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

Prerequisite: Python programming

1 Python Basics

This chapter is a very brief introduction to python. 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 Python language basics

1.1.1 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.

1.1.2 Assigning variable name to object

1.1.2.1 Call by reference

Python utilizes a system, which is known as *Call by Object Reference*. 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.

1.1.2.2 Assigning multiple variable names

Values can be assigned to multiple variables in a single statement by separating the variable names and values with commas.

```
color1, color2, color3 = "red", "green", "blue"
```

```
color1
```

```
'red'
```

```
color3
```

```
'blue'
```

The same value can be assigned to multiple variables by chaining multiple assignment operations within a single statement.

```
color4 = color5 = color6 = "magenta"
```

1.1.2.3 Rules for variable names

Variable names can be short (`a`, `x`, `y`, etc.) or descriptive (`my_favorite_color`, `profit_margin`, `the_3_musketeers`, etc.). However, we recommend that you use descriptive variable names as it makes it easier to understand the code.

The rules below must be followed while naming Python variables:

- A variable's name must start with a letter or the underscore character `_`. It cannot begin with a number.
- A variable name can only contain lowercase (small) or uppercase (capital) letters, digits, or underscores (`a-z`, `A-Z`, `0-9`, and `_`).
- Variable names are case-sensitive, i.e., `a_variable`, `A_Variable`, and `A_VARIABLE` are all different variables.

Here are some valid variable names:

```
a_variable = 23
is_today_Saturday = False
my_favorite_car = "Delorean"
the_3_musketeers = ["Athos", "Porthos", "Aramis"]
```

Let's try creating some variables with invalid names. Python prints a syntax error if the variable's name is invalid.

> **Syntax**: The syntax of a programming language refers to the rules that govern the structure of a valid instruction or *statement*. If a statement does not follow these rules, Python stops execution and informs you that there is a *syntax error*. Syntax can be thought of as the rules of grammar for a programming language.

```
a variable = 23
```

```
is_today_$aturday = False
```

```
my-favorite-car = "Delorean"
```

```
3_musketeers = ["Athos", "Porthos", "Aramis"]
```

1.1.3 Built-in objects

1.1.3.1 Built-in data types

Variable is created as soon as a value is assigned to it. We don't have to define the type of variable explicitly as in other programming languages because Python can automatically guess the type of data entered **(dynamically typed)**.

Any data or information stored within a Python variable has a *type*. We can view the type of data stored within a variable using the `type` function.

```
a_variable
```

```
23
```

```
type(a_variable)
```

```
int
```

```python
is_today_Saturday
```

```
False
```

```python
type(is_today_Saturday)
```

```
bool
```

```python
my_favorite_car
```

```
'Delorean'
```

```python
type(my_favorite_car)
```

```
str
```

```python
the_3_musketeers
```

```
['Athos', 'Porthos', 'Aramis']
```

```python
type(the_3_musketeers)
```

```
list
```

Python has several built-in data types for storing different kinds of information in variables.

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

Primitive: Integer, float, boolean, None, and string are *primitive data types* because they represent a single value.

Containers: Other data types like list, tuple, and dictionary are often called *data structures* or *containers* because they hold multiple pieces of data together. We'll discuss these datatypes in chapter 2.

The data type of the object can be identified using the in-built python function `type()`. For example, see the following objects and their types:

```python
type(4)
```

```
int
```

```python
type(4.4)
```

```
float
```

```python
type('4')
```

```
str
```

```python
type(True)
```

```
bool
```

1.1.3.2 Built-in modules and functions

Built-in functions in Python are a set of predefined functions that are available for use without the need to import any additional libraries or modules. The Python Standard Library is very extensive. Besides built-in functions, it also contains many Python scripts (with the `.py` extension) containing useful utilities and modules written in Python that provide standardized solutions for many problems that occur in everyday programming.

Below are a couple of examples:

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:

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

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

The advantage of the range type over a regular list or tuple is that a range object will always take the same (small) amount of memory, no matter the size of the range it represents (as it only stores the start, stop and step values, calculating individual items and subranges as needed).

Date time: Python as 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'
```

1.1.4 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 a analyzing data. Some of the popular libraries and their primary purposes are as follows:

1. **NumPy**: NumPy is a fundamental library for numerical computing in Python. It provides support for arrays, matrices, and mathematical functions, making it essential for scientific and data analysis tasks.. It is mostly used for performing numerical operations and efficiently storing numerical data.
2. **Pandas**: Pandas is a powerful data manipulation and analysis library. It offers data structures like DataFrames and Series, which facilitate data reading, cleaning, transformation, and analysis, making it indispensable in data science projects.
3. **Matplotlib, Seaborn**: Matplotlib is a comprehensive library for creating static, animated, or interactive plots and visualizations. It is commonly used for data visualization and exploration in data science. Seaborn is a Python data visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics.
4. **SciPy**: SciPy is used for performing scientific computing such as solving differential equations, optimization, statistical tests, etc.
5. **Scikit-learn**: Scikit-learn is a machine learning library that provides a wide range of tools for data pre-procesing, classification, regression, clustering, dimensionality reduction, and more. It simplifies the implementation of machine learning algorithms and model evaluation.
6. **Statsmodels**: Statsmodels is used for developing statistical models with a focus on inference *(in contrast to focus on prediction as in scikit-learn)*.

To use libraries like NumPy, pandas, Matplotlib, and scikit-learn in Python, you typically need to follow these steps:

1. Install the libraries (Anaconda already does this)
2. Import the libraries in the python script or jupyter notebook
3. Use the Library Functions and Classes: After importing the libraries, you can use their functions, classes, and methods in your code. For instance, you can create NumPy arrays, manipulate data with pandas, create plots with Matplotlib, or train machine learning models with scikit-learn.

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` keyboard, 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])
```

There's different ways to import:

- Import the whole module using its original name: `import math, os`
- Import specific things from the module: `from random import randint from math import pi`
- Import the whole library and rename it, usually using a shorter variable name: `import pandas as pd`
- Import a specific method from the module and rename it as it is imported: `from os.path import join as join_path`

1.1.5 User-defined functions

A function is a reusable set of instructions that takes one or more inputs, performs some operations, and often returns an output. **Indeed, while python's standard library and ecosystem libraries offer a wealth of pre-defined functions for a wide range of tasks, there are situations where defining your own functions is not just beneficial but necessary.**

1.1.5.1 Creating and using functions

You can define a new function using the def keyword.

```
def say_hello():
    print('Hello there!')
    print('How are you?')
```

Note the round brackets or parentheses `()` and colon `:` after the function's name. Both are essential parts of the syntax. The function's *body* contains an indented block of statements.

The statements inside a function's body are not executed when the function is defined. To execute the statements, we need to *call* or *invoke* the function.

```
say_hello()
```

```
Hello there!
How are you?
```

```
def say_hello_to(name):
    print('Hello ', name)
    print('How are you?')
```

```
say_hello_to('Lizhen')
```

```
Hello  Lizhen
How are you?
```

```
name = input ('Please enter your name: ')
say_hello_to(name)
```

```
Please enter your name: George
Hello  George
How are you?
```

1.1.5.2 Variable scope: Local and global Variables

Local variable: When we declare variables inside a function, these variables will have a local scope (within the function). We cannot access them outside the function. These types of variables are called local variables. For example,

```
def greet():
    message = 'Hello'  # local variable
    print('Local', message)
greet()
```

```
Local Hello
```

```python
print(message) # try to access message variable outside greet() function
```

```
NameError: name 'message' is not defined
```

As `message` was defined within the function `greet()`, it is local to the function, and cannot be called outside the function.

Global variable: Aa variable declared outside of the function or in global scope is known as a global variable. This means that a global variable can be accessed inside or outside of the function.

Let's see an example of how a global variable is created.

```python
message = 'Hello'  # declare global variable

def greet():
    print('Local', message)  # declare local variable

greet()
print('Global', message)
```

```
Local Hello
Global Hello
```

1.1.5.3 Named arguments

Invoking a function with many arguments can often get confusing and is prone to human errors. Python provides the option of invoking functions with *named* arguments for better clarity. You can also split function invocation into multiple lines.

```python
def loan_emi(amount, duration, rate, down_payment=0):
    loan_amount = amount - down_payment
    emi = loan_amount * rate * ((1+rate)**duration) / (((1+rate)**duration)-1)
    return emi
```

```python
emi1 = loan_emi(
    amount=1260000,
    duration=8*12,
    rate=0.1/12,
    down_payment=3e5
```

```
)
```

```
emi1
```

```
14567.19753389219
```

1.1.5.4 Optional Arguments

Functions with optional arguments offer more flexibility in how you can use them. You can call the function with or without the argument, and if there is no argument in the function call, then a default value is used.

```
emi2 = loan_emi(
    amount=1260000,
    duration=8*12,
    rate=0.1/12)

emi2
```

```
19119.4467632335
```

1.1.5.5 *args and **kwargs

We can pass a variable number of arguments to a function using special symbols. There are two special symbols:

Special Symbols Used for passing arguments: 1. *args (Non-Keyword Arguments) 2. **kwargs (Keyword Arguments) > Note: "We use the "wildcard" or "" notation like this – *args OR **kwargs – as our function's argument when we have doubts about the number of arguments we should pass in a function."*

```
def myFun(*args,**kwargs):
    print("args: ", args)
    print("kwargs: ", kwargs)


# Now we can use both *args ,**kwargs
# to pass arguments to this function :
myFun('John',22,'cs',name="John",age=22,major="cs")
```

```
args:  ('John', 22, 'cs')
kwargs:  {'name': 'John', 'age': 22, 'major': 'cs'}
```

1.1.6 Branching and looping (control flow)

As in other languages, python has built-in keywords that provide conditional flow of control in the code.

1.1.6.1 Branching with `if`, `else` and `elif`

One of the most powerful features of programming languages is *branching*: the ability to make decisions and execute a different set of statements based on whether one or more conditions are true.

The `if` statement

In Python, branching is implemented using the `if` statement, which is written as follows:

```
if condition:
    statement1
    statement2
```

The `condition` can be a value, variable or expression. If the condition evaluates to `True`, then the statements within the *`if` block* are executed. Notice the four spaces before `statement1`, `statement2`, etc. The spaces inform Python that these statements are associated with the `if` statement above. This technique of structuring code by adding spaces is called *indentation*.

> **Indentation**: Python relies heavily on *indentation* (white space before a statement) to define code structure. This makes Python code easy to read and understand. You can run into problems if you don't use indentation properly. Indent your code by placing the cursor at the start of the line and pressing the `Tab` key once to add 4 spaces. Pressing `Tab` again will indent the code further by 4 more spaces, and press `Shift+Tab` will reduce the indentation by 4 spaces.

For example, let's write some code to check and print a message if a given number is even.

```python
a_number = 34
```

```python
if a_number % 2 == 0:
    print("We're inside an if block")
    print('The given number {} is even.'.format(a_number))
```

```
We're inside an if block
The given number 34 is even.
```

The `else` statement

We may want to print a different message if the number is not even in the above example. This can be done by adding the `else` statement. It is written as follows:

```
if condition:
    statement1
    statement2
else:
    statement4
    statement5
```

If `condition` evaluates to `True`, the statements in the `if` block are executed. If it evaluates to `False`, the statements in the `else` block are executed.

```python
if a_number % 2 == 0:
    print('The given number {} is even.'.format(a_number))
else:
    print('The given number {} is odd.'.format(a_number))
```

```
The given number 34 is even.
```

The `elif` statement

Python also provides an `elif` statement (short for "else if") to chain a series of conditional blocks. The conditions are evaluated one by one. For the first condition that evaluates to `True`, the block of statements below it is executed. The remaining conditions and statements are not evaluated. So, in an `if`, `elif`, `elif`… chain, at most one block of statements is executed, the one corresponding to the first condition that evaluates to `True`.

```python
today = 'Wednesday'
```

```python
if today == 'Sunday':
    print("Today is the day of the sun.")
elif today == 'Monday':
    print("Today is the day of the moon.")
elif today == 'Tuesday':
    print("Today is the day of Tyr, the god of war.")
```

```python
elif today == 'Wednesday':
    print("Today is the day of Odin, the supreme diety.")
elif today == 'Thursday':
    print("Today is the day of Thor, the god of thunder.")
elif today == 'Friday':
    print("Today is the day of Frigga, the goddess of beauty.")
elif today == 'Saturday':
    print("Today is the day of Saturn, the god of fun and feasting.")
```

```
Today is the day of Odin, the supreme diety.
```

In the above example, the first 3 conditions evaluate to `False`, so none of the first 3 messages are printed. The fourth condition evaluates to `True`, so the corresponding message is printed. The remaining conditions are skipped. Try changing the value of `today` above and re-executing the cells to print all the different messages.

Using `if`, `elif`, and `else` together

You can also include an `else` statement at the end of a chain of `if`, `elif`… statements. This code within the `else` block is evaluated when none of the conditions hold true.

```python
a_number = 49
```

```python
if a_number % 2 == 0:
    print('{} is divisible by 2'.format(a_number))
elif a_number % 3 == 0:
    print('{} is divisible by 3'.format(a_number))
elif a_number % 5 == 0:
    print('{} is divisible by 5'.format(a_number))
else:
    print('All checks failed!')
    print('{} is not divisible by 2, 3 or 5'.format(a_number))
```

```
All checks failed!
49 is not divisible by 2, 3 or 5
```

Non-Boolean Conditions

Note that conditions do not necessarily have to be booleans. In fact, a condition can be any value. The value is converted into a boolean automatically using the `bool` operator. Any value in Python can be converted to a Boolean using the `bool` function.

Only the following values evaluate to `False` (they are often called *falsy* values):

1. The value `False` itself
2. The integer `0`
3. The float `0.0`
4. The empty value `None`
5. The empty text `""`
6. The empty list `[]`
7. The empty tuple `()`
8. The empty dictionary `{}`
9. The empty set `set()`
10. The empty range `range(0)`

Everything else evaluates to `True` (a value that evaluates to `True` is often called a *truthy* value).

```
if '':
    print('The condition evaluted to True')
else:
    print('The condition evaluted to False')
```

```
The condition evaluted to False
```

```
if 'Hello':
    print('The condition evaluted to True')
else:
    print('The condition evaluted to False')
```

```
The condition evaluted to True
```

```
if { 'a': 34 }:
    print('The condition evaluted to True')
else:
    print('The condition evaluted to False')
```

```
The condition evaluted to True
```

```
if None:
    print('The condition evaluted to True')
else:
    print('The condition evaluted to False')
```

```
The condition evaluted to False
```

Nested conditional statements

The code inside an `if` block can also include an `if` statement inside it. This pattern is called `nesting` and is used to check for another condition after a particular condition holds true.

```
a_number = 15
```

```
if a_number % 2 == 0:
    print("{} is even".format(a_number))
    if a_number % 3 == 0:
        print("{} is also divisible by 3".format(a_number))
    else:
        print("{} is not divisibule by 3".format(a_number))
else:
    print("{} is odd".format(a_number))
    if a_number % 5 == 0:
        print("{} is also divisible by 5".format(a_number))
    else:
        print("{} is not divisibule by 5".format(a_number))
```

```
15 is odd
15 is also divisible by 5
```

Notice how the `print` statements are indented by 8 spaces to indicate that they are part of the inner `if`/`else` blocks.

> Nested `if`, `else` statements are often confusing to read and prone to human error. It's good to avoid nesting whenever possible, or limit the nesting to 1 or 2 levels.

Shorthand `if` conditional expression

A frequent use case of the `if` statement involves testing a condition and setting a variable's value based on the condition.

Python provides a shorter syntax, which allows writing such conditions in a single line of code. It is known as a *conditional expression*, sometimes also referred to as a *ternary operator*. It has the following syntax:

```
x = true_value if condition else false_value
```

It has the same behavior as the following `if-else` block:

```
if condition:
    x = true_value
else:
    x = false_value
```

Let's try it out for the example above.

```
parity = 'even' if a_number % 2 == 0 else 'odd'
```

```
print('The number {} is {}.'.format(a_number, parity))
```

```
The number 15 is odd.
```

The `pass` statement

`if` statements cannot be empty, there must be at least one statement in every `if` and `elif` block. We can use the `pass` statement to do nothing and avoid getting an error.

```
a_number = 9
```

```
if a_number % 2 == 0:

elif a_number % 3 == 0:
    print('{} is divisible by 3 but not divisible by 2')
```

```
IndentationError: expected an indented block (1562158884.py, line 3)
```

As there must be at least one statement withihng the `if` block, the above code throws an error.

```
if a_number % 2 == 0:
    pass
elif a_number % 3 == 0:
    print('{} is divisible by 3 but not divisible by 2'.format(a_number))
```

```
9 is divisible by 3 but not divisible by 2
```

1.1.6.2 Iteration with `while` loops

Another powerful feature of programming languages, closely related to branching, is running one or more statements multiple times. This feature is often referred to as *iteration* on *looping*, and there are two ways to do this in Python: using `while` loops and `for` loops.

`while` loops have the following syntax:

```
while condition:
    statement(s)
```

Statements in the code block under `while` are executed repeatedly as long as the `condition` evaluates to `True`. Generally, one of the statements under `while` makes some change to a variable that causes the condition to evaluate to `False` after a certain number of iterations.

Let's try to calculate the factorial of `100` using a `while` loop. The factorial of a number `n` is the product (multiplication) of all the numbers from `1` to `n`, i.e., `1*2*3*...*(n-2)*(n-1)*n`.

```python
result = 1
i = 1

while i <= 10:
    result = result * i
    i = i+1

print('The factorial of 100 is: {}'.format(result))
```

```
The factorial of 100 is: 3628800
```

1.1.6.3 Infinite Loops

Suppose the condition in a `while` loop always holds true. In that case, Python repeatedly executes the code within the loop forever, and the execution of the code never completes. This situation is called an infinite loop. It generally indicates that you've made a mistake in your code. For example, you may have provided the wrong condition or forgotten to update a variable within the loop, eventually falsifying the condition.

If your code is *stuck* in an infinite loop during execution, just press the "Stop" button on the toolbar (next to "Run") or select "Kernel > Interrupt" from the menu bar. This will *interrupt* the execution of the code. The following two cells both lead to infinite loops and need to be interrupted.

```python
# INFINITE LOOP - INTERRUPT THIS CELL

result = 1
i = 1

while i <= 100:
    result = result * i
    # forgot to increment i
```

```python
# INFINITE LOOP - INTERRUPT THIS CELL

result = 1
i = 1

while i > 0 : # wrong condition
    result *= i
    i += 1
```

1.1.6.4 `break` and `continue` statements

In Python, `break` and `continue` statements can alter the flow of a normal loop.

We can use the `break` statement within the loop's body to immediately stop the execution and *break* out of the loop. with the continue statement. If the condition evaluates to `True`, then the loop will move to the next iteration.

```python
i = 1
result = 1

while i <= 100:
    result *= i
    if i == 42:
        print('Magic number 42 reached! Stopping execution..')
        break
    i += 1

print('i:', i)
print('result:', result)
```

```
Magic number 42 reached! Stopping execution..
i: 42
```

```
result: 140500611775287989854314260624451156993638400000000
```

```
i = 1
result = 1

while i < 8:
    i += 1
    if i % 2 == 0:
        print('Skipping {}'.format(i))
        continue
    print('Multiplying with {}'.format(i))
    result = result * i

print('i:', i)
print('result:', result)
```

```
Skipping 2
Multiplying with 3
Skipping 4
Multiplying with 5
Skipping 6
Multiplying with 7
Skipping 8
i: 8
result: 105
```

In the example above, the statement `result = result * i` inside the loop is skipped when `i` is even, as indicated by the messages printed during execution.

> **Logging**: The process of adding `print` statements at different points in the code *(often within loops and conditional statements)* for inspecting the values of variables at various stages of execution is called logging. As our programs get larger, they naturally become prone to human errors. Logging can help in verifying the program is working as expected. In many cases, `print` statements are added while writing & testing some code and are removed later.

Task: Guess the output and explain it.

```
# Use of break statement inside the loop

for val in "string":
    if val == "i":
```

```
        break
    print(val)

print("The end")
```

```
s
t
r
The end
```

```
# Program to show the use of continue statement inside loops

for val in "string":
    if val == "i":
        continue
    print(val)

print("The end")
```

```
s
t
r
n
g
The end
```

1.1.6.5 Iteration with `for` loops

A `for` loop is used for iterating or looping over sequences, i.e., lists, tuples, dictionaries, strings, and *ranges*. For loops have the following syntax:

```
for value in sequence:
    statement(s)
```

The statements within the loop are executed once for each element in `sequence`. Here's an example that prints all the element of a list.

```python
days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday']

for day in days:
    print(day)
```

```
Monday
Tuesday
Wednesday
Thursday
Friday
```

```python
# Looping over a string
for char in 'Monday':
    print(char)
```

```
M
o
n
d
a
y
```

```python
# Looping over a dictionary
person = {
    'name': 'John Doe',
    'sex': 'Male',
    'age': 32,
    'married': True
}

for key, value in person.items():
    print("Key:", key, ",", "Value:", value)
```

```
Key: name , Value: John Doe
Key: sex , Value: Male
Key: age , Value: 32
Key: married , Value: True
```

1.1.7 Iterating using `range` and `enumerate`

The `range` function is used to create a sequence of numbers that can be iterated over using a `for` loop. It can be used in 3 ways:

- `range(n)` - Creates a sequence of numbers from `0` to `n-1`
- `range(a, b)` - Creates a sequence of numbers from `a` to `b-1`
- `range(a, b, step)` - Creates a sequence of numbers from `a` to `b-1` with increments of `step`

Let's try it out.

```python
for i in range(4):
    print(i)
```

```
0
1
2
3
```

```python
for i in range(3, 8):
    print(i)
```

```
3
4
5
6
7
```

```python
for i in range(3, 14, 4):
    print(i)
```

```
3
7
11
```

Ranges are used for iterating over lists when you need to track the index of elements while iterating.

```python
a_list = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday']

for i in range(len(a_list)):
    print('The value at position {} is {}.'.format(i, a_list[i]))
```

```
The value at position 0 is Monday.
The value at position 1 is Tuesday.
The value at position 2 is Wednesday.
The value at position 3 is Thursday.
The value at position 4 is Friday.
```

Another way to achieve the same result is by using the `enumerate` function with `a_list` as an input, which returns a tuple containing the index and the corresponding element.

```python
for i, val in enumerate(a_list):
    print('The value at position {} is {}.'.format(i, val))
```

```
The value at position 0 is Monday.
The value at position 1 is Tuesday.
The value at position 2 is Wednesday.
The value at position 3 is Thursday.
The value at position 4 is Friday.
```

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
```

2.1.1 Tuple Indexing

Tuple is ordered, meaning you can access specific elements in a list using their index. Indexing in lists includes both positive indexing (starting from 0 for the first element) and negative indexing (starting from -1 for the last element).

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
```

```python
tuple_example[-1]
```

```
4
```

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*.

```python
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.

2.1.2 Concatenating tuples

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

```python
(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:

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

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

2.1.3 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.

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

```python
x
```

```
4.5
```

```python
y
```

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

```python
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:

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

```python
x
```

```
4.5
```

```python
y
```

```
'99'
```

```python
z
```

```
99
```

2.1.4 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:

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

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

```
3
```

```python
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 characeterisics 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.

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

List indexing works the same way as tuple indexing.

2.2.1 Slicing a list

List slicing is a technique in Python that allows you to extract a portion of a list by specifying a range of indices. It creates a new list containing the elements from the original list within that specified range. List slicing uses the colon : operator to indicate the start, stop, and step values for the slice. The general syntax is: `new_list = original_list[start:stop:step]`

Here's what each part of the slice means: * **start**: The index at which the slice begins (inclusive). If omitted, it starts from the beginning (index 0). * **stop**: The index at which the slice ends (exclusive). If omitted, it goes until the end of the list. * **step**: The interval between elements in the slice. If omitted, it defaults to 1.

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

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

```python
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.

```python
list_example6[:7]
```

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

```python
list_example6[2:]
```

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

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

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

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

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

```
[1, 5]
```

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

```python
#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]
```

2.2.2 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 occurence 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 occurence will be
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 intergers 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, iterating over the elements of the original list,
#but updating a copy of the original list
```

```
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. After an element is removed from the list, all the elements that come afterward have their index/position reduced by one. After the elment `95` is removed, `96` is at index `0`, but the for loop will now look at the element at index `1`, which is now `97`. So, iterating over the same list that is being updated in the loop will keep 96 and 98. Using a new list gets rid of the issue by keeping the original list unchanged, so the for-loop iterates over all elements of the original list.

Another method could have been to interate over a copy of the original list and update the original list as shown below.

```
#Method 2: For loop with remove, iterating over the elements of a copy of the original lis
#but updating the original list
for element in list_example3[:]: #Slicing a list creates a new list, thus the loop is iter
    if element<100:
        list_example3.remove(element)
print(list_example3)
```

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

Below is another method that uses a shorthand notation - list comprehension (explained in the next section).

```
#Method 3: For loop with condition in list comprehension
list_example3 = list(range(95,106))
[element for element in list_example3 if element>=100]
```

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

2.2.3 List comprehensions

List comprehensions provide a concise and readable way to create new lists by applying an expression to each item in an iterable (e.g., a list, tuple, or range) and optionally filtering the items based on a condition. They are a powerful and efficient way to generate lists without the need for explicit loops. The basic syntax of a list comprehension is as follows:

`new_list = [expression for item in iterable if condition]`

- **expression**: This is the expression that is applied to each item in the iterable. It defines what will be included in the new list.
- **item**: This is a variable that represents each element in the iterable as the comprehension iterates through it.
- **iterable**: This is the source from which the elements are taken. It can be any iterable, such as a list, tuple, range, or other iterable objects.
- **condition (optional)**: This is an optional filter that can be applied to control which items from the iterable are included in the new list. If omitted, all items from the iterable are included.

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), (1
```

Example: Creating a list of words that start with the letter 'a' in a given list of words.

```
words = ['apple', 'banana', 'avocado', 'grape', 'apricot']
a_words = [word for word in words if word.startswith('a')]
print(a_words)
```

```
['apple', 'avocado', 'apricot']
```

Example: Create a list of even numbers from 1 to 20.

```
even_numbers = [x for x in range(1, 21) if x % 2 == 0]
print(even_numbers)
```

```
[2, 4, 6, 8, 10, 12, 14, 16, 18, 20]
```

List comprehensions are not only concise but also considered more Pythonic and often more efficient than using explicit loops for simple operations. They can make your code cleaner and easier to read, especially for operations that transform or filter data in a list.

2.2.4 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:

2.2.4.1

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
```

2.2.4.2

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_marr
```

```
Mean age when people expect to marry =  28.955801104972377
```

2.2.4.3

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 %
```

2.2.4.4

Redo Q2.2.4.2 using the if-else statement within list comprehension.

2.2.5 Practice exercise 2

Below is a list consisting of responses to the question: "What do you expect your starting salary to be after graduation, to the nearest thousand dollars? (ex: 47000)" from students of the STAT303-1 Fall 2023. class.

```
expected_salary = ['90000', '110000', '100000', '90k', '80000', '47000', '100000', '70000'
```

Clean `expected_salary` using list comprehensions only, and find the mean expected salary.

2.2.6 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]
```

2.2.7 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]
```

2.2.8 Practice exercise 3

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

2.2.8.1

Set the second entry (index 1) to 17

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

2.2.8.2

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

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

2.2.8.3

Remove the first entry from the list

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

```
8
```

2.2.8.4

Sort the list

```
L.sort()
```

2.2.8.5

Double the list (concatenate the list to itself)

```
L=L+L
```

2.2.8.6

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.

```
&lt;IPython.core.display.HTML object&gt;
```

2.2.9 Other list operations

You can test whether a list contains a value using the `in` operator.

```
list_example6
```

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

```
6 in list_example6
```

```
False
```

```
7 in list_example6
```

```
True
```

2.2.10 Lists: methods

Just like strings, there are several in-built methods to manipulate a list. However, unlike strings, most list methods modify the original list rather than returning a new one. Here are some common list operations:

2.2.11 Lists vs tuples

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

Unlike lists and tuples, a dictionary is an unordered collection of items. Each item stored in a dictionary has a key and value. You can use a key to retrieve the corresponding value from the dictionary. Dictionaries have the type `dict`.

Dictionaries are often used to store many pieces of information e.g. details about a person, in a single variable. Dictionaries are created by enclosing key-value pairs within braces or curly brackets `{` and `}`, colons to separate keys and values, and commas to separate elements of a dictionary.

The dictionary keys and values are python objects. While values can be any python object, keys need to be immutable python objects, like strings, integers, tuples, etc. Thus, a list can be a value, but not a key, as elements of list can be changed.

```
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 Viewing keys and values

```
dict_example.keys()
```

```
dict_keys(['USA', 'India', 'China'])
```

```
dict_example.values()
```

```
dict_values(['Joe Biden', 'Narendra Modi', 'Xi Jinping'])
```

```
dict_example.items()
```

```
dict_items([('USA', 'Joe Biden'), ('India', 'Narendra Modi'), ('China', 'Xi Jinping')])
```

The results of `keys`, `values`, and `items` look like lists. However, they don't support the indexing operator `[]` for retrieving elements.

```python
dict_example.items()[1]
```

```
TypeError: 'dict_items' object is not subscriptable
```

2.3.2 Adding and removing elements in a dictionary

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

```python
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:

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

```python
dict_example
```

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

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

```
'Joe Biden'
```

```python
dict_example
```

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

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

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

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

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

```python
dict_example
```

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

2.3.3 Iterating over elements of a dictionary

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

```python
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
```

2.3.4 Practice exercise 4

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 5

The object `deck` defined below corresponds to a deck of cards. Estimate the probablity 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+chck_flush(deck[0:5])

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

```
Probability of obtaining a flush= 0.18 %
```

2.5 Practice exercise 6

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.

```
starbucks_drinks_nutrition={'Cool Lime Starbucks Refreshers Beverage': [{'Nutrition_type': 'Cal
, 'value': 1}, {'Nutrition_type': 'Sodium', 'value': 10}], 'Featured Dark Roast': [{'Nutrition_type': 'Calo
```

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 dictonary, 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 dictonary, 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}
```

2.5.1.6

Answer Q2.5.1.5 using only dictionary comprehension.

Part II

Getting started: Coding environment

3 Setting up your environment with VS Code

3.1 Introduction to Visual Studio Code (VS Code)

Visual Studio Code (VS Code) is a free, open-source, and lightweight code editor developed by Microsoft. It's widely used for coding, debugging, and working with **various programming languages** and frameworks. Here's an overview of its key features and functionalities:

3.1.0.1 Core Features

- **Multi-language Support:** VS Code supports a wide range of programming languages out of the box, including Python, JavaScript, TypeScript, HTML, CSS, and more. Additional language support can be added via extensions.
- **Extensibility:** The editor has a rich ecosystem of extensions available through the Visual Studio Code Marketplace. These extensions add support for additional programming languages, themes, debuggers, and tools like Git integration.
- **IntelliSense:** Provides intelligent code completion, parameter info, quick info, and code navigation for many languages, enhancing productivity and reducing errors.
- **Integrated Terminal:** Allows you to run command-line tools directly from the editor, making it easy to execute scripts, install packages, and more without leaving the coding environment.
- **Version Control Integration:** Seamless integration with Git and other version control systems, allowing you to manage source code repositories, stage changes, commit, and view diffs within the editor.
- **Debugging:** Supports debugging with breakpoints, call stacks, and an interactive console for various languages and frameworks.

3.1.0.2 User Interface

- **Explorer:** A file explorer on the left side that lets you navigate your project files and folders.
- **Editor:** The central area where you write and edit your code. You can open multiple files in separate tabs or split the editor to view multiple files side-by-side.
- **Sidebar:** Displays additional views like Search, Source Control, Extensions, and more.

- **Status Bar:** Shows information about the current file, like the programming language mode, current branch (for version control), and any active extensions or warnings.
- **Command Palette:** Accessed with `Ctrl+Shift+P` (or `Cmd+Shift+P` on macOS), it provides a quick way to execute commands, switch themes, change settings, and more.

3.1.0.3 Extensions

- **Language Extensions:** Add support for additional languages such as Rust, Go, C++, and more.
- **Linters and Formatters:** Extensions like ESLint, Prettier, and Pylint help with code quality and formatting.
- **Development Tools:** Extensions for Docker, Kubernetes, database management, and more.
- **Productivity Tools:** Extensions for snippets, file explorers, and workflow enhancements.

3.1.0.4 Use Cases

- **Web Development:** VS Code is popular among web developers for its robust support for HTML, CSS, JavaScript, and front-end frameworks like React, Angular, and Vue.
- **Python Development:** With the Python extension, it provides features like IntelliSense, debugging, linting, and Jupyter Notebook support.
- **Data Science:** Supports Jupyter notebooks, allowing data scientists to write and run Python code interactively.
- **DevOps and Scripting:** Useful for writing and debugging scripts in languages like PowerShell, Bash, and YAML for CI/CD pipelines.

3.1.0.5 Cross-Platform

- Available on Windows, macOS, and Linux, making it accessible to developers across different operating systems.

Overall, VS Code is a versatile and powerful tool for a wide range of development activities, from simple scripting to complex software projects.

3.2 Installing Visual Studio Code

3.2.0.1 Step 1: Download VS Code:

- Go to the official VS Code website and download the installer for your operating system.

3.2.0.2 Step 2: Install VS Code:

- Run the installer and follow the prompts to complete the installation.

3.2.0.3 Step 3: Launch VS Code:

- Open VS Code after installation to ensure it's working correctly.

3.3 Setting Up Python Development Environment in VS Code using python `venv`

Unlike `Spyder` and `PyCharm`, which are specifically designed for Python development, VS Code is a versatile code editor with multi-language support. As a result, setting up the Python environment requires some additional configuration.

This guide will walk you through setting up your Python environment in Visual Studio Code from scratch using `venv`. After the lecture, you will be tasked with creating and managing virtual environments using `conda`.

3.3.0.1 Step 1: Install Python

1. **Download Python:**
   - Go to the official Python website and download the latest version of Python for your operating system.
   - Ensure that you check the box **"Add Python to PATH"** during installation.
2. **Verify Python Installation:**
   - Open a terminal (Command Prompt on Windows, Terminal on macOS/Linux) and type:

     ```
     python --version
     ```

   - You should see the installed Python version.

3.3.0.2 Step 2: Install Visual Studio Code Extensions

1. **Open VS Code.**
2. **Go to Extensions:**
   - Click on the Extensions icon on the sidebar or press `Ctrl+Shift+X`.
3. **Install Python Extension:**
   - Search for the "Python" extension by Microsoft and install it.
4. **Install Jupyter Extension:**
   - Search for the "Jupyter" extension by Microsoft and install it.

3.3.0.3 Step 3: Set Up a Python Workspace for this course

1. **Create a New Folder:**
   - Create a new folder on your computer where you want to store your Python code for this course.
2. **Open Folder in VS Code:**
   - Go to `File > Open Folder` and select the newly created folder.

3.3.0.4 Step 4: Create a Notebook for your work

- In VS Code, go to `File > New File` and select `Jupyter Notebook`.

3.3.0.5 Step 5: Create a Python environment for your work - GUI method

- When you start a Jupyter Notebook in VS Code, you need to choose a kernel. Kernel is the "engine" that runs your code within your Jupyter notebook, and it is tied to a specific Python interpreter or environment.
  - **What's the difference between an interpreter and an environment?** An interpreter is a program that runs your Python code. An environment, on the other hand, is a standalone "space" where your code runs. It's like a container that holds its own interpreter and environment-specific libraries/dependencies, so each project can have its own environment setup without affecting others.

- **Why do we prefer creating an environment for this course rather than using the global interpreter that comes with your Python installation?** As a data scientist, you may work on multiple projects and attend different courses that require different sets of packages, dependencies, or even Python versions. By creating a separate environment, you can prevent conflicts between libraries, dependencies, and Python versions across your projects (dependency hell) and also ensure code reproducibility. It is always good practice to work within python environments, especially when you have different projects going on.
- Let's create a Python environment for the upcoming coursework.

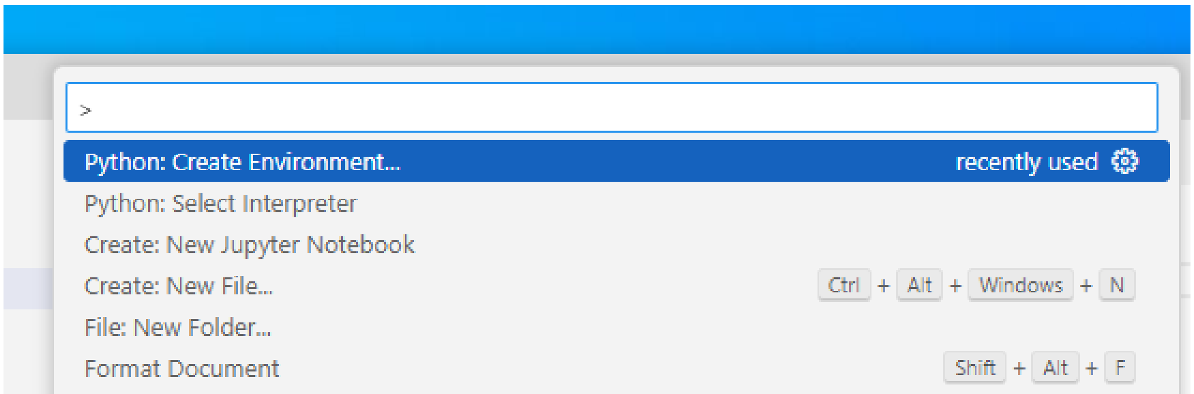
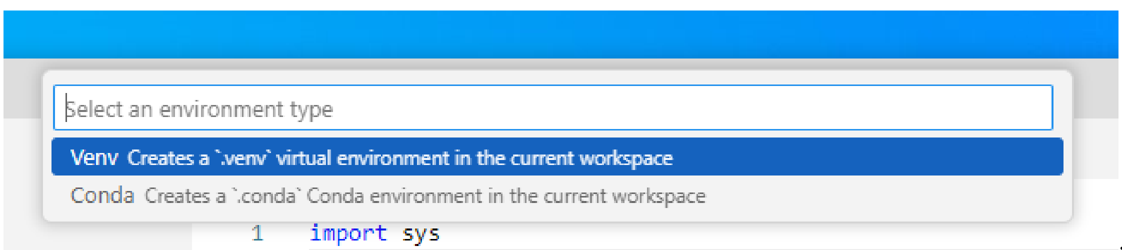


Figure 3.1: Alt Text

- Create using `venv` in the current workspace



Key Differences between `venv` and `conda`

1. **Ecosystem**:

- `venv` is specifically for Python and is part of the standard library.
- `conda` is part of the broader Anaconda ecosystem, which supports multiple languages and is focused on data science.

2. **Package Management**:

- `venv` relies on `pip` for package management.

  - `conda` has its own package management system, which can sometimes resolve dependencies better, especially for data science libraries that require non-Python dependencies.

. **Environment Creation**:

  - `venv` creates lightweight virtual environments tied to a specific version of Python.
  - `conda` allows you to specify not just Python but also other packages during environment creation, which can save time and ensure compatibility.

4. **Cross-Platform**:

  - Both tools are cross-platform, but `conda` is often favored in data science for its ability to manage complex dependencies.

How to choose

  - Use `venv` for lightweight, Python-only projects where you want a simple way to manage dependencies. We are going with `venv` for our course.
  - Use `conda` for data science projects, or when you need to manage packages across multiple languages and require better dependency management.

- Choose python interpreter for your environment:

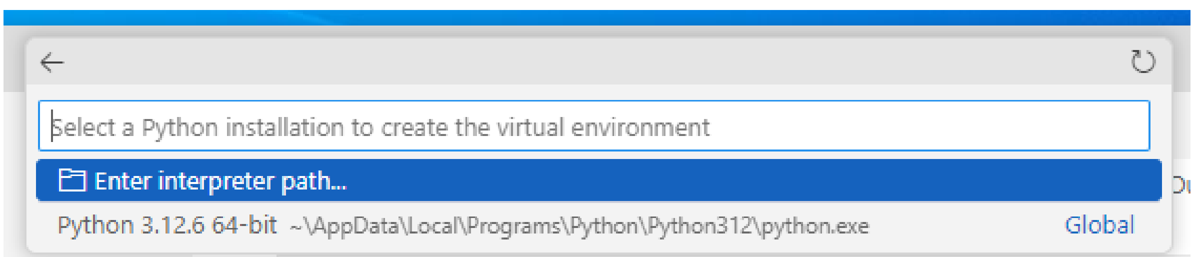


Figure 3.2: Alt Text

Congratulations! A virtual environment named `.venv` has been successfully created in your project folder.

3.3.0.6 Step 5: Create a Python environment for your work - Command Line Method

Instead of using the VSCode GUI, we can also create a `venv` environment with command line commands.

1. **Create a Virtual Environment:**
   - Open the terminal in VS Code and run:

```
python -m venv venv
```

- This creates a virtual environment named **venv** in your project folder.

2. **Activate the Virtual Environment:**

   - Windows:

   ```
   venv\Scripts\activate
   ```

   - macOS/Linux:

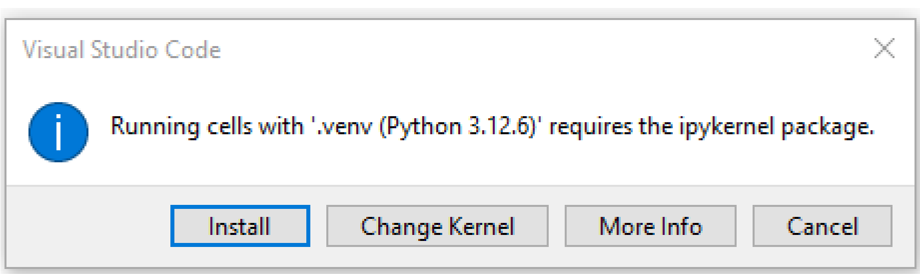
   ```
   source venv/bin/activate
   ```

3.3.0.7 Step 6: Choose the `.venv` environment as the kernel to run the notebook

For all your upcoming work in this project, you can select this environment to ensure a consistent setup.

3.3.0.8 Step 7: Installing `ipykernel` for your notebook

Create a code cell in the notebook and run it. The first time you run a code cell, you will run into



- After installing `ipykernel`, you should be able to run the following cell.

```
import sys
print("Current Python executable:", sys.executable)
```

```
Current Python executable: c:\Users\lsi8012\OneDrive - Northwestern University\FA24\303-1\te
```

`sys.executable` is an attribute in the Python `sys` module that returns the path to the Python interpreter that is currently executing your code.

However, none of the data science packages are installed in the environment by default. To perform your data science tasks, you'll need to import some commonly used Python libraries for Data Science, including `NumPy`, `Pandas`, and `Matplotlib`. While Anaconda typically has these libraries installed automatically, in VS Code, you'll need to install them for your specific environment. If you don't, you may encounter errors when trying to use these libraries.

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

```
ModuleNotFoundError: No module named 'nummpy'
```

3.3.0.9 Step 8: Install Data Science packages within the created Environment

Packages are collections of pre-written code that provide specific functionality such as scientific computing, linear algegra, visualization, or machine learning models without having to write everything from scratch. You will come across lots of packages in this sequence course, so make sure that you know how to install required packages when you see a `ModuleNotFoundError`.

You have two primary ways to install DS packages 1. Installing from the Terminal 2. Installing from the Notebook

3.3.0.9.1 Installing from the terminal

1. **Open a New Terminal:** Check the terminal prompt to see if the active environment is consistent with the kernel you've chosen for your notebook.

   - If you see `(.venv)` at the beginning of the prompt, it means the virtual environment `.venv` is active and matches the notebook kernel.
   - If you see something else, for example, `(base)` at the beginning of the prompt, it indicates that the base conda environment (installed by Anaconda) is currently active
   - You can also use the `which` or `where` (`where.exe` in windows) command: On macOS/Linux, use: `which python` ; On windows, use: `where.exe python`

   Note that when you have both Anaconda and VS Code installed on your system, sometimes the environments can conflict with each other. If the terminal environment is inconsistent with the notebook kernel, packages may be installed in a different environment than intended. This can lead to issues where the notebook cannot access the installed packages.

2. Using `pip` (if you create a `venv` environment)

```
pip install numpy pandas matplotlib
```

3.3.0.9.2 Installing from the Notebook

You can also install packages directly from a Jupyter Notebook cell using a magic command. This is often convenient because it allows you to install packages without leaving the notebook interface.

```
pip install numpy pandas matplotlib
```

Let's rerun this code cell and see whether the error is addressed

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

Key takeaway

Both methods are valid, and the choice depends on your preference and workflow. Installing from the terminal is common for batch installations or when setting up a new environment, while installing from the notebook can be handy for quick additions during your data analysis work.

3.3.0.10 Step 9: Create a `requirement.txt` to back up your environment or share with your collaborator

`pip freeze` outputs the packages and their versions installed in the current environment in a format that can be used as `requirements.txt`, which allows you to easily recreate the environment or share it with others for consistent setups.

```
pip freeze
```

```
asttokens==2.4.1
colorama==0.4.6
comm==0.2.2
contourpy==1.3.0
cycler==0.12.1
debugpy==1.8.6
decorator==5.1.1
executing==2.1.0
```

```
fonttools==4.54.1
ipykernel==6.29.5
ipython==8.27.0
jedi==0.19.1
jupyter_client==8.6.3
jupyter_core==5.7.2
kiwisolver==1.4.7
matplotlib==3.9.2
matplotlib-inline==0.1.7
nest-asyncio==1.6.0
numpy==2.1.1
packaging==24.1
pandas==2.2.3
parso==0.8.4
pillow==10.4.0
platformdirs==4.3.6
prompt_toolkit==3.0.48
psutil==6.0.0
pure_eval==0.2.3
Pygments==2.18.0
pyparsing==3.1.4
python-dateutil==2.9.0.post0
pytz==2024.2
pywin32==306
pyzmq==26.2.0
six==1.16.0
stack-data==0.6.3
tornado==6.4.1
traitlets==5.14.3
tzdata==2024.2
wcwidth==0.2.13
Note: you may need to restart the kernel to use updated packages.
```

Using the redirection operator `>`, you can save the output of `pip freeze` to a `requirement.txt`. This file can be used to install the same versions of packages in a different environment.

```
pip freeze > requirement.txt
```

```
Note: you may need to restart the kernel to use updated packages.
```

Let's check whether the `requirement.txt` is in the current working directory

```
%ls
```

```
 Volume in drive C is Windows
 Volume Serial Number is A80C-7DEC

 Directory of c:\Users\lsi8012\OneDrive - Northwestern University\FA24\303-1\test_env

09/27/2024  02:25 PM    <DIR>          .
09/27/2024  02:25 PM    <DIR>          ..
09/27/2024  07:44 AM    <DIR>          .venv
09/27/2024  01:42 PM    <DIR>          images
09/27/2024  02:25 PM               695 requirement.txt
09/27/2024  02:25 PM            21,352 venv_setup.ipynb
               2 File(s)         22,047 bytes
               4 Dir(s)  166,334,562,304 bytes free
```

You can copy the `requirements.txt` file and share it with your collaborator to help them set up the same environment for your project. They can quickly install the necessary dependencies from the file using the following command:

```
pip install -r requirement.txt
```

```
Requirement already satisfied: asttokens==2.4.1 in c:\users\lsi8012\onedrive - northwestern u
Requirement already satisfied: colorama==0.4.6 in c:\users\lsi8012\onedrive - northwestern un
Requirement already satisfied: comm==0.2.2 in c:\users\lsi8012\onedrive - northwestern unive
Requirement already satisfied: contourpy==1.3.0 in c:\users\lsi8012\onedrive - northwestern u
Requirement already satisfied: cycler==0.12.1 in c:\users\lsi8012\onedrive - northwestern uni
Requirement already satisfied: debugpy==1.8.6 in c:\users\lsi8012\onedrive - northwestern uni
Requirement already satisfied: decorator==5.1.1 in c:\users\lsi8012\onedrive - northwestern u
Requirement already satisfied: executing==2.1.0 in c:\users\lsi8012\onedrive - northwestern u
Requirement already satisfied: fonttools==4.54.1 in c:\users\lsi8012\onedrive - northwestern
Requirement already satisfied: ipykernel==6.29.5 in c:\users\lsi8012\onedrive - northwestern
Requirement already satisfied: ipython==8.27.0 in c:\users\lsi8012\onedrive - northwestern un
Requirement already satisfied: jedi==0.19.1 in c:\users\lsi8012\onedrive - northwestern unive
Requirement already satisfied: jupyter_client==8.6.3 in c:\users\lsi8012\onedrive - northwest
Requirement already satisfied: jupyter_core==5.7.2 in c:\users\lsi8012\onedrive - northwester
Requirement already satisfied: kiwisolver==1.4.7 in c:\users\lsi8012\onedrive - northwestern
Requirement already satisfied: matplotlib==3.9.2 in c:\users\lsi8012\onedrive - northwestern
Requirement already satisfied: matplotlib-inline==0.1.7 in c:\users\lsi8012\onedrive - northw
Requirement already satisfied: nest-asyncio==1.6.0 in c:\users\lsi8012\onedrive - northwester
Requirement already satisfied: numpy==2.1.1 in c:\users\lsi8012\onedrive - northwestern unive
```

```
Requirement already satisfied: packaging==24.1 in c:\users\lsi8012\onedrive - northwestern un
Requirement already satisfied: pandas==2.2.3 in c:\users\lsi8012\onedrive - northwestern univ
Requirement already satisfied: parso==0.8.4 in c:\users\lsi8012\onedrive - northwestern unive
Requirement already satisfied: pillow==10.4.0 in c:\users\lsi8012\onedrive - northwestern uni
Requirement already satisfied: platformdirs==4.3.6 in c:\users\lsi8012\onedrive - northwester
Requirement already satisfied: prompt_toolkit==3.0.48 in c:\users\lsi8012\onedrive - northwes
Requirement already satisfied: psutil==6.0.0 in c:\users\lsi8012\onedrive - northwestern univ
Requirement already satisfied: pure_eval==0.2.3 in c:\users\lsi8012\onedrive - northwestern u
Requirement already satisfied: Pygments==2.18.0 in c:\users\lsi8012\onedrive - northwestern u
Requirement already satisfied: pyparsing==3.1.4 in c:\users\lsi8012\onedrive - northwestern u
Requirement already satisfied: python-dateutil==2.9.0.post0 in c:\users\lsi8012\onedrive - no
Requirement already satisfied: pytz==2024.2 in c:\users\lsi8012\onedrive - northwestern unive
Requirement already satisfied: pywin32==306 in c:\users\lsi8012\onedrive - northwestern unive
Requirement already satisfied: pyzmq==26.2.0 in c:\users\lsi8012\onedrive - northwestern univ
Requirement already satisfied: six==1.16.0 in c:\users\lsi8012\onedrive - northwestern univer
Requirement already satisfied: stack-data==0.6.3 in c:\users\lsi8012\onedrive - northwestern
Requirement already satisfied: tornado==6.4.1 in c:\users\lsi8012\onedrive - northwestern uni
Requirement already satisfied: traitlets==5.14.3 in c:\users\lsi8012\onedrive - northwestern
Requirement already satisfied: tzdata==2024.2 in c:\users\lsi8012\onedrive - northwestern uni
Requirement already satisfied: wcwidth==0.2.13 in c:\users\lsi8012\onedrive - northwestern un
Note: you may need to restart the kernel to use updated packages.
```

This will ensure that both of you are working with the same setup.

3.4 Jupyter Notebooks in VS Code

After setting up your environment, follow this instruction to become familiar with the native support for Jupyter Notebooks in VS Code

3.5 Exercise: Setting Up Your Python Data Science Environment using `pip` and `conda`

Objective: Practice creating and managing Python packages and environments using `pip` and `conda`, and verifying your setup.

Note: Feel free to use ChatGPT to find the commands you need.

3.5.1 Using `pip`

3.5.1.1 Instructions

Step 1: **Create a New Workplace** - Create a folder named `test_pip_env`. - Open the folder in VS code - Within the workplace, create a new notebook

Step 2: **Create a pip environment named `stat303_pip_env` in the current workplace**

- Create the env using pip command line
- Activate the environment.

Step 3: **Install Required Packages for the env**

- Inside the `stat303_pip_env`, install the following packages using `pip`:
  - `numpy`
  - `pandas`
  - `matplotlib`
- Install the following packages using `conda`
  - `statsmodels`

Step 4: **Export the Environment Configuration**

- Export the configuration of your `stat303_pip_env` environment to a file named `stat303_env.txt`.

Step 6: **Deactivate and Remove the Environment**

- Deactivate the `stat303_pip_env` environment.
- Remove the `stat303_pip_env` environment to ensure you understand how to clean up.

Step 7: **Recreate the Environment Using the YML File**

- Create a new environment using the `stat303_env.txt` file.
- Activate the `stat303_pip_env` environment.
- Verify that the packages `numpy`, `pandas`, `matplotlib`, and `scikit-learn` are installed.

Step 8: **Run a Jupyter Notebook**

- Launch Jupyter Notebook within the created environment.
- Create a new notebook and write a simple Python script to:
  - Import `numpy`, `pandas`, `matplotlib`, and `scikit-learn`.
  - Print the versions of these packages.

3.5.2 Using `conda`

3.5.2.1 Instructions

Step 1: **Create a New Workplace** - Create a folder named `test_conda_env`. - Open the folder in VS code - Within the workplace, create a new notebook

Step 2: **Create a conda environment named `stat303_conda_env`**

- Create the env using conda command line
- Activate the environment.

Step 3: **Install Required Packages for the env**

- Inside the `stat303_conda_env`, install the following packages using `conda`:
  - `numpy`
  - `pandas`
  - `matplotlib`
- Install the following packages using `pip`
  - `scikit-learn`
  - `statsmodels`

Step 4: **Export the Environment Configuration**

- Export the configuration of your `stat303_conda_env` environment to a file named `stat303_env.yml`.

Step 5: **Deactivate and Remove the Environment**

- Deactivate the `stat303_conda_env` environment.
- Remove the `stat303_conda_env` environment to ensure you understand how to clean up.

Step 6: **Recreate the Environment Using the YML File**

- Create a new environment using the `stat303_env.yml` file.
- Activate the `stat303_conda_env` environment.
- Verify that the packages `numpy`, `pandas`, `matplotlib`, `scikit-learn`, and `statsmodels` are installed.

Step 7: **Run a Jupyter Notebook**

- Launch Jupyter Notebook within the created environment.
- Create a new notebook and write a simple Python script to:

- Import `numpy`, `pandas`, `matplotlib`, and `scikit-learn`.
- Print the versions of these packages.

3.6 Expected Outcome

By completing this lecture, you will be able to:

- Create and manage Python virtual environments using both `pip` and `conda`.
- Install and verify packages within these environments.
- Export and recreate environments using env files.
- Use Jupyter Notebook for data science tasks.

3.7 Reference

- Jupyter Notebooks in VS Code
- Install Python Packages
- Managing environments with `conda`

4 Enhancing Workflow in Jupyter Notebooks

In this lecture, we'll explore how to optimize your workflow in Jupyter notebooks by leveraging **magic commands**, **shell commands**, and understanding **file paths**. These powerful tools allow you to:

- Seamlessly interact with the underlying operating system.
- Streamline file management and navigation.
- Control notebook behavior and enhance productivity directly within your code cells.
- Interact with the `os` module to manage files and directories programmatically, enabling you to automate tasks such as navigating directories, checking file existence, and executing system commands.

By mastering these techniques, you'll be able to work more efficiently and handle complex data science tasks with ease.

4.1 Magic Commands

4.1.1 What are Magic Commands?

Magic commands in Jupyter are shortcuts that extend the functionality of the notebook environment. There are two types of magic commands: - **Line magics**: Commands that operate on a single line. - **Cell magics**: Commands that operate on the entire cell.

In Jupyter notebooks, line magic commands are invoked by placing a single percentage sign (`%`) in front of the statement, allowing for quick, inline operations, while cell magic commands are denoted with double percentage signs (`%%`) at the beginning of the cell, enabling you to apply commands to the entire cell for more complex tasks.

You can access the full list of magic commands by typing:

```
%lsmagic

::: {.cell execution_count=1}
``` {.python .cell-code}
# show all the avaiable magic commands on the system
```
```

```python
%lsmagic
```

```
Available line magics:
%alias  %alias_magic  %autoawait  %autocall  %automagic  %autosave  %bookmark  %cd  %clear  %

Available cell magics:
%%!  %%HTML  %%SVG  %%bash  %%capture  %%cmd  %%code_wrap  %%debug  %%file  %%html  %%javasc

Automagic is ON, % prefix IS NOT needed for line magics.
```

:::

4.1.2 Line Magic Commands

4.1.2.1 `%time`: Timing the execution of code

In data science, it is often crucial to evaluate the performance of specific code snippets or algorithms, and the `%time` magic command provides a simple and efficient way to measure the execution time of individual statements, helping you identify bottlenecks and optimize your code for better performance.

```python
def my_dot(a, b):
    """
   Compute the dot product of two vectors

    Args:
      a (ndarray (n,)):  input vector
      b (ndarray (n,)):  input vector with same dimension as a

    Returns:
      x (scalar):
    """
    x=0
    for i in range(a.shape[0]):
        x = x + a[i] * b[i]
    return x
```

```python
import numpy as np
np.random.seed(1)
a = np.random.rand(10000000)  # very large arrays
```

```
b = np.random.rand(10000000)
```

Let's use `%time` to measure the execution time of a single line of code.

```
# Example: Timing a list comprehension
%time np.dot(a, b)
#
```

```
CPU times: total: 0 ns
Wall time: 4.78 ms
```

```
2501072.5816813153
```

```
%time my_dot(a, b)
```

```
CPU times: total: 1.88 s
Wall time: 1.86 s
```

```
2501072.5816813707
```

To capture the output of `%time` (or `%timeit`), you cannot directly assign it to a variable as it's a magic command that prints the result to the notebook's output. However, you can use Python's built-in `time` module to manually time your code and assign the execution time to a variable.

Here's how you can do it using the `time` module:

```
import time
tic = time.time()  # capture start time
c = np.dot(a, b)
toc = time.time()  # capture end time

print(f"np.dot(a, b) =  {c:.4f}")
print(f"Vectorized version duration: {1000*(toc-tic):.4f} ms ")

tic = time.time()  # capture start time
c = my_dot(a,b)
toc = time.time()  # capture end time

print(f"my_dot(a, b) =  {c:.4f}")
```

```python
print(f"loop version duration: {1000*(toc-tic):.4f} ms ")

del(a);del(b)  #remove these big arrays from memory
```

```
np.dot(a, b) =  2501072.5817
Vectorized version duration: 0.0000 ms
my_dot(a, b) =  2501072.5817
loop version duration: 2228.7092 ms
```

4.1.2.2 `%who` and `%whos`: Listing variables

- `%who`: Lists all variables in the current namespace.
- `%whos`: Lists variables along with their types, sizes, and values

```python
# Example: Checking variables in memory
a = 10
b = "data science"
%who
%whos
```

```
A    B    C    a    b    c    current_dir     file_path    my_dot
np   os   plt       sys       tic      time    toc     x    y
```

```
Variable      Type        Data/Info
-----------------------------------
A             ndarray     1000x1000: 1000000 elems, type `float64`, 8000000 bytes (7.62939453
B             ndarray     1000x1000: 1000000 elems, type `float64`, 8000000 bytes (7.62939453
C             ndarray     1000x1000: 1000000 elems, type `float64`, 8000000 bytes (7.62939453
a             int         10
b             str         data science
c             float64     2501072.5816813707
current_dir   str         c:\Users\lsi8012\OneDrive<...>iversity\FA24\303-1\Week2
file_path     str         C:Users\Username\Documents\data.csv
my_dot        function    <function my_dot at 0x00000267B1EFBCE0>
np            module      <module 'numpy' from 'c:\<...>ges\\numpy\\__init__.py'>
os            module      <module 'os' (frozen)>
plt           module      <module 'matplotlib.pyplo<...>\\matplotlib\\pyplot.py'>
sys           module      <module 'sys' (built-in)>
tic           float       1727812577.7224722
time          module      <module 'time' (built-in)>
```

```
toc            float       1727812579.9511814
x              ndarray     100: 100 elems, type `float64`, 800 bytes
y              ndarray     100: 100 elems, type `float64`, 800 bytes
```

Both `%who` and `%whos` will list all variables, including those defined in the notebook's code cells. If you want to list only specific types of variables (like only lists or integers), you can use:

```
%who int
%whos int
```

```
a
Variable   Type    Data/Info
----------------------------
a          int     10
```

```
%who str
%whos str
```

```
b    current_dir     file_path
Variable      Type    Data/Info
-------------------------------
b             str     data science
current_dir   str     c:\Users\lsi8012\OneDrive<...>iversity\FA24\303-1\Week2
file_path     str     C:Users\Username\Documents\data.csv
```

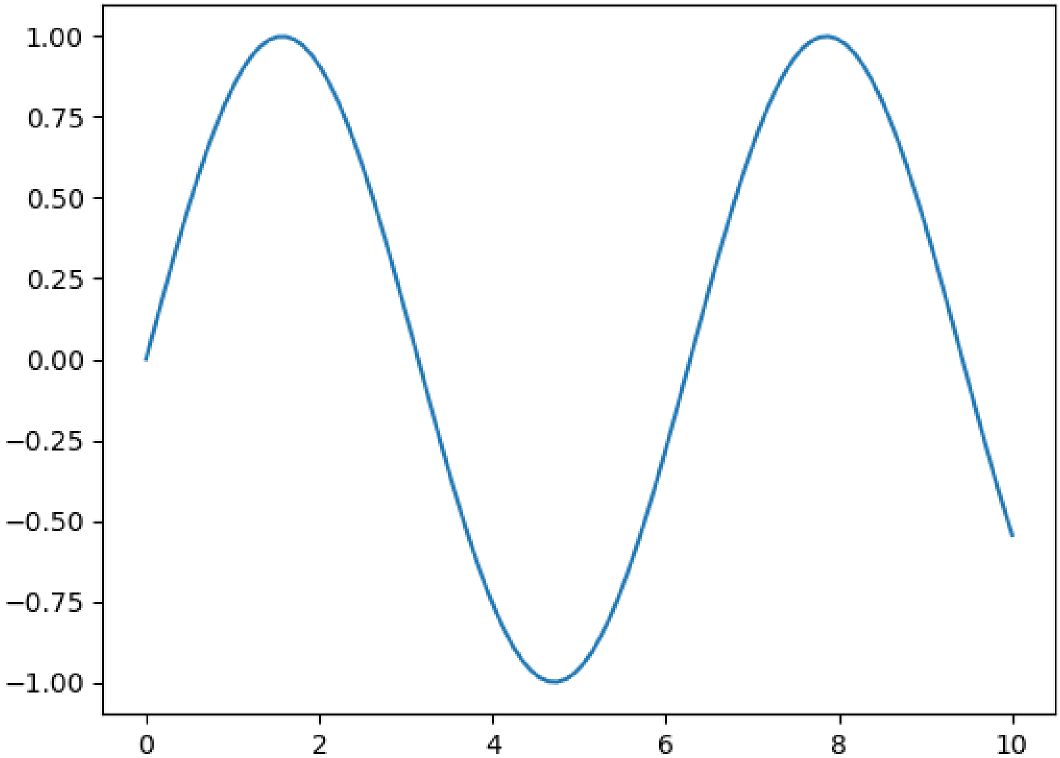
4.1.2.3 `%matplotlib inline`: Displaying plots inline

This command allows you to embed plots within the notebook.

```
# Example: Using %matplotlib inline to display a plot
import matplotlib.pyplot as plt
import numpy as np

%matplotlib inline

x = np.linspace(0, 10, 100)
y = np.sin(x)
plt.plot(x, y);
```



4.1.3 Cell Magic Commands

A cell magic command in Jupyter notebook has to be the first line in the code cell

4.1.3.1 `%%time`: Timing cell execution

This cell magic is useful for measuring the execution time of an entire cell.

```
%%time
# Example: Timing a cell with matrix multiplication

import numpy as np

A = np.random.rand(1000, 1000)
B = np.random.rand(1000, 1000)
C = np.dot(A, B)
```

```
UsageError: Line magic function `%%time` not found.
```

4.1.3.2 `%%writefile`: Writing content to a file

This command writes the contents of the cell to a file. **Note that, it has to be the first line in the code cell**

```
%%writefile sample.txt
This is an example of writing content to a file using %%writefile magic command.
```

```
Overwriting sample.txt
```

Question: there are several timing magic commands that can be confusing due to their similarities, they are `%time`,`%timeit`, `%%time`, and `%timeit`. Do your own research on the differences among them

4.2 Shell Commands in Jupyter Notebooks

What are Shell Commands?

Shell commands allow you to interact with the underlying operating system. You can execute them directly within Jupyter by prefixing the command with an exclamation mark (`!`). In a Jupyter notebook, while the `IPython kernel` executes the Python code, it delegates the shell commands to the operating system's shell. They are not executed by the same engine. The IPython kernel is for Python code, while the shell commands are handled by underlying `operating system shell` (e.g., Bash on macOS/Linux, or Command Prompt/PowerShell on Windows).

4.2.1 Using Shell Commands

4.2.1.1 `!pwd`(`!cd` in windows): Print working directory

You can check current working directory with the `!pwd`(`!cd` in windows) command.

```
!cd
```

```
c:\Users\lsi8012\OneDrive - Northwestern University\FA24\303-1\Week2
```

4.2.1.2 `!ls`(`!dir` in windows): Listing files and directories

List the contents of the current directory.

```
!dir
```

```
 Volume in drive C is Windows
 Volume Serial Number is A80C-7DEC

 Directory of c:\Users\lsi8012\OneDrive - Northwestern University\FA24\303-1\Week2

10/01/2024  12:37 PM    <DIR>          .
10/01/2024  12:37 PM    <DIR>          ..
09/30/2024  04:49 PM         1,088,640 Environments.pptx
09/29/2024  02:19 PM           985,591 env_setup.html
09/29/2024  01:18 PM             5,289 Exercise1_Environment.ipynb
09/29/2024  03:23 PM    <DIR>          images
10/01/2024  12:44 PM            46,267 magic_shell_path_specification.ipynb
09/16/2024  02:25 PM            72,461 python-os-and-filesystem.ipynb
10/01/2024  12:38 PM                82 sample.txt
09/29/2024  03:20 PM           783,205 Setup_env.pdf
09/29/2024  02:19 PM            36,228 venv_setup.ipynb
               8 File(s)      3,017,763 bytes
               3 Dir(s)  153,680,662,528 bytes free
```

4.2.1.3 `!mkdir`: Creating a new directory

You can create a new directory using the `!mkdir` command.

```
!mkdir new_folder
```

4.2.1.4 `!cat`(`type` in windows): Displaying file content

Use `!cat`(`type` in windows) to display the contents of a file.

```
!type sample.txt
```

```
This is an example of writing content to a file using %%writefile magic command.
```

4.3 Installing required packages within your notebook

When installing packages from within a Jupyter notebook, you have two main options: using a shell command or a magic command

- `!pip install package_name`
- `%pip install package_name`

To ensure the installation occurs in the correct environment (i.e., the environment in which the notebook kernel is running), you can use the Python executable associated with the current notebook.

```
import sys
!{sys.executable} -m pip install numpy
```

```
Requirement already satisfied: numpy in c:\users\lsi8012\appdata\local\anaconda3\lib\site-pa
```

In contrast, magic Command (`%pip`) is Jupyter-specific and automatically ensures that packages are installed in the correct environment (the notebook's environment).

```
%pip install numpy
```

```
Requirement already satisfied: numpy in c:\users\lsi8012\appdata\local\anaconda3\lib\site-pa
Note: you may need to restart the kernel to use updated packages.
```

In real cases, we don't need to use `%` before `pip install numpy` because automagic is enabled by default in IPython kernels. This allows magic commands to be run without the `%` prefix, as long as there is no variable named `pip` in the current scope, which would take precedence over the magic command. Automagic allows some line magic commands to be run without the % prefix, but not all magic commands.

```
pip install numpy
```

```
Requirement already satisfied: numpy in c:\users\lsi8012\appdata\local\anaconda3\lib\site-pa
Note: you may need to restart the kernel to use updated packages.
```

4.4 File Path in Data Science

Next, we will discuss how to specify file paths in Python for loading and saving data, with an emphasis on **absolute** and **relative** paths. File paths are crucial when working with files in Python, such as reading datasets and writing results to files. Let's explore the difference between **absolute paths** and **relative paths**.

4.4.0.1 Absolute Path

An **absolute path** provides the complete location of a file or directory from the root directory of your file system. It is independent of the current working directory.

4.4.0.2 Example of an Absolute Path (Windows):

```
# Absolute path example (Windows)
file_path = r"C:\Users\Username\Documents\data.csv"

::: {.cell execution_count=25}
``` {.python .cell-code}
!conda env list
```

```
# conda environments:
#
base                  *  C:\Users\lsi8012\AppData\Local\anaconda3
                         c:\Users\lsi8012\Documents\Courses\STAT303-Fa24\stat303_conda\.conda
```

:::

The path associated with each conda env is absolute path.

4.4.0.3 Relative Path

A **relative path** specifies the file location in relation to the current working directory. It is shorter and more flexible since it doesn't require the full path from the root.

To find the current working directory in Python, you can use either a magic command or a shell command, as shown below:

```
# Magic command
%pwd
```

```
'c:\\Users\\lsi8012\\OneDrive - Northwestern University\\FA24\\303-1\\Week2'
```

```
# Shell command
!cd
```
```

```
c:\Users\lsi8012\OneDrive - Northwestern University\FA24\303-1\Week2
```

Example of a Relative Path:

```
# Example of relative path
file_path = "sample.txt"  # Relative to the current directory
```

The relative path `sample.txt` means that there is a file in the current working directory.

4.4.0.4 Methods to Specify file path in Windows

Windows uses backslashes (\) to separate directories in file paths. However, in Python, the backslash is an escape character, so you need to either: * Escape backslashes by using a double backslash (\\), or * Use raw strings by prefixing the path with `r`.

4.4.0.4.1 Method 1: Using escaped backslashes

```
file_path = "C:\\Users\\Username\\Documents\\data.csv"
```

4.4.0.4.2 Method 2: Using Raw Strings

```
file_path = r"C:\Users\Username\Documents\data.csv"
```

4.4.0.4.3 Method 3: Using forward slashes (/)

```
file_path = "C:/Users/Username/Documents/data.csv"
```

4.4.0.4.4 Method 4: Using `os.path.join`

```
import os
file_path = os.path.join("C:", "Users", "Username", "Documents", "data.csv")
```

This method works across different operating systems because `os.path.join` automatically uses the correct path separator (\ for Windows and /for Linux/Mac).

macOS does not have the same issue as Windows when specifying file paths because macOS (like Linux) uses forward slashes (/) as the path separator, which is consistent with Python's expectations.

4.4.0.5 Best Practices for File Paths in Data Science

- Use relative paths when working in a project structure, as it allows the project to be portable.
- Use absolute paths when working with external or shared files that aren't part of your project.
- Check the current working directory to ensure you are referencing files correctly.
- Avoid hardcoding file paths directly in the code to make your code reusable on different machines.
- Use the forward slash (/) as a path separator or `os.path.join` to specify file path if your code will work across different operating systems

4.5 Interacting with the OS and filesystem

In data science, you frequently work with data files (e.g., CSVs, Excel, JSON) stored in different directories. The `os` module allow you to interact with the OS and the filesystem. Let's import it and try out some commonly used functions in this module.

```
import os
```

We can get the location of the current working directory using the `os.getcwd` function.

```
os.getcwd()
```

```
'c:\\Users\\lsi8012\\OneDrive - Northwestern University\\FA24\\303-1\\Week2'
```

The command `os.chdir('..')` in Python changes the current working directory to the parent directory of the current one.

Note that `..` as the path notation for the parent directory is universally true across all major operating systems, including Windows, macOS, and Linux. It allows you to move one level up in the directory hierarchy, which is very useful when navigating directories programmatically, especially in scripts where directory traversal is needed.

```
os.chdir('..')
```

```
os.getcwd()
```

```
'c:\\Users\\lsi8012\\OneDrive - Northwestern University\\FA24\\303-1'
```

`os.chdir()` is used to change the current working directory.

```
os.chdir('./week2')
```

`./week2` is a relative path: * `.` refers to the current directory. * week2 is a folder inside the current directory.

```
os.getcwd()
```

```
'c:\\Users\\lsi8012\\OneDrive - Northwestern University\\FA24\\303-1\\week2'
```

The `os.listdir()` function in Python returns a list of all files and directories in the specified path. If no path is provided, it returns the contents of the current working directory.

```
os.listdir()
```

```
['Environments.pptx',
 'env_setup.html',
 'Exercise1_Environment.ipynb',
 'images',
 'magic_shell_path_specification.ipynb',
 'python-os-and-filesystem.ipynb',
 'Setup_env.pdf',
 'venv_setup.ipynb']
```

Check whether a specific folder/file exist in the current working directory

```
'data' in os.listdir('.')
```

```
False
```

Part III

Exploratory data analysis

5 Reading Data

5.1 Types of data

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

5.2 Using Pandas to Read CSVs

Pandas is a popular Python library used for working in tabular data (similar to the data stored in a spreadsheet). Pandas provides helper functions to read data from various file formats like CSV, Excel spreadsheets, HTML tables, JSON, SQL, and more.

The below format of storing data is known as *comma-separated values* or CSV. It contains day-wise Covid-19 data for Italy:

```
date,new_cases,new_deaths,new_tests
2020-04-21,2256.0,454.0,28095.0
2020-04-22,2729.0,534.0,44248.0
2020-04-23,3370.0,437.0,37083.0
2020-04-24,2646.0,464.0,95273.0
2020-04-25,3021.0,420.0,38676.0
2020-04-26,2357.0,415.0,24113.0
2020-04-27,2324.0,260.0,26678.0
2020-04-28,1739.0,333.0,37554.0
...
```

> **CSVs**: A comma-separated values (CSV) file is a delimited text file that uses a comma to separate values. Each line of the file is a data record. Each record consists of one or more fields, separated by commas. A CSV file typically stores tabular data (numbers and text) in plain text, in which case each line will have the same number of fields. (Wikipedia)

First, let's import the Pandas library. As a convention, it is imported with the alias `pd`.

```python
import pandas as pd
import os
```

5.2.1 Using the `read_csv` function

The `pd.read_csv` function can be used to read a CSV file into a pandas `DataFrame`: a spreadsheet-like object for analyzing and processing data.

```python
movie_ratings = pd.read_csv('../data/movie_ratings.csv')
```

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

```python
type(movie_ratings)
```

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

We'll learn more about `DataFrame` in a future lesson.

Note that I use the **`relative path`** to specify the file path for *movie_ratings.csv*, you may need to change it based on where you store the data file.

5.2.2 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.

```python
movie_ratings.head()
```

	Title	US Gross	Worldwide Gross	Production Budget	Release Date	MPAA Rating	Source	Major
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		

Row Indices and column names (axis labels)

By default, when you create a pandas DataFrame (or Series) without specifying an index, pandas will automatically assign integer-based row indices starting from 0. These indices serve as the row labels and uniquely identify each row in the DataFrame. For example, the index 2 correponds 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**.

Basic information We can view some basic information about the data frame using the `.info` method.

```
movie_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2228 entries, 0 to 2227
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Title              2228 non-null   object 
 1   US Gross           2228 non-null   int64  
 2   Worldwide Gross    2228 non-null   int64  
 3   Production Budget  2228 non-null   int64  
 4   Release Date       2228 non-null   object 
 5   MPAA Rating        2228 non-null   object 
 6   Source             2228 non-null   object 
 7   Major Genre        2228 non-null   object 
 8   Creative Type      2228 non-null   object 
 9   IMDB Rating        2228 non-null   float64
 10  IMDB Votes         2228 non-null   int64  
dtypes: float64(1), int64(4), object(6)
memory usage: 191.6+ KB
```

The `shape` property of a pandas DataFrame provides a tuple that represents the dimensions of the DataFrame:

- The first value in the tuple is the number of rows.
- The second value in the tuple is the number of columns.

```
movie_ratings.shape
```

```
(2228, 11)
```

The `columns` property contains the list of columns within the data frame.

```
movie_ratings.columns
```

```
Index(['Title', 'US Gross', 'Worldwide Gross', 'Production Budget',
       'Release Date', 'MPAA Rating', 'Source', 'Major Genre', 'Creative Type',
       'IMDB Rating', 'IMDB Votes'],
      dtype='object')
```

You can view statistical information for numerical columns (mean, standard deviation, minimum/maximum values, and the number of non-empty values) using the `.describe` method.

```
movie_ratings.describe()
```

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

Functions & Methods we've looked so far

- `pd.read_csv` - Read data from a CSV file into a Pandas `DataFrame` object
- `.info()` - View basic infomation about rows, columns & data types
- `.shape` - Get the number of rows & columns as a tuple
- `.columns` - Get the list of column names
- `.describe()` - View statistical information about numeric columns

5.3 Data Selection and Filtering

5.3.1 Extracting Column(s) from pandas

The first step when working with a DataFrame is often to extract one or more columns. To do this effectively, it's helpful to understand the internal structure of a DataFrame. Conceptually, you can think of a DataFrame as a dictionary of lists, where the keys are column names, and the values are lists or arrays containing data for the respective columns.

```
# Pandas format is simliar to this
movie_ratings_dict = {
    'Title':  ['Opal Dreams', 'Major Dundee', 'The Informers', 'Buffalo Soldiers', 'The La
    'US Gross':  [14443, 14873, 315000, 353743, 388390],
    'Worldwide Gross': [14443, 14873, 315000, 353743, 388390],
    'Production Budget': [9000000, 3800000, 18000000, 15000000, 2200000]
}
```

For dictionary, we use key to retrive its values

```
movie_ratings_dict['Title']
```

```
['Opal Dreams',
 'Major Dundee',
 'The Informers',
 'Buffalo Soldiers',
 'The Last Sin Eater']
```

Similar like dictionary, we can extract a column by its column name

```
movie_ratings['Title']
```

```
0                          Opal Dreams
1                         Major Dundee
2                        The Informers
3                     Buffalo Soldiers
4                   The Last Sin Eater
                        ...
2223                       King Arthur
2224                             Mulan
2225                        Robin Hood
2226    Robin Hood: Prince of Thieves
2227                        Spiceworld
Name: Title, Length: 2228, dtype: object
```

Each column is a feature of the dataframe, we can also use `.` operator to extract a single column

```
movie_ratings.Title
```

```
0                         Opal Dreams
1                        Major Dundee
2                       The Informers
3                    Buffalo Soldiers
4                   The Last Sin Eater
                     ...
2223                      King Arthur
2224                            Mulan
2225                       Robin Hood
2226    Robin Hood: Prince of Thieves
2227                       Spiceworld
Name: Title, Length: 2228, dtype: object
```

When extracting multiple columns, you need to place the column names inside a list.

```
movie_ratings[['Title', 'US Gross', 'Worldwide Gross' ]]
```

	Title	US Gross	Worldwide Gross
0	Opal Dreams	14443	14443
1	Major Dundee	14873	14873
2	The Informers	315000	315000
3	Buffalo Soldiers	353743	353743
4	The Last Sin Eater	388390	388390
...	...	...	...
2223	King Arthur	51877963	203877963
2224	Mulan	120620254	303500000
2225	Robin Hood	105269730	310885538
2226	Robin Hood: Prince of Thieves	165493908	390500000
2227	Spiceworld	29342592	56042592

5.3.2 Extracting 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.

Let us first sort the `movie_ratings` data frame by `IMDB Rating`.

```
movie_ratings_sorted = movie_ratings.sort_values(by = 'IMDB Rating', ascending = False)
movie_ratings_sorted.head()
```

	Title	US Gross	Worldwide Gross	Production Budget	Release Date	MPAA Rating	Source	Major
182	The Shawshank Redemption	28241469	28241469	25000000	Sep 23 1994	R		
2084	Inception	285630280	753830280	160000000	Jul 16 2010	PG		
2092	Toy Story 3	410640665	1046340665	200000000	Jun 18 2010	G		
1962	Pulp Fiction	107928762	212928762	8000000	Oct 14 1994	R		
790	Schindler's List	96067179	321200000	25000000	Dec 15 1993	R		

5.3.2.1 Subsetting the DataFrame by `loc`

The operator `loc` uses axis labels (row indices and column names) to subset the data.

Let's subset the `title`, `worldwide gross`, `production budget`, and `IMDB raring` of top 3 movies.

```
# Subsetting the DataFrame by loc - using axis labels
movies_subset = movie_ratings_sorted.loc[[182,2084, 2092],[ 'Title', 'IMDB Rating', 'US Gr
movies_subset
```

	Title	IMDB Rating	US Gross	Worldwide Gross	Production Budget
182	The Shawshank Redemption	9.2	28241469	28241469	25000000
2084	Inception	9.1	285630280	753830280	160000000
2092	Toy Story 3	8.9	410640665	1046340665	200000000

The `:` symbol in `.loc` and `.iloc` is a slicing operator that represents a range or all elements in the specified dimension (rows or columns). Use `:` alone to select all rows/columns, or with start/end points to slice specific parts of the DataFrame.

```
# Subsetting the DataFrame by loc - using axis labels. the colon is used to select all row
movies_subset = movie_ratings_sorted.loc[:,['Title','Worldwide Gross','Production Budget',
movies_subset
```

	Title	Worldwide Gross	Production Budget	IMDB Rating
182	The Shawshank Redemption	28241469	25000000	9.2
2084	Inception	753830280	160000000	9.1
2092	Toy Story 3	1046340665	200000000	8.9

	Title	Worldwide Gross	Production Budget	IMDB Rating
1962	Pulp Fiction	212928762	8000000	8.9
790	Schindler's List	321200000	25000000	8.9
...	...	...	...	...
516	Son of the Mask	59918422	100000000	2.0
1495	Disaster Movie	34690901	20000000	1.7
1116	Crossover	7009668	5600000	1.7
805	From Justin to Kelly	4922166	12000000	1.6
1147	Super Babies: Baby Geniuses 2	9109322	20000000	1.4

```
# Subsetting the DataFrame by loc - using axis labels. the colon is used to select a range
movies_subset = movie_ratings_sorted.loc[182:561,['Title','Worldwide Gross','Production Bu
movies_subset
```

	Title	Worldwide Gross	Production Budget	IMDB Rating
182	The Shawshank Redemption	28241469	25000000	9.2
2084	Inception	753830280	160000000	9.1
2092	Toy Story 3	1046340665	200000000	8.9
1962	Pulp Fiction	212928762	8000000	8.9
790	Schindler's List	321200000	25000000	8.9
561	The Dark Knight	1022345358	185000000	8.9

5.3.2.2 Subsetting the DataFrame by `iloc`

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.

```
movie_ratings_sorted.head()
```

	Title	US Gross	Worldwide Gross	Production Budget	Release Date	MPAA Rating	Source	Major
182	The Shawshank Redemption	28241469	28241469	25000000	Sep 23 1994	R		
2084	Inception	285630280	753830280	160000000	Jul 16 2010	PG		
2092	Toy Story 3	410640665	1046340665	200000000	Jun 18 2010	G		
1962	Pulp Fiction	107928762	212928762	8000000	Oct 14 1994	R		
790	Schindler's List	96067179	321200000	25000000	Dec 15 1993	R		

Title	US Gross	Worldwide Gross	Production Budget	Release Date	MPAA Rating	Source	Major

```
movie_ratings_sorted.iloc[0:3,[0,2,3,9]]
```

	Title	Worldwide Gross	Production Budget	IMDB Rating
182	The Shawshank Redemption	28241469	25000000	9.2
2084	Inception	753830280	160000000	9.1
2092	Toy Story 3	1046340665	200000000	8.9

```
# Subsetting the DataFrame by iloc - using index of the position of rows and columns
movies_iloc_subset = movie_ratings_sorted.iloc[182:561,[0,2,3,9]]
movies_iloc_subset
```

	Title	Worldwide Gross	Production Budget	IMDB Rating
227	The Boy in the Striped Pyjamas	39830581	12500000	7.8
1463	Lage Raho Munnabhai	31517561	2700000	7.8
363	Coraline	124062750	60000000	7.8
1628	Lucky Number Slevin	55495466	27000000	7.8
1418	Dark City	27257061	27000000	7.8
...	...	...	...	...
1720	Coach Carter	76669806	45000000	7.1
249	Little Women	50003303	15000000	7.1
1752	Drag Me To Hell	85724728	30000000	7.1
1150	Black Snake Moan	9396870	15000000	7.1
665	Find Me Guilty	1788077	13000000	7.1

Why `iloc` returns different rows?

```
# Subsetting the DataFrame by iloc - using index of the position of rows and columns
movies_iloc_subset1 = movie_ratings_sorted.iloc[0:10,[0,2,3,9]]
movies_iloc_subset1
```

	Title	Worldwide Gross	Production Budget	IMDB Rating
182	The Shawshank Redemption	28241469	25000000	9.2
2084	Inception	753830280	160000000	9.1
2092	Toy Story 3	1046340665	200000000	8.9

	Title	Worldwide Gross	Production Budget	IMDB Rating
1962	Pulp Fiction	212928762	8000000	8.9
790	Schindler's List	321200000	25000000	8.9
561	The Dark Knight	1022345358	185000000	8.9
184	Cidade de Deus	28763397	3300000	8.8
487	The Lord of the Rings: The Fellowship of the Ring	868621686	109000000	8.8
497	The Lord of the Rings: The Return of the King	1133027325	94000000	8.8
1081	C'era una volta il West	5321508	5000000	8.8

5.3.2.3 Key differences between `loc` and `iloc` in pandas

- **Indexing Type:**
  - loc uses labels (names) for indexing.
  - iloc uses integer positions for indexing.
- **Inclusion of Endpoints:**
  - In a loc slice, both endpoints are included.
  - In an iloc slice, the endpoint is excluded.

Example:

```python
# Assuming you have a DataFrame like this:
import pandas as pd

data = {'A': [1, 2, 3, 4, 5],
        'B': [10, 20, 30, 40, 50],
        'C': [100, 200, 300, 400, 500]}

df = pd.DataFrame(data, index=['row1', 'row2', 'row3', 'row4', 'row5'])
df
```

	A	B	C
row1	1	10	100
row2	2	20	200
row3	3	30	300
row4	4	40	400
row5	5	50	500

```
# using 'loc'
df.loc['row2':'row4', 'B']
```

```
row2    20
row3    30
row4    40
Name: B, dtype: int64
```

```
# using 'iloc'
df.iloc[1:4, 1]
```

```
row2    20
row3    30
row4    40
Name: B, dtype: int64
```

Note that in the `loc` example, both ‘row2’ and ‘row4’ are included in the result, whereas in the `iloc` example, the row at position 4 is excluded.

5.3.3 Extracting rows based on a Single Condition or Multiple Conditions

In many cases, we need to filter data based on specific conditions or a combination of multiple conditions. Next, let’s explore how to use these conditions effectively to extract rows that meet our criteria, whether it’s a single condition or multiple conditions combined

```
# extracting the rows that have IMDB Rating greater than 8
movie_ratings[movie_ratings['IMDB Rating'] > 8]
```

	Title	US Gross	Worldwide Gross	Production Budget	Release Date	MPAA Rating	Source	Major
21	Gandhi, My Father	240425	1375194	5000000	Aug 03 2007	Other		
56	Ed Wood	5828466	5828466	18000000	Sep 30 1994	R		
67	Requiem for a Dream	3635482	7390108	4500000	Oct 06 2000	Other		
164	Trainspotting	16501785	24000785	3100000	Jul 19 1996	R		
181	The Wizard of Oz	28202232	28202232	2777000	Aug 25 2039	G		
...	...	...	...	...	...	...		
2090	Finding Nemo	339714978	867894287	94000000	May 30 2003	G		
2092	Toy Story 3	410640665	1046340665	200000000	Jun 18 2010	G		

	Title	US Gross	Worldwide Gross	Production Budget	Release Date	MPAA Rating	Source	Major
2094	Avatar	760167650	2767891499	237000000	Dec 18 2009	PG/PG-1		
2130	Scarface	44942821	44942821	25000000	Dec 09 1983	Other		
2194	The Departed	133311000	290539042	90000000	Oct 06 2006	R		

To combine multiple conditions in pandas, you need to use the `&` (AND) and `|` (OR) operators. Make sure to enclose each condition in parentheses () for clarity and to ensure proper evaluation order.

```
# extracting the rows that have IMDB Rating greater than 8 and US Gross less than 1000000
movie_ratings[(movie_ratings['IMDB Rating'] > 8) & (movie_ratings['US Gross'] < 1000000)]
```

	Title	US Gross	Worldwide Gross	Production Budget	Release Date	MPAA Rating	Source	Major
21	Gandhi, My Father	240425	1375194	5000000	Aug 03 2007	Other		
636	Lake of Fire	25317	25317	6000000	Oct 03 2007	Other		

Combining `.loc` with condition(s) to extract specific rows and columns based on criteria

```
# extracting the rows that have IMDB Rating greater than 8 or US Gross less than 1000000,
movie_ratings[(movie_ratings['IMDB Rating'] > 8) & (movie_ratings['US Gross'] < 1000000)][

#using loc to extract the rows that have IMDB Rating greater than 8 or US Gross less than
movie_ratings.loc[(movie_ratings['IMDB Rating'] > 8) & (movie_ratings['US Gross'] < 100000
```

	Title	IMDB Rating
21	Gandhi, My Father	8.1
636	Lake of Fire	8.4

Can you use `.iloc` for conditional filtering, why or why not?

5.3.4 Finding minimum/maximum of a column

When working with pandas, there are two main options for locating the minimum or maximum values in a DataFrame column:

- `idxmin()` and `idxmax()`: return the **index label** of the first occurrence of the maximum or minimum value in a specified column.

```python
# movie_ratings_sorted.iloc[position_max_wgross,:]
max_index = movie_ratings_sorted['Worldwide Gross'].idxmax()
min_index = movie_ratings_sorted['Worldwide Gross'].idxmin()
print("Max index: ", max_index)
print("Min index: ", min_index)
```

```
Max index:  2094
Min index:  896
```

`idxmin()` and `idxmax()` return the index label of the minimum or maximum value in a column. You can use these returned index labels with `.loc` to extract the corresponding row.

```python
print(movie_ratings_sorted.loc[max_index,'Worldwide Gross'])
print(movie_ratings_sorted.loc[min_index,'Worldwide Gross'])
```

```
2767891499
884
```

- `argmax()` and `argmin()`: Return the **integer position** of the first occurrence of the maximum or minimum value in a column. You can use these integer positions with `.iloc` to extract the corresponding row

```python
# using argmax and argmin, which return the index of the maximum and minimum values
max_position = movie_ratings_sorted['Worldwide Gross'].argmax()
min_position = movie_ratings_sorted['Worldwide Gross'].argmin()
print("max position:", max_position)
print("min position:", min_position)

# using iloc to get the row with the maximum and minimum values
print(movie_ratings_sorted.iloc[max_position, 2])
print(movie_ratings_sorted.iloc[min_position, 2])
```

```
max position: 43
min position: 2146
2767891499
884
```

Additional Tips: * If you are dealing with non-unique or non-default indices, prefer using `idxmax()/idxmin()` to get the index labels, as `argmax()` might be less intuitive in such cases. * For DataFrames, consider using `.idxmax(axis=1)` or `.idxmin(axis=1)` to find the max/min index labels along rows instead of columns.

5.4 DataType and DataType Conversion

```
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
```

The `dtypes` property is used to find the dtypes in the DataFrame.

This returns a Series with the data type of each column.

While it's common for columns containing strings to have the `object` data type, it can also include other types such as lists, dictionaries, or even mixed types within the same column. The `object` data type is a catch-all for columns that contain mixed types or types that aren't easily categorized.

5.4.1 Available Data Types and Associated Built-in Functions

In a DataFrame, columns can have different data types. Here are the common data types you'll encounter and some built-in functions associated with each type:

1. **Numerical Data (int, float)**
   - Built-in functions: `mean()`, `sum()`, `min()`, `max()`, `std()`, `median()`, `quantile()`, etc.
2. **Object Data (str or mixed types)**
   - Built-in functions: `str.contains()`, `str.startswith()`, `str.endswith()`, `str.lower()`, `str.upper()`, `str.replace()`, etc.
3. **Datetime Data (datetime64)**

- Built-in functions: `dt.year`, `dt.month`, `dt.day`, `dt.strftime()`, `dt.weekday()`, `dt.hour`, etc.

These functions help in exploring and transforming the data effectively depending on the type of data in each column.

5.4.2 Data Type Conversion

When you work on a specific column, being mindful of which data type it is, the data type depends on its built in function.

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

```
movie_ratings['Release Date']
```

```
0       Nov 22 2006
1       Apr 07 1965
2       Apr 24 2009
3       Jul 25 2003
4       Feb 09 2007
           ...
2223    Jul 07 2004
2224    Jun 19 1998
2225    May 14 2010
2226    Jun 14 1991
2227    Jan 23 1998
Name: Release Date, Length: 2228, dtype: object
```

```
# check the datatype of release data column
movie_ratings['Release Date'].dtypes
```

```
dtype('O')
```

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

Next, 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'])
```

```
# Let's check the datatype of release data column again
movie_ratings['Release Date'].dtypes
```

```
dtype('<M8[ns]')
```

`dtype('<M8[ns]')` means a 64-bit datetime object with nanosecond precision stored in little-endian format. This data type is commonly used to represent timestamps in high-resolution time series data.

Next, we can use the built-in datetime functions to extract the year from this variable and create the 'release year' column.

```
# Extracting the year from the 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	Source	Major
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		

In Pandas, the `errors='coerce'` parameter is often used in the context of data conversion, specifically when using the `pd.to_numeric` function. This argument tells Pandas to convert values that it can and set the ones it cannot convert to `NaN`. It's a way of gracefully handling errors without raising an exception. Read the textbook for an example

5.4.3 Data Type Filtering

We can filter the columns based on its data types

```
# select just object columns
```

```
movie_ratings.select_dtypes(include='object').head()
```

	Title	MPAA Rating	Source	Major Genre	Creative Type
0	Opal Dreams	PG/PG-13	Adapted screenplay	Drama	Fiction
1	Major Dundee	PG/PG-13	Adapted screenplay	Western/Musical	Fiction
2	The Informers	R	Adapted screenplay	Horror/Thriller	Fiction
3	Buffalo Soldiers	R	Adapted screenplay	Comedy	Fiction
4	The Last Sin Eater	PG/PG-13	Adapted screenplay	Drama	Fiction

```
# select the numeric columns
movie_ratings.select_dtypes(include='number').head()
```

	US Gross	Worldwide Gross	Production Budget	IMDB Rating	IMDB Votes	Release Year	ratio_wg
0	14443	14443	9000000	6.5	468	2006	0.00160
1	14873	14873	3800000	6.7	2588	1965	0.00391
2	315000	315000	18000000	5.2	7595	2009	0.01750
3	353743	353743	15000000	6.9	13510	2003	0.02358
4	388390	388390	2200000	5.7	1012	2007	0.17654

5.4.4 Summary statistics across rows/columns in Pandas: Numeric Columns

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

By default, functions like `mean()` and `sum()` compute the statistics for each column (i.e., all rows are aggregated) in the DataFrame. Let us compute the mean of all the numeric columns of the data:

```
movie_ratings.describe()
```

	US Gross	Worldwide Gross	Production Budget	IMDB Rating	IMDB Votes
count	2.228000e+03	2.228000e+03	2.228000e+03	2228.000000	2228.000000
mean	5.076370e+07	1.019370e+08	3.816055e+07	6.239004	33585.154847
std	6.643081e+07	1.648589e+08	3.782604e+07	1.243285	47325.651561
min	0.000000e+00	8.840000e+02	2.180000e+02	1.400000	18.000000
25%	9.646188e+06	1.320737e+07	1.200000e+07	5.500000	6659.250000
50%	2.838649e+07	4.266892e+07	2.600000e+07	6.400000	18169.000000

	US Gross	Worldwide Gross	Production Budget	IMDB Rating	IMDB Votes
75%	6.453140e+07	1.200000e+08	5.300000e+07	7.100000	40092.750000
max	7.601676e+08	2.767891e+09	3.000000e+08	9.200000	519541.000000

```
# select the numeric columns
movie_ratings.mean(numeric_only=True)
```

```
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
Release Year              2.002005e+03
ratio_wgross_by_budget    1.259483e+01
dtype: float64
```

Using the `axis` parameter:

The `axis` parameter controls whether to compute the statistic across rows or columns: * The argument `axis=0`(deafult) 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
```

Pandas `sum` function

```
data = [[10, 18, 11], [13, 15, 8], [9, 20, 3]]
df = pd.DataFrame(data )
df
```

	0	1	2
0	10	18	11
1	13	15	8
2	9	20	3

```
# By default, the sum method adds values accross rows and returns the sum for each column
df.sum()
```

```
0    32
1    53
2    22
dtype: int64
```

```
# By specifying the column axis (axis='columns'), the sum() method add values accross colu
df.sum(axis = 'columns')
```

```
0    39
1    36
2    32
dtype: int64
```

```
# in python, axis=1 stands for column, while axis=0 stands for rows
df.sum(axis = 1)
```

```
0    39
1    36
2    32
dtype: int64
```

5.5 Writing data to a `.csv` file

The Pandas function `to_csv` can be used to write (or export) data to a csv. Below is an example.

```
#Exporting the data of the top 250 movies to a csv file
movie_ratings.to_csv('../data/movie_rating_exported.csv')
```

```
# check if the file has been exported
os.listdir('../data')
```

```
['bestseller_books.txt',
 'country-capital-lat-long-population.csv',
 'covid.csv',
 'fifa_data.csv',
 'food_quantity.csv',
 'gas_prices.csv',
 'gdp_lifeExpectancy.csv',
 'LOTR 2.csv',
 'LOTR.csv',
 'movies.csv',
 'movies_cleaned.csv',
 'movie_ratings.csv',
 'movie_ratings.txt',
 'movie_rating_exported.csv',
 'party_nyc.csv',
 'price.csv',
 'question_json_data.json',
 'spotify_data.csv',
 'stocks.csv']
```

5.6 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`.

5.6.1 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('../data/movie_ratings.txt',sep='\t')
movie_ratings_txt.head()
```

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

We use the function *read_csv* to read a *txt* file. However, we mention the tab character (r””) 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.

5.6.2 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:

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

	Unnamed: 0.1	Unnamed: 0	Name	Author	User Rating	Reviews	Price	Year	Genre
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],"colum
```

```
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('../data/bestseller_books.txt',sep=None, engine = 'python')
bestseller_books.head()
```

	Unnamed: 0.1	Unnamed: 0	Name	Author	User Rating	Reviews	Price	Year	Genre
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					

5.6.3 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	>$60,000 $50,000–$60,000 $40,000–$50,000 $30,0...	$20,000–$30,000 $10,000–$20,000 $5,000–$10,000...	$

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	IMF[4][5]		World Bank[6]		United Nations[7]	
	Country/Territory	Estimate	Year	Estimate	Year	Estimate	Year
0	Monaco	—	—	240862	2022	234317	2021
1	Liechtenstein	—	—	187267	2022	169260	2021
2	Luxembourg	131384	2024	128259	2023	133745	2021
3	Bermuda	—	—	123091	2022	112653	2021
4	Ireland	106059	2024	103685	2023	101109	2021
...	...	...	...	...	...	...	...
218	Malawi	481	2024	673	2023	613	2021
219	South Sudan	422	2024	1072	2015	400	2021
220	Afghanistan	422	2022	353	2022	373	2021
221	Syria	—	—	421	2021	925	2021
222	Burundi	230	2024	200	2023	311	2021

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 'Co
tables = pd.read_html('https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)_pe
```

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	IMF[4][5]		World Bank[6]		United Nations[7]	
	Country/Territory	Estimate	Year	Estimate	Year	Estimate	Year
0	Monaco	—	—	240862	2022	234317	2021
1	Liechtenstein	—	—	187267	2022	169260	2021
2	Luxembourg	131384	2024	128259	2023	133745	2021
3	Bermuda	—	—	123091	2022	112653	2021
4	Ireland	106059	2024	103685	2023	101109	2021
...	...	...	...	...	...	...	...
218	Malawi	481	2024	673	2023	613	2021
219	South Sudan	422	2024	1072	2015	400	2021
220	Afghanistan	422	2022	353	2022	373	2021
221	Syria	—	—	421	2021	925	2021
222	Burundi	230	2024	200	2023	311	2021

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

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

```
1
Number of rows = 25 and number of columns= 6
```

	Team	Titles	Runners-up	Third place	Fourth place	Top 4 total
0	Brazil	5 (1958, 1962, 1970, 1994, 2002)	2 (1950 *, 1998)	2 (1938, 1978)	2	
1	Germany1	4 (1954, 1974 *, 1990, 2014)	4 (1966, 1982, 1986, 2002)	4 (1934, 1970, 2006 *, 2010)	1	
2	Italy	4 (1934 *, 1938, 1982, 2006)	2 (1970, 1994)	1 (1990 *)	1	
3	Argentina	3 (1978 *, 1986, 2022)	3 (1930, 1990, 2014)	NaN	N	
4	France	2 (1998 *, 2018)	2 (2006, 2022)	2 (1958, 1986)	1	

5.6.5 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 hierachical 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/
```

```
tedtalks_data.head()
```

	id	speaker	headline	URL	description	transcript_URL	month_filmed	year_filmed	event	dura
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 G			
4	5	Chris Bangle	Great cars are great art			http://www.ted.com/talks/view/id/5	America			


```
[{'question': "What is the data type of values in the last column (named 'rates') of the abov
  'type': 'multiple_choice',
  'answers': [{'answer': 'list', 'correct': True, 'feedback': 'Correct!'},
   {'answer': 'string',
    'correct': False,
    'feedback': 'Incorrect. Use the type function on the variable to find its datatype.'},
   {'answer': 'numeric',
    'correct': False,
    'feedback': 'Incorrect. Use the type function on the variable to find its datatype.'},
   {'answer': 'dictionary',
    'correct': False,
    'feedback': 'Incorrect. Use the type function on the variable to find its datatype.'}]}]
```


This JSON data contains nested structures, such as lists and dictionaries, which require a deeper understanding to effectively structure. We will address this in future lectures

5.6.6 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
```

5.6.7 Reading data from a URL in Python

This process typically involves using the `requests` library, which allows you to send HTTP requests and handle responses easily.

You'll need to install it using `pip`

We'll use the CoinGecko API, which provides cryptocurrency market data. Here's an example of how to retrieve current market data:

```
import requests

# Define the URL of the API
url = 'https://api.coingecko.com/api/v3/coins/markets?vs_currency=usd'

# Send a GET request to the URL
response = requests.get(url)

# Check if the request was successful
if response.status_code == 200:
    # Parse the JSON data
    data = response.json()
    print(data)
else:
    print(f"Failed to retrieve data: {response.status_code}")
```


```
[{'id': 'bitcoin', 'symbol': 'btc', 'name': 'Bitcoin', 'image': 'https://coin-images.coingec
```


```
# Loop through the data and print the name and current price
for coin in data:
    name = coin['name']
    price = coin['current_price']
    print(f"Coin: {name}, Price: ${price}")
```

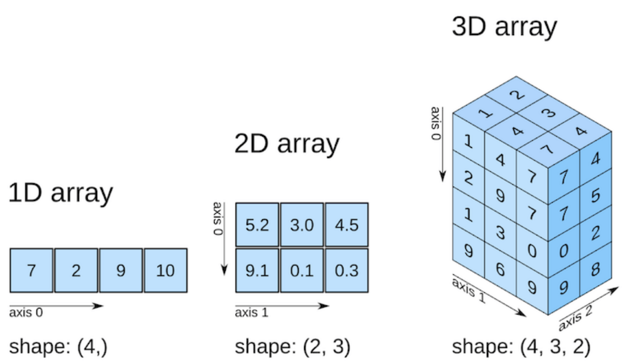
```
Coin: Bitcoin, Price: $62490
Coin: Ethereum, Price: $2434.1
Coin: Tether, Price: $0.999711
Coin: BNB, Price: $568.59
Coin: Solana, Price: $144.62
Coin: USDC, Price: $0.99982
Coin: XRP, Price: $0.531761
Coin: Lido Staked Ether, Price: $2433.54
Coin: Dogecoin, Price: $0.109138
Coin: TRON, Price: $0.156189
Coin: Toncoin, Price: $5.23
Coin: Cardano, Price: $0.35311
Coin: Avalanche, Price: $26.86
Coin: Shiba Inu, Price: $1.759e-05
```

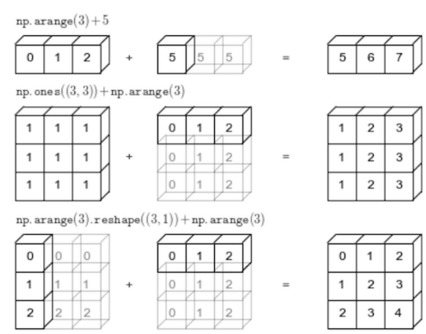
```
Coin: Wrapped stETH, Price: $2870.49
Coin: Wrapped Bitcoin, Price: $62339
Coin: WETH, Price: $2434.35
Coin: Chainlink, Price: $11.22
Coin: Bitcoin Cash, Price: $325.66
Coin: Polkadot, Price: $4.15
Coin: Dai, Price: $0.999811
Coin: Sui, Price: $2.06
Coin: NEAR Protocol, Price: $5.11
Coin: LEO Token, Price: $6.01
Coin: Uniswap, Price: $7.24
Coin: Litecoin, Price: $65.04
Coin: Bittensor, Price: $617.07
Coin: Aptos, Price: $8.91
Coin: Pepe, Price: $9.89e-06
Coin: Wrapped eETH, Price: $2554.88
Coin: Artificial Superintelligence Alliance, Price: $1.49
Coin: Internet Computer, Price: $8.13
Coin: Kaspa, Price: $0.137693
Coin: POL (ex-MATIC), Price: $0.376926
Coin: Ethereum Classic, Price: $18.7
Coin: Stellar, Price: $0.091505
Coin: Monero, Price: $144.06
Coin: Stacks, Price: $1.77
Coin: First Digital USD, Price: $0.999501
Coin: dogwifhat, Price: $2.56
Coin: OKB, Price: $41.75
Coin: Ethena USDe, Price: $0.998868
Coin: Immutable, Price: $1.49
Coin: Filecoin, Price: $3.74
Coin: Aave, Price: $146.68
Coin: Cronos, Price: $0.078844
Coin: Optimism, Price: $1.67
Coin: Render, Price: $5.32
Coin: Injective, Price: $20.63
Coin: Arbitrum, Price: $0.55172
Coin: Hedera, Price: $0.052714
Coin: Mantle, Price: $0.594723
Coin: Fantom, Price: $0.680296
Coin: VeChain, Price: $0.02305745
Coin: Cosmos Hub, Price: $4.44
Coin: THORChain, Price: $5.09
Coin: WhiteBIT Coin, Price: $11.61
```

```
Coin: The Graph, Price: $0.16643
Coin: Sei, Price: $0.436364
Coin: Bitget Token, Price: $1.075
Coin: Bonk, Price: $2.134e-05
Coin: Binance-Peg WETH, Price: $2434.55
Coin: FLOKI, Price: $0.00013831
Coin: Rocket Pool ETH, Price: $2719.44
Coin: Theta Network, Price: $1.31
Coin: Popcat, Price: $1.28
Coin: Arweave, Price: $19.03
Coin: Maker, Price: $1406.89
Coin: Mantle Staked Ether, Price: $2540.6
Coin: MANTRA, Price: $1.4
Coin: Pyth Network, Price: $0.327718
Coin: Helium, Price: $6.89
Coin: Solv Protocol SolvBTC, Price: $62563
Coin: Celestia, Price: $5.39
Coin: Gate, Price: $8.86
Coin: Jupiter, Price: $0.772541
Coin: Algorand, Price: $0.125351
Coin: Polygon, Price: $0.377139
Coin: Ondo, Price: $0.711239
Coin: Worldcoin, Price: $1.95
Coin: Quant, Price: $67.87
Coin: Lido DAO, Price: $1.079
Coin: KuCoin, Price: $7.95
Coin: JasmyCoin, Price: $0.01934656
Coin: Bitcoin SV, Price: $45.98
Coin: Conflux, Price: $0.198997
Coin: BitTorrent, Price: $9.23941e-07
Coin: Brett, Price: $0.088115
Coin: Core, Price: $0.937112
Coin: Fasttoken, Price: $2.6
Coin: GALA, Price: $0.02149496
Coin: ether.fi Staked ETH, Price: $2424.85
Coin: Wormhole, Price: $0.324805
Coin: Flow, Price: $0.540995
Coin: Notcoin, Price: $0.00801109
Coin: Beam, Price: $0.01552574
Coin: Renzo Restaked ETH, Price: $2482.56
Coin: Ethena, Price: $0.287191
Coin: Klaytn, Price: $0.132756
Coin: Aerodrome Finance, Price: $1.2
```

6 NumPy

NumPy is a foundational library in Python, providing support for large, multi-dimensional arrays and matrices, along with a variety of mathematical functions. It's a critical tool in data science and machine learning because it enables efficient numerical computations, data manipulation, and linear algebra operations. Many machine learning algorithms rely on these operations to process data and perform complex calculations quickly. Moreover, popular libraries like `Pandas`, `SciPy`, and `TensorFlow` are built on top of NumPy, making it essential to understand for implementing and optimizing machine learning models.





6.1 Learning Objectives

By the end of this lecture, students should be able to:

1. Understand the basic structure and functionarlity of NumPy
2. Create and manipulate NumPy arrays.
3. Perform mathematical and statistical operations on arrays.
4. Utilize advanced concepts such as slicing, broadcasting, and vectorization.
5. Apply NumPy operations to real-world data science problems.

6.2 Getting Started

```
import numpy as np
import pandas as pd
```

If you encounter a 'ModuleNotFoundError', please ensure that the module is installed in your current environment before attempting to import it

```
#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
```

Numpy arrays can have any number of dimensions and different lengths along each dimension. We can inspect the length along each dimension using the `.shape` property of an array.

```
numpy_array.ndim
```

```
2
```

6.3 Data Types in NumPy

Unlike lists and tuples, NumPy arrays are designed to store elements of the same type, enabling more efficient memory usage and faster computations. The data type of the elements in a NumPy array can be accessed using the `.dtype` attribute

```
numpy_array.dtype
```

```
dtype('int64')
```

NumPy supports a wide range of data types, each with a specific memory size. Here is a list of common NumPy data types and the memory they consume:

Note that: these data type correspond directly to C data types, since NumPy uses C for the core computational operations. This C implementation allows NumPy to perform array operations much faster and more efficiently than native Python data structures.

Data Type	Memory Size
`np.int8`	1 byte
`np.int16`	2 bytes
`np.int32`	4 bytes
`np.int64`	8 bytes
`np.uint8`	1 byte
`np.uint16`	2 bytes
`np.uint32`	4 bytes
`np.uint64`	8 bytes
`np.float16`	2 bytes
`np.float32`	4 bytes
`np.float64`	8 bytes
`np.complex64`	8 bytes
`np.complex128`	16 bytes
`np.bool_`	1 byte
`np.string_`	1 byte per character
`np.unicode_`	4 bytes per character
`np.object_`	Variable
`np.datetime64`	8 bytes
`np.timedelta64`	8 bytes

6.3.1 Upcasting

When creating a NumPy array with elements of different data types, NumPy automatically attempts to **upcast** the elements to a compatible data type that can accommodate all of them. This process is known as **type coercion** or **type promotion**. The rules for upcasting follow a hierarchy of data types to ensure no data is lost.

Below are two common types of upcasting with examples:

Numeric Upcasting: If you mix integers and floats, NumPy will convert the entire array to floats.

```
arr = np.array([1, 2.5, 3])
print(arr.dtype)
```

```
float64
```

String Upcasting: If you mix numbers and strings, NumPy will upcast all elements to strings.

```
arr = np.array([1, 'hello', 3.5])
print(arr.dtype)
```

```
<U32
```

`<U21` is a NumPy data type that stands for a Unicode string with a maximum length of 21 characters.

6.4 Why do we need NumPy arrays?

NumPy arrays can store data similarly to lists and tuples, and the same computations can be performed across these structures. However, NumPy is preferred because it is significantly more efficient, particularly when handling large datasets, due to its optimized memory usage and computational speed.

6.4.1 Numpy arrays are memory efficient: Homogeneity and Contiguous Memory Storage

A NumPy array is a collection of elements of the same data type, stored in contiguous memory locations. In contrast, data structures like lists can hold elements of different data types, stored in non-contiguous memory locations. This homogeneity and contiguous storage allow NumPy arrays to be densely packed, leading to lower memory consumption. The following example demonstrates how NumPy arrays are more memory-efficient compared to other data structures.

```
import sys

# Create a NumPy array, Python list, and tuple with the same elements
array = np.arange(1000)
py_list = list(range(1000))
py_tuple = tuple(range(1000))

# Calculate memory usage
array_memory = array.nbytes
```

```
list_memory = sys.getsizeof(py_list) + sum(sys.getsizeof(item) for item in py_list)
tuple_memory = sys.getsizeof(py_tuple) + sum(sys.getsizeof(item) for item in py_tuple)

# Display the memory usage
memory_usage = {
    "NumPy Array (in bytes)": array_memory,
    "Python List (in bytes)": list_memory,
    "Python Tuple (in bytes)": tuple_memory
}

memory_usage
```

```
{'NumPy Array (in bytes)': 8000,
 'Python List (in bytes)': 36056,
 'Python Tuple (in bytes)': 36040}
```

```
# each element in the array is a 64-bit integer
array.dtype
```

```
dtype('int64')
```

6.4.2 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 up to 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()
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 =  0.021925687789916992
Time take to multiply numbers in a tuple =  0.028903484344482422
Time take to multiply numbers in a NumPy array =  0.011997461318969727
```

6.5 Basics of NumPy Arrays

6.5.1 Creating Arrays:

You can create a NumPy array using various methods, such as:

- `np.array()`: Creates an array from a list or iterable.
- `np.zeros()`, `np.ones()`: Creates arrays filled with zeros or ones.
- `np.arange()`, `np.linespace()`: Creates arrays with evenly spaced values.
- `np.random` module: Generates arrays with random values.

Each method is designed for different use cases. I encourage you to explore and experiment with these functions to see the types of arrays they produce and how they can be used in different scenarios.

6.5.2 Array Attributes:

Let us define a NumPy array in order to access its attributes:

```
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:

6.5.2.1 `ndim`

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

```
numpy_ex.ndim
```

```
2
```

6.5.2.2 `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)
```

6.5.2.3 `size`

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

```
numpy_ex.size
```

```
6
```

6.5.2.4 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('int64')
```

6.6 Array Indexing and Slicing

6.6.1 Array Indexing

Similar to Python lists, NumPy uses zero-based indexing, meaning the first element of an array is accessed using index `0`. You can use positive or negative indices to access elements

```
array = np.array([10, 20, 30, 40, 50])

print(array[0])
print(array[4])
print(array[-1])
print(array[-3])
```

```
10
50
50
30
```

In multi-dimensional arrays, indices are separated by commas. The first index refers to the row, and the second index refers to the column in a 2D array.

```
# 2D array (3 rows, 3 columns)
array_2d = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])
print(array_2d)
print(array_2d[0, 1])
print(array_2d[1, -1])
print(array_2d[-1, -1])
```

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

You can use boolean arrays to filter or select elements based on a condition

```
array = np.array([10, 20, 30, 40, 50])
mask = array > 30  # Boolean mask for elements greater than 30
print(array[mask])  # Output: [40 50]
```

```
[40 50]
```

6.6.2 Array Slicing

Slicing is used to extract a sub-array from an existing array.

The Syntax for slicing is ‘array[start:stop:step]

```
array = np.array([10, 20, 30, 40, 50])

print(array[1:4])
print(array[:3])
print(array[2:])
print(array[::2])
print(array[::-1])
```

```
[20 30 40]
[10 20 30]
[30 40 50]
```

```
[10 30 50]
[50 40 30 20 10]
```

For slicing in Multi-Dimensional Arrays, use commas to separate slicing for different dimensions

```
array_2d = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])

# Extract a sub-array: elements from the first two rows and the first two columns
sub_array = array_2d[:2, :2]
print(sub_array)

# Extract all rows for the second column
col = array_2d[:, 1]
print(col)

# Extract the last two rows and last two columns
sub_array = array_2d[-2:, -2:]
print(sub_array)
```

```
[[1 2]
 [4 5]]
[2 5 8]
[[5 6]
 [8 9]]
```

The `step` parameter can be used to select elements at regular intervals.

```
array = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

print(array[1:8:2])
print(array[::-2])
```

```
[1 3 5 7]
[9 7 5 3 1]
```

6.6.3 Modify Sub-Arrays through Slicing

Slices are views of the original array, not copies. Modifying a slice will change the original array.

```
array = np.array([10, 20, 30, 40, 50])
array[1:4] = 100  # Replace elements from index 1 to 3 with 100
print(array)  # Output: [ 10 100 100 100  50]
```

```
[ 10 100 100 100  50]
```

6.6.4 Combining Indexing and Slicing

You can combine indexing and slicing to extract specific elements or sub-arrays

```
# Create a 3D array
array_3d = np.array([[[1, 2, 3], [4, 5, 6]], [[7, 8, 9], [10, 11, 12]]])

# Select specific elements and slices
print(array_3d[0, :, 1])  # Output: [2 5] (second element from each row in the first sub-a
print(array_3d[1, 1, :2])  # Output: [10 11] (first two elements in the last row of the se
```

```
[2 5]
[10 11]
```

6.6.5 `np.where()` and `np.select()`

You can also use `np.where` and `np.select` for array slicing and conditional selection.

```
array_3d
```

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

       [[ 7,  8,  9],
        [10, 11, 12]]])
```

```
# Using np.where to create a mask and select elements greater than 5
greater_than_5 = np.where(array_3d > 5, array_3d, 0)
print("Elements greater than 5:\n", greater_than_5)

# Using np.select to categorize elements into three categories
conditions = [array_3d < 4, (array_3d >= 4) & (array_3d <= 8), array_3d > 8]
```

```
choices = ['low', 'medium', 'high']
categorized_array = np.select(conditions, choices, default='unknown')
print("\nCategorized array:\n", categorized_array)
```

```
Elements greater than 5:
 [[[ 0  0  0]
  [ 0  0  6]]

 [[ 7  8  9]
  [10 11 12]]]

Categorized array:
 [[['low' 'low' 'low']
  ['medium' 'medium' 'medium']]

 [['medium' 'medium' 'high']
  ['high' 'high' 'high']]]
```

This example shows how `np.where` and `np.select` can be used to filter, manipulate, and categorize elements within a 3D array based on specific conditions.

6.6.6 `np.argmin()` and `np.argmax()`

You can use `np.argmin` and `np.argmax` to quickly find the index of the minimum or maximum value in an array along a specified axis. You'll see their usage in the practice example below

6.7 Array Operations

6.7.1 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]])
```

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

```
array([[1, 2, 3, 0],
       [1, 2, 3, 0],
       [1, 1, 2, 3]])
```

6.7.2 Comparison and Logical Operation

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

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

```python
arr1 == arr2
```

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

```python
arr1 != arr2
```

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

```python
arr1 >= arr2
```

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

```python
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.

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

```
np.int64(3)
```

6.7.3 Aggregate Functions: `np.sum()`, `np.mean()`, `np.min()`, `np.max()`

6.7.3.1 Overall Aggregate Calculations:

- `np.sum(array)`: Calculates the sum of all elements in the array.
- `np.mean(array)`: Calculates the mean of all elements in the array.
- `np.min(array)`: Finds the minimum value in the entire array.
- `np.max(array)`: Finds the maximum value in the entire array.

6.7.3.2 Row-Wise Calculations (axis=1):

- `np.sum(array, axis=1)`: Computes the sum of elements in each row.
- `np.mean(array, axis=1)`: Computes the mean of elements in each row.
- `np.min(array, axis=1)`: Finds the minimum value in each row.
- `np.max(array, axis=1)`: Finds the maximum value in each row.

6.7.3.3 Column-Wise Calculations (axis=0):

- `np.sum(array, axis=0)`: Computes the sum of elements in each column.
- `np.mean(array, axis=0)`: Computes the mean of elements in each column.
- `np.min(array, axis=0)`: Finds the minimum value in each column.
- `np.max(array, axis=0)`: Finds the maximum value in each column.

```python
# Create a 3x4 array of integers
array = np.array([[4, 7, 1, 3],
                  [5, 8, 2, 6],
                  [9, 3, 5, 2]])

# Display the original array
print("Original Array:\n", array)

# Calculate the sum, mean, minimum, and maximum for the entire array
total_sum = np.sum(array)
mean_value = np.mean(array)
min_value = np.min(array)
```

```python
max_value = np.max(array)

print(f"\nSum of all elements: {total_sum}")
print(f"Mean of all elements: {mean_value}")
print(f"Minimum value in the array: {min_value}")
print(f"Maximum value in the array: {max_value}")

# Calculate the sum, mean, minimum, and maximum along each row (axis=1)
row_sum = np.sum(array, axis=1)
row_mean = np.mean(array, axis=1)
row_min = np.min(array, axis=1)
row_max = np.max(array, axis=1)

print("\nSum along each row:", row_sum)
print("Mean along each row:", row_mean)
print("Minimum value along each row:", row_min)
print("Maximum value along each row:", row_max)

# Calculate the sum, mean, minimum, and maximum along each column (axis=0)
col_sum = np.sum(array, axis=0)
col_mean = np.mean(array, axis=0)
col_min = np.min(array, axis=0)
col_max = np.max(array, axis=0)

print("\nSum along each column:", col_sum)
print("Mean along each column:", col_mean)
print("Minimum value along each column:", col_min)
print("Maximum value along each column:", col_max)
```

```
Original Array:
 [[4 7 1 3]
 [5 8 2 6]
 [9 3 5 2]]

Sum of all elements: 55
Mean of all elements: 4.583333333333333
Minimum value in the array: 1
Maximum value in the array: 9

Sum along each row: [15 21 19]
Mean along each row: [3.75 5.25 4.75]
Minimum value along each row: [1 2 2]
```

```
Maximum value along each row: [7 8 9]

Sum along each column: [18 18  8 11]
Mean along each column: [6.         6.         2.66666667 3.66666667]
Minimum value along each column: [4 3 1 2]
Maximum value along each column: [9 8 5 6]
```

6.8 Array Reshaping

Certain functions and machine learning models require input data in a specific shape or format. For instance, operations like matrix multiplication and broadcasting depend on the alignment of array dimensions. Many deep learning models expect input data to be in a 4D array format (batch size, height, width, channels). Reshaping enables us to convert data into the necessary shape, ensuring compatibility without altering the underlying values.

Below are some methods to reshape NumPy arrays:

6.8.1 `reshape()`

The `reshape` method in NumPy allows you to change the shape of an existing array without changing its data.

```
arr = np.array([1, 2, 3, 4, 5, 6])
reshaped_arr = arr.reshape(2, 3)
print(reshaped_arr)
```

```
[[1 2 3]
 [4 5 6]]
```

Using-`1` for automatic dimension inference

```
arr = np.arange(12)
reshaped_arr = arr.reshape(3, -1)
print(reshaped_arr)
```

```
[[ 0  1  2  3]
 [ 4  5  6  7]
 [ 8  9 10 11]]
```

Here, -1 means "calculate this dimension based on the remaining dimensions and the total size of the array". So, (3, -1) becomes (3, 4).

6.8.2 `flatten()` and `ravel()`

The `flatten` method returns a copy of the array collapsed into one dimension. It is useful when you need to perform operations that require 1D input or need to pass the array data as a linear sequence. `order` specifies the order in which elements are read, options include but not limited to: * `C` (default): Row-major (C-style). * `F`: Column-major (Fortran-style).

In contrast, `ravel()` returns a flattened view of the original array whenever possible, without creating a copy.

```
arr = np.array([[1, 2, 3], [4, 5, 6]])
flattened_arr = arr.flatten()
print(flattened_arr)
```

```
[1 2 3 4 5 6]
```

```
# using ravel() to flatten the array
flattened_arr = arr.ravel()
print(flattened_arr)
```

```
[1 2 3 4 5 6]
```

6.8.3 `resize()`

Changes the shape and size of an array in place. Unlike `reshape()`, it can modify the array and fill additional elements with zeros if necessary.

```
arr = np.array([1, 2, 3, 4])
arr.resize(2, 3)
print(arr)
```

```
[[1 2 3]
 [4 0 0]]
```

6.8.4 `tranpose()` or `T`

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

```
arr = np.array([[1, 2, 3], [4, 5, 6]])
transposed_arr = arr.transpose()  # Output: [[1 4], [2 5], [3 6]]
print(transposed_arr)

T_arr = arr.T  # Output: [[1 4], [2 5], [3 6]]
print(T_arr)
```

```
[[1 4]
 [2 5]
 [3 6]]
[[1 4]
 [2 5]
 [3 6]]
```

6.9 Arrays Concaternating

NumPy provides several functions to concatenate arrays along different axes.

6.9.1 `np.concatenate()`

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]])
```

Here's a visual explanation of `np.concatenate` along `axis=1` (can you guess what `axis=0` results in?):

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.

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

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

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

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

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

6.9.2 `np.vstack()` and `np.hstack()`

- `np.vstack()`: Stacks arrays vertically (along rows).
- `np.hstack()`: Stacks arrays horizontally (along columns).

```python
# Vertical stacking
vstack = np.vstack((arr1, arr2))
print("\nVertical Stack:\n", vstack)

# Horizontal stacking
hstack = np.hstack((arr1, arr2))
print("\nHorizontal Stack:\n", hstack)
```

```

Vertical Stack:
 [[1 2 3]
 [3 4 5]
 [2 2 3]
 [1 2 5]]

Horizontal Stack:
 [[1 2 3 2 2 3]
 [3 4 5 1 2 5]]
```