to each group independently.
3. Combining the results in a DataFrame.

Out of these, the split step is the most straightforward. In fact, in many situations we may wish to split the data set into groups and do something with those groups. In the apply step, we may wish to do one of the following:

1. Aggregation: compute a summary statistic (or statistics) for each group. Some examples:

- Compute group sums or means.
- Compute group sizes / counts.

2. Transformation: perform some group-specific computations and return a like-indexed object. Some examples:

- Standardize data (*zscore*) within a group.
- Filling *NAs* within groups with a value derived from each group.

3. Filtration: discard some groups, according to a group-wise computation that evaluates True or False. Some examples:

- Discard data that belongs to groups with only a few members.
- Filter out data based on the group *sum* or *mean*.

Some combination of the above: *GroupBy* will examine the results of the *apply* step and try to return a sensibly combined result if it doesn't fit into either of the above two categories.

We'll use Pandas to group the data and perform *GroupBy* operations.

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

9.1 The GroupBy object

9.1.1 Creating a GroupBy object: `groupby`

This Pandas DataFrame method `groupby()` is used to create a `GroupBy` object.

A string passed to `groupby()` may refer to either a column or an index level. If a string matches both a column name and an index level name, a `ValueError` will be raised.

Example: Consider the life expectancy dataset, *gdp_lifeExpectancy.csv*. Suppose we want to group by the observations by `continent`.

```
gdp_lifeExp_data = pd.read_csv('./Datasets/gdp_lifeExpectancy.csv')
gdp_lifeExp_data.head()
```

| | country | continent | year | lifeExp | pop | gdpPercap |
|---|-------------|-----------|------|---------|----------|------------|
| 0 | Afghanistan | Asia | 1952 | 28.801 | 8425333 | 779.445314 |
| 1 | Afghanistan | Asia | 1957 | 30.332 | 9240934 | 820.853030 |
| 2 | Afghanistan | Asia | 1962 | 31.997 | 10267083 | 853.100710 |
| 3 | Afghanistan | Asia | 1967 | 34.020 | 11537966 | 836.197138 |
| 4 | Afghanistan | Asia | 1972 | 36.088 | 13079460 | 739.981106 |

We will pass the column `continent` as an argument to the `groupby()` method.

```
#Creating a GroupBy object
grouped = gdp_lifeExp_data.groupby('continent')
#This will split the data into groups that correspond to values of the column 'continent'
```

The `groupby()` method returns a *GroupBy* object.

```
#A 'GroupBy' objects is created with the `groupby()` function  
type(grouped)
```

```
pandas.core.groupby.generic.DataFrameGroupBy
```

The *GroupBy* object `grouped` contains the information of the groups in which the data is distributed. Each observation has been assigned to a specific group of the column(s) used to group the data. However, note that the dataset is not physically split into different *DataFrames*. For example, in the above case, each observation is assigned to a particular group depending on the value of the `continent` for that observation. However, all the observations are still in the same *DataFrame* `data`.

9.1.2 Attributes and methods of the *GroupBy* object

9.1.2.1 keys

The object(s) grouping the data are called *key(s)*. Here `continent` is the group key. The keys of the *GroupBy* object can be seen using Its `keys` attribute.

```
#Key(s) of the GroupBy object  
grouped.keys
```

```
'continent'
```

9.1.2.2 `ngroups`

The number of groups in which the data is distributed based on the keys can be seen with the `ngroups` attribute.

```
#The number of groups based on the key(s)  
grouped.ngroups
```

9.1.2.3 groups

The `groups` attribute of the *GroupBy* object contains the group labels (or names) and the row labels of the observations in each group, as a dictionary.

```
#The groups (in the dictionary format)
grouped.groups
```

```
{'Africa': [24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44,
```

The group names are the *keys* of the dictionary, while the row labels are the corresponding *values*

```
#Group names
grouped.groups.keys()
```

```
dict_keys(['Africa', 'Americas', 'Asia', 'Europe', 'Oceania'])
```

```
#Group values are the row labels corresponding to a particular group
grouped.groups.values()
```

```
dict_values([Int64Index([ 24,  25,  26,  27,  28,  29,  30,  31,  32,  33,
...
1694, 1695, 1696, 1697, 1698, 1699, 1700, 1701, 1702, 1703],
dtype='int64', length=624), Int64Index([ 48,  49,  50,  51,  52,  53,  54,
...
1634, 1635, 1636, 1637, 1638, 1639, 1640, 1641, 1642, 1643],
dtype='int64', length=300), Int64Index([  0,   1,   2,   3,   4,   5,   6,
...
1670, 1671, 1672, 1673, 1674, 1675, 1676, 1677, 1678, 1679],
dtype='int64', length=396), Int64Index([ 12,  13,  14,  15,  16,  17,  18,
...
1598, 1599, 1600, 1601, 1602, 1603, 1604, 1605, 1606, 1607],
dtype='int64', length=360), Int64Index([ 60,  61,  62,  63,  64,  65,  66,
71, 1092, 1093, 1094, 1095, 1096, 1097, 1098, 1099, 1100, 1101,
1102, 1103],
dtype='int64')])
```

9.1.2.4 `size()`

The `size()` method of the *GroupBy* object returns the number of observations in each group.

```
#Number of observations in each group
grouped.size()
```

```
continent
Africa      624
Americas    300
Asia        396
Europe      360
Oceania     24
dtype: int64
```

9.1.2.5 `first()`

The first non missing element of each group is returned with the `first()` method of the *GroupBy* object.

```
#The first element of the group can be printed using the first() method
grouped.first()
```

| | country | year | lifeExp | pop | gdpPercap |
|-----------|-------------|------|---------|----------|--------------|
| continent | | | | | |
| Africa | Algeria | 1952 | 43.077 | 9279525 | 2449.008185 |
| Americas | Argentina | 1952 | 62.485 | 17876956 | 5911.315053 |
| Asia | Afghanistan | 1952 | 28.801 | 8425333 | 779.445314 |
| Europe | Albania | 1952 | 55.230 | 1282697 | 1601.056136 |
| Oceania | Australia | 1952 | 69.120 | 8691212 | 10039.595640 |

9.1.2.6 `get_group()`

This method returns the observations for a particular group of the *GroupBy* object.

```
#Observations for individual groups can be obtained using the get_group() function
grouped.get_group('Asia')
```

| | country | continent | year | lifeExp | pop | gdpPercap |
|------|-------------|-----------|------|---------|----------|-------------|
| 0 | Afghanistan | Asia | 1952 | 28.801 | 8425333 | 779.445314 |
| 1 | Afghanistan | Asia | 1957 | 30.332 | 9240934 | 820.853030 |
| 2 | Afghanistan | Asia | 1962 | 31.997 | 10267083 | 853.100710 |
| 3 | Afghanistan | Asia | 1967 | 34.020 | 11537966 | 836.197138 |
| 4 | Afghanistan | Asia | 1972 | 36.088 | 13079460 | 739.981106 |
| ... | ... | ... | ... | ... | ... | ... |
| 1675 | Yemen, Rep. | Asia | 1987 | 52.922 | 11219340 | 1971.741538 |
| 1676 | Yemen, Rep. | Asia | 1992 | 55.599 | 13367997 | 1879.496673 |
| 1677 | Yemen, Rep. | Asia | 1997 | 58.020 | 15826497 | 2117.484526 |
| 1678 | Yemen, Rep. | Asia | 2002 | 60.308 | 18701257 | 2234.820827 |
| 1679 | Yemen, Rep. | Asia | 2007 | 62.698 | 22211743 | 2280.769906 |

9.2 Data aggregation with groupby() methods

9.2.1 `mean()`

This method returns the mean of each group of the *GroupBy* object.

9.2.1.1 Grouping observations

Example: Find the mean life expectancy, population and GDP per capita for each country since 1952.

First, we'll group the data such that all observations corresponding to a country make a unique group.

```
#Grouping the observations by 'country'
grouped = gdp_lifeExp_data.groupby('country')
```

Now, we'll find the mean statistics for each group with the `mean()` method. The method will be applied on all columns of the DataFrame and all groups.

```
#Finding the mean statistic of all columns of the DataFrame and all groups
grouped.mean()
```

| | year | lifeExp | pop | gdpPercap |
|-------------|--------|-----------|--------------|------------|
| country | | | | |
| Afghanistan | 1979.5 | 37.478833 | 1.582372e+07 | 802.674598 |

| | year | lifeExp | pop | gdpPercap |
|--------------------|--------|-----------|--------------|-------------|
| country | | | | |
| Albania | 1979.5 | 68.432917 | 2.580249e+06 | 3255.366633 |
| Algeria | 1979.5 | 59.030167 | 1.987541e+07 | 4426.025973 |
| Angola | 1979.5 | 37.883500 | 7.309390e+06 | 3607.100529 |
| Argentina | 1979.5 | 69.060417 | 2.860224e+07 | 8955.553783 |
| ... | ... | ... | ... | ... |
| Vietnam | 1979.5 | 57.479500 | 5.456857e+07 | 1017.712615 |
| West Bank and Gaza | 1979.5 | 60.328667 | 1.848606e+06 | 3759.996781 |
| Yemen, Rep. | 1979.5 | 46.780417 | 1.084319e+07 | 1569.274672 |
| Zambia | 1979.5 | 45.996333 | 6.353805e+06 | 1358.199409 |
| Zimbabwe | 1979.5 | 52.663167 | 7.641966e+06 | 635.858042 |

Note that if we wished to retain the `continent` in the above dataset, we can group the data by both `continent` and `country`. If the data is to be grouped by multiple columns, we need to put them within `[]` brackets:

```
#Grouping the observations by 'continent' and 'country'
grouped = gdp_lifeExp_data.groupby(['continent','country'])

#Finding the mean statistic of all columns of the DataFrame and all groups
grouped.mean()
```

| | | year | lifeExp | pop | gdpPercap |
|-----------|----------------|--------|-----------|--------------|--------------|
| continent | country | | | | |
| Africa | Algeria | 1979.5 | 59.030167 | 1.987541e+07 | 4426.025973 |
| | Angola | 1979.5 | 37.883500 | 7.309390e+06 | 3607.100529 |
| | Benin | 1979.5 | 48.779917 | 4.017497e+06 | 1155.395107 |
| | Botswana | 1979.5 | 54.597500 | 9.711862e+05 | 5031.503557 |
| | Burkina Faso | 1979.5 | 44.694000 | 7.548677e+06 | 843.990665 |
| ... | ... | ... | ... | ... | ... |
| Europe | Switzerland | 1979.5 | 75.565083 | 6.384293e+06 | 27074.334405 |
| | Turkey | 1979.5 | 59.696417 | 4.590901e+07 | 4469.453380 |
| | United Kingdom | 1979.5 | 73.922583 | 5.608780e+07 | 19380.472986 |
| Oceania | Australia | 1979.5 | 74.662917 | 1.464931e+07 | 19980.595634 |
| | New Zealand | 1979.5 | 73.989500 | 3.100032e+06 | 17262.622813 |

Here the data has been aggregated according to the group keys - `continent` and `country`, and a new DataFrame is created that is indexed by the unique values of `continent-country`.

For large datasets, it may be desirable to aggregate only a few columns. For example, if we wish to compute the means of only `lifeExp` and `gdpPercap`, then we can filter those columns in the `GroupBy` object (*just like we filter columns in a `DataFrame`*), and then apply the `mean()` method:

```
grouped[['lifeExp', 'gdpPercap']].mean()
```

| continent | country | lifeExp | | gdpPercap | |
|-----------|----------------|-----------|--------------|-----------|-----------|
| | | lifeExp | gdpPercap | lifeExp | gdpPercap |
| Africa | Algeria | 59.030167 | 4426.025973 | | |
| | Angola | 37.883500 | 3607.100529 | | |
| | Benin | 48.779917 | 1155.395107 | | |
| | Botswana | 54.597500 | 5031.503557 | | |
| | Burkina Faso | 44.694000 | 843.990665 | | |
| ... | ... | ... | ... | | |
| Europe | Switzerland | 75.565083 | 27074.334405 | | |
| | Turkey | 59.696417 | 4469.453380 | | |
| | United Kingdom | 73.922583 | 19380.472986 | | |
| Oceania | Australia | 74.662917 | 19980.595634 | | |
| | New Zealand | 73.989500 | 17262.622813 | | |

9.2.1.2 Grouping columns

By default, the grouping takes place by rows. However, as with several other Pandas methods, grouping can also be done by columns by using the `axis = 1` argument.

Example: Consider we have the above dataset in the wide-format as follows.

```
gdp_lifeExp_data_wide = gdp_lifeExp_data.pivot(index = ['continent', 'country'], columns = 'year', values = 'lifeExp')
```

| continent | country | lifeExp | | | | | | | | |
|-----------|--------------|---------|--------|--------|--------|--------|--------|--------|--------|--------|
| | | 1952 | 1957 | 1962 | 1967 | 1972 | 1977 | 1982 | 1987 | 1992 |
| Africa | Algeria | 43.077 | 45.685 | 48.303 | 51.407 | 54.518 | 58.014 | 61.368 | 65.799 | 67.744 |
| | Angola | 30.015 | 31.999 | 34.000 | 35.985 | 37.928 | 39.483 | 39.942 | 39.906 | 40.647 |
| | Benin | 38.223 | 40.358 | 42.618 | 44.885 | 47.014 | 49.190 | 50.904 | 52.337 | 53.919 |
| | Botswana | 47.622 | 49.618 | 51.520 | 53.298 | 56.024 | 59.319 | 61.484 | 63.622 | 62.745 |
| | Burkina Faso | 31.975 | 34.906 | 37.814 | 40.697 | 43.591 | 46.137 | 48.122 | 49.557 | 50.260 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |

| continent | year country | lifeExp | | | | | | | | |
|-----------|-----------------|---------|--------|--------|--------|--------|--------|--------|--------|--------|
| | | 1952 | 1957 | 1962 | 1967 | 1972 | 1977 | 1982 | 1987 | 1992 |
| Europe | Switzerland | 69.620 | 70.560 | 71.320 | 72.770 | 73.780 | 75.390 | 76.210 | 77.410 | 78.030 |
| | Turkey | 43.585 | 48.079 | 52.098 | 54.336 | 57.005 | 59.507 | 61.036 | 63.108 | 66.146 |
| | United Kingdom | 69.180 | 70.420 | 70.760 | 71.360 | 72.010 | 72.760 | 74.040 | 75.007 | 76.420 |
| Oceania | Australia | 69.120 | 70.330 | 70.930 | 71.100 | 71.930 | 73.490 | 74.740 | 76.320 | 77.560 |
| | New Zealand | 69.390 | 70.260 | 71.240 | 71.520 | 71.890 | 72.220 | 73.840 | 74.320 | 76.330 |

Now, find the mean GDP per capita, life expectancy and population for each country.

Here, we can group by the outer level column labels to obtain the means. Also, we need to use the argument `axis=1` to indicate that we intend to group columns, instead of rows.

```
gdp_lifeExp_data_wide.groupby(axis=1,level=0).mean()
```

| continent | country | | | | |
|-----------|----------------|--------------|-----------|--------------|--|
| | | gdpPercap | lifeExp | pop | |
| Africa | Algeria | 4426.025973 | 59.030167 | 1.987541e+07 | |
| | Angola | 3607.100529 | 37.883500 | 7.309390e+06 | |
| | Benin | 1155.395107 | 48.779917 | 4.017497e+06 | |
| | Botswana | 5031.503557 | 54.597500 | 9.711862e+05 | |
| | Burkina Faso | 843.990665 | 44.694000 | 7.548677e+06 | |
| ... | ... | ... | ... | ... | |
| Europe | Switzerland | 27074.334405 | 75.565083 | 6.384293e+06 | |
| | Turkey | 4469.453380 | 59.696417 | 4.590901e+07 | |
| | United Kingdom | 19380.472986 | 73.922583 | 5.608780e+07 | |
| Oceania | Australia | 19980.595634 | 74.662917 | 1.464931e+07 | |
| | New Zealand | 17262.622813 | 73.989500 | 3.100032e+06 | |

9.2.2 Practice exercise 1

Read the table consisting of GDP per capita of countries from the webpage: https://en.wikipedia.org/wiki/List_of_countries_by_GDP_per_capita.

To only read the relevant table, read the tables that contain the word ‘*Country*’.

Estimate the GDP per capita of each country as the average of the estimates of the three agencies - IMF, United Nations and World Bank.

We need to do a bit of data cleaning before we could directly use the `groupby()` function. Follow the steps below to answer this question:

1. Set the first 2 columns containing country, and UN region as hierarchical row labels.
2. Apply the following function on all the columns to convert them to numeric: `f = lambda x:pd.to_numeric(x,errors = 'coerce')`
3. Now use `groupby()` to find estimate the GDP per capita for each country.

Solution:

```
dfs = pd.read_html('https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)_per_c
gdp_per_capita = dfs[0]
gdp_per_capita_reindexed = gdp_per_capita.set_index(['Country/Territory','Country/Territo
              ('UN Region','UN Region'))
gdp_per_capita_numeric=gdp_per_capita_reindexed.apply(lambda x:pd.to_numeric(x,errors = 'c
gdp_per_capita_numeric.groupby(axis=1,level=1).mean().drop(columns='Year')
```

9.2.3 `agg()`

Directly applying the aggregate methods of the *GroupBy* object such as mean, count, etc., lets us apply only one function at a time. Also, we may wish to apply an aggregate function of our own, which is not there in the set of methods of the *GroupBy* object, such as the range of values of a column.

The `agg()` function of a *GroupBy* object lets us aggregate data using:

1. Multiple aggregation functions
2. Custom aggregate functions (in addition to in-built functions like mean, std, count etc.)

Consider the spotify dataset containing information about tracks and artists.

```
spotify_data = pd.read_csv('./Datasets/spotify_data.csv')
spotify_data.head(3)
```

| | artist_followers | genres | artist_name | artist_popularity | track_name | track_popularity |
|---|------------------|--------|-------------|-------------------|------------------------|------------------|
| 0 | 16996777 | rap | Juice WRLD | 96 | All Girls Are The Same | 0 |
| 1 | 16996777 | rap | Juice WRLD | 96 | Lucid Dreams | 0 |
| 2 | 16996777 | rap | Juice WRLD | 96 | Hear Me Calling | 0 |

Suppose, we wish to find the average popularity of tracks for each genre. We can do that by using the `mean()` method of a *GroupBy* object, as shown in the previous section. We will also sort the table by decreasing average popularity.

```
grouped=spotify_data.groupby('genres')
grouped['track_popularity'].mean().sort_values(ascending = False)
```

```
genres
rap          51.162959
hip hop      48.700665
metal        46.334539
electronic   43.253165
country      41.132686
pop          37.783194
latin        37.563765
rock         36.749623
miscellaneous 36.167401
pop & rock   35.619242
hoerspiel    31.258670
folk         29.716767
jazz         20.349472
Name: track_popularity, dtype: float64
```

Let us also find the standard deviation of the popularity of the tracks for each genre. We will also sort the table by decreasing standard deviation of popularity.

```
grouped['track_popularity'].std().sort_values(ascending = False)
```

```
genres
rap          20.912240
country      20.544338
pop          17.790385
miscellaneous 16.240129
electronic   16.075841
pop & rock   15.560975
folk         15.150717
jazz         15.087119
latin        14.492199
rock         14.350580
metal        14.331154
hip hop      12.824901
```

```
hoerspiel          6.459370
Name: track_popularity, dtype: float64
```

Even though rap is the most popular genre on an average, its popularity varies the most among listeners. So, it should probably be recommended only to rap listeners or the criteria to accept rap songs on Spotify should be more stringent.

9.2.3.1 Multiple aggregate functions

Let us use the `agg()` method of the *GroupBy* object to simultaneously find the mean and standard deviation of the track popularity for each genre.

For aggregating by multiple functions, we pass a list of strings to `agg()`, where the strings are the function names.

```
grouped['track_popularity'].agg(['mean','std']).sort_values(by = 'mean',ascending = False)
```

| | mean | std |
|---------------|-----------|-----------|
| genres | | |
| rap | 51.162959 | 20.912240 |
| hip hop | 48.700665 | 12.824901 |
| metal | 46.334539 | 14.331154 |
| electronic | 43.253165 | 16.075841 |
| country | 41.132686 | 20.544338 |
| pop | 37.783194 | 17.790385 |
| latin | 37.563765 | 14.492199 |
| rock | 36.749623 | 14.350580 |
| miscellaneous | 36.167401 | 16.240129 |
| pop & rock | 35.619242 | 15.560975 |
| hoerspiel | 31.258670 | 6.459370 |
| folk | 29.716767 | 15.150717 |
| jazz | 20.349472 | 15.087119 |

From the above table, we observe that people not just like hip-hop the second most on average, but they also like it more consistently than almost all other genres. We have also sorted the above table by decreasing average track popularity.

9.2.3.2 Custom aggregate functions

In addition to the mean and standard deviation of the track popularity of each genre, let us also include the 90th percentile of track popularity in the table above, and sort it by the same.

```
#Defining a function that returns the 90th percentile value
def Ninety_pc(x):
    return x.quantile(0.9)
```

```
grouped['track_popularity'].agg(['mean','std',Ninety_pc]).sort_values(by = 'Ninety_pc',asc
```

| | mean | std | Ninety_pc |
|---------------|-----------|-----------|-----------|
| genres | | | |
| rap | 51.162959 | 20.912240 | 74 |
| country | 41.132686 | 20.544338 | 67 |
| hip hop | 48.700665 | 12.824901 | 64 |
| metal | 46.334539 | 14.331154 | 63 |
| electronic | 43.253165 | 16.075841 | 61 |
| pop | 37.783194 | 17.790385 | 60 |
| miscellaneous | 36.167401 | 16.240129 | 57 |
| latin | 37.563765 | 14.492199 | 56 |
| pop & rock | 35.619242 | 15.560975 | 56 |
| rock | 36.749623 | 14.350580 | 56 |
| folk | 29.716767 | 15.150717 | 50 |
| jazz | 20.349472 | 15.087119 | 43 |
| hoerspiel | 31.258670 | 6.459370 | 37 |

From the above table, we observe that even though country songs are not as popular as hip-hop on an average, the top 10% country tracks are more popular than the top 10% hip hop tracks.

For aggregating by multiple functions & changing the column names resulting from those functions, we pass a list of tuples to `agg()`, where each tuple is of length two, and contains the new column name & the function to be applied.

```
#Simultaneous renaming of columns while grouping
grouped['track_popularity'].agg([('Average','mean'),('Standard deviation','std'),('90th pe
```

| | Average | Standard deviation | 90th percentile |
|---------------|-----------|--------------------|-----------------|
| genres | | | |
| rap | 51.162959 | 20.912240 | 74 |
| country | 41.132686 | 20.544338 | 67 |
| hip hop | 48.700665 | 12.824901 | 64 |
| metal | 46.334539 | 14.331154 | 63 |
| electronic | 43.253165 | 16.075841 | 61 |
| pop | 37.783194 | 17.790385 | 60 |
| miscellaneous | 36.167401 | 16.240129 | 57 |
| latin | 37.563765 | 14.492199 | 56 |
| pop & rock | 35.619242 | 15.560975 | 56 |
| rock | 36.749623 | 14.350580 | 56 |
| folk | 29.716767 | 15.150717 | 50 |
| jazz | 20.349472 | 15.087119 | 43 |
| hoerspiel | 31.258670 | 6.459370 | 37 |

We can put use a lambda function as well instead of separately defining the function `Ninety_pc` in the above code:

```
#Simultaneous renaming of columns while grouping
grouped['track_popularity'].agg([('Average','mean'),('Standard deviation','std'),('90th pe
```

| | Average | Standard deviation | 90th percentile |
|---------------|-----------|--------------------|-----------------|
| genres | | | |
| rap | 51.162959 | 20.912240 | 74 |
| country | 41.132686 | 20.544338 | 67 |
| hip hop | 48.700665 | 12.824901 | 64 |
| metal | 46.334539 | 14.331154 | 63 |
| electronic | 43.253165 | 16.075841 | 61 |
| pop | 37.783194 | 17.790385 | 60 |
| miscellaneous | 36.167401 | 16.240129 | 57 |
| latin | 37.563765 | 14.492199 | 56 |
| pop & rock | 35.619242 | 15.560975 | 56 |
| rock | 36.749623 | 14.350580 | 56 |
| folk | 29.716767 | 15.150717 | 50 |
| jazz | 20.349472 | 15.087119 | 43 |
| hoerspiel | 31.258670 | 6.459370 | 37 |

9.2.3.3 Grouping by multiple columns

Let us find aggregate statistics when we group data by multiple columns. For that, let us create a new categorical column `energy_lvl` that has two levels - *Low energy* and *High energy*, depending on the `energy` of the track.

```
#Creating a new categorical column 'energy_lvl'
spotify_data['energy_lvl'] = pd.qcut(spotify_data.energy,2,labels=['Low energy', 'High energy'])
```

Now, let us find the mean, standard deviation and 90th percentile value of the track popularity for each genre-energy level combination simultaneously.

```
#Grouping the data with 'genres' and 'energy_lvl'
grouped=spotify_data.groupby(['genres','energy_lvl'])

#Finding aggregate statistics of data grouped with multiple columns
grouped['track_popularity'].agg(['mean','std','Ninety_pc'])
```

| | | mean | std | Ninety_pc |
|---------------|-------------|-----------|-----------|-----------|
| genres | energy_lvl | | | |
| country | Low energy | 34.982069 | 19.877274 | 64.0 |
| | High energy | 49.859100 | 18.196092 | 69.0 |
| electronic | Low energy | 43.754789 | 13.294925 | 59.0 |
| | High energy | 43.005671 | 17.290356 | 61.2 |
| folk | Low energy | 29.617831 | 15.360910 | 51.0 |
| | High energy | 29.991957 | 14.556622 | 49.0 |
| hip hop | Low energy | 50.283669 | 12.423124 | 66.0 |
| | High energy | 48.012067 | 12.936656 | 63.0 |
| hoerspiel | Low energy | 31.534779 | 5.953968 | 37.0 |
| | High energy | 30.514032 | 7.609088 | 38.0 |
| jazz | Low energy | 19.421085 | 14.599499 | 41.0 |
| | High energy | 25.715373 | 16.662754 | 50.0 |
| latin | Low energy | 34.308370 | 15.126721 | 53.0 |
| | High energy | 39.992605 | 13.504109 | 58.0 |
| metal | Low energy | 38.612403 | 16.000151 | 60.4 |
| | High energy | 46.985621 | 13.993685 | 64.0 |
| miscellaneous | Low energy | 34.157235 | 16.516910 | 56.0 |
| | High energy | 39.394186 | 15.241620 | 59.0 |
| pop | Low energy | 34.722631 | 18.340408 | 59.0 |
| | High energy | 40.597155 | 16.784034 | 61.0 |
| pop & rock | Low energy | 32.987221 | 15.594202 | 54.0 |

| genres | energy_lvl | mean | std | Ninety_pc |
|--------|-------------|-----------|-----------|-----------|
| rap | High energy | 37.413357 | 15.280915 | 57.0 |
| | Low energy | 57.177966 | 16.491203 | 75.0 |
| | High energy | 48.225166 | 22.182320 | 74.0 |
| rock | Low energy | 34.654871 | 14.387263 | 54.0 |
| | High energy | 38.256199 | 14.133726 | 57.0 |

For most of the genres, there is not much difference between the average popularity of low energy and high energy tracks. However, in case of country tracks people seem to prefer high energy tracks a lot more as compared to low energy tracks.

9.2.3.4 Multiple aggregate functions on multiple columns

Let us find the mean and standard deviation of track popularity and danceability for each genre and energy level.

```
spotify_popularity_danceability = grouped[['track_popularity', 'danceability']].agg(['Average', 'Standard deviation'])
spotify_popularity_danceability
```

| genres | track_popularity | | danceability | |
|---------------|------------------|--------------------|--------------|--------------------|
| | Average | Standard deviation | Average | Standard deviation |
| country | 41.132686 | 20.544338 | 0.600392 | 0.119116 |
| electronic | 43.253165 | 16.075841 | 0.610729 | 0.190133 |
| folk | 29.716767 | 15.150717 | 0.525161 | 0.150081 |
| hip hop | 48.700665 | 12.824901 | 0.719329 | 0.128615 |
| hoerspiel | 31.258670 | 6.459370 | 0.661288 | 0.078628 |
| jazz | 20.349472 | 15.087119 | 0.518045 | 0.149548 |
| latin | 37.563765 | 14.492199 | 0.607981 | 0.152661 |
| metal | 46.334539 | 14.331154 | 0.419201 | 0.125717 |
| miscellaneous | 36.167401 | 16.240129 | 0.576601 | 0.178777 |
| pop | 37.783194 | 17.790385 | 0.588314 | 0.153629 |
| pop & rock | 35.619242 | 15.560975 | 0.545856 | 0.143857 |
| rap | 51.162959 | 20.912240 | 0.723586 | 0.133588 |
| rock | 36.749623 | 14.350580 | 0.520255 | 0.154649 |

We get a couple of insights from the above table:

- High energy songs have higher danceability for most genres as expected. However, for hip-hop, country, rock and hoerspiel, even low-energy songs have comparable danceability.
- Hip hop has the highest danceability as expected. However, high energy rap also has relatively high danceability.

9.2.3.5 Distinct aggregate functions on multiple columns

For aggregating by multiple functions, we pass a list of strings to `agg()`, where the strings are the function names.

For aggregating by multiple functions & changing the column names resulting from those functions, we pass a list of tuples to `agg()`, where each tuple is of length two, and contains the new column name as the first object and the function to be applied as the second object of the tuple.

For aggregating by multiple functions such that a distinct set of functions is applied to each column, we pass a dictionary to `agg()`, where the keys are the column names on which the function is to be applied, and the values are the list of strings that are the function names, or a list of tuples if we also wish to name the aggregated columns.

Example: For each genre and energy level, find the mean and standard deviation of the track popularity, and the minimum and maximum values of loudness.

```
#Specifying arguments to the function as a dictionary if distinct functions are to be applied
grouped.agg({'track_popularity': [('Average', 'mean'), ('Standard deviation', 'std')], 'loudness':
```

| genres | energy_lvl | track_popularity | | loudness | |
|------------|-------------|------------------|--------------------|----------|--------|
| | | Average | Standard deviation | min | max |
| country | Low energy | 34.982069 | 19.877274 | -23.163 | -4.145 |
| | High energy | 49.859100 | 18.196092 | -16.763 | -0.716 |
| electronic | Low energy | 43.754789 | 13.294925 | -60.000 | -4.936 |
| | High energy | 43.005671 | 17.290356 | -19.756 | -0.533 |
| folk | Low energy | 29.617831 | 15.360910 | -28.715 | -0.972 |
| | High energy | 29.991957 | 14.556622 | -16.383 | 0.501 |
| hip hop | Low energy | 50.283669 | 12.423124 | -25.947 | -1.595 |
| | High energy | 48.012067 | 12.936656 | -18.273 | 0.642 |
| hoerspiel | Low energy | 31.534779 | 5.953968 | -29.907 | -4.910 |
| | High energy | 30.514032 | 7.609088 | -22.046 | -2.130 |
| jazz | Low energy | 19.421085 | 14.599499 | -60.000 | -2.962 |
| | High energy | 25.715373 | 16.662754 | -27.563 | -1.166 |
| latin | Low energy | 34.308370 | 15.126721 | -31.897 | -2.331 |

| genres | energy_lvl | track_popularity | | loudness | |
|---------------|-------------|------------------|--------------------|----------|--------|
| | | Average | Standard deviation | min | max |
| metal | High energy | 39.992605 | 13.504109 | -18.357 | -1.204 |
| | Low energy | 38.612403 | 16.000151 | -32.032 | -4.311 |
| miscellaneous | High energy | 46.985621 | 13.993685 | -16.244 | -1.275 |
| | Low energy | 34.157235 | 16.516910 | -44.410 | -1.409 |
| pop | High energy | 39.394186 | 15.241620 | -37.684 | 1.634 |
| | Low energy | 34.722631 | 18.340408 | -41.182 | -0.045 |
| pop & rock | High energy | 40.597155 | 16.784034 | -27.575 | 0.330 |
| | Low energy | 32.987221 | 15.594202 | -60.000 | -1.823 |
| rap | High energy | 37.413357 | 15.280915 | -22.234 | 1.107 |
| | Low energy | 57.177966 | 16.491203 | -23.611 | -1.218 |
| rock | High energy | 48.225166 | 22.182320 | -15.012 | 0.457 |
| | Low energy | 34.654871 | 14.387263 | -42.488 | -1.708 |
| | High energy | 38.256199 | 14.133726 | -25.291 | 3.744 |

From the above table, we observe that high energy songs are always louder than low energy songs. High energy Rock songs can be very loud.

9.3 `apply()`: Data aggregation, filtering & transformation

With the `apply()` method of the *GroupBy* object, we can perform several operations on groups, other than data aggregation.

9.3.1 Filtering data by group

Example: Find the top 3 most popular tracks of each genre in the spotify dataset.

We'll first define a function that sorts a dataset by decreasing track popularity and returns the top 3 rows. Then, we'll apply this function on each group using the `apply()` method of the *GroupBy* object.

```
#Defining the function that finds the top 3 most popular tracks from the dataset 'x'
def top_stats(x,col='track_popularity',n=3):
    return x.sort_values(by=col,ascending = False)[0:n]

#Defining the groups in the spotify data
grouped_spotify_data = spotify_data.groupby('genres')
```

Now we'll use the `apply()` method to apply the `top_stats()` function on each group of the object `grouped_spotify_data`.

```
#Top 3 tracks of each genre
top3_tracks = grouped_spotify_data.apply(top_stats)
top3_tracks.head()
```

| | | artist_followers | genres | artist_name | artist_popularity | track_name | tra |
|------------|-------|------------------|------------|---------------|-------------------|-------------------|-----|
| genres | | | | | | | |
| country | 4047 | 4755356 | country | Luke Combs | 85 | Forever After All | 82 |
| | 2403 | 1678738 | country | Morgan Wallen | 88 | Wasted On You | 81 |
| | 16244 | 1678738 | country | Morgan Wallen | 88 | Whiskey Glasses | 81 |
| electronic | 83058 | 7650304 | electronic | Daft Punk | 86 | One More Time | 81 |
| | 13068 | 28026432 | electronic | Alan Walker | 85 | Faded | 80 |

The `top_stats()` function is applied to each group, and the results are concatenated internally with the `concat()` function. The output therefore has a hierarchical index whose outer level indices are the group keys.

We can also use a lambda function instead of separately defining the function `top_tracks()`:

```
#Top 3 tracks of each genre - using lambda function
top3_tracks = grouped_spotify_data.apply(lambda x:x.sort_values(by = 'track_popularity',as
top3_tracks.head()
```

| | | artist_followers | genres | artist_name | artist_popularity | track_name | tra |
|------------|-------|------------------|------------|---------------|-------------------|-------------------|-----|
| genres | | | | | | | |
| country | 4047 | 4755356 | country | Luke Combs | 85 | Forever After All | 82 |
| | 2403 | 1678738 | country | Morgan Wallen | 88 | Wasted On You | 81 |
| | 16244 | 1678738 | country | Morgan Wallen | 88 | Whiskey Glasses | 81 |
| electronic | 83058 | 7650304 | electronic | Daft Punk | 86 | One More Time | 81 |
| | 13068 | 28026432 | electronic | Alan Walker | 85 | Faded | 80 |

We can also pass arguments to the `top_stats()` function with the `apply()` function.

Example: Find the most popular artist from each genre.

```
#Applying the 'top_stats()' function to each group of the data (based on 'genre') to find
#Dropping the inner row label as it is not informative
grouped_spotify_data.apply(top_stats,col='artist_popularity',n=1)['artist_name'].droplevel
```

```

genres
country          Morgan Wallen
electronic        Daft Punk
folk              Bon Iver
hip hop           Eminem
hoerspiel         Die drei ???
jazz              Earth, Wind & Fire
latin             Maluma
metal             Linkin Park
miscellaneous     Pop Smoke
pop               Justin Bieber
pop & rock         Maroon 5
rap               Bad Bunny
rock              Imagine Dragons
Name: artist_name, dtype: object

```

9.3.2 Practice exercise 2

Filter the first 4 columns of the spotify dataset. Drop duplicate observations in the resulting dataset using the Pandas DataFrame method `drop_duplicates()`. Find the top 3 most popular artists for each genre.

Solution:

```
spotify_data.iloc[:,0:4].drop_duplicates().groupby('genres').apply(lambda x:x.sort_values(
```

9.3.3 Transforming data by group

Recall [method 3](#) for imputing missing values in Chapter 7. The method was to impute missing values based on correlated variables in data.

In the example shown for the method, values of GDP per capita for a few countries were missing. We imputed the missing value of GDP per capita for those countries as the average GDP per capita of the corresponding continent.

We will compare the approach we used with the approach using the `groupby()` & `apply()` methods.

Let us read the datasets and the function that makes a visualization to compare the imputed values with the actual values.

```

#Importing data with missing values
gdp_missing_data = pd.read_csv('./Datasets/GDP_missing_data.csv')

#Importing data with all values
gdp_complete_data = pd.read_csv('./Datasets/GDP_complete_data.csv')

#Index of rows with missing values for GDP per capita
null_ind_gdpPC = gdp_missing_data.index[gdp_missing_data.gdpPerCapita.isnull()]

#Defining a function to plot the imputed values vs actual values
def plot_actual_vs_predicted():
    fig, ax = plt.subplots(figsize=(8, 6))
    plt.rc('xtick', labels=15)
    plt.rc('ytick', labels=15)
    x = gdp_complete_data.loc[null_ind_gdpPC, 'gdpPerCapita']
    y = gdp_imputed_data.loc[null_ind_gdpPC, 'gdpPerCapita']
    plt.scatter(x, y)
    z = np.polyfit(x, y, 1)
    p = np.poly1d(z)
    plt.plot(x, p(x), color='orange')
    plt.xlabel('Actual GDP per capita', fontsize=20)
    plt.ylabel('Imputed GDP per capita', fontsize=20)
    ax.xaxis.set_major_formatter('${x:,.0f}')
    ax.yaxis.set_major_formatter('${x:,.0f}')
    rmse = np.sqrt(((x-y).pow(2)).mean())
    print("RMSE=", rmse)

```

Approach 1: Using the approach we used in Section [7.1.5.3](#)

```

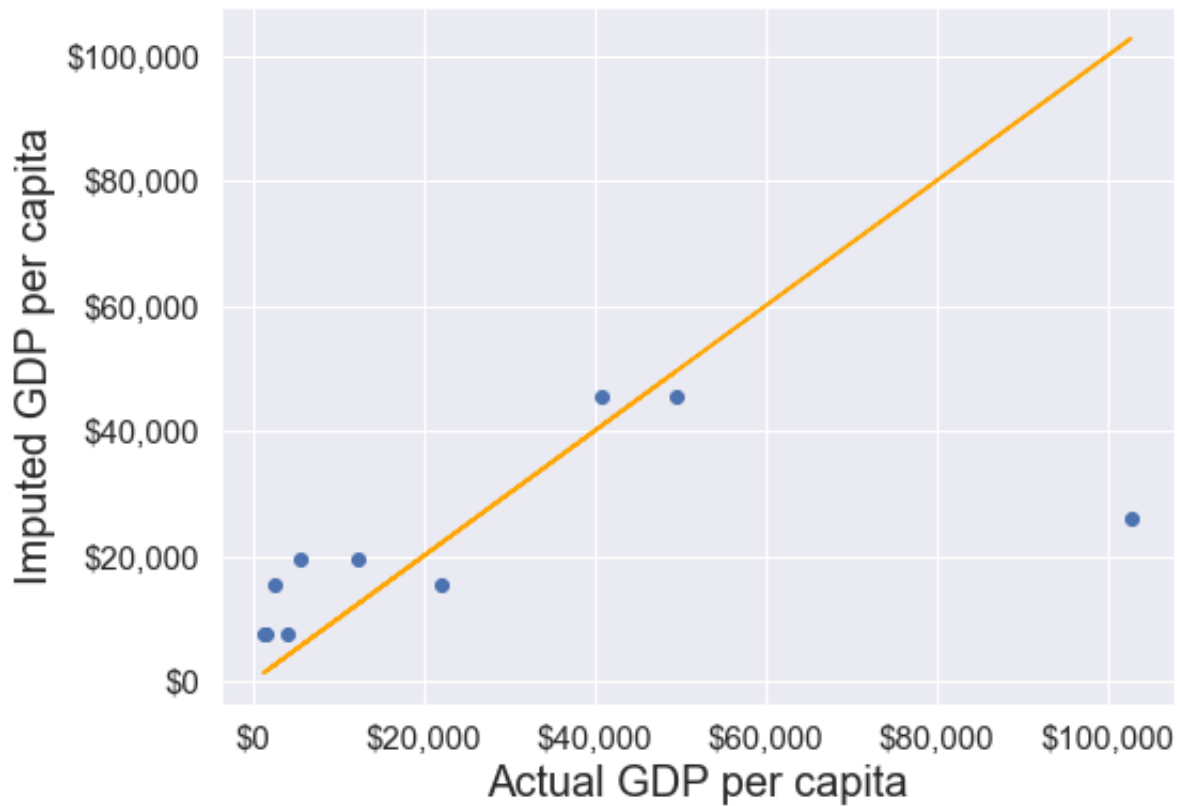
#Finding the mean GDP per capita of the continent
avg_gdpPerCapita = gdp_missing_data['gdpPerCapita'].groupby(gdp_missing_data['continent'])

#Creating a copy of missing data to impute missing values
gdp_imputed_data = gdp_missing_data.copy()

#Replacing missing GDP per capita with the mean GDP per capita for the corresponding conti
for cont in avg_gdpPerCapita.index:
    gdp_imputed_data.loc[(gdp_imputed_data.continent==cont) & (gdp_imputed_data.gdpPerCapi
        'gdpPerCapita']=avg_gdpPerCapita[cont]
plot_actual_vs_predicted()

```

RMSE= 25473.20645170116



Approach 2: Using the `groupby()` and `apply()` methods.

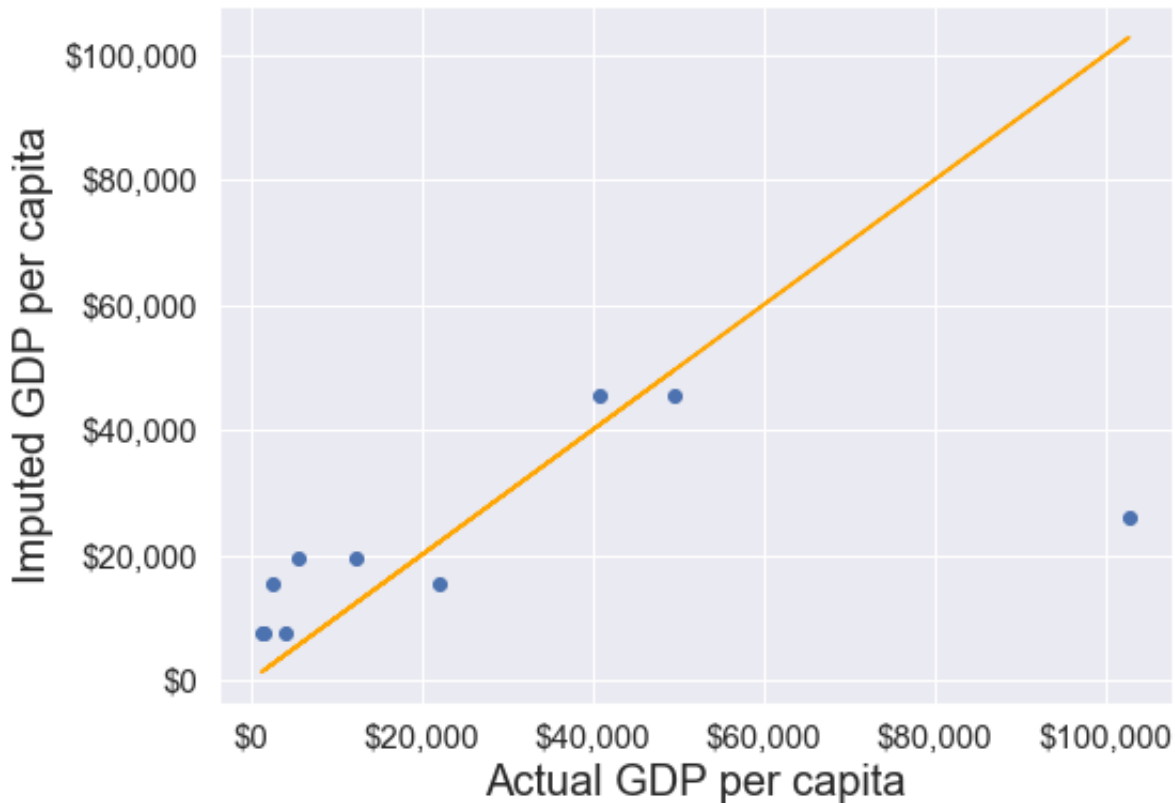
```
#Creating a copy of missing data to impute missing values
gdp_imputed_data = gdp_missing_data.copy()

#Grouping data by continent
grouped = gdp_missing_data.groupby('continent')

#Applying the lambda function on the 'gdpPerCapita' column of the groups
gdp_imputed_data['gdpPerCapita'] = grouped['gdpPerCapita'].apply(lambda x: x.fillna(x.mean()))

plot_actual_vs_predicted()
```

RMSE= 25473.20645170116



With the `apply()` function, the missing value of `gdpPerCapita` for observations of each group are filled by the mean `gdpPerCapita` of that group. The code is not only more convenient to write, but also faster as compared to `for` loops. The `for` loop imputes the missing values of observations of one group at a time, while the imputation may happen in parallel for all groups with the `apply()` function.

9.3.4 Sampling data by group

The `groupby()` and `apply()` method can be used to for stratified random sampling from a large dataset.

The spotify dataset has more than 200k observations. It may be expensive to operate with so many observations. Suppose, we wish to take a random sample of 650 observations to analyze spotify data, such that all genres are equally represented.

Before taking the random sample, let us find the number of tracks in each genre.

```
spotify_data.genres.value_counts()
```

| | |
|---------------|-------|
| pop | 70441 |
| rock | 49785 |
| pop & rock | 43437 |
| miscellaneous | 35848 |
| jazz | 13363 |
| hoerspiel | 12514 |
| hip hop | 7373 |
| folk | 2821 |
| latin | 2125 |
| rap | 1798 |
| metal | 1659 |
| country | 1236 |
| electronic | 790 |

Name: genres, dtype: int64

Let us take a random sample of 650 observations from the entire dataset.

```
sample_spotify_data = spotify_data.sample(650)
```

Now, let us see the number of track of each genre in our sample.

```
sample_spotify_data.genres.value_counts()
```

| | |
|---------------|-----|
| pop | 185 |
| rock | 150 |
| miscellaneous | 102 |
| pop & rock | 98 |
| jazz | 37 |
| hoerspiel | 25 |
| hip hop | 22 |
| rap | 7 |
| metal | 7 |
| latin | 5 |
| country | 5 |
| folk | 5 |
| electronic | 2 |

Name: genres, dtype: int64

Some of the genres have a very low representation in the data. To rectify this, we can take a random sample of 50 observations from each of the 13 genres. In other words, we can take a random sample from each of the genre-based groups.


```
evenly_sampled_spotify_data = spotify_data.groupby('genres').apply(lambda x:x.sample(50))
evenly_sampled_spotify_data.genres.value_counts()
```

```
hoerspiel      50
hip hop        50
pop & rock     50
latin          50
country        50
rap            50
electronic     50
metal          50
folk           50
pop            50
miscellaneous  50
rock           50
jazz           50
Name: genres, dtype: int64
```

The above stratified random sample equally represents all the genres.

9.4 `corr()`: Correlation by group

The `corr()` method of the *GroupBy* object returns the correlation between all pairs of columns within each group.

Example: Find the correlation between danceability and track popularity for each genre-energy level combination.

```
spotify_data.groupby(['genres','energy_lvl']).apply(lambda x:x['danceability'].corr(x['tra
```

```
genres      energy_lvl
country    Low energy  -0.171830
           High energy -0.154823
electronic  Low energy  0.378330
           High energy  0.072343
folk        Low energy  0.187482
           High energy  0.230419
hip hop     Low energy  0.113421
           High energy  0.027074
```

```

hoerspiel      Low energy  -0.053908
               High energy -0.044211
jazz           Low energy   0.005733
               High energy  0.332356
latin          Low energy  -0.083971
               High energy  0.030276
metal          Low energy   0.127439
               High energy  0.256165
miscellaneous  Low energy   0.163185
               High energy  0.148818
pop            Low energy   0.208942
               High energy  0.156764
pop & rock     Low energy   0.063127
               High energy  0.060195
rap            Low energy  -0.008394
               High energy -0.129873
rock           Low energy   0.027876
               High energy  0.065908
dtype: float64

```

The popularity of low energy electronic music is the most correlated with its danceability.

9.5 `pivot_table()`

The Pandas `pivot_table()` function is used to aggregate data groupwise where some of the group keys are along the rows and some along the columns. Note that `pivot_table()` is the same as `pivot()` except that `pivot_table()` aggregates the data as well in addition to re-arranging it.

Example: Find the mean of track popularity for each genre-energy lvl combination such that each row corresponds to a genre, and the energy levels correspond to columns.

```
pd.pivot_table(data = spotify_data, values = 'track_popularity', index = 'genres', columns =
```

| energy_lvl genres | Low energy | High energy | All |
|----------------------|------------|-------------|-----------|
| country | 34.982069 | 49.859100 | 41.132686 |
| electronic | 43.754789 | 43.005671 | 43.253165 |
| folk | 29.617831 | 29.991957 | 29.716767 |
| hip hop | 50.283669 | 48.012067 | 48.700665 |

| energy_lvl genres | Low energy | High energy | All |
|----------------------|------------|-------------|-----------|
| hoerspiel | 31.534779 | 30.514032 | 31.258670 |
| jazz | 19.421085 | 25.715373 | 20.349472 |
| latin | 34.308370 | 39.992605 | 37.563765 |
| metal | 38.612403 | 46.985621 | 46.334539 |
| miscellaneous | 34.157235 | 39.394186 | 36.167401 |
| pop | 34.722631 | 40.597155 | 37.783194 |
| pop & rock | 32.987221 | 37.413357 | 35.619242 |
| rap | 57.177966 | 48.225166 | 51.162959 |
| rock | 34.654871 | 38.256199 | 36.749623 |
| All | 33.015545 | 39.151701 | 36.080772 |

We can use also use custom *GroupBy* aggregate functions with `pivot_table()`.

Example: Find the 90th percentile of track popularity for each genre-energy lvl combination such that each row corresponds to a genre, and the energy levels correspond to columns.

```
pd.pivot_table(data = spotify_data, values = 'track_popularity', index = 'genres', columns =
```

| energy_lvl genres | Low energy | High energy |
|----------------------|------------|-------------|
| country | 64.0 | 69.0 |
| electronic | 59.0 | 61.2 |
| folk | 51.0 | 49.0 |
| hip hop | 66.0 | 63.0 |
| hoerspiel | 37.0 | 38.0 |
| jazz | 41.0 | 50.0 |
| latin | 53.0 | 58.0 |
| metal | 60.4 | 64.0 |
| miscellaneous | 56.0 | 59.0 |
| pop | 59.0 | 61.0 |
| pop & rock | 54.0 | 57.0 |
| rap | 75.0 | 74.0 |
| rock | 54.0 | 57.0 |

9.6 crosstab()

The `crosstab()` method is a special case of a pivot table for computing group frequencies (or size of each group). We may often use it to check if the data is representative of all groups that are of interest to us.

Example: Find the number of observations in each group, where each groups corresponds to a distinct genre-energy lvl combination

```
#Cross tabulation of 'genres' and 'energy_lvl'  
pd.crosstab(spotify_data.genres,spotify_data.energy_lvl,margins = True).sort_values(by = '')
```

| energy_lvl genres | Low energy | High energy | All |
|----------------------|------------|-------------|--------|
| All | 121708 | 121482 | 243190 |
| pop | 33742 | 36699 | 70441 |
| rock | 20827 | 28958 | 49785 |
| pop & rock | 17607 | 25830 | 43437 |
| miscellaneous | 22088 | 13760 | 35848 |
| jazz | 11392 | 1971 | 13363 |
| hoerspiel | 9129 | 3385 | 12514 |
| hip hop | 2235 | 5138 | 7373 |
| folk | 2075 | 746 | 2821 |
| latin | 908 | 1217 | 2125 |
| rap | 590 | 1208 | 1798 |
| metal | 129 | 1530 | 1659 |
| country | 725 | 511 | 1236 |
| electronic | 261 | 529 | 790 |

The above table can be generated with the `pivot_table()` function using `'count'` as the `aggfunc` argument, as shown below. However, the `crosstab()` function is more compact to code.

```
#Generating cross-tabulation of 'genres' and 'energy_lvl' with 'pivot_table()'  
pd.pivot_table(data = spotify_data,values = 'track_popularity',index = 'genres', columns = '')
```

| energy_lvl genres | Low energy | High energy | All |
|----------------------|------------|-------------|------|
| country | 725 | 511 | 1236 |
| electronic | 261 | 529 | 790 |

| energy_lvl genres | Low energy | High energy | All |
|----------------------|------------|-------------|--------|
| folk | 2075 | 746 | 2821 |
| hip hop | 2235 | 5138 | 7373 |
| hoerspiel | 9129 | 3385 | 12514 |
| jazz | 11392 | 1971 | 13363 |
| latin | 908 | 1217 | 2125 |
| metal | 129 | 1530 | 1659 |
| miscellaneous | 22088 | 13760 | 35848 |
| pop | 33742 | 36699 | 70441 |
| pop & rock | 17607 | 25830 | 43437 |
| rap | 590 | 1208 | 1798 |
| rock | 20827 | 28958 | 49785 |
| All | 121708 | 121482 | 243190 |

Example: Find the percentage of observations in each group of the above table.

```
pd.crosstab(spotify_data.genres,spotify_data.energy_lvl,margins = True).sort_values(by = 'All')
```

| energy_lvl genres | Low energy | High energy | All |
|----------------------|------------|-------------|------------|
| All | 50.046466 | 49.953534 | 100.000000 |
| pop | 13.874748 | 15.090670 | 28.965418 |
| rock | 8.564086 | 11.907562 | 20.471648 |
| pop & rock | 7.240018 | 10.621325 | 17.861343 |
| miscellaneous | 9.082610 | 5.658127 | 14.740738 |
| jazz | 4.684403 | 0.810477 | 5.494881 |
| hoerspiel | 3.753855 | 1.391916 | 5.145771 |
| hip hop | 0.919034 | 2.112751 | 3.031786 |
| folk | 0.853242 | 0.306756 | 1.159998 |
| latin | 0.373371 | 0.500432 | 0.873802 |
| rap | 0.242609 | 0.496731 | 0.739340 |
| metal | 0.053045 | 0.629138 | 0.682183 |
| country | 0.298121 | 0.210124 | 0.508245 |
| electronic | 0.107323 | 0.217525 | 0.324849 |

9.6.1 Practice exercise 3

What percentage of unique tracks are contributed by the top 5 artists of each genre?

Hint: Find the top 5 artists based on `artist_popularity` for each genre. Count the total number of unique tracks (`track_name`) contributed by these artists. Divide this number by the total number of unique tracks in the data. The `nunique()` function will be useful.

Solution:

```
top5artists = spotify_data.iloc[:,0:4].drop_duplicates().groupby('genres').apply(lambda x:
                                         ascending = False)[0:5]).droplevel(axis=0,level=1)['artist_name']
top5artists_tracks = spotify_data.loc[spotify_data.artist_name.isin(top5artists),:]
top5artists_tracks.track_name.nunique()/spotify_data.track_name.nunique()
```

10 Alternative solutions by students

This chapter will consist of solutions suggested by students of the STAT303-1 Fall 2022 class, which are more efficient than those presented in the book. However, these solutions do not replace those in the book to preserve the simplicity of the book.

10.1 Missing value imputation based on correlated variables in the data

The code below refers to **Section 7.1.5.3** of the book. Students have proposed some ways to avoid a **for** loop in the code, which will lead to parallel computations, thereby saving execution time.

10.1.1 Original code (in the book)

```
start_time = tm.time()
gdp_imputed_data = gdp_missing_values_data.copy()
for cont in avg_gdpPerCapita.index:
    gdp_imputed_data.loc[(gdp_imputed_data.continent==cont) & (gdp_imputed_data.gdpPerCapita.isnull())
                        'gdpPerCapita']=avg_gdpPerCapita[cont]
plot_actual_vs_predicted()
print("Time taken to execute code: ",np.round(tm.time()-start_time,3), "seconds")
```

RMSE= 25473.20645170116

Time taken to execute code: 0.032 seconds



Below are some more efficient ways to impute the missing values, as they avoid using the `for` loop.

10.1.2 Alternative code 1:

By Victoria Shi

```
start_time = tm.time()
gdp_imputed_data = gdp_missing_values_data.copy()
gdp_imputed_data["gdpPerCapita"] = gdp_missing_values_data[['continent', 'gdpPerCapita']].
plot_actual_vs_predicted()
print("Time taken to execute code: ", np.round(tm.time()-start_time, 3), "seconds")
```

RMSE= 25473.20645170116

Time taken to execute code: 0.024 seconds



10.1.3 Alternative code 2:

By Elijah Nacar

```
start_time = tm.time()
gdp_imputed_data = gdp_missing_values_data.copy()
gdp_imputed_data.gdpPerCapita = gdp_imputed_data.apply(lambda x: avg_gdpPerCapita[x['conti
plot_actual_vs_predicted()
print("Time taken to execute code: ",np.round(tm.time()-start_time,3), "seconds")
```

RMSE= 25473.20645170116

Time taken to execute code: 0.024 seconds



10.1.4 Alternative code 3:

By Erica Zhou

```
start_time = tm.time()
gdp_imputed_data = gdp_missing_values_data.copy()

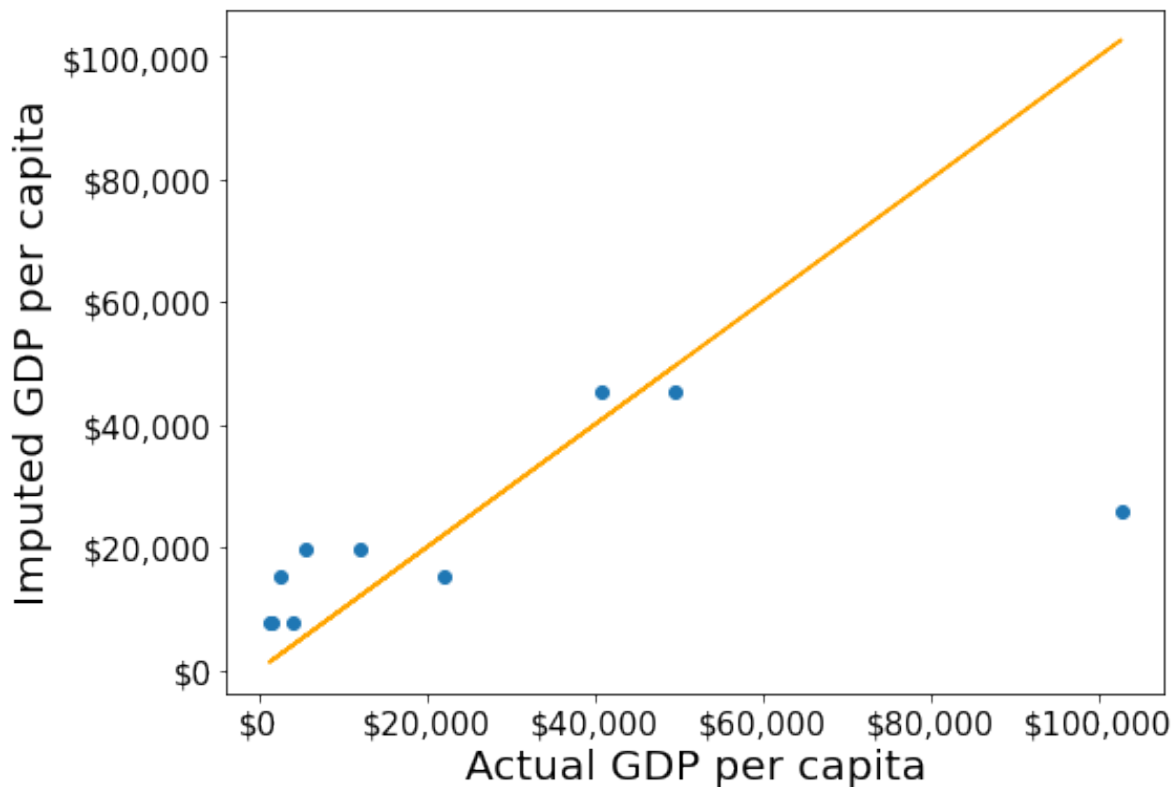
cond_list = [gdp_imputed_data['continent'] == 'Africa',gdp_imputed_data['continent'] == 'A
              gdp_imputed_data['continent'] == 'Europe',gdp_imputed_data['continent'] == 'N
              gdp_imputed_data['continent'] == 'Oceania',gdp_imputed_data['continent'] == '

choice_list = list(avg_gdpPerCapita)

gdp_imputed_data.gdpPerCapita = np.select(cond_list, choice_list, gdp_imputed_data.gdpPerC
plot_actual_vs_predicted()
print("Time taken to execute code: ",np.round(tm.time()-start_time,3), "seconds")
```

RMSE= 25473.20645170116

Time taken to execute code: 0.024 seconds



10.2 Binning with equal sized bins

The code below refers to **Section 7.2.2** of the book. A student has proposed a way to avoid the `for` loop in the code, which will lead to parallel computations, thereby saving execution time.

10.2.1 Original code (in the book)

```
#Bootstrapping to find 95% confidence intervals of Graduation Rate of US universities base
start_time = tm.time()
for expend_bin in college.Expend_bin.unique():
    data_sub = college.loc[college.Expend_bin==expend_bin,:]
    samples = np.random.choice(data_sub['Grad.Rate'], size=(10000,data_sub.shape[0]))
    print("95% Confidence interval of Grad.Rate for "+expend_bin+" univeristies = ["+str(n
```

```
print("Time taken to execute code: ",np.round(tm.time()-start_time,3), "seconds")
```

```
95% Confidence interval of Grad.Rate for Low expend univeristies = [55.31,59.35]
95% Confidence interval of Grad.Rate for High expend univeristies = [71.03,74.9]
95% Confidence interval of Grad.Rate for Med expend univeristies = [64.17,67.95]
Time taken to execute code: 0.151 seconds
```

10.2.2 Alternative code:

By Victoria Shi

```
start_time = tm.time()
def confidence_interval(df):
    samples = np.random.choice(df['Grad.Rate'], size=(10000, df.shape[0]))
    print("95% Confidence interval of Grad.Rate for "+df["Expend_bin"].iloc[0]+" univeristies = ",np.percentile(samples,5),np.percentile(samples,95))
college.groupby('Expend_bin').apply(confidence_interval)
print("Time taken to execute code: ",np.round(tm.time()-start_time,3), "seconds")
```

```
95% Confidence interval of Grad.Rate for Low expend univeristies = [55.35,59.35]
95% Confidence interval of Grad.Rate for Med expend univeristies = [64.16,67.95]
95% Confidence interval of Grad.Rate for High expend univeristies = [71.05,74.96]
Time taken to execute code: 0.139 seconds
```

A Datasets & Templates

Datasets used in the book, and assignment / project templates can be found [here](#)

References

Rubin, Donald B. 1976. "Inference and Missing Data." *Biometrika* 63 (3): 581–92.