Deccan Education Society's

Navinchandra Mehta Institute of Technology and Development

C E R T I F I C A T E

This is to certify that **Mr.** **Rushikesh Ghanshyam Chapke** of M.C. A. Semester II with Roll No. **C22019** has completed **All** practicals of **Artificial Intelligence and Machine Learning** under my supervision in this college during the year 2022-2023.

CO	R1 (Attendance)	R2 (Performance during lab session)	R3 (Innovation in problem solving technique)	R4 (Mock Viva)	R5 **(V**ariation in implementation of learnt topics on projects)
CO1					
CO2					
CO3					
CO4					

Practical-in-charge

Head of Department

MCA Department (NMITD)

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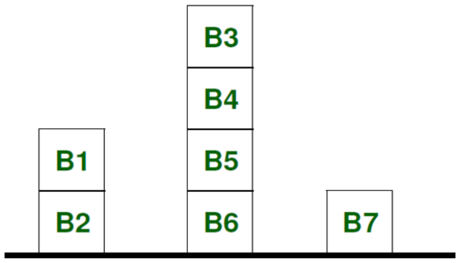
1.	**Logic Programming with Prolog – Representing Family Relationships**		
a)	Implement family relationships in Prolog as a Family KB using predicates: child, father, mother, male, female, parent, grandfather using Prolog. Make your own assumptions with respect to the needed atomic and conditional sentences. Demonstrate the program by establishing various types of queries pertaining to family relationships.	13-06-2023	
2.	**Problem Solving with Prolog**		
a)	**Blocks World:** Describe the “Blocks World” scene shown below to Prolog such that the following can be determined through Prolog queries: • Block 3 is above Block 5 • Block 1 is to the left of Block 7 • Block 4 is to the right of Block 2 	14-06-2023	
b)	**Map Coloring Problem**: Illustrate the solving of the popular constraint satisfaction problem known as Map Coloring problem using Prolog.	15-06-2023	

Artificial Intelligence

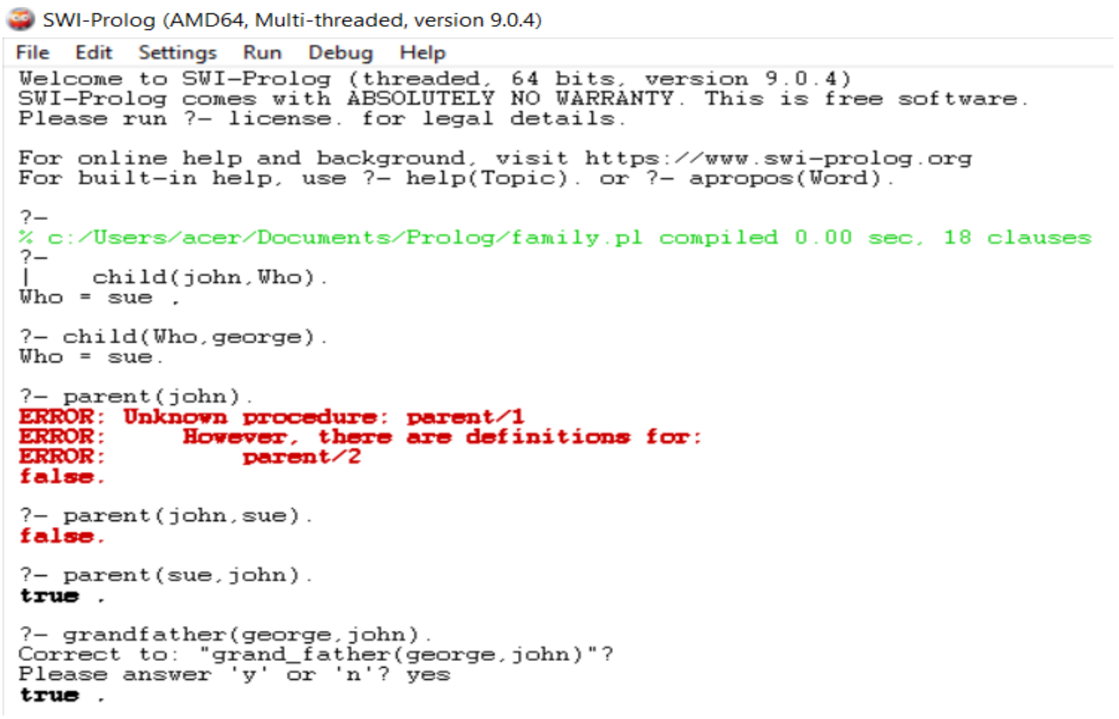
1. Logic Programming with Prolog – Representing Family Relationships

a. Implement family relationships in Prolog as a Family KB using predicates: child, father, mother, male, female, parent, grandfather using Prolog. Make your own assumptions with respect to the needed atomic and conditional sentences. Demonstrate the program by establishing various types of queries pertaining to family relationships.

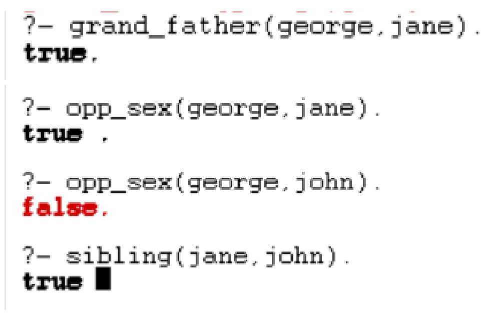
Code:

```
% This is the Prolog version of the family example

child(john,sue).   child(john,sam).% john is a child of sam
child(jane,sue).   child(jane,sam).
child(sue,george).   child(sue,gina).

male(john).   male(sam).     male(george).% George is a male
female(sue). female(jane). female(june).

parent(Y,X) :- child(X,Y).
father(Y,X) :- child(X,Y), male(Y).
opp_sex(X,Y) :- male(X), female(Y).
opp_sex(Y,X) :- male(X), female(Y).
grand_father(X,Z) :- father(X,Y), parent(Y,Z).
sibling(X,Y) :- parent(Z,X), parent(Z,Y).
```

Output:


SWI-Prolog (AMD64, Multi-threaded, version 9.0.4)
File Edit Settings Run Debug Help

```
Welcome to SWI-Prolog (threaded, 64 bits, version 9.0.4)
SWI-Prolog comes with ABSOLUTELY NO WARRANTY. This is free software.
Please run ?- license. for legal details.

For online help and background, visit https://www.swi-prolog.org
For built-in help, use ?- help(Topic). or ?- apropos(Word).

?-
% c:/Users/acer/Documents/Prolog/family.pl compiled 0.00 sec, 18 clauses
?-
|    child(john,Who).
Who = sue .

?- child(Who,george).
Who = sue.

?- parent(john).
ERROR: Unknown procedure: parent/1
ERROR:     However, there are definitions for:
ERROR:         parent/2
false.

?- parent(john,sue).
false.

?- parent(sue,john).
true .

?- grandfather(george,john).
Correct to: "grand_father(george,john)"?
Please answer 'y' or 'n'? yes
true .
```

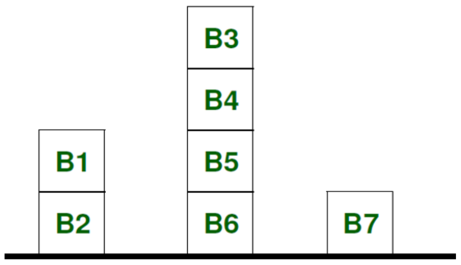


```
?- grand_father(george,jane).
true.

?- opp_sex(george,jane).
true .

?- opp_sex(george,john).
false.

?- sibling(jane,john).
true
```

2. Problem Solving with Prolog

a. Blocks World: Describe the "Blocks World" scene shown below to Prolog such that the following can be determined through Prolog queries:

a. Block 3 is above Block 5
b. Block 1 is to the left of Block 7
c. Block 4 is to the right of Block 2



Code:

% on(X,Y) means that block X is directly on top of block Y.

on(b1,b2). on(b3,b4). on(b4,b5). on(b5,b6).
% just left(X,Y) means that blocks X and Y are on the table

% and that X is immediately to the left of Y.

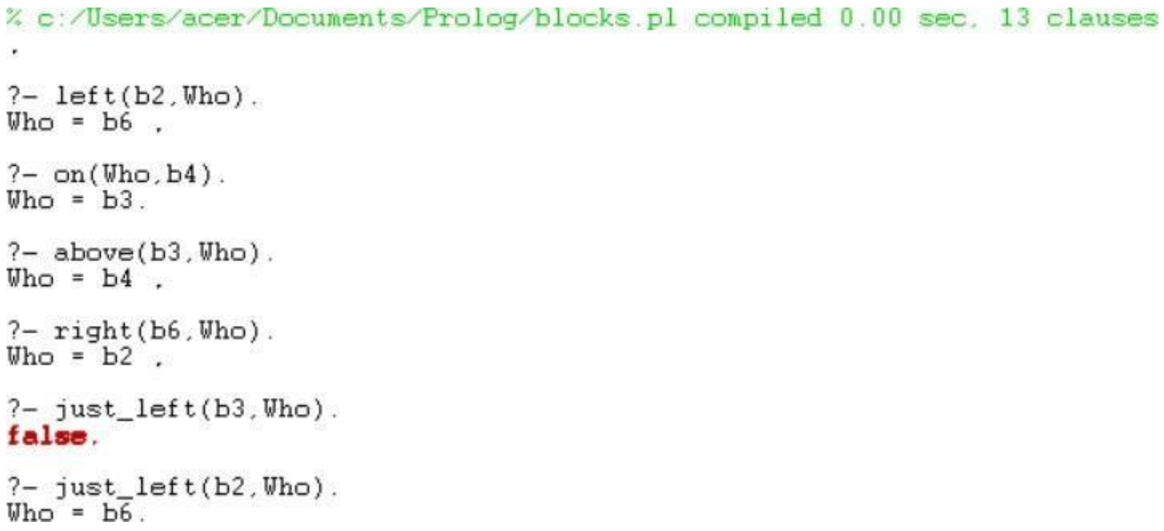
just_left(b2,b6). just_left(b6,b7).
% above(X,Y) means that block X is somewhere above block Y

% in the pile where Y occurs.
above(X,Y) :- on(X,Y). above(X,Y) :-
on(X,Z),above(Z,Y).

% left(X,Y) means that block X is somewhere to the left

```
% of block Y but perhaps higher or lower than Y.

left(X,Y) :- just_left(X,Y).



left(X,Y) :- just_left(X,Z), left(Z,Y).
left(X,Y) :- on(X,Z), left(Z,Y).          % leftmost is on something.

left(X,Y) :- on(Y,Z), left(X,Z).          % rightmost is on something.


% right(X,Y) is the opposite of left(X,Y).
right(Y,X) :- left(X,Y).
```

Output:



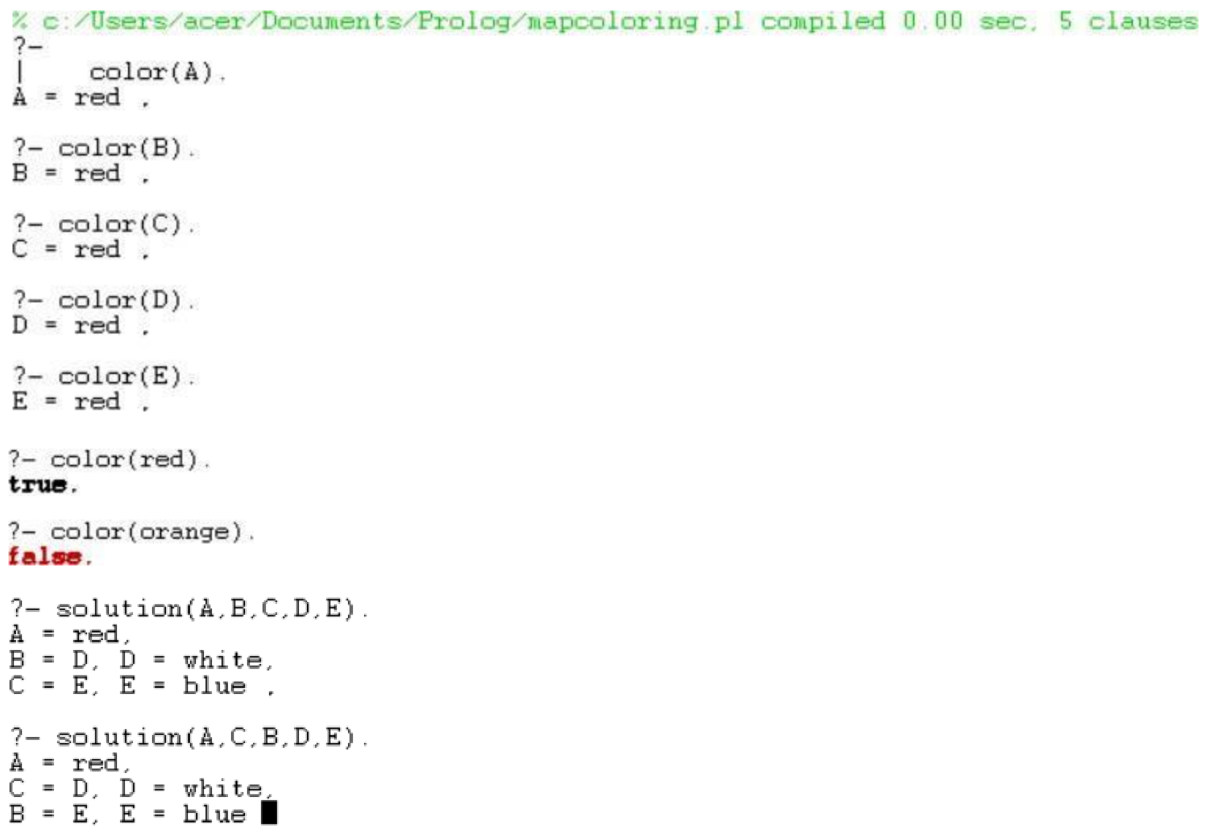
```
% c:/Users/acer/Documents/Prolog/blocks.pl compiled 0.00 sec, 13 clauses
.

?- left(b2,Who).
Who = b6 ,

?- on(Who,b4).
Who = b3.

?- above(b3,Who).
Who = b4 ,

?- right(b6,Who).
Who = b2 ,

?- just_left(b3,Who).
false.

?- just_left(b2,Who).
Who = b6.
```

b. Map Coloring Problem: Illustrate the solving of the popular constraint satisfaction problem known as Map Coloring problem using Prolog.

Code:

```
% Solution for the map coloring problem as described in Figure 5.1.

% A map is depicted with 5 countries A, B, C, D, and E. The goal is to colour the countries onthe map using just the color’s red, white, and blue in such a way that no countries with a border between them have the same color.

% solution(A,B,C,D,E) holds if A,B,C,D,E are colours that solve the described map colouring problem. This is a particular example of the general class called 'constraint satisfaction problems'.

print_colors :- solution(A,B,C,D,E),nl,write('Country A is colored:  '), write(A)
                        ,nl,write('Country B is colored:  '), write(B)
                        ,nl,write('Country C is colored:  '), write(C)
                        ,nl,write('Country D is colored:  '), write(D)
                        ,nl,write('Country E is colored: '), write(E).
solution(A,B,C,D,E) :- color(A), color(B), color(C), color(D), color(E),
                 \+ A=B, \+ A=C, \+ A=D, \+ A=E, \+ B=C, \+ C=D, \+ D=E.

% The three colours are these:
color(red).


color(white).
color(blue).
```

Output:



```
% c:/Users/acer/Documents/Prolog/mapcoloring.pl compiled 0.00 sec, 5 clauses
?-
|    color(A).
A = red .

?- color(B).
B = red .

?- color(C).
C = red .

?- color(D).
D = red .

?- color(E).
E = red .

?- color(red).
true.

?- color(orange).
false.

?- solution(A,B,C,D,E).
A = red,
B = D, D = white,
C = E, E = blue .

?- solution(A,C,B,D,E).
A = red,
C = D, D = white,
B = E, E = blue
```

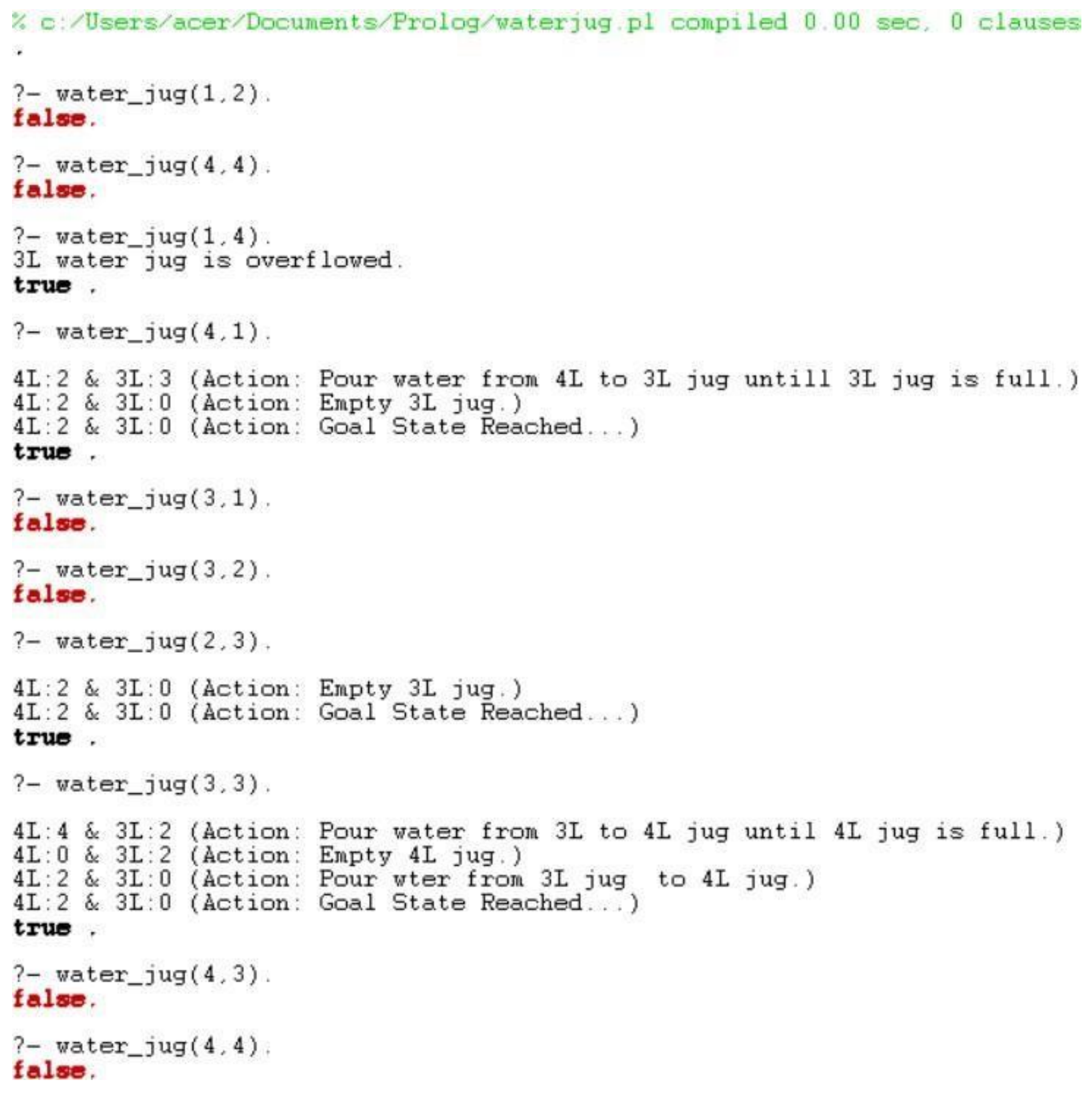
c. **Water-Jug Puzzle:** Illustrate the solving of a Water-Jug puzzle using prolog. There are two jugs, one with 4 litre capacity and one with 3 litre capacity. There are no measurement markings on them. You can fill them, empty them or pour water from one jug to another. Initially both are empty. The final state should be such that you get 1 litre of water in one of the jug.

Code:

```
water_jug(X,Y):-X>4,Y<3, write('4L water jug overflowed.'),nl.
water_jug(X,Y):-X<4,Y>3, write('3L water jug is overflowed.'),nl.
water_jug(X,Y):-X>4,Y>3,write('Both water jugs overflowed.'),nl.
water_jug(X,Y):-(X=:=0,Y=:=0,nl,write('4L:0 & 3L:3 (Action: Fill 3L jug.)'),YY is
3,water_jug(X,YY));
            (X=:=0,Y=:=0,nl,write('4L:4 & 3L:0 (Action: Fill 4L jug.)'),XX is 4,
water_jug(XX,Y));
            (X=:=2,Y=:=0,nl,write('4L:2 & 3L:0 (Action: Goal State Reached...)'));
            (X=:=4,Y=:=0,nl,write('4L:1 & 3L:3 (Action: Pour water from 4L to 3L jug.)'),XX is
X-3,YY is 3, water_jug(XX,YY));
            (X=:=0,Y=:=3,nl,write('4L:3 & 3L:0 (Action: Pour water from 3L to 4L jug.)'),XX is
3,YY is 0, water_jug(XX,YY));
            (X=:=1,Y=:=3,nl,write('4L:1 & 3L:0 (Action: Empty 3L jug.)'),YY is 0,
water_jug(X,YY));
```

```
	(X=:=3,Y=:=3,nl,write('4L:4 & 3L:2 (Action: Pour water from 3L to 4L jug until 4L jug is full.)'),XX is X+1,YY is Y-1, water_jug(XX,YY));
	(X=:=1,Y=:=0,nl,write('4L:0 & 3L:1 (Action: Pour water from 4L to 3L jug.)'),XX is Y,YY is X, water_jug(XX,YY));
	(X=:=0,Y=:=1,nl,write('4L:4 & 3L:1 (Action: Fill 4L jug.)'),XX is 4, water_jug(XX,Y));
	(X=:=4,Y=:=1,nl,write('4L:2 & 3L:3 (Action: Pour water from 4L to 3L jug untill 3L jug is full.)'),XX is X-2,YY is Y+2, water_jug(XX,YY));
	(X=:=2,Y=:=3,nl,write('4L:2 & 3L:0 (Action: Empty 3L jug.)'),YY is 0, water_jug(X,YY));
	(X=:=4,Y=:=2,nl,write('4L:0 & 3L:2 (Action: Empty 4L jug.)'),XX is 0, water_jug(XX,Y));
	(X=:=0,Y=:=2,nl,write('4L:2 & 3L:0 (Action: Pour wter from 3L jug to 4L jug.)'),XX is Y, YY is X, water_jug(XX,YY)).
```

Output:



```
% c:/Users/acer/Documents/Prolog/waterjug.pl compiled 0.00 sec, 0 clauses
.

?- water_jug(1,2).
false.

?- water_jug(4,4).
false.

?- water_jug(1,4).
3L water jug is overflowed.
true .

?- water_jug(4,1).

4L:2 & 3L:3 (Action: Pour water from 4L to 3L jug untill 3L jug is full.)
4L:2 & 3L:0 (Action: Empty 3L jug.)
4L:2 & 3L:0 (Action: Goal State Reached...)
true .

?- water_jug(3,1).
false.

?- water_jug(3,2).
false.

?- water_jug(2,3).

4L:2 & 3L:0 (Action: Empty 3L jug.)
4L:2 & 3L:0 (Action: Goal State Reached...)
true .

?- water_jug(3,3).

4L:4 & 3L:2 (Action: Pour water from 3L to 4L jug until 4L jug is full.)
4L:0 & 3L:2 (Action: Empty 4L jug.)
4L:2 & 3L:0 (Action: Pour wter from 3L jug  to 4L jug.)
4L:2 & 3L:0 (Action: Goal State Reached...)
true .

?- water_jug(4,3).
false.

?- water_jug(4,4).
false.
```

Machine Learning Section

1. Coding in Basic Python and Python Packages for ML

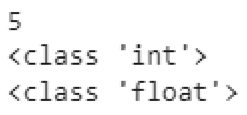
1. Introduction to Python

1.1 Basic Datatypes in Python

Numbers and Arithmetic Operations on Numbers

```
# Numbers
x = 5
print(x)
print(type(x))

x = 5.5
print(type(x))
```

output



```
5
<class 'int'>
<class 'float'>
```

```
# Arithmetical operations in Pyhton
x = 5
print(type(x))
print(x+1)
print(x-1)
print(x*2) # Multiplication
print(x**2) # Exponentiation
x +=1
print(x)
x *=2
print(x)
y =3.5
print(type(y))
print(y, y+1, y*2, y**2)

#Division
x =10
y= 5
print(x/y) # division
print(x//y) # integer result - fraction gets truncated
```

Output:

```
<class 'int'>
6
4
10
25
6
12
<class 'float'>
3.5 4.5 7.0 12.25
2.0
2
```

```python
# Booleans and Logical Operations on Booleans
t = True
f = False
print(type(t))
print(type(f))
print(t and f) #AND Operation
print(t or f) #OR operations
print(not t) #NOT operations
print(t!=f) #XOR operations
```

output:

```
<class 'bool'>
<class 'bool'>
False
True
False
True
```

```python
#string and string methods in python

hello = 'Hello'
world = "World!"
print(hello)
print(len(hello))
hw = hello + ' ' + world
print(hw)
hw12 ='%s %s %d' % (hello, world, 12.34) #fstring formatted string
print(hw12)
```

output:

```
Hello
5
Hello World!
Hello World! 12
```

```python
#String Functions
s="hello"
print(s.capitalize())
print(s.upper())
print(s.lower())
print(s.rjust(7))
print(s.center(7))
print(s.ljust(7))
print(s.replace('l','(ell)'))
print('          world'.strip())
```

output:

```
Hello
HELLO
hello
  hello
 hello
hello
he(ell)(ell)o
world
```

1.2 Container Types in Python:

Lists: A list in Python is equivalent to an array, but it is resizable and can contain elements of different types:

```python
xs=[3,1,2]
print(xs, xs[2])
print(xs[-2])
xs[2] ='bar'
print(xs)
xs.append('harbar')
print(xs)
x= xs.pop()
print(x,xs)
```

output:

```
[3, 1, 2] 2
1
[3, 1, 'bar']
[3, 1, 'bar', 'harbar']
harbar [3, 1, 'bar']
```

List Slicing: Python provides a concise syntax to access sublists; this is knownas slicing.

```
nums = list(range(5))
print(nums)
print(nums[2:4])
print(nums[2:])
print(nums[:])
print(nums[:2])
print(nums[:-1])
nums[2:4] = [8,9]
print(nums)
```

output:

```
[0, 1, 2, 3, 4]
[2, 3]
[2, 3, 4]
[0, 1, 2, 3, 4]
[0, 1]
[0, 1, 2, 3]
[0, 1, 8, 9, 4]
```

Loops: The block of code is executed based on a certain condition.

```
#loops:you can loop over the elemenst of a list like this:
animalss=['cat','dog','Lion']
for animal in animalss:
  print(animal)
```

output:

```
#1: cat
#2: dog
#3: elephant
```

Enumerate function: If you want to access the index of each element within theloop body you will have to use the built-in function *enumerate().*

```
#Enumerate function
animals =['cat','dog','elephant']
for idx, animal in enumerate(animals):
  print('#%d: %s' % (idx + 1, animal))
```

Output:

```
#1: cat
#2: dog
#3: elephant
```

List Comprehensions: List comprehension provides a very concise syntax toconstruct a new list from scratch given an existing list of elements.

```
#List comprehension
nums=[0,1,2,3,4]
squares =[]
for x in nums:
  squares.append(x ** 2)
print(squares)
```

Output:

```
[0, 1, 4, 9, 16]
```

```
# Above code can be done by this
nums =[0,1,2,3,4]
squares =[x ** 2 for x in nums]
print(squares)
```

Output:

```
[0, 1, 4, 9, 16]
```

Dictionaries: This is another Container type in Python. A dictionary stores (key,value) pairs, similar to a **Map** in Java or an object in Javascript.

```
#dictionary
d={'cat':'cute','dog':'furry','monkey':'smart'}
print(type(d))
print(d['cat'])
print('cat' in d)
d['fish'] = 'wet'
print(d['fish'])
print(d['monkey'])
#print(d.get['monkey'])
print(d.get('monkey','N/A'))
del d['fish']
print(d.get('fish','N.A'))
```

Output:

```
<class 'dict'>
cute
True
wet
smart
smart
N.A
```

Looping over Dictionary: It is easy to iterate over the keys in a dictionary:

```
d={'person':2, 'cat':4, 'spider':8}
for animal in d:
  legs =d[animal]
  print('A %s has %d legs' % (animal, legs))
```

Output:

```
A person has 2 legs
A cat has 4 legs
A spider has 8 legs
```

Dictionary comprehensions: These are similar to list comprehensions, but allowyou to easily construct dictionaries.

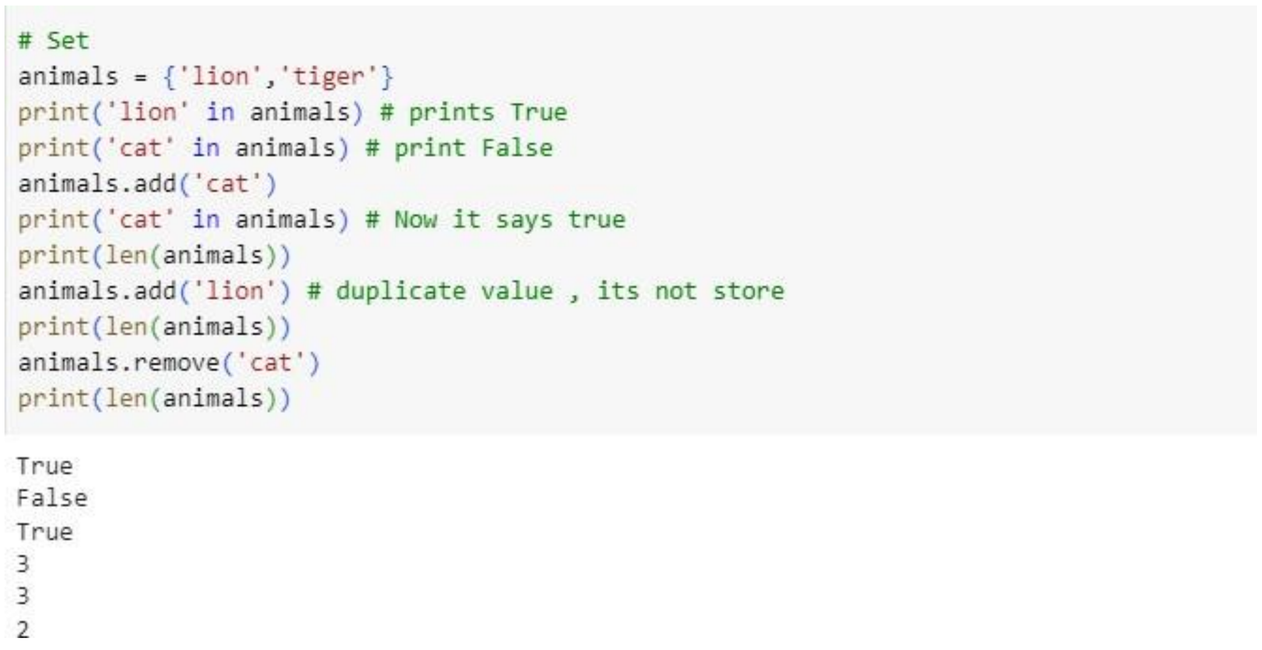
```
nums =[0,1,2,3,4]
even_num_to_square = {x:x**2 for x in nums if x % 2==0}
print(even_num_to_square)
```

Output:

```
{0: 0, 2: 4, 4: 16}
```

Sets: A set is another container type like a list and a dictionary. However it is anunordered collection of distinct elements.

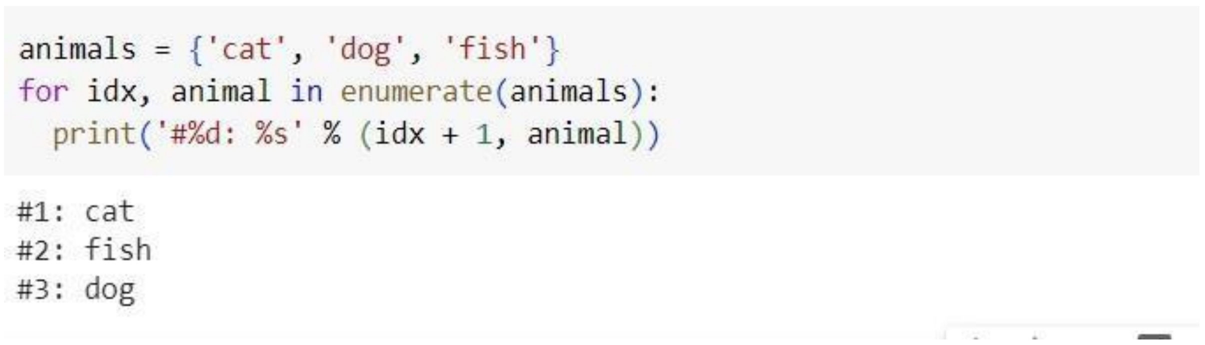
Thus order is not maintained in Set and duplicates are not allowed.



```
# Set
animals = {'lion','tiger'}
print('lion' in animals) # prints True
print('cat' in animals) # print False
animals.add('cat')
print('cat' in animals) # Now it says true
print(len(animals))
animals.add('lion') # duplicate value , its not store
print(len(animals))
animals.remove('cat')
print(len(animals))
```

```
True
False
True
3
3
2
```

Looping over sets



```
animals = {'cat', 'dog', 'fish'}
for idx, animal in enumerate(animals):
  print('#%d: %s' % (idx + 1, animal))
```

```
#1: cat
#2: fish
#3: dog
```

Set Comprehensions: Like lists and dictionaries, we can easily construct sets usingset comprehensions.

```python
from math import sqrt
nums = {int(sqrt(x)) for x in range(30)}
print(nums)
```

```
{0, 1, 2, 3, 4, 5}
```

Tuples: A tuple is an (immutable) ordered list of values. A tuple is in many ways similar to a list; One of the most important differences is that tuples can be used askeys in dictionaries and as elements of sets, while lists cannot.

```python
d = {(x, x + 1): x for x in range(10)}
t = (5,6) # Create a tuple having two elements
print(d)
print(type(t))
print(d[t]) # print 5
print(d[(1,2)]) # prints 1
```

```
{(0, 1): 0, (1, 2): 1, (2, 3): 2, (3, 4): 3, (4, 5): 4, (5, 6): 5, (6, 7): 6, (7, 8): 7, (8, 9): 8,
<class 'tuple'>
5
1
```

1.3 Functions in Python

Python functions are defined using **def** keyword.

```
def sign(x):
  if x>0:
    return 'positive'
  elif x<0:
    return 'negative'
  else:
    return 'zero'
for x in [-1,0,1]:
    print(sign(x))
```

Output:

```
negative
zero
positive
```

```
# function for implementing quick sort in Python
def quicksort(arr):
  if len(arr) <= 1:
    return arr
  pivot = arr[len(arr) // 2]
  left = [x for x in arr if x < pivot]
  middle = [ x for x in arr if x == pivot]
  right =[x for x in arr if x >pivot]
  return quicksort(left) + middle + quicksort(right)
print(quicksort([4,54,6,45,4323,6,6,567,7,6,5,4,34343,43434,434,434,323]))
```

Output:

```
[4, 4, 5, 6, 6, 6, 6, 7, 45, 54, 323, 434, 434, 567, 4323, 34343, 43434]
```

1.4 Classes in Python

The syntax for defining classes in Python is straightforward:

```
class Greeter(object):
  # Constructor
  def __init__(self, name):
    self.name = name # create an instance variable

  # Instance method
  def greet(self,loud=False):
    if loud:
      print('HELLO, %s!' % self.name.upper())
    else:
      print('Hello, %s' % self.name)

g = Greeter('Fred')
g.greet()
g.greet(loud=True)
```

```
Hello, Fred
HELLO, FRED!
```

2. Numpy

Numpy is the core library for scientific computing in Python. It provides a high-performance multi-dimensional array object, and tools for working with these arrays.

2.1 Arrays

A **numpy** array is a grid of values, all of the same type, and is indexed by a tuple ofnon-negative integers.

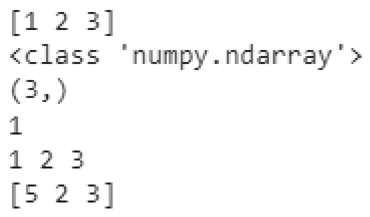
rank: The number of dimensions is the *rank* of the array.

shape: The *shape* of an array is a tuple of integers giving the size of the array along each dimension.

```
import numpy as np
a = np.array([1,2,3])
print(a)
print(type(a))
print(a.shape)
print(a.ndim)
print(a[0], a[1], a[2])
a[0] = 5
```

```
print(a)
```

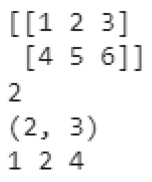
Output:



```
[1 2 3]
<class 'numpy.ndarray'>
(3,)
1
1 2 3
[5 2 3]
```

```
import numpy as np
b = np.array([[1,2,3],[4,5,6]])
print(b)
print(b.ndim)
print(b.shape)
print(b[0,0],b[0,1],b[1,0])
```

Output:



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

```
#difference between rank1 and rank2
import numpy as np
a = np.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])
b= a[:2, 1:3]
print(a)
print(a.shape)
print(b)
print(b.shape)

print(a[0,1])
b[0,0] =45
print(a[0,1])
```

Output:

```
[[ 1  2  3  4]
 [ 5  6  7  8]
 [ 9 10 11 12]]
(3, 4)
[[2 3]
 [6 7]]
(2, 2)
2
45
```

1.2 Array Indexing

Numpy offers several ways to index into arrays.

Slicing: Similar to Python lists, **numpy** arrays can be sliced. Since arrays may bemulti-dimensional, you must specify a slice for each dimension of the array:

```
import numpy as np
a = np.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])

row_r1 = a[1, :]
print(row_r1, row_r1.shape)

row_r2 =a[1:2, :]
print(row_r2, row_r2.shape)
col_r1 = a[:, 1]
col r2 =a[:, 1:2]

print(col_r1, col_r1.shape)
print(col_r2, col_r2.shape)
```

Output:

```
[5 6 7 8] (4,)
[[5 6 7 8]] (1, 4)
[ 2  6 10] (3,)
[[ 2]
 [ 6]
 [10]] (3, 1)
```

When mixing integer indexing with slice indexing, the rank of the resulting arrayreduces.

```
import numpy as np
a = np.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])

row_r1 = a[1, :] # Rank 1 view of the second row of a
print(row_r1, row_r1.shape)

row_r2 = a[1:2, :] # Rank 2 view of the second row of a
print(row_r2, row_r2.shape)

# We can make the same distinctions when accessing columns of an array
col_r1 = a[:, 1]
col_r2 = a[:, 1:2]

print(col_r1, col_r1.shape)
print(col_r2, col_r2.shape)
```

```
[5 6 7 8] (4,)
[[5 6 7 8]] (1, 4)
[ 2  6 10] (3,)
[[ 2]
 [ 6]
 [10]] (3, 1)
```

Integer array indexing: Allows you to construct arbitrary arrays using data fromanother array.

```
import numpy as np
a=np.array([[1,2],[3,4],[5,6]])
print(a[[0,1,2],[0,1,0]])
print(a[0,0], a[1,1],a[2,0])

print(a[[0,0],[1,1]])
print(a[0,1])
```

Output:

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

Boolean array indexing: It lets you pick out arbitrary elements of an array. It is usedto select the elements of an array that satisfy some condition.

```
import numpy as np
a =np.array([[1,2],[3,4],[5,6]])

bool_indx = (a>2)
print(bool_indx)
print(a[bool_indx])
print(a[a>2])
```

Output:

```
[[False False]
 [ True  True]
 [ True  True]]
[3 4 5 6]
[3 4 5 6]
```

2.3 Datatypes

Every **numpy** array is a grid of elements of the same type. **Numpy** provides a largeset of numeric datatypes that we can use to construct arrays.

Numpy tries to guess a datatype when you create an array. However, an optionalargument can specify the type you want.

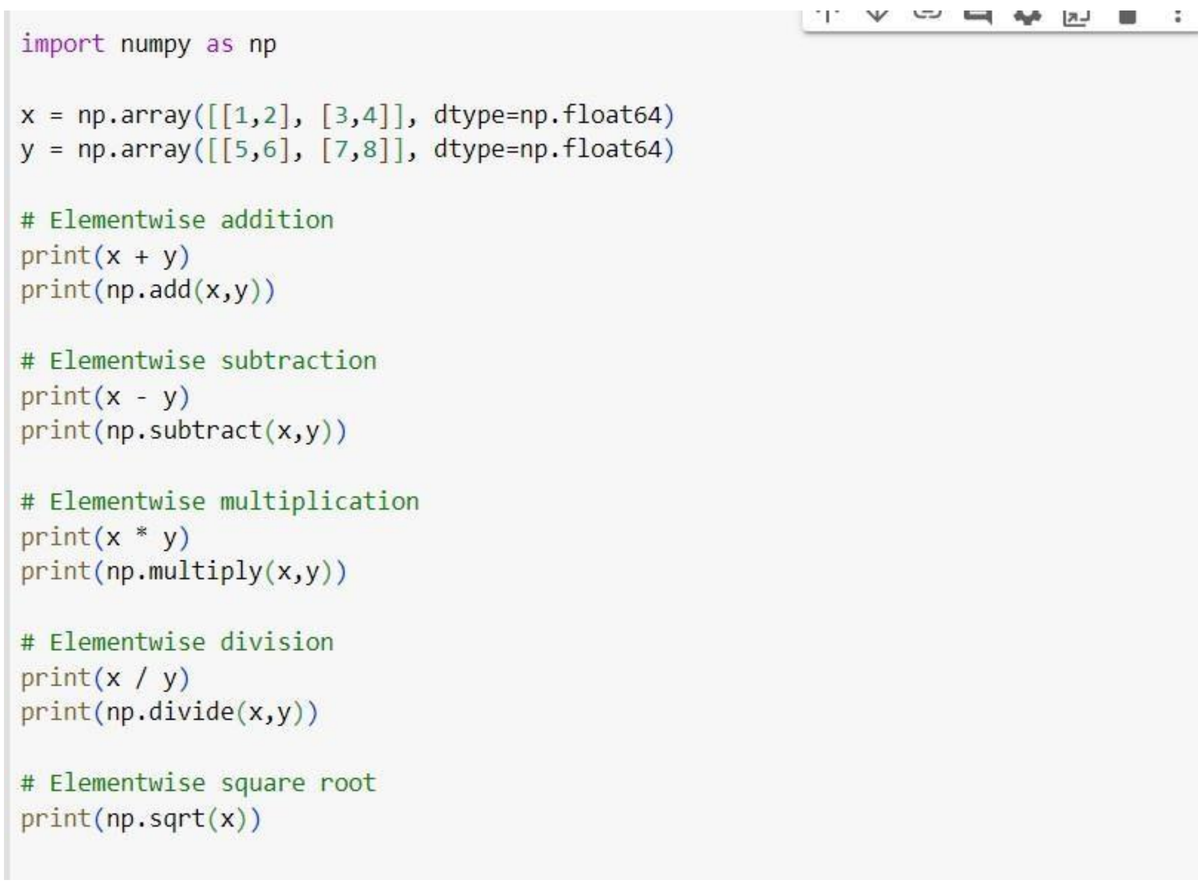
```
import numpy as np
x=np.array([1,2])S
print(x.dtype)
x=np.array([1.0, 2.0])
print(x.dtype)
x=np.array([1.0, 2.0], dtype=np.int64)
print(x.dtype)
```

Output:

```
int64
float64
int64
```

1.4 Array Maths

Basic mathematical functions operate element wise on arrays.



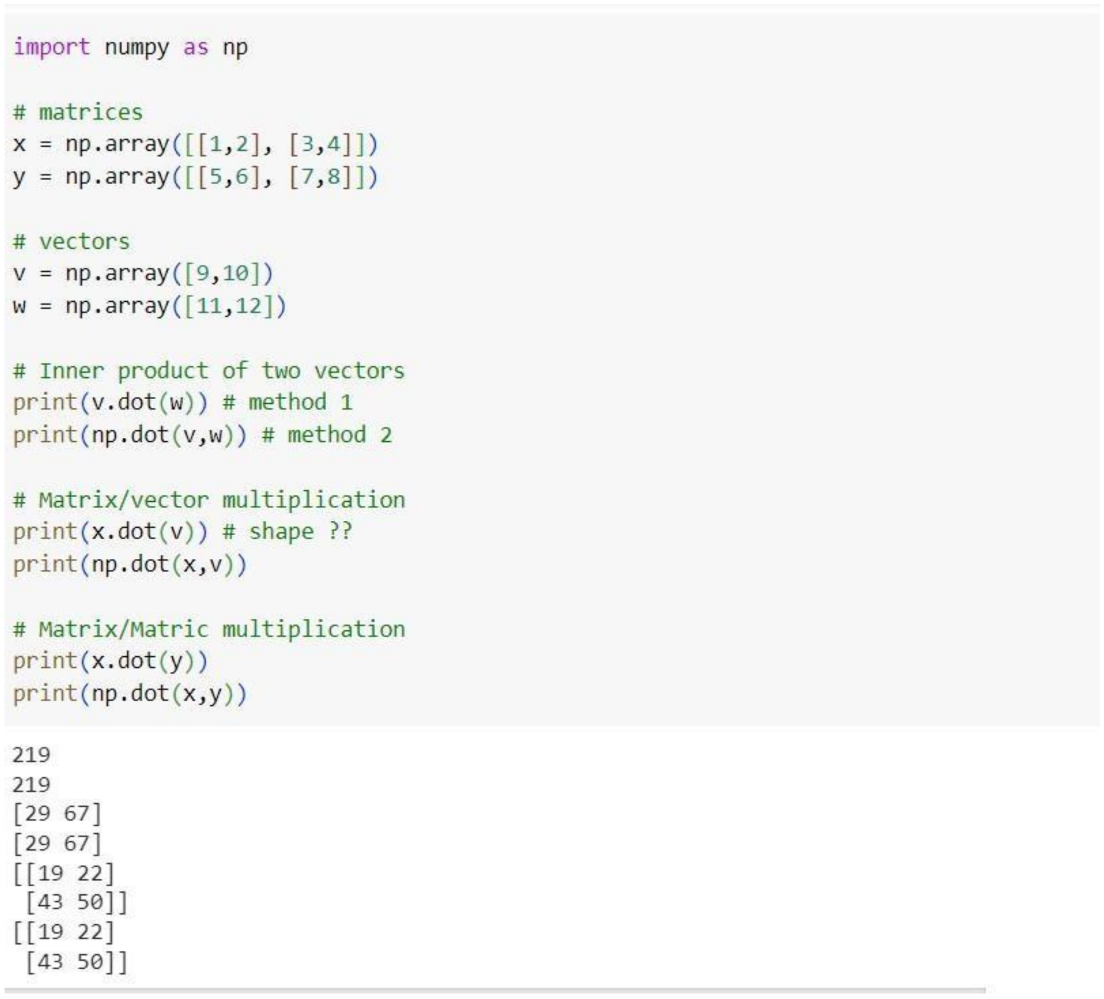
```
import numpy as np

x = np.array([[1,2], [3,4]], dtype=np.float64)
y = np.array([[5,6], [7,8]], dtype=np.float64)

# Elementwise addition
print(x + y)
print(np.add(x,y))

# Elementwise subtraction
print(x - y)
print(np.subtract(x,y))

# Elementwise multiplication
print(x * y)
print(np.multiply(x,y))

# Elementwise division
print(x / y)
print(np.divide(x,y))

# Elementwise square root
print(np.sqrt(x))
```

Output:

```
[[ 6.  8.]
 [10. 12.]]
[[ 6.  8.]
 [10. 12.]]
[[-4. -4.]
 [-4. -4.]]
[[-4. -4.]
 [-4. -4.]]
[[ 5. 12.]
 [21. 32.]]
[[ 5. 12.]
 [21. 32.]]
[[0.2        0.33333333]
 [0.42857143 0.5       ]]
[[0.2        0.33333333]
 [0.42857143 0.5       ]]
[[1.         1.41421356]
 [1.73205081 2.        ]]
```

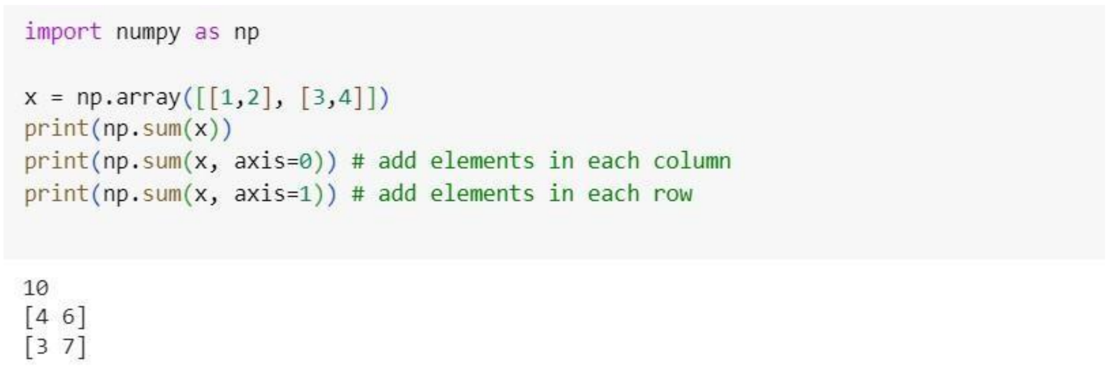
To do matrix or vector multiplication, we need to use *dot* function. It is useful to compute the inner dot product of two vectors, to multiply a vector by a matrix, and tomultiply two matrices.

dot is available both as a function in the **numpy** module as well as an instance methodin the array object:


```
import numpy as np

# matrices
x = np.array([[1,2], [3,4]])
y = np.array([[5,6], [7,8]])

# vectors
v = np.array([9,10])
w = np.array([11,12])

# Inner product of two vectors
print(v.dot(w)) # method 1
print(np.dot(v,w)) # method 2

# Matrix/vector multiplication
print(x.dot(v)) # shape ??
print(np.dot(x,v))

# Matrix/Matric multiplication
print(x.dot(y))
print(np.dot(x,y))
```

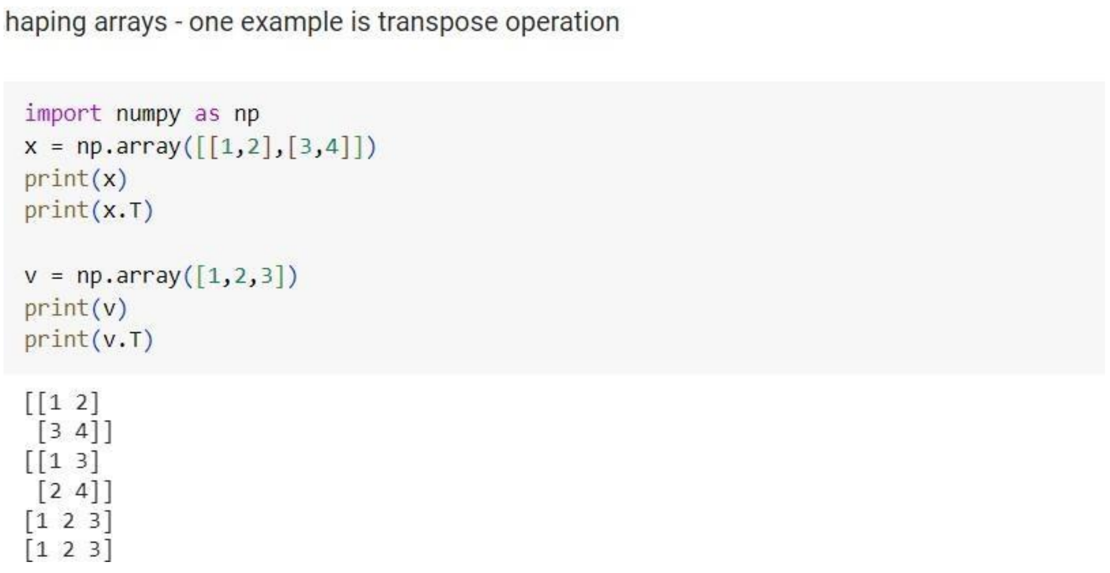
```
219
219
[29 67]
[29 67]
[[19 22]
 [43 50]]
[[19 22]
 [43 50]]
```

some other mathematical functions in **numpy**



```
import numpy as np

x = np.array([[1,2], [3,4]])
print(np.sum(x))
print(np.sum(x, axis=0)) # add elements in each column
print(np.sum(x, axis=1)) # add elements in each row
```

```
10
[4 6]
[3 7]
```



haping arrays - one example is transpose operation

```
import numpy as np
x = np.array([[1,2],[3,4]])
print(x)
print(x.T)

v = np.array([1,2,3])
print(v)
print(v.T)
```

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

1.4 Broadcasting

Broadcasting is a mechanism that allows **numpy** to work with arrays of differentshapes when performing mathematical operations.

Typically, the smaller tensor will be **broadcasted** to match the shape of the largertensor.

Broadcasting consists of two steps:

1.2.1 Axes (called broadcast axes) are added to the smaller tensor to matchthe **ndim** of the larger tensor.

1.2.2 The smaller tensor is repeated alongside these new axes to match the fullshape of the larger tensor.

```
import numpy as np
x = np.array([[1,2,3], [4,5,6], [7,8,9], [10,11,12,]])
y = np.array([1,2,0])
z = np.empty_like(x)

for i in range(4):
  z[i,:] = x[i,:] + y

print(z)

print(x+y)
z1=x+5
print(z1)
```

Output:

```
[[ 2  4  3]
 [ 5  7  6]
 [ 8 10  9]
 [11 13 12]]
[[ 2  4  3]
 [ 5  7  6]
 [ 8 10  9]
 [11 13 12]]
[[ 6  7  8]
 [ 9 10 11]
 [12 13 14]
 [15 16 17]]
```

3. Scipy

Numpy provides a high-performance multidimensional array and basic tools to compute and manipulate these arrays.

SciPy builds on this, and provides a large number of functions that operate on **numpy** arrays and are useful for different types of scientific and engineering applications.

1.1 Image Operations

SciPy provides some basic functions to work with images. For example, it has functions to read images into **numpy** arrays. To write **numpy** arrays as images onto your disk and resize images.

1.2 Distance between Points

The function *scipy.spatial.distance.pdist* computes the distance between all pairs of points given a set.

```
import numpy as np
from scipy.spatial.distance import pdist, squareform
x=np.array([[0,1],[1,0],[2,0]])
print(x)
d=squareform(pdist(x, 'euclidean'))
print(d)
```

Output:

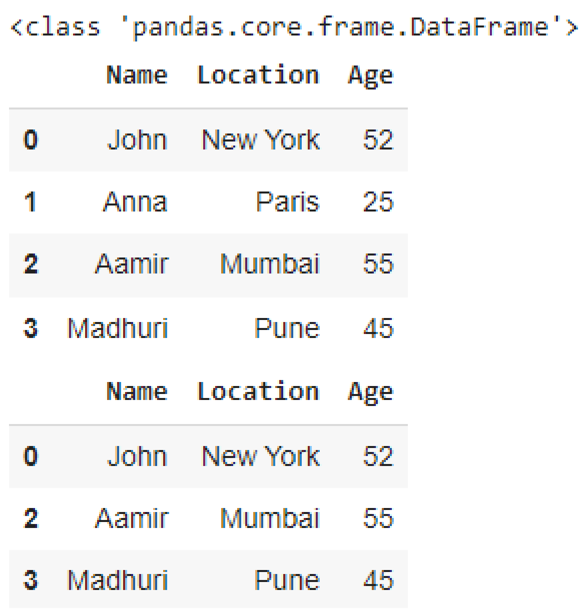
```
[[0 1]
 [1 0]
 [2 0]]
[[0.         1.41421356 2.23606798]
 [1.41421356 0.         1.        ]
 [2.23606798 1.         0.        ]]
```

4. Pandas

Pandas is a Python library for data analysis. It is built around a data structure called as the DataFrame.

```
import pandas as pd
data={"Name" : ["John", "Anna", "Aamir", "Madhuri"],
"Location": ["New York", "Paris","Mumbai","Pune"],
"Age" :[52,25,55,45]
}
data_pandas = pd.DataFrame(data)
print(type(data_pandas))
display(data_pandas)
display(data_pandas[data_pandas.Age>30])
```

Output:



```
<class 'pandas.core.frame.DataFrame'>
      Name  Location  Age
0     John  New York   52
1     Anna     Paris   25
2    Aamir    Mumbai   55
3  Madhuri      Pune   45
      Name  Location  Age
0     John  New York   52
2    Aamir    Mumbai   55
3  Madhuri      Pune   45
```

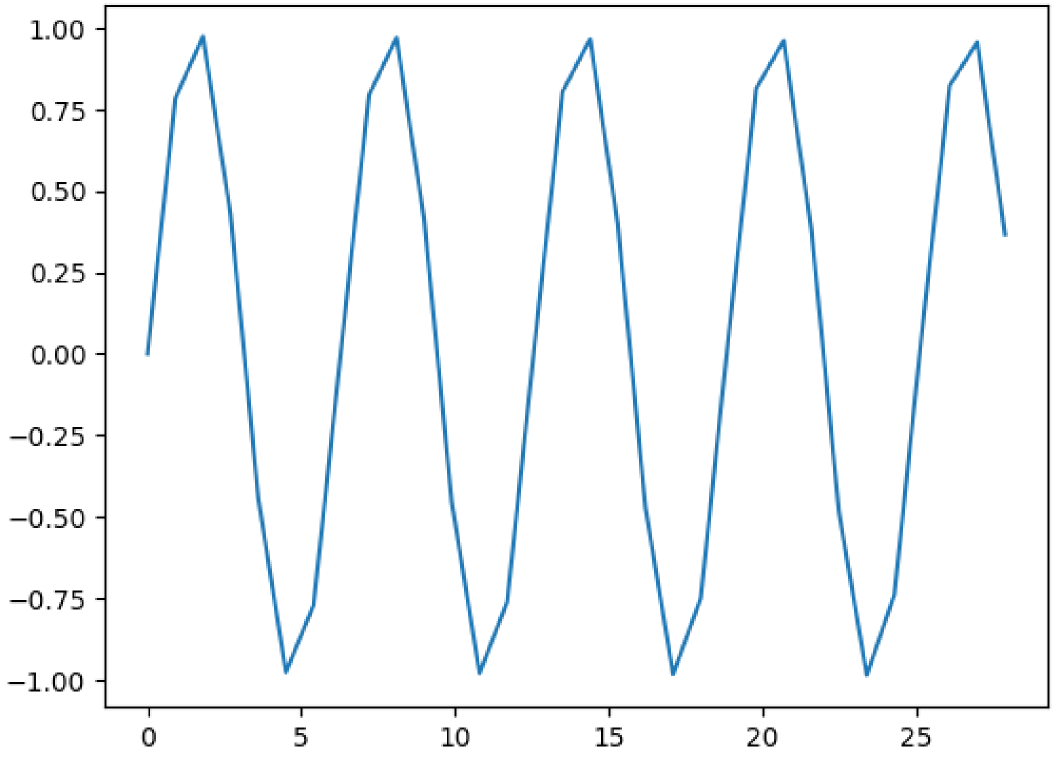
5. Matplotlib

Matplotlib is a plotting library. It provides functions to visualize data and mathematical functions.
Adding multiple plots together with title, legend etc.

```
import numpy as np
import matplotlib.pyplot as plt
x= np.arange(0,9 * np.pi,0.9)
y= np.sin(x)
plt.plot(x,y)
```

Output:

```
[<matplotlib.lines.Line2D at 0x7f25f8305ea0>]
```

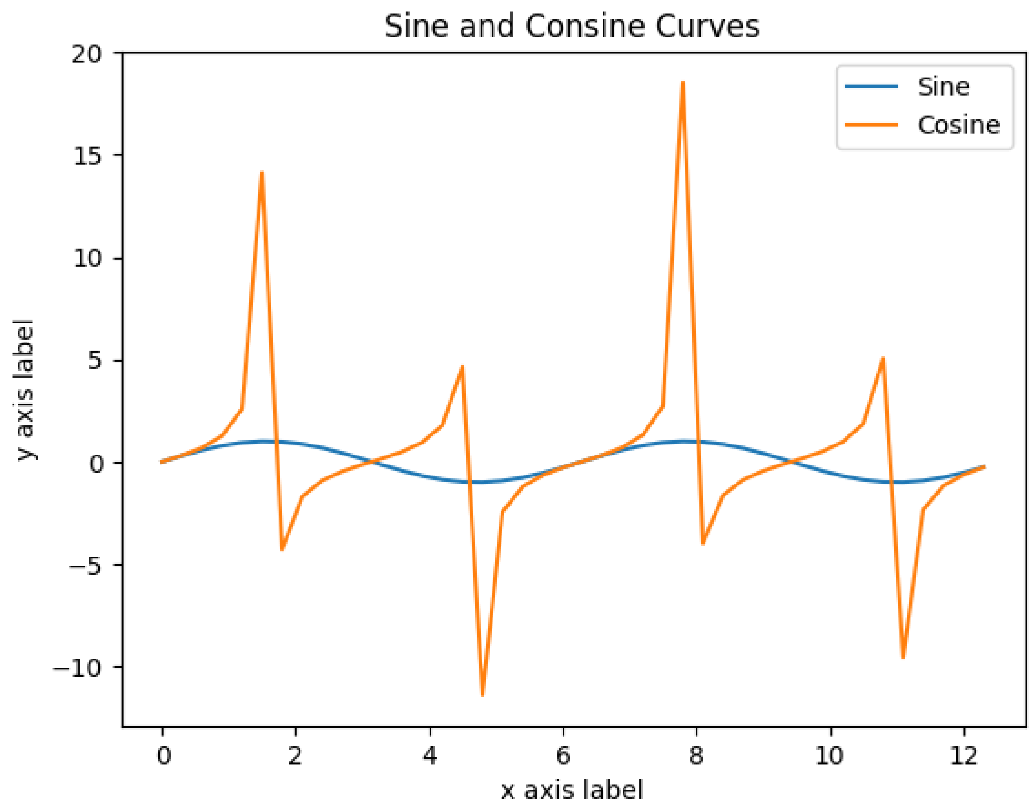


Sine and cosine Curves

```
import numpy as np
import matplotlib.pyplot as plt
x= np.arange(0,4 * np.pi,0.3)
y_sin= np.sin(x)
y_tan= np.tan(x)


plt.plot(x,y_sin)
plt.plot(x,y_tan)
plt.xlabel('x axis label')
plt.ylabel('y axis label')
plt.title('Sine and Consine Curves')
plt.legend(['Sine', 'Cosine'])
```

Output:

```
<matplotlib.legend.Legend at 0x7f25f833a770>
```

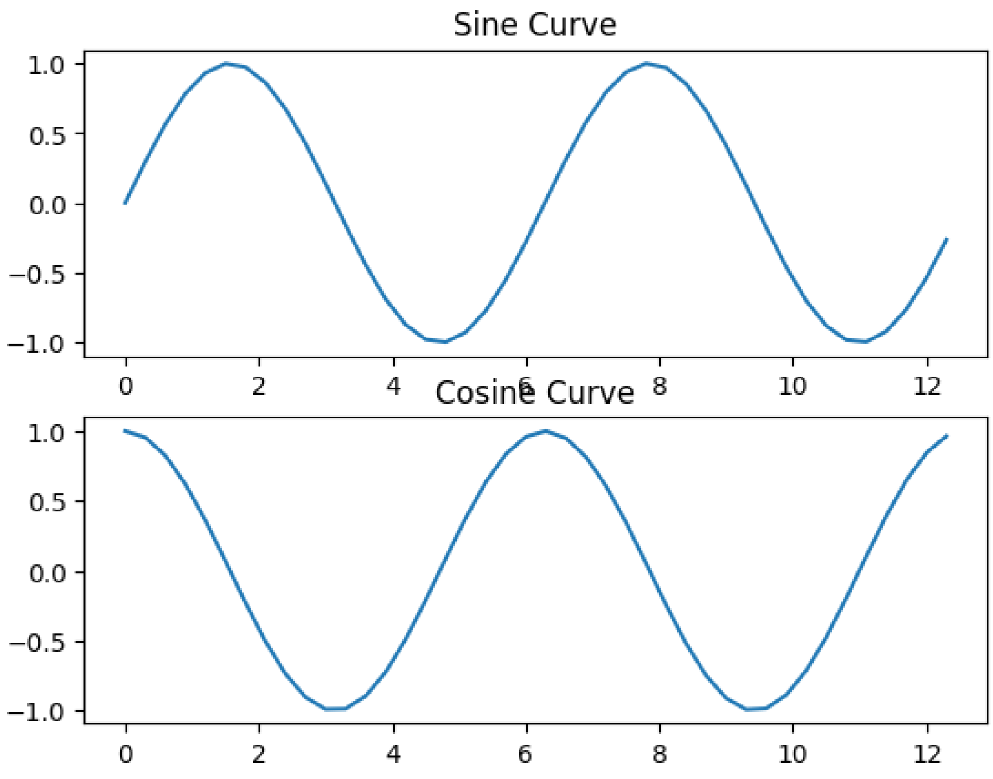


SubPlot of sine and cosine curves

```
import numpy as np
import matplotlib.pyplot as plt
x= np.arange(0,4 * np.pi,0.3)
y_sin= np.sin(x)
y_cos= np.cos(x)

plt.subplot(2,1,1)
plt.plot(x,y_sin)
plt.title('Sine Curve')

plt.subplot(2,1,2)
plt.plot(x, y_cos)
plt.title('Cosine Curve')
```

Output:

```
Text(0.5, 1.0, 'Cosine Curve')
```



2. Prediction Using a Linear Regression Model

Problem Statement: Use Scikit Learn to implement a Linear Regression Model that predicts average per capita life satisfaction index for a Country/Region given its GDP per capita value. Make use of OECD Better Life Index data along with IMF's GDP per capita data to train the Linear Regression Model.

Finally predict life satisfaction value for a region/country whose OECD BLI value is not in the training data on the basis of its GDP per capita.

```
## Code to understand how 'pivot' function of Pandas work
import pandas as pd
import numpy as np
df = pd.DataFrame({'foo':['one', 'one', 'one','two','two','two'],
                   'bar': ['A', 'B', 'C', 'A','B','C'],
                   'baz':[1,2,3,4,5,6],
                   'zoo':['x','y','z','q','w','t']})
print('Original Dataframe')
print(df)
print('\n')
print('Reshaped Dataframe after pivot')
print(df.pivot(index='foo', columns='bar',values='baz'))
print('\n')
```

Output:

```
Original Dataframe
   foo bar  baz zoo
0  one   A    1   x
1  one   B    2   y
2  one   C    3   z
3  two   A    4   q
4  two   B    5   w
5  two   C    6   t


Reshaped Dataframe after pivot
bar  A  B  C
foo
one  1  2  3
two  4  5  6
```

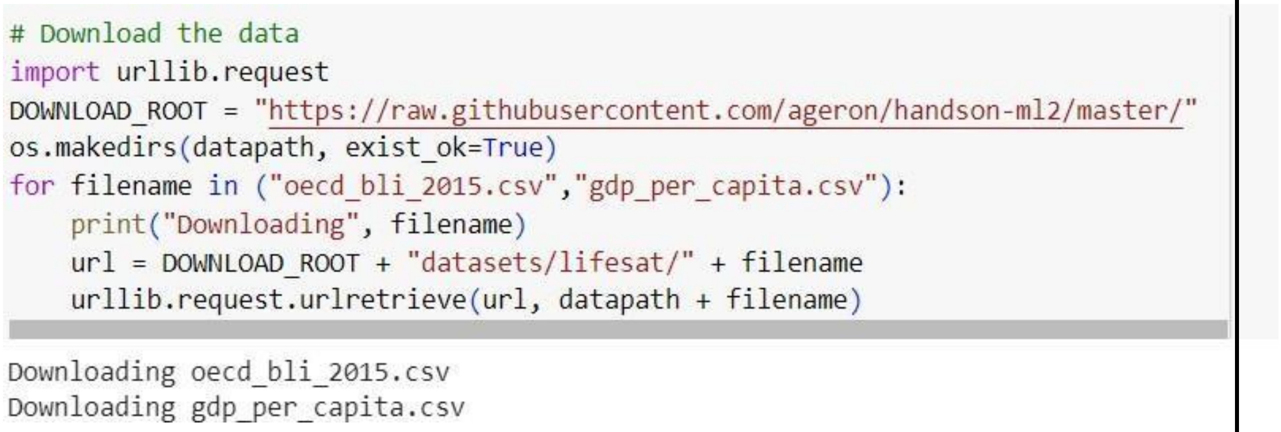
The below function merges the OECD's life satisfaction data and the IMF's GDP per capita data

```
def prepare_country_stats(oecd_bli, gdp_per_capita):
    oecd_bli = oecd_bli[oecd_bli["INEQUALITY"] == "TOT"]
    oecd_bli = oecd_bli.pivot(index="Country", columns="Indicator", values="Value")
    gdp_per_capita.rename(columns={"2015":"GDP per capita"},inplace=True)
    gdp_per_capita.set_index("Country", inplace=True)
    full_country_stats = pd.merge(left=oecd_bli, right=gdp_per_capita,
left_index=True, right_index=True)
    full_country_stats.sort_values(by="GDP per capita", inplace=True)
    remove_indices = [0,1,6,8,33,34,35]
    keep_indices = list(set(range(36)) - set(remove_indices))
    return full_country_stats[["GDP per capita","Life
satisfaction"]].iloc[keep_indices]
```

```
import os
datapath = os.path.join("datasets","lifesat","")
```

```
# To plot pretty figures directly within Jupyter
import matplotlib as mpl
mpl.rc('axes',labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)
```

Step 1: Download the OECD life satisfaction csv and GDP per capita csv from the respective web sources.



```
# Download the data
import urllib.request
DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master/"
os.makedirs(datapath, exist_ok=True)
for filename in ("oecd_bli_2015.csv","gdp_per_capita.csv"):
    print("Downloading", filename)
    url = DOWNLOAD_ROOT + "datasets/lifesat/" + filename
    urllib.request.urlretrieve(url, datapath + filename)
```

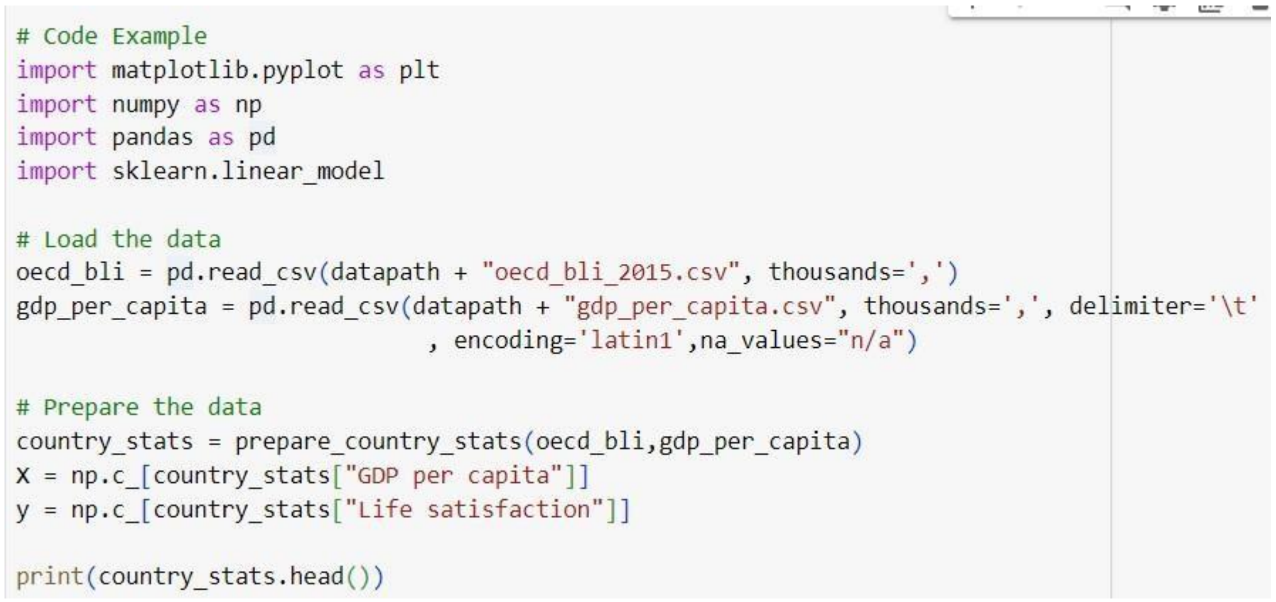
```
Downloading oecd_bli_2015.csv
Downloading gdp_per_capita.csv
```

Step 2: Load the csv files for OECD BLI Index data and IMF's GDP per capita data intorespective pandas data frames.

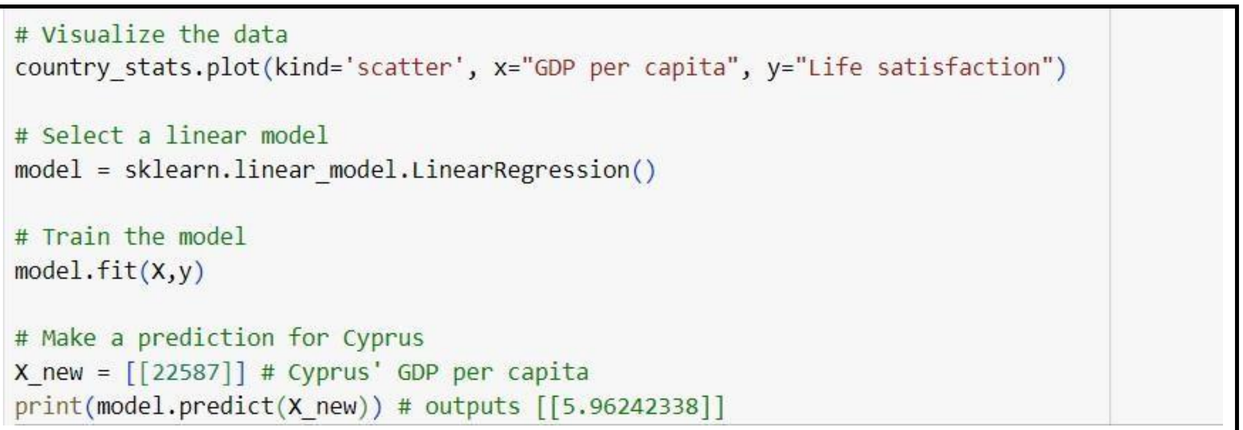
Merge it into a single dataframe after pivoting the data having Country column as index.

Visualize the correlation between GDP per capita with Life Satisfaction index using scatter plot.

Finally build, train and use the Scikit Learn's Linear Regression Model using the data.

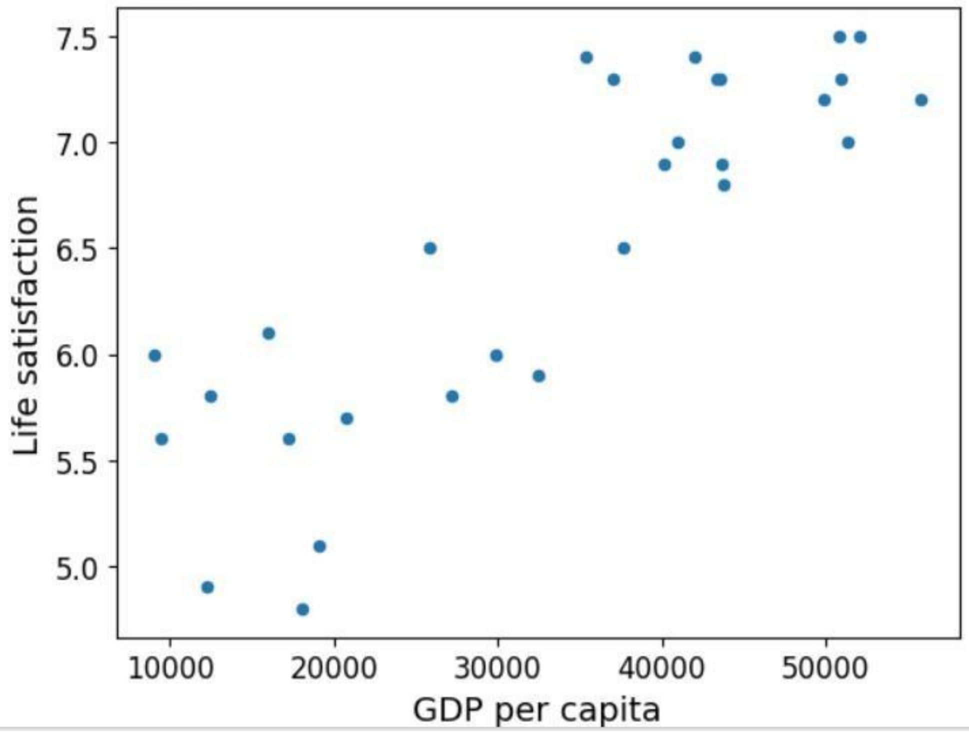


```
# Code Example
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import sklearn.linear_model

# Load the data
oecd_bli = pd.read_csv(datapath + "oecd_bli_2015.csv", thousands=',')
gdp_per_capita = pd.read_csv(datapath + "gdp_per_capita.csv", thousands=',', delimiter='\t'
                             , encoding='latin1',na_values="n/a")

# Prepare the data
country_stats = prepare_country_stats(oecd_bli,gdp_per_capita)
X = np.c_[country_stats["GDP per capita"]]
y = np.c_[country_stats["Life satisfaction"]]

print(country_stats.head())
```



```python
# Visualize the data
country_stats.plot(kind='scatter', x="GDP per capita", y="Life satisfaction")

# Select a linear model
model = sklearn.linear_model.LinearRegression()

# Train the model
model.fit(X,y)

# Make a prediction for Cyprus
X_new = [[22587]] # Cyprus' GDP per capita
print(model.predict(X_new)) # outputs [[5.96242338]]
```

```
                 GDP per capita  Life satisfaction
Country
Russia                 9054.914                6.0
Turkey                 9437.372                5.6
Hungary               12239.894                4.9
Poland                12495.334                5.8
Slovak Republic       15991.736                6.1
[[5.96242338]]
```



3. Binary Classification using a Logistic Regression Model

Problem Statement 1: Build and train a Logistic Regression Model to do binary classification of iris flowers using the iris dataset. In particular, the model should predict whether a particular iris flower instance belongs to the class Iris Virginica or not using only **petal width** as the input feature

```python
import numpy as np
from sklearn import datasets

iris = datasets.load_iris()
print(type(iris))
print(list(iris.keys()))
X = iris["data"][:,3:] # petal width
y = (iris["target"] == 2).astype(np.int64) # 1 if Iris-Virginica, else 0
```

```
<class 'sklearn.utils._bunch.Bunch'>
['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filename', 'data_module']
```

Training the Logistic Regression Model

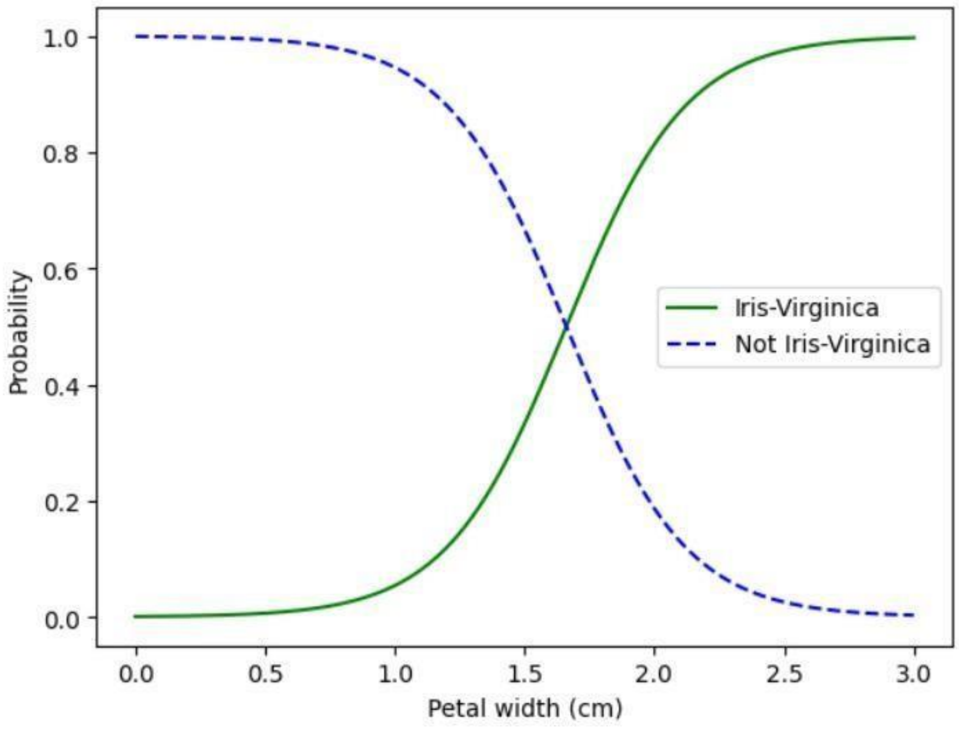
```python
from sklearn.linear_model import LogisticRegression

log_reg = LogisticRegression(solver="lbfgs", random_state=42)
log_reg.fit(X,y)
```

```
▾         LogisticRegression
LogisticRegression(random_state=42)
```

A look at the model's estimated probabilities for flowers with petal widths varying from 0 to 3 cm.

```python
import matplotlib.pyplot as plt

X_new = np.linspace(0,3,1000).reshape(-1,1)
y_proba = log_reg.predict_proba(X_new)
plt.plot(X_new, y_proba[:,1],"g-")
plt.plot(X_new, y_proba[:,0], "b--")
plt.xlabel('Petal width (cm)')
plt.ylabel('Probability')
plt.legend(['Iris-Virginica','Not Iris-Virginica'])
```

```
<matplotlib.legend.Legend at 0x7f03fcb2bd30>
```



The petal width of Iris-Virginica flowers (represented by triangles) ranges from 1.4 cm to 2.5 cm, while the other iris flowers (represented by squares) generally have a smaller petal width, ranging from 0.1 cm to 1.8 cm.

There is a bit of overlap. Above about 2 cm the classifier is highly confident that the flower is an Iris-Virginica (it outputs a high probability to that class), while below 1 cm it is highly confident that it is not an Iris-Virginica (high probability for the "Not Iris-Virginica" class). In between these extremes, the classifier is unsure.

There is a decision boundary at around 1.6 cm where both probabilities are equal to 50%: if the petal width is higher than 1.6 cm, the classifier will predict that the flower is an Iris-Virginica, or else it will predict that it is not (even if it is not very confident):

```
[ ]  log_reg.predict([[1.7],[1.5]])

     array([1, 0])
```

Problem Statement 2: Logistic Regression for predicting class using two features: Petal length and width.

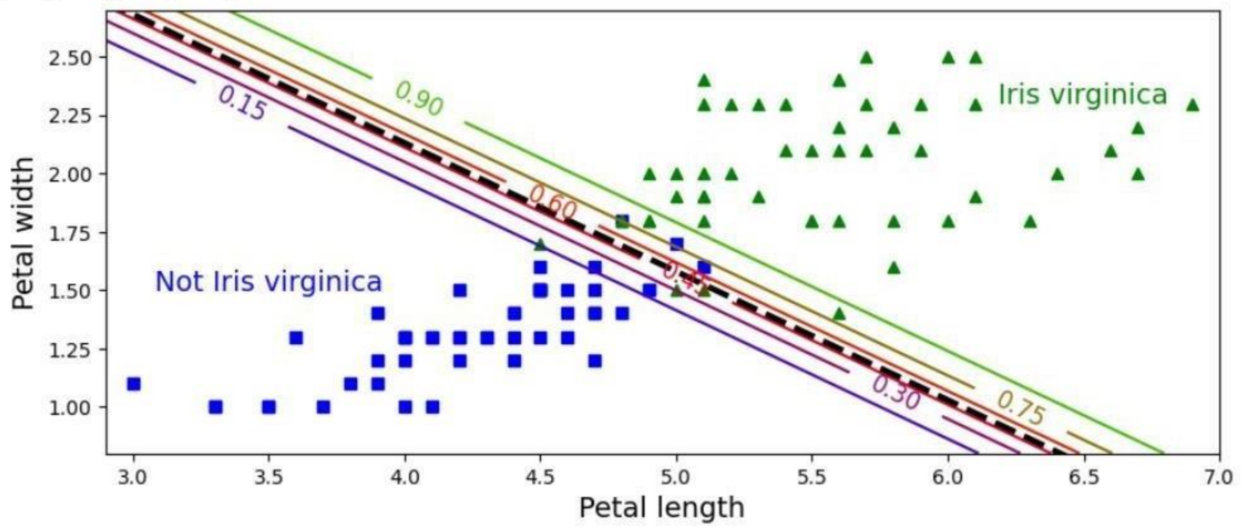
Below we use the same dataset but use two features: petal width and petal length to train the Logistic Regression model to estimate the probability that a new flower is an Iris-Virginica based on these two features.

The dashed line represents the points where the model estimates a 50% probability. This is the models decision boundary. Note that it is a linear boundary.

Each parallel line represents the points where the model outputs a specific probability, from 15% (bottom left) to 90% (top right). All the flowers beyond the top-right line have an over 90% chance of being Iris-Virginica according to the model.

```python
from sklearn.linear_model import LogisticRegression

X = iris["data"][:, (2, 3)]  # petal length, petal width
y = (iris["target"] == 2).astype(np.int64)

log_reg2 = LogisticRegression(solver="lbfgs", C=10**10, random_state=42)
log_reg2.fit(X, y)

x0, x1 = np.meshgrid(
        np.linspace(2.9, 7, 500).reshape(-1, 1),
        np.linspace(0.8, 2.7, 200).reshape(-1, 1),
    )
X_new = np.c_[x0.ravel(), x1.ravel()]
print(X_new.shape)

y_proba = log_reg2.predict_proba(X_new)

plt.figure(figsize=(10, 4))
plt.plot(X[y==0, 0], X[y==0, 1], "bs")
plt.plot(X[y==1, 0], X[y==1, 1], "g^")

zz = y_proba[:, 1].reshape(x0.shape)
contour = plt.contour(x0, x1, zz, cmap=plt.cm.brg)


left_right = np.array([2.9, 7])
boundary = -(log_reg2.coef_[0][0] * left_right + log_reg2.intercept_[0]) / log_reg2.coef_[0][1]

plt.clabel(contour, inline=1, fontsize=12)
plt.plot(left_right, boundary, "k--", linewidth=3)
plt.text(3.5, 1.5, "Not Iris virginica", fontsize=14, color="b", ha="center")
plt.text(6.5, 2.3, "Iris virginica", fontsize=14, color="g", ha="center")
plt.xlabel("Petal length", fontsize=14)
plt.ylabel("Petal width", fontsize=14)
plt.axis([2.9, 7, 0.8, 2.7])
```

```
(100000, 2)
(2.9, 7.0, 0.8, 2.7)
```



3. Multi-Class Classification using k-Nearest Neighbours

Implement & Train a k-Nearest Neighbour Model for Detecting Iris Flower SpeciesProblem

Statement: Load the iris dataset. Build a k-NN model with k=3.

Explore the Iris Data using visualizations to understand the relationships among different input features with respect to each species.

Then use all four features: sepal length (cm), sepal width (cm), petal length (cm), and petal width (cm) to train the k-NN model to classify a new iris flower into one of three species classes: Iris Virginica, Iris Setosa or Iris Versicolor.

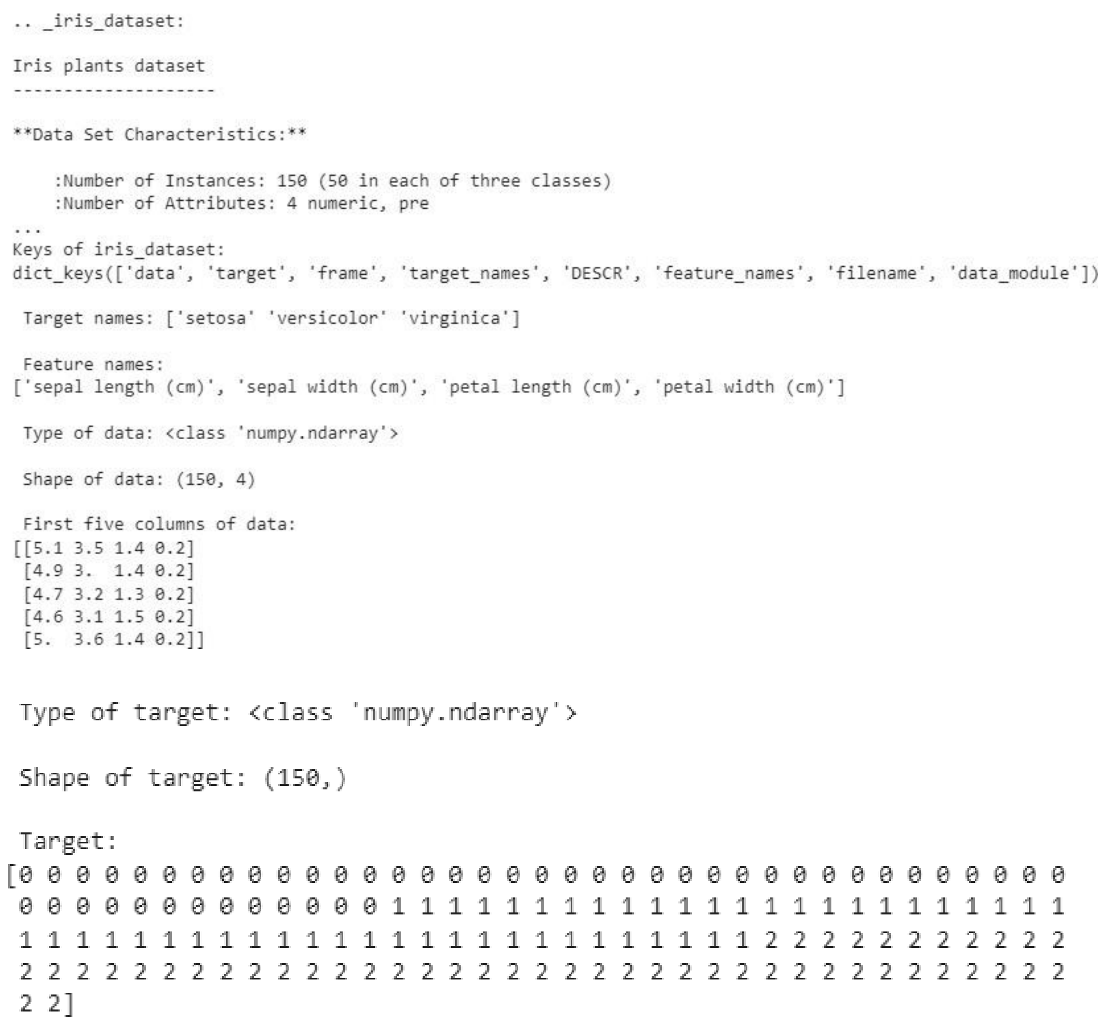
Finally evaluate the model accuracy on the held-out Test Data.

The data we will use for this example is the Iris dataset, a classical dataset in machine learning and statistics. It is included in scikit-learn in the datasets module. We can load it by calling the load_iris function:

```
from sklearn.datasets import load_iris

iris_dataset = load_iris()

# Code that shows the short description of the Iris Dataset
print(iris_dataset['DESCR'][:193] + "\n...")
print("Keys of iris_dataset:\n{}".format(iris_dataset.keys()))

# The value of the key target_names is an array of strings, containing the species
 of
# flower that we want to predict:
print("\n Target names: {}".format(iris_dataset['target_names']))

# The value of feature_names is a list of strings, giving the description of each
feature:
print("\n Feature names: \n{}".format(iris_dataset['feature_names']))

# The data itself is contained in the target and data fields. data contains the
numeric
# measurements of sepal length, sepal width, petal length, and petal width in a
NumPy array:
print("\n Type of data: {}".format(type(iris_dataset['data'])))

#The rows in the data array correspond to flowers, while the columns represent the
four
# measurements that were taken for each flower:
print("\n Shape of data: {}".format(iris_dataset['data'].shape))

# We see that the array contains measurements for 150 different flowers.
# Here are the feature values for the first five samples:
print("\n First five columns of data:\n{}".format(iris_dataset['data'][:5]))
```

```
# From this data, we can see that all of the first five flowers have a petal
width of 0.2 cm

# and that the first flower has the longest sepal, at 5.1 cm
# The target array that contains the species of each of the flowers that were
measured is a
# numpy array:
print("\n Type of target: {}".format(type(iris_dataset['target'])))
print("\n Shape of target: {}".format(iris_dataset['target'].shape))

# The species are encoded as integers from 0 to 2:
print("\n Target:\n{}".format(iris_dataset['target']))
```

Output:



```
.. _iris_dataset:

Iris plants dataset
--------------------

**Data Set Characteristics:**

    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, pre
...
Keys of iris_dataset:
dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filename', 'data_module'])

 Target names: ['setosa' 'versicolor' 'virginica']

 Feature names:
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']

 Type of data: <class 'numpy.ndarray'>

 Shape of data: (150, 4)

 First five columns of data:
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]]

 Type of target: <class 'numpy.ndarray'>

 Shape of target: (150,)

 Target:
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
```

Splitting the Data into Training and Testing Data

To assess the model's performance we split the labelled data we have (our 150 flower measurements) into two parts: training data and testing data.

Scikit-learn contains a function that shuffles the dataset and splits it for you: the train_test_split function. This function extracts 75% of the rows in the data as the training set, together with the corresponding labels for this data. The remaining 25% of the data, together with the remaining labels, is declared as the test set.

Let's call train_test_split on our data and assign the outputs using this nomenclature:

```
from sklearn.model_selection import train_test_split


# The output of the train_test_split function is X_train, X_test, y_train, and y_test,
# which are all NumPy arrays.
X_train, X_test, y_train, y_test = train_test_split(iris_dataset['data'],
                                                    iris_dataset['target'],
random_state=0)

# X_train contains 75% of the rows of the dataset, and X_test contains the remaining
25%:
print("X_train shape: {}".format(X_train.shape))
print("y_train shape: {}".format(y_train.shape))
print("X_test shape: {}".format(X_test.shape))
print("y_test shape: {}".format(y_test.shape))
```

Output:

```
X_train shape: (112, 4)
y_train shape: (112,)
X_test shape: (38, 4)
y_test shape: (38,)
```

Knowing Your Data

One of the best ways to inspect data is to visualize it. One way to do this is by using a scatter plot for each pair of features. This is also known as a scatter matrix or a pair plot. A pair plot looks at all possible pairs of features. If you have a small number of features, such as the four we have here, this is quite reasonable.

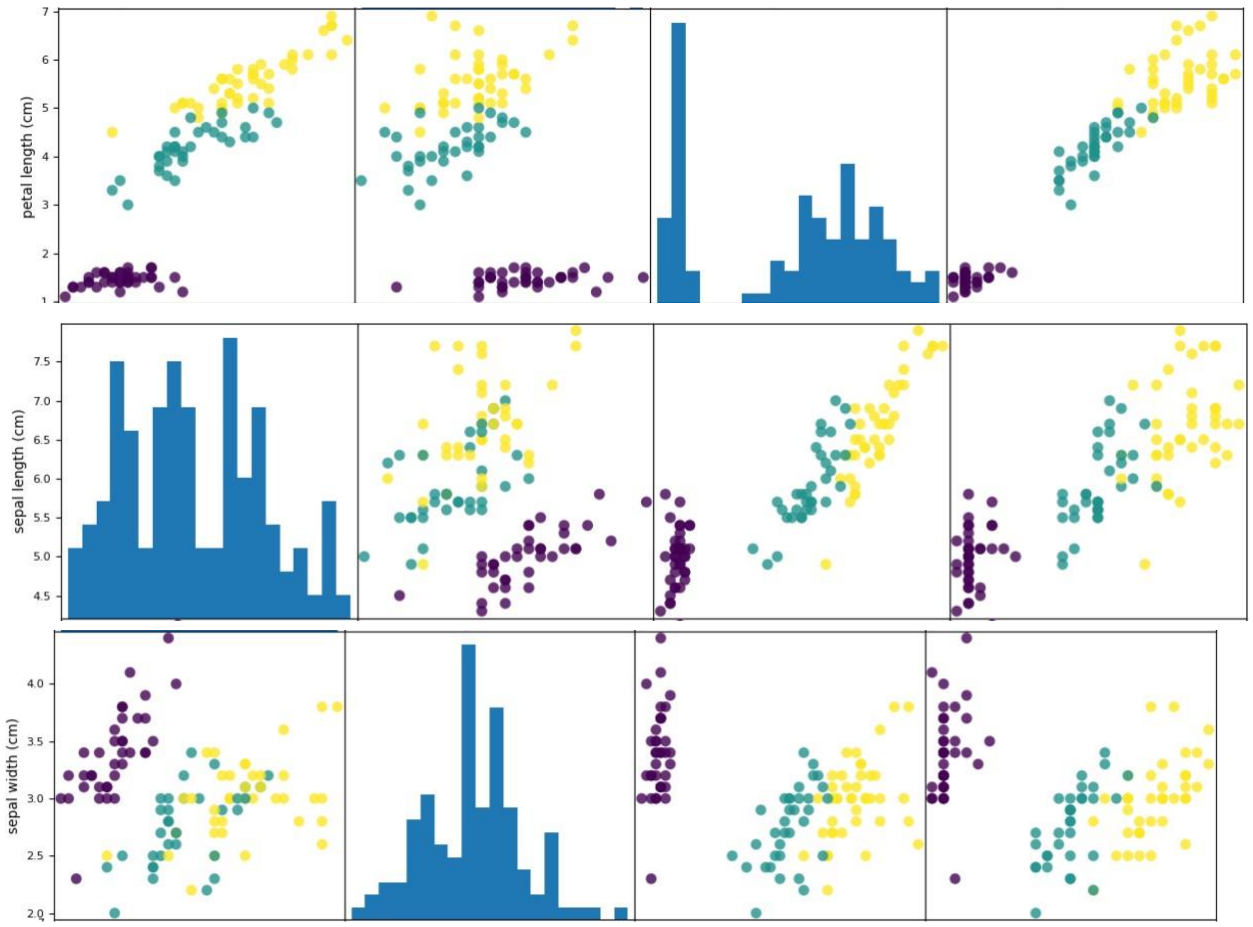
Below we draw a pair plot of the features in the training set. The data points are colored according to the species the iris belongs to.

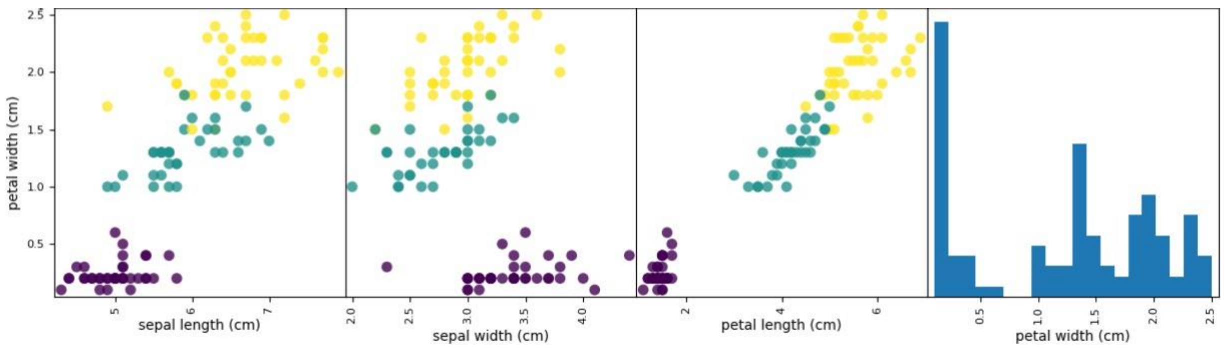
To create the plot, we first convert the NumPy array into a pandas DataFrame. pandas has a function to create pair plots called scatter_matrix. The diagonal of this matrix is filled with histograms of each feature:

```
import pandas as pd
# create dataframe from data in X_train
# label the columns using the strings in iris_dataset.feature_names
iris_dataframe = pd.DataFrame(X_train, columns=iris_dataset.feature_names)
```

```
# create a scatter matrix from the dataframe, color by y_train
grr = pd.plotting.scatter_matrix(iris_dataframe, c=y_train, figsize=(15, 15),
marker='o',
hist_kwds={'bins': 20}, s=60, alpha=.8)
```

Output:





From the plots, we can see that the three classes seem to be relatively well separated using the sepal and petal measurements.

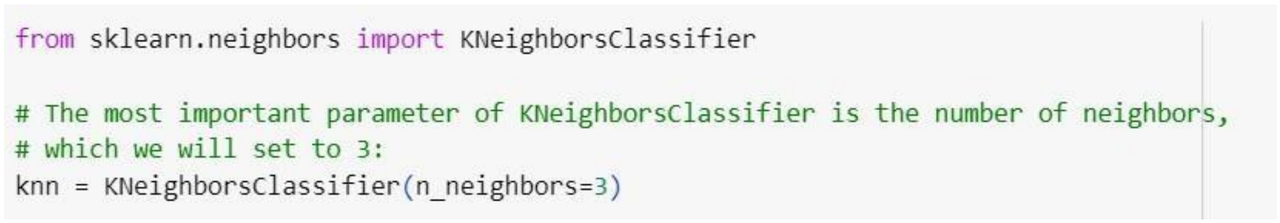
This means that a machine learning model will likely be able to learn to separate them.

Building our K-Nearest Neighbours (K-NN) Model

We train a k-nearest neighbours classifier with our training data. Once trained our model should be able to predict the species of any new iris flower given its four features: petal lenght, petal width, sepal length and sepal width in centimeters.

To make a prediction for a new data point, the k-NN algorithm finds the k points in the training set that are closest to the new point. Then, a prediction is made using the majority class among these neighbors.

The k-nearest neighbors classification algorithm is implemented in the KNeighborsClassifier class in the neighbors module:



```
from sklearn.neighbors import KNeighborsClassifier

# The most important parameter of KNeighborsClassifier is the number of neighbors,
# which we will set to 3:
knn = KNeighborsClassifier(n_neighbors=3)
```

Training the k-NN Model

To train the model on the training set, we call the fit method of the knn object, which takes as arguments the NumPy array X_train containing the training data and the NumPy array y_train of the corresponding training labels.

The fit method returns the knn object itself (and modifies it in place), so we get a string representation of our classifier.

```
knn.fit(X_train, y_train)
```

```
▾       KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

Making Predictions

We can now make predictions using this model on new data for which we might not know the correct labels.

Imagine we found an iris in the wild with a sepal length of 5 cm, a sepal width of 2.9 cm, a petal length of 1 cm, and a petal width of 0.2 cm. What species of iris would this be?

We can put this data into a NumPy array with shape as number of samples (1) multiplied by number of features (4):

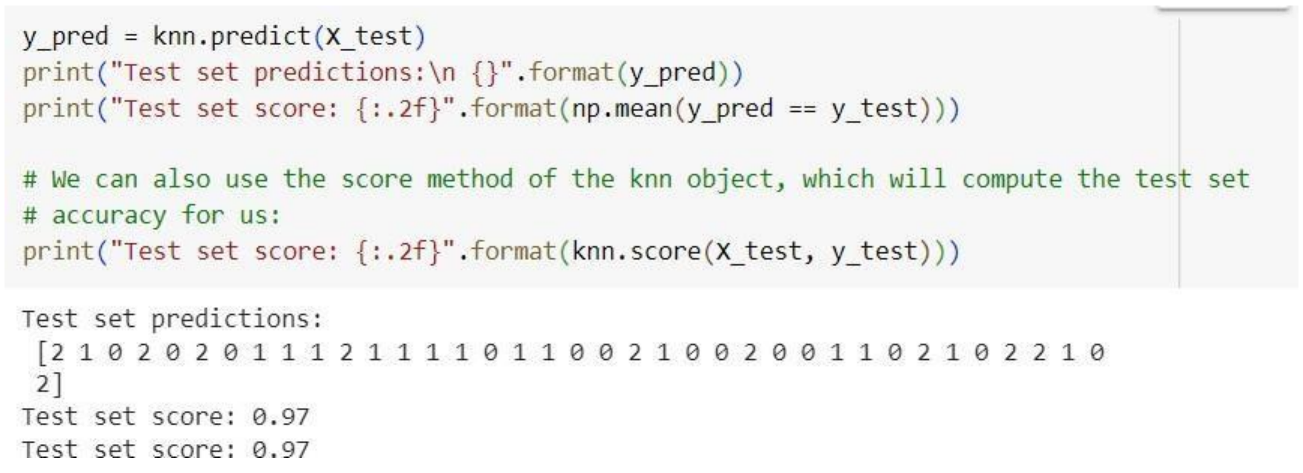
```
import numpy as np

# Note that we made the measurements of this single flower into a row in a twodimensional
# NumPy array, as scikit-learn always expects two-dimensional arrays for the data.
X_new = np.array([[5, 2.9, 1, 0.2]])
print("X_new.shape: {}".format(X_new.shape))

# To make a prediction, we call the predict method of the knn object:
prediction = knn.predict(X_new)
print("Prediction: {}".format(prediction))
print("Predicted target name: {}".format(iris_dataset['target_names'][prediction]))
```

```
X_new.shape: (1, 4)
Prediction: [0]
Predicted target name: ['setosa']
```

Evaluating our k-NN model

we can make a prediction for each iris in the test data and compare it against its label (the known species).

We can measure how well the model works by computing the accuracy, which is the fraction of flowers for which the right species was predicted:



```
y_pred = knn.predict(X_test)
print("Test set predictions:\n {}".format(y_pred))
print("Test set score: {:.2f}".format(np.mean(y_pred == y_test)))

# We can also use the score method of the knn object, which will compute the test set
# accuracy for us:
print("Test set score: {:.2f}".format(knn.score(X_test, y_test)))
```

```
Test set predictions:
 [2 1 0 2 0 2 0 1 1 1 2 1 1 1 1 0 1 1 0 0 2 1 0 0 2 0 0 1 1 0 2 1 0 2 2 1 0
 2]
Test set score: 0.97
Test set score: 0.97
```

Conclusion

For this model, the test set accuracy is about 0.97, which means we made the right predictionfor 97% of the irises in the test set. Under some mathematical assumptions, this means that we can expe

5. Linear and Non-Linear SVM Classification

Train & Implement a SVM Model for Linear and Non-Linear Classification.Problem

Statement 1 - Linear SVM Classification:

Load the iris dataset, scale the petal-width and petal-length features and then train a linear SVM model to detect Iris-Virginica flowers. Use the petal length and petal width features totrain the model. Scale the features before training the model. Use the resulting model to do.

```
import numpy as np
from sklearn import datasets
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC

iris = datasets.load_iris()
X = iris["data"][:, (2, 3)] # petal length, petal width
y = (iris["target"] == 2).astype(np.float64) # Iris-Virginica has code 2

svm_clf = Pipeline([
    ("scaler", StandardScaler()),
    ("linear_svc", LinearSVC(C=1, loss="hinge"))
])

svm_clf.fit(X,y)

# predict for a sample iris flower with petal length 5.5 and petal width 1.7
svm_clf.predict([[5.5, 1.7]]) # detected as Iris Virginica
                              # [1 -- Virginica, 0 --  Not Virginica]
```

Output:

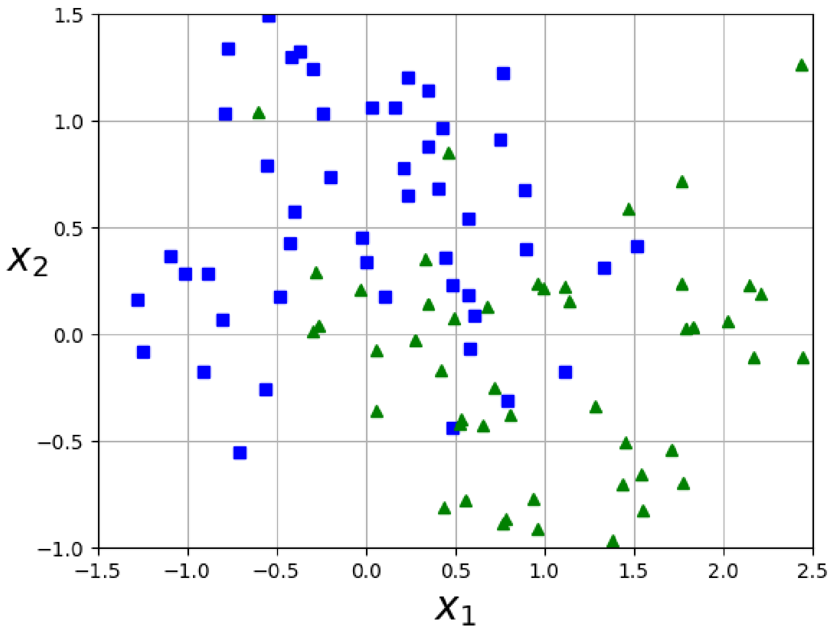
```
array([1.])
```

Problem Statement 2 - Nonlinear SVM Classification: Train and implement a SVM model to do binary classification on moons dataset. Since the dataset is linearly inseparabledo a transformation and add polynomial features to the dataset.

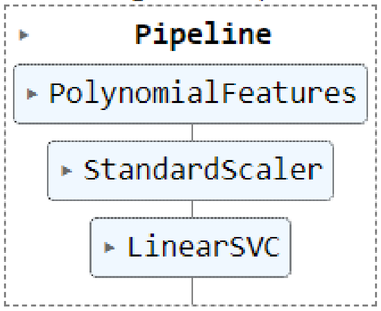
```
# Plotting Moons data to illustrate its linear inseparability
import matplotlib.pyplot as plt
from sklearn.datasets import make_moons

X, y = make_moons(n_samples = 100, noise=0.4)
```

```
def plot_dataset(X,y,axes):
    plt.plot(X[:,0][y==0], X[:,1][y==0], "bs") # bs stands for blue square
    plt.plot(X[:,0][y==1], X[:,1][y==1], "g^") # g^ stands for green triangle
    plt.axis(axes)

    plt.grid(True, which='both')
    plt.xlabel(r"$x_1$", fontsize=20)
    plt.ylabel(r"$x_2$", fontsize=20, rotation=0)

plot_dataset(X,y,[-1.5,2.5,-1,1.5])
```

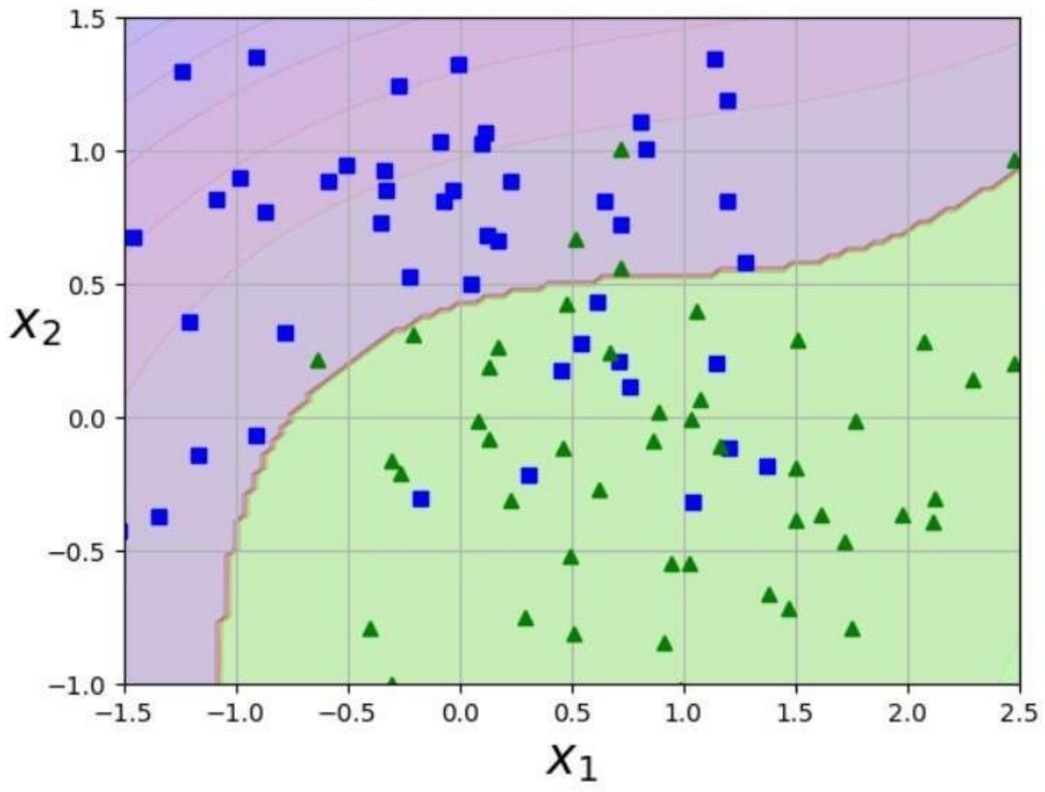
Output:



```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
from sklearn.svm import LinearSVC

polynomial_svm_clf = Pipeline([
    ("poly_features", PolynomialFeatures(degree=3)),
    ("scaler", StandardScaler()),
    ("svm_clf", LinearSVC(C=10, loss='hinge', random_state=42))
])

polynomial_svm_clf.fit(X,y)
```



```python
def plot_predictions(clf, axes):
    x0s = np.linspace(axes[0], axes[1], 100)
    x1s = np.linspace(axes[2], axes[3], 100)
    x0, x1 = np.meshgrid(x0s, x1s)
    X = np.c_[x0.ravel(), x1.ravel()]
    y_pred = clf.predict(X).reshape(x0.shape)
    y_decision = clf.decision_function(X).reshape(x0.shape)
    plt.contourf(x0, x1, y_pred, cmap=plt.cm.brg, alpha=0.2)
    plt.contourf(x0, x1, y_decision, cmap=plt.cm.brg, alpha=0.1)

# plot predictions and decision boundary
# of the previously trained SVM classifier for given x and y axes values
plot_predictions(polynomial_svm_clf, [-1.5, 2.5, -1, 1.5])

# plot the linearly inseparable Moons Dataset as was done previously
plot_dataset(X,y,[-1.5,2.5,-1,1.5])
```


1.5
1.0
0.5
0.0
−0.5
−1.0
x_2
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
x_1

6. Decision Tree Learning for Classification

Problem Statement: Use the Iris dataset to train and visualize a decision tree for classifying an Iris flower based on its petal length (in cms) and petal width (in cms) features.

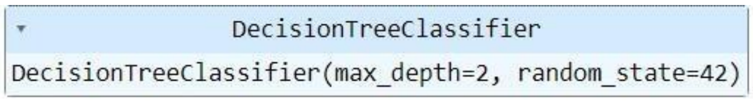
Use the trained model to predict the class for a flower having petal-length and petal-width of 5 cms and 1.5 cms respectively. Also try predicting class probabilities instead of a class for the same flower.

Finally, plot the decision boundaries for the induced decision tree classifier.

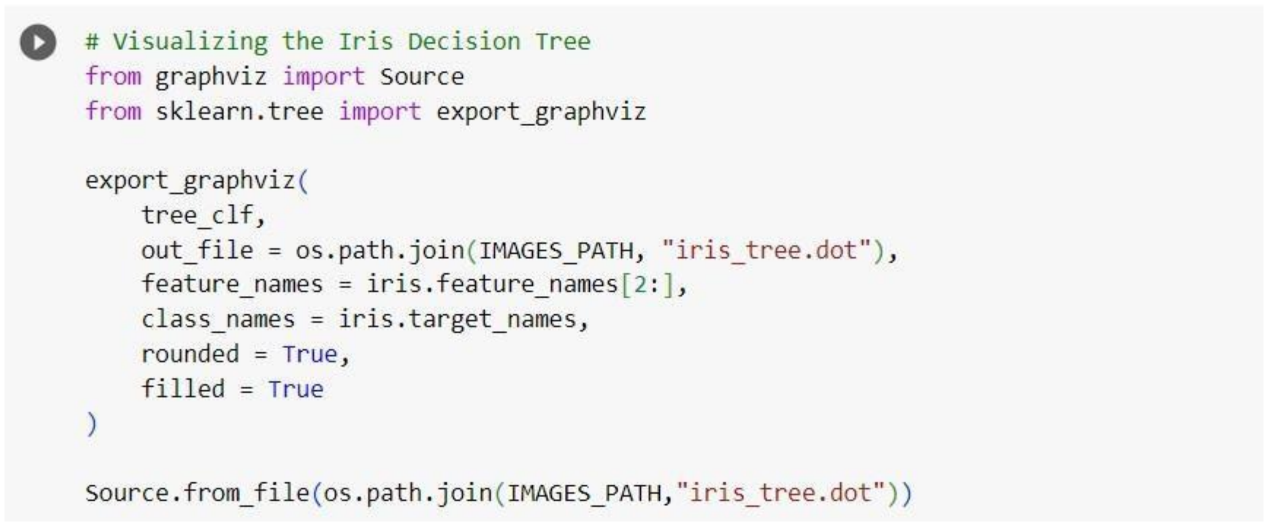
Step 1 - Training and Visualizing a Decision Tree

```
# creating images folder for decision tree lab
import os

PROJECT_ROOT_DIR = "."
SUB_DIR = "decision_trees"
IMAGES_PATH = os.path.join(PROJECT_ROOT_DIR, "images", SUB_DIR)
os.makedirs(IMAGES_PATH,exist_ok=True)
```

```
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier

iris = load_iris()
X = iris.data[:, 2:] # petal length and width
y = iris.target

tree_clf = DecisionTreeClassifier(max_depth=2, random_state=42)
tree_clf.fit(X,y)
```



```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=2, random_state=42)
```



```
# Visualizing the Iris Decision Tree
from graphviz import Source
from sklearn.tree import export_graphviz

export_graphviz(
    tree_clf,
    out_file = os.path.join(IMAGES_PATH, "iris_tree.dot"),
    feature_names = iris.feature_names[2:],
    class_names = iris.target_names,
    rounded = True,
    filled = True
)

Source.from_file(os.path.join(IMAGES_PATH,"iris_tree.dot"))
```

Step 2- Making Predictions using the induced DT Classifier

```
# predict the class for flower with petal length 5 cm and petal-width 1.5 cm
tree_clf.predict([[5,1.5]]) # class 1 is predicted - which is for Iris-Versicolor
```

```
array([1])
```

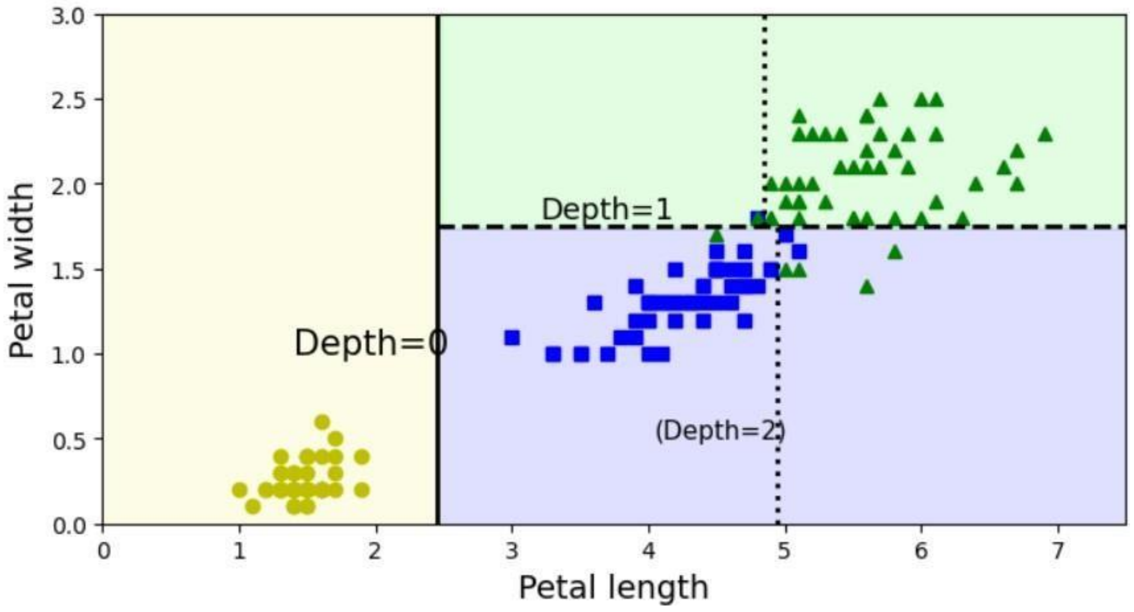
```
# predict class probabilities instead for the same flower
tree_clf.predict_proba([[5,1.5]])
```

```
array([[0.        , 0.90740741, 0.09259259]])
```

Step 3 - Visualizing the Decision Boundary for our Decision Tree

```
import numpy as np
from matplotlib import pyplot as plt
from matplotlib.colors import ListedColormap

def plot_decision_boundary(clf, X, y, axes=[0, 7.5, 0, 3], iris=True, legend=False, plot_training=True):
    x1s = np.linspace(axes[0], axes[1], 100)
    x2s = np.linspace(axes[2], axes[3], 100)
    x1, x2 = np.meshgrid(x1s, x2s)
    X_new = np.c_[x1.ravel(),x2.ravel()]
    y_pred = clf.predict(X_new).reshape(x1.shape)
    custom_cmap = ListedColormap(['#fafab0', '#9898ff','#a0faa0'])
    plt.contourf(x1, x2, y_pred, alpha=0.3, cmap=custom_cmap)

    if not iris:
        custom_cmap2 = ListedColormap(['#7d7d58','#4c4c7f','#507d50'])
        plt.contour(x1,x2,y_pred,cmap=custom_cmap2,alpha=0.8)
    if plot_training:
        plt.plot(X[:, 0][y==0], X[:, 1][y==0], "yo", label="Iris setosa")
        plt.plot(X[:, 0][y==1], X[:, 1][y==1], "bs", label="Iris versicolor")
        plt.plot(X[:, 0][y==2], X[:, 1][y==2], "g^", label="Iris virginica")
        plt.axis(axes)
    if iris:
        plt.xlabel("Petal length", fontsize=14)
        plt.ylabel("Petal width", fontsize=14)
    else:
        plt.xlabel(r"$x_1$", fontsize=18)
        plt.ylabel(r"$x_2$", fontsize=18, rotation=0)
    if legend:
        plt.legend(loc="lower right", fontsize=14)
plt.figure(figsize=(8, 4))
plot_decision_boundary(tree_clf, X, y)
plt.plot([2.45, 2.45], [0, 3], "k-", linewidth=2)
plt.plot([2.45, 7.5], [1.75, 1.75], "k--", linewidth=2)
plt.plot([4.95, 4.95], [0, 1.75], "k:", linewidth=2)
plt.plot([4.85, 4.85], [1.75, 3], "k:", linewidth=2)
plt.text(1.40, 1.0, "Depth=0", fontsize=15)
plt.text(3.2, 1.80, "Depth=1", fontsize=13)
plt.text(4.05, 0.5, "(Depth=2)", fontsize=11)
```

```
Text(4.05, 0.5, '(Depth=2)')
```



7. Ensemble Learning with AdaBoost Classifier

Problem Statement: Build and train an AdaBoost classifier where Decision Tree acts as the first base classifier. In particular, train an AdaBoost classifier based on 200 *Decision Stumps* on Moons Dataset using Scikit-Learn's AdaBoostClassifier class.

Compare the accuracy of the AdaBoostClassifier with the individual DecisionStump on the Test Set.

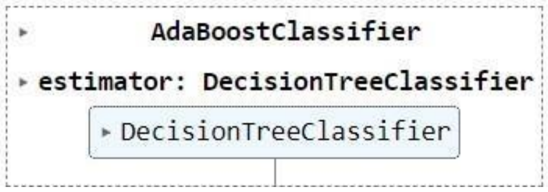
Finally draw the decision boundary of the AdaBoostClassifier.

Step 1: Loading the Moons Data and Splitting into Training and Testing Sets

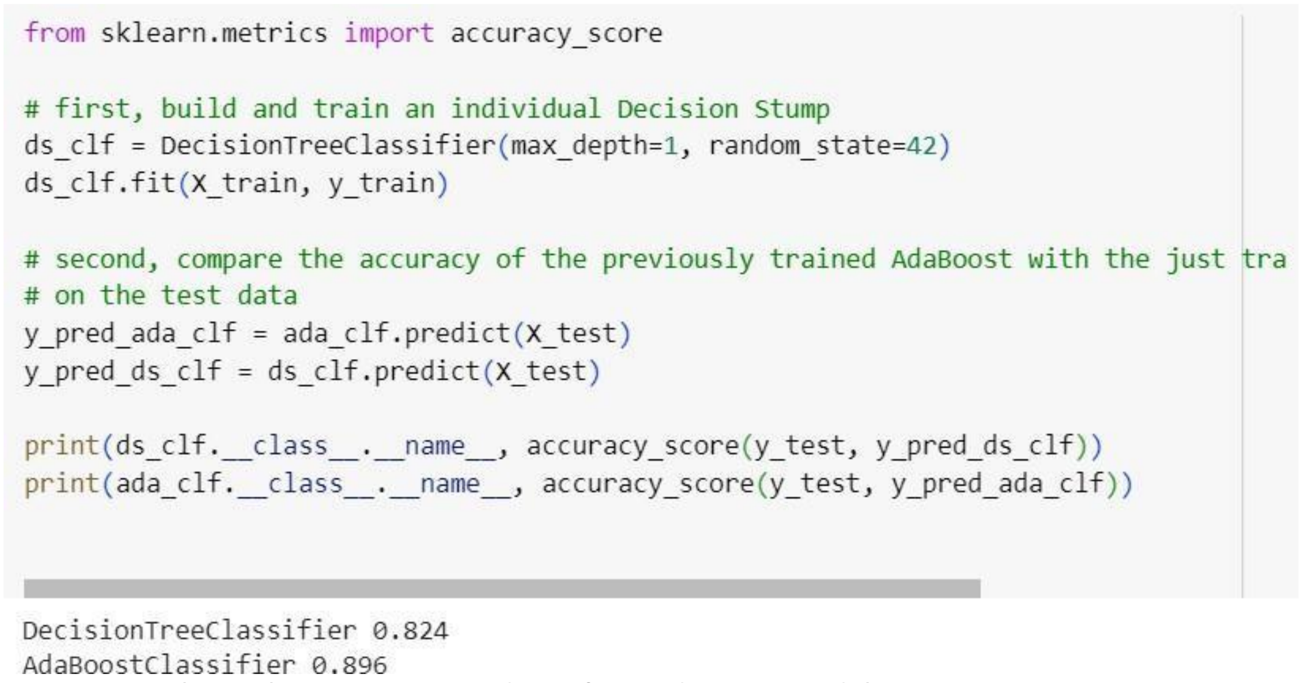
```python
import sklearn
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.datasets import make_moons

X, y = make_moons(n_samples=500, noise=0.30, random_state=42)
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
```

Step 2: Building and Training the AdaBoost Classifier

```python
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier

ada_clf = AdaBoostClassifier(
        DecisionTreeClassifier(max_depth=1), n_estimators=200,
        algorithm="SAMME.R", learning_rate=0.5, random_state=42)
ada_clf.fit(X_train,y_train)
```



Step 3 : Comparing Performance of the AdaBoost Classifier with Individual DecisionStump on Test Set

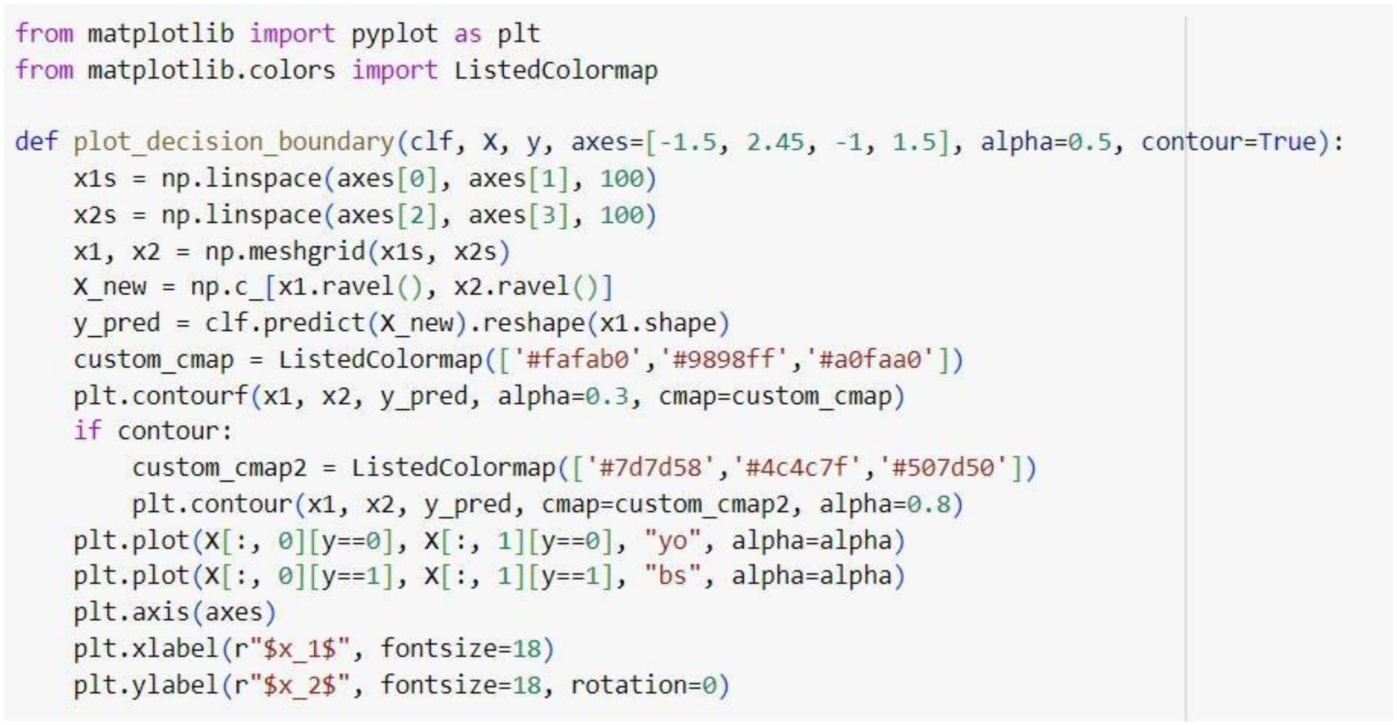


```
from sklearn.metrics import accuracy_score

# first, build and train an individual Decision Stump
ds_clf = DecisionTreeClassifier(max_depth=1, random_state=42)
ds_clf.fit(X_train, y_train)

# second, compare the accuracy of the previously trained AdaBoost with the just tra
# on the test data
y_pred_ada_clf = ada_clf.predict(X_test)
y_pred_ds_clf = ds_clf.predict(X_test)

print(ds_clf.__class__.__name__, accuracy_score(y_test, y_pred_ds_clf))
print(ada_clf.__class__.__name__, accuracy_score(y_test, y_pred_ada_clf))
```

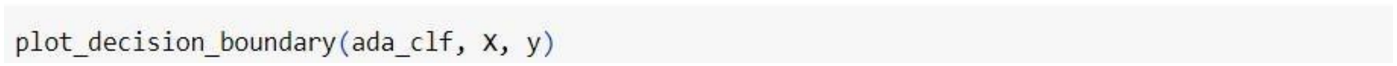
```
DecisionTreeClassifier 0.824
AdaBoostClassifier 0.896
```

Step 4 : Visualizing the Decision Boundary of our AdaBoost Model

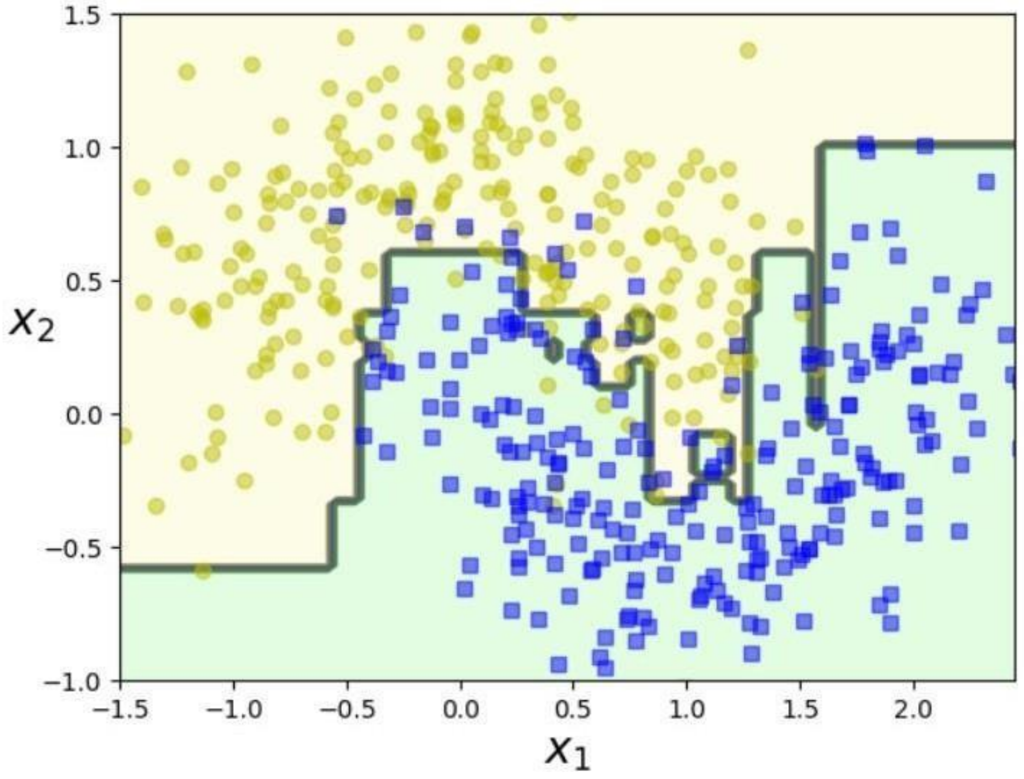
Define a function named **plot_decision_boundary** for the purpose and then invoke it passing ourAdaBoost model and training data as arguments.



```
from matplotlib import pyplot as plt
from matplotlib.colors import ListedColormap

def plot_decision_boundary(clf, X, y, axes=[-1.5, 2.45, -1, 1.5], alpha=0.5, contour=True):
    x1s = np.linspace(axes[0], axes[1], 100)
    x2s = np.linspace(axes[2], axes[3], 100)
    x1, x2 = np.meshgrid(x1s, x2s)
    X_new = np.c_[x1.ravel(), x2.ravel()]
    y_pred = clf.predict(X_new).reshape(x1.shape)
    custom_cmap = ListedColormap(['#fafab0','#9898ff','#a0faa0'])
    plt.contourf(x1, x2, y_pred, alpha=0.3, cmap=custom_cmap)
    if contour:
        custom_cmap2 = ListedColormap(['#7d7d58','#4c4c7f','#507d50'])
        plt.contour(x1, x2, y_pred, cmap=custom_cmap2, alpha=0.8)
    plt.plot(X[:, 0][y==0], X[:, 1][y==0], "yo", alpha=alpha)
    plt.plot(X[:, 0][y==1], X[:, 1][y==1], "bs", alpha=alpha)
    plt.axis(axes)
    plt.xlabel(r"$x_1$", fontsize=18)
    plt.ylabel(r"$x_2$", fontsize=18, rotation=0)
```

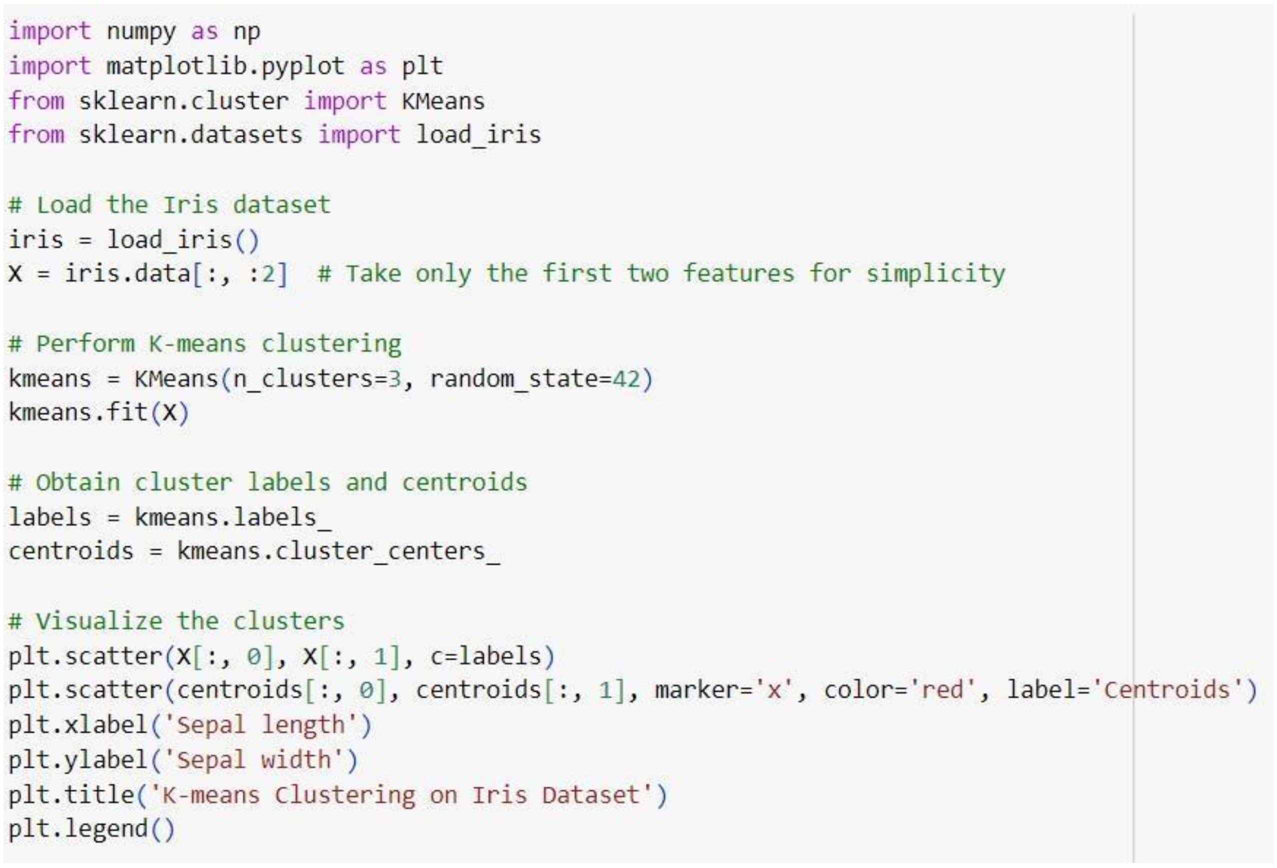


```
plot_decision_boundary(ada_clf, X, y)
```


1.5
1.0
0.5
0.0
−0.5
−1.0
x_2
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
x_1

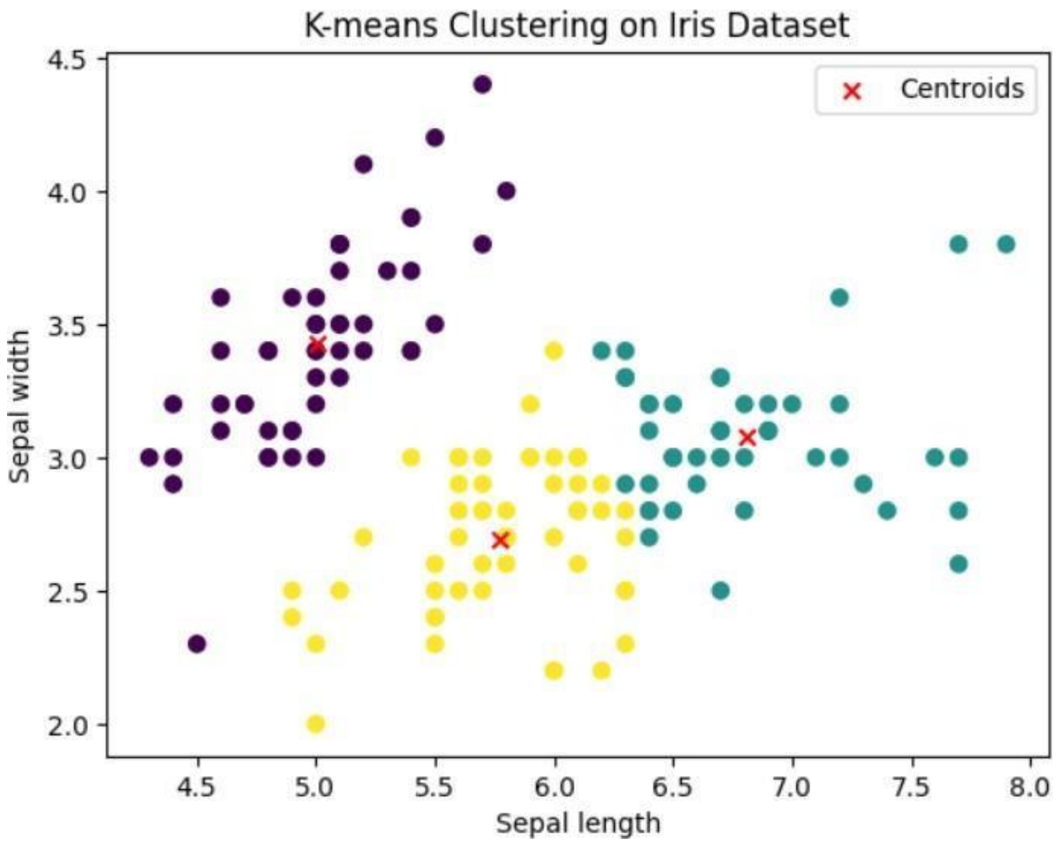
8. Clustering with k-Means Algorithm

Problem Statement: Build the k-Means cluster model, with K=3 and using the two features: **Sepal Length** and **Sepal Width,** for the purpose of training the k-Means clusteringmodel. Finally, visualize the formed clusters along with their respective centroids.



```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.datasets import load_iris

# Load the Iris dataset
iris = load_iris()
X = iris.data[:, :2]  # Take only the first two features for simplicity

# Perform K-means clustering
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(X)

# Obtain cluster labels and centroids
labels = kmeans.labels_
centroids = kmeans.cluster_centers_

# Visualize the clusters
plt.scatter(X[:, 0], X[:, 1], c=labels)
plt.scatter(centroids[:, 0], centroids[:, 1], marker='x', color='red', label='Centroids')
plt.xlabel('Sepal length')
plt.ylabel('Sepal width')
plt.title('K-means Clustering on Iris Dataset')
plt.legend()
```

Output:


K-means Clustering on Iris Dataset
Centroids
Sepal width
Sepal length
4.5
4.0
3.5
3.0
2.5
2.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0