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 **Anish D Joshi** of M.C.A. Semester II with Roll No. **C22057** has completed practical of **AIML** under my supervision **Prof Mr. Pratik Desai** 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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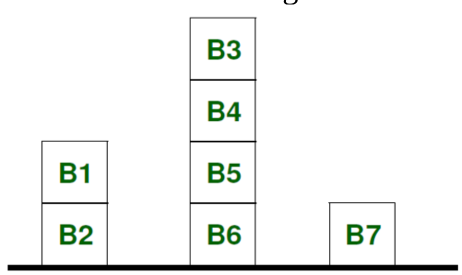
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INDEX – AI & ML Lab

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.

What is Prolog?
Prolog or PROgramming in LOGics is a logical and declarative programming language. It is one major example of the fourth generation language that supports the declarative programming paradigm. This is particularly suitable for programs that involve symbolic or non-numeric computation.

Prolog programs have a sequence of clauses. Facts or rules are described by these clauses. Example of facts is dog(rottweiler) and cat(munchkin). They mean that 'rottweiler is a dog' and 'munchkin is a cat'.

Prolog stands for programming in logic. it is a logic programming language for artificial intelligence. An artificial intelligence developed in Prolog will examine the link between a fact, a true statement, and a rule, a conditional statement, in order to come up with a question, or end objective.

Knowledge Base consisting of Propositional Sentences

- **A Special Type of Knowledge Base:** consisting of just two types of sentences: i) **atomic sentences** and ii) **conditional sentences.**
- **Atomic Sentences or Atoms:** Simple basic sentences which can be believed to be either true or false. For now we denote these by symbols P1, P2 etc.
- **Conditional Sentences:** Sentences of the form *If* $P1$ *and . . . and* P_n *then* Q, where the P_i and Q are atomic sentences.
- In both cases, the sentences may contain **variables** (written as capitalized) and **constants** (written in small case form).
- **Atomic Sentence:**
    - *sue is a child of george.*

- **Conditional Sentence:**
    - ***If*** *X is a child of Y* ***and*** *Y is male* ***then*** *Y is a father of X*
- In these two sentences, the words ***If***, ***and***, and ***then*** are **keywords**, X and Y are **variables**, and all the rest of the words are considered as **constants**.

Code:

```
% This id the Prolog version of Family example

% Atomic Sentences or Atoms

child(john,sue).     child(john,sam).  %john is child of sam

child(jane,sue).     child(jane,sam).    %jane is child of sam

child(sue,george).    child(sue,gina).


male(john).     male(sam).   male(george).  %george is a male

female(sue).  female(jane).   female(june). %june is a female

% Conditional Sentences

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).
```

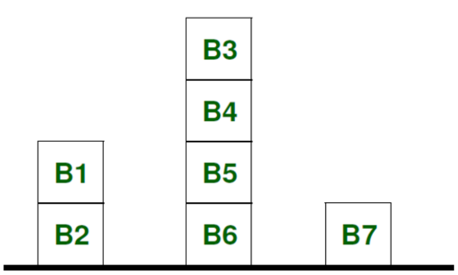
Screenshot

```
?- child(george,sue).
false.

?- female(gina).
false.

?- male(gina).
false.

?- female(sue).
true.

?- child(sue,george).
true.

?- grand_father(george,jane).
true.

?- father(X,john).
X = sam.

?- father(sam,X).
X = john ,

?- father(X,sam).
false.

?- father(sam,X).
X = john ,

?- father(john,X).
false.

?-
```

2: Problem Solving with Prolog

(a)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



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:

```
?- above(b3,b5).
true .

?- left(b1,b7).
true .
```

```
[trace]  ?- left(b1,b7).
   Call: (10) left(b1, b7) ? creep
   Call: (11) just_left(b1, b7) ? creep
   Fail: (11) just_left(b1, b7) ? creep
   Redo: (10) left(b1, b7) ? creep
   Call: (11) just_left(b1, _9702) ? creep
   Fail: (11) just_left(b1, _9702) ? creep
   Redo: (10) left(b1, b7) ? creep
   Call: (11) on(b1, _12134) ? creep
   Exit: (11) on(b1, b2) ? creep
   Call: (11) left(b2, b7) ? creep
   Call: (12) just_left(b2, b7) ? creep
   Fail: (12) just_left(b2, b7) ? creep
   Redo: (11) left(b2, b7) ? creep
   Call: (12) just_left(b2, _16996) ? creep
   Exit: (12) just_left(b2, b6) ? creep
   Call: (12) left(b6, b7) ? creep
   Call: (13) just_left(b6, b7) ? creep
   Exit: (13) just_left(b6, b7) ? creep
   Exit: (12) left(b6, b7) ? creep
   Exit: (11) left(b2, b7) ? creep
   Exit: (10) left(b1, b7) ? creep
true .

[trace]  ?- above(b3,b5).
   Call: (10) above(b3, b5) ? creep
   Call: (11) on(b3, b5) ? creep
   Fail: (11) on(b3, b5) ? creep
   Redo: (10) above(b3, b5) ? creep
   Call: (11) on(b3, _29394) ? creep
   Exit: (11) on(b3, b4) ? creep
   Call: (11) above(b4, b5) ? creep
   Call: (12) on(b4, b5) ? creep
   Exit: (12) on(b4, b5) ? creep
   Exit: (11) above(b4, b5) ? creep
   Exit: (10) above(b3, b5) ? creep
true .
```

B). **Map Coloring Problem**:

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

Code:

```
% A map is depicted with 5 countries A, B, C, D, and E. The goal is to

% colour the countries on the map using just the colours 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:

```
?- print_colors.

Country A is colored:  red
Country B is colored:  white
Country C is colored:  blue
Country D is colored:  white
Country E is colored:  blue
true
```

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 jugs.

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=:=0,nl,write('4L:3 & 3L:3 (Action: Fill 3L jug.)'),YY is 3,
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:

```
?- water_jug(0,0).

4L:0 & 3L:3 (Action: Fill 3L jug.)
4L:3 & 3L:0 (Action: Pour water from 3L to 4L jug.)
4L:3 & 3L:3 (Action: Fill 3L jug.)
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(2,1).
false.

?- water_jug(4,2).

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(0,2).

4L:2 & 3L:0 (Action: Pour wter from 3L jug  to 4L jug.)
4L:2 & 3L:0 (Action: Goal State Reached...)
true .
```

Machine Learning Section

1) Coding in Basic Python and Python Packages for ML

Numbers and Arithmetic Operations on Numbers

```
[ ]  # Numbers
     x = 3
     print(x)
     print(type(x))

     x = 3.2
     print(type(x))
```

```
3
<class 'int'>
<class 'float'>
```

```
# Arithmetic operations in python
x = 3
print(type(x))
print(x+1)
print(x - 1)
print(x * 2) # multiplication
print(x ** 2) # exponentiation
x += 1 # short-hand for x = x + 1
print(x)
x *= 2
print(x)
y = 2.5
print(type(y))
print(y, y+1, y * 2, y ** 2)

# Division
x = 5
y = 2
print(x / y) # division
print(x // y) #integer result - fraction gets truncated
```

```
<class 'int'>
4
2
6
9
4
8
<class 'float'>
2.5 3.5 5.0 6.25
2.5
2
```

Booleans and Logical Operations on Booleans

```
[ ]  t = True
     f = False
     print(type(t))
     print(t and f) # AND
     print(t or f) # OR
     print(not t) # Not
     print(t != f) # XOR
```

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

Strings 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) # fstring formatted string
print(hw12)
```

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

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

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

1.2 Container Types in Python: Python includes several built-in container types: lists, dictionaries, tuples, and sets.

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

```
xs = [3, 1, 2]
print(xs, xs[2])
print(xs[-1])
xs[2] = 'A A'
print(xs)
xs.append('B B')
print(xs)
x = xs.pop()
print(x, xs)
```

```
[3, 1, 2] 2
2
[3, 1, 'A A']
[3, 1, 'A A', 'B B']
B B [3, 1, 'A A']
```

List Slicing: Python provides a concise syntax to access sublists; this is known as *slicing*

```
nums = list(range(5)) # range is a built-in function that creates a list of integers
print(type(nums))
print(nums)
print(nums[2:4])
print(nums[2:])
print(nums[:2])
print(nums[:])
print(nums[:-1])
nums[2:4] = [8,9]
print(nums)
```

```
<class 'list'>
[0, 1, 2, 3, 4]
[2, 3]
[2, 3, 4]
[0, 1]
[0, 1, 2, 3, 4]
[0, 1, 2, 3]
[0, 1, 8, 9, 4]
```

```
[6] animals = ['cat', 'dog', 'elephant']
    for animal in animals:
      print(animal)
```

```
cat
dog
elephant
```

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

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

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

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

```
[8] # Code without List comprehension
    nums = [0,1,2,3,4]
    squares = []
    for x in nums:
      squares.append(x ** 2)
    print(squares)

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

```
# The same job as done above but using List Comprehension
nums = [0,1,2,3,4]
squares = [x ** 2 for x in nums]
print(squares)

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

List comprehensions can also include conditions

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

    [0, 4, 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.

```
[ ] d = {'cat':'cute','dog':'furry'}
    print(type(d))
    print(d['cat'])
    print('cat' in d) # Check if a dictionary has a given key; Prints True
    d['fish'] = 'wet'
    print(d['fish'])
    #print(d['monkey']) # you will get a Key error
    print(d.get('monkey','N/A')) # prints an element value or a default
    print(d.get('fish','N/A'))
    del d['fish'] # removes an element from the dictionary
    print(d.get('fish','N/A'))

    <class 'dict'>
    cute
    True
    wet
    N/A
    wet
    N/A
```

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

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

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

If you want access to keys and their corresponding values, use the ***items*** method

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

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

Dictionary comprehensions: These are similar to list comprehensions, but allow you to easily construct dictionaries. For example:

```
[ ] 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)
```

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

Sets: A set is another container type like a list and a dictionary. However it is an unordered collection of distinct elements. Thus order is not maintained and duplicates are not allowed

```
[ ] animals = {'cat', 'dog'}
    print('cat' in animals) # prints True
    print('fish' in animals) # prints False
    animals.add('fish')
    print('fish' in animals)
    print(len(animals))
    animals.add('cat') # nothing happens, because cat is already there
    print(len(animals))
    animals.remove('cat') # Removes an element
    print(len(animals))
```

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

Looping over Sets

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

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

Set Comprehensions: Like lists and dictionaries, we can easily construct sets using set comprehensions

```
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 as keys in dictionaries and as elements of sets, while lists cannot.

Here is a small example:

```
[ ] 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, (9, 10): 9}
<class 'tuple'>
5
1
```

1.3 Functions in Python

Python functions are defined using *def* keyword. An example:

```
[15] 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))
```

```
negative
zero
positive
```

```
[16] # 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([4,55,7,12,11,6,78,34,4,12,101]))
```

```
[4, 4, 6, 7, 11, 12, 12, 34, 55, 78, 101]
```

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('Virat')
g.greet()
g.greet(loud=True)
```

```
Hello, Virat
HELLO, VIRAT!
```

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 of non-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.

[22]

```
import numpy as np

a = np.array([1,2,3]) # create a rank 1 array
print(a)
print(type(a))
print(a.shape)
print(a.ndim) # rank or number of dimensions
print(a[0], a[1], a[2])
a[0] = 5
print(a)
```

```
[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]]) # create an array of rank 2
print(b)
print(b.ndim) # rank 2 array
print(b.shape)
print(b[0,0],b[0,1],b[1,0])
```

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

[ ]

```
# differentiating between rank 1 and rank 2 numpy arrays
import numpy as np

a = np.array([1,2,3,4,5,6]) # rank 1 array
b = np.array([[1,2,3,4,5,6]]) # rank 2 array

print('a.shape = ', a.shape, ' a.ndim = ', a.ndim)
print('b.shape = ', b.shape, ' b.ndim = ', b.ndim)
```

```
a.shape =  (6,)  a.ndim =  1
b.shape =  (1, 6)  b.ndim =  2
```

2.2 Array Indexing

Numpy offers several ways to index into arrays

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

```
import numpy as np

# Use slicing to pull out the subarray consisting of the first 2 rows
# and columns 1 and 2. So b will be a 2 x 2 array consisting of following elements:
#[[2,3],
#  [6,7]]
a = np.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]]) # create an array of rank 2 and shape (3,4)
b = a[:2, 1:3] # shape of b = (2,2); [[2,3], [6,7]]

print(a)
print(a.shape)
print(b)
print(b.shape)

print(a[0,1]) # prints 2
b[0,0] = 45
print(a[0,1])

print('a:', a)
print('b:',b)
```

```
[[ 1  2  3  4]
 [ 5  6  7  8]
 [ 9 10 11 12]]
(3, 4)
[[2 3]
 [6 7]]
(2, 2)
a: [[ 1  0  0  4]
 [ 5  0  0  8]
```

Integer array indexing: Allows you to construct arbitrary arrays using data from another array. Here is an example:

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

print(a[[0,1,2], [0,1,0]]) # Prints 1, 4 and 5
print(a[0,0], a[1,1], a[2,0])

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

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

One useful trick with integer array indexing is selecting or mutating one element from each row of a matrix:

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

# Create an array of indices
b = np.array([0, 2, 0, 1])

print(a[np.arange(4),b]) # prints [1,6,7,11]

a[np.arange(4),b] += 10
print(a)
```

```
[[ 1  2  3]
 [ 4  5  6]
 [ 7  8  9]
 [10 11 12]]
[ 1  6  7 11]
[[11  2  3]
 [ 4  5 16]
```

2.3 Datatypes

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

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

```
[ ] import numpy as np

    x = np.array([1, 2]) # Let numpy choose the datatype
    print(x.dtype)

    x = np.array([1.0, 2.0]) # Let numpy choose the datatype
    print(x.dtype)

    x = np.array([1.0, 2.0], dtype=np.int64) # Force a particular datatype
    print(x.dtype)
```

```
int64
float64
int64
```

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]
```

Reshaping 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]
```

2.5 Broadcasting

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

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

Broadcasting consists of two steps:

1. Axes (called *broadcast axes*) are added to the smaller tensor to match the *ndim* of the larger tensor.
2. The smaller tensor is repeated alongside these new axes to match the full shape of the larger tensor

```
[ ]  import numpy as np

     x = np.array([[1,2,3], [4,5,6], [7,8,9], [10,11,12]])
     v = np.array([1,0,1]) # vv = [[1,0,1],[1,0,1],[1,0,1],[1,0,1]]
     y = np.empty_like(x)

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

     print(y)
     print(x + v) # implicitly v will be broadcasted to become a matrix of shape (4,3)

     z = x + 5 # scalar 5 is broadcasted
     print(z)
```

```
[[ 2  2  4]
 [ 5  5  7]
 [ 8  8 10]
 [11 11 13]]
[[ 2  2  4]
 [ 5  5  7]
 [ 8  8 10]
 [11 11 13]]
[[ 6  7  8]
 [ 9 10 11]
```

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.

3.1 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.

3.2 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)
```

```
[[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" : ["Virat", "Anna", "Ankita", "Madhuri"],
        "Location" : ["New York", "London", "Mumbai", "Pune"],
        "Age" : [52, 25, 55, 45]
        }

data_pandas = pd.DataFrame(data)
display(data_pandas)
display(data_pandas[data_pandas.Age > 30])
```

	Name	Location	Age
0	John	New York	52
1	Anna	Paris	25
2	Aamir	Mumbai	55
3	Madhuri	Pune	45

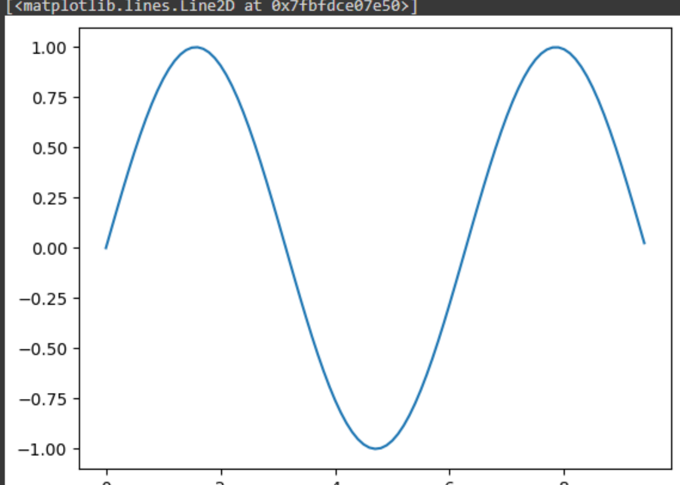
	Name	Location	Age
0	John	New York	52
2	Aamir	Mumbai	55
3	Madhuri	Pune	45

4. Matplotlib

Matplotlib is a plotting library. It provides functions to visualize data and mathematical functions.

```
[ ] import numpy as np
    import matplotlib.pyplot as plt

    # compute x and y coordinates for points on a sine curve
    x = np.arange(0, 3 * np.pi, 0.1)
    y = np.sin(x)

    # Plot the points using matplotlib
    plt.plot(x, y)
```

```
[<matplotlib.lines.Line2D at 0x7fbfdce07e50>]
```



2) Prediction Using a Linear Regression Model

Lab 2 - Implementing 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.

```python
## 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')
```

```
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
```

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

```python
# 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 into respective pandas data frames.

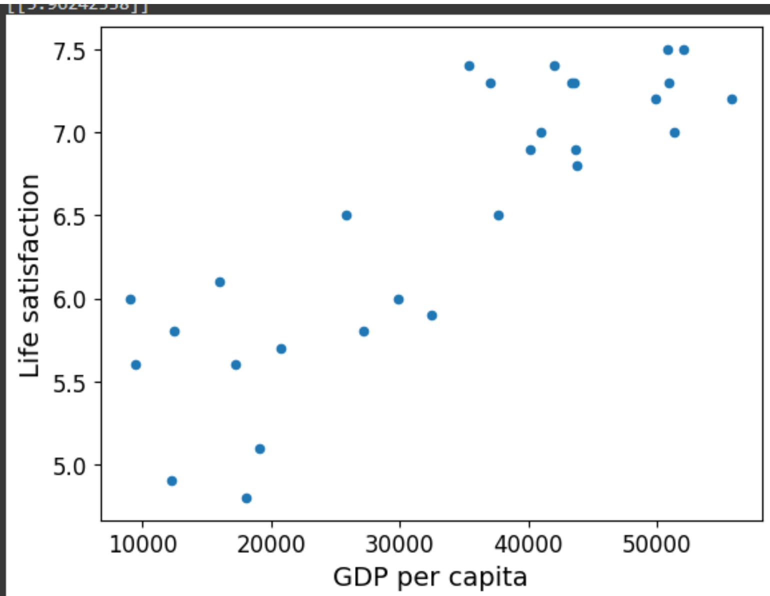
Merge it into a single dataframe after pivoting the data having Country column as index.

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.

```python
# 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())
# 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

Logistic Regression

Logistic Regression (also called Logit Regression) is commonly used to estimate the probability that an instance belongs to a particular class (e.g., what is the probability that this email is spam?).

If the estimated probability is greater than 50%, then the model predicts that the instance belongs to that class (called the positive class, labeled "1"), or else it predicts that it does not (i.e., it belongs to the negative class, labeled "0").

Thus it acts as a binary classifier.

```
[ ] 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']
```

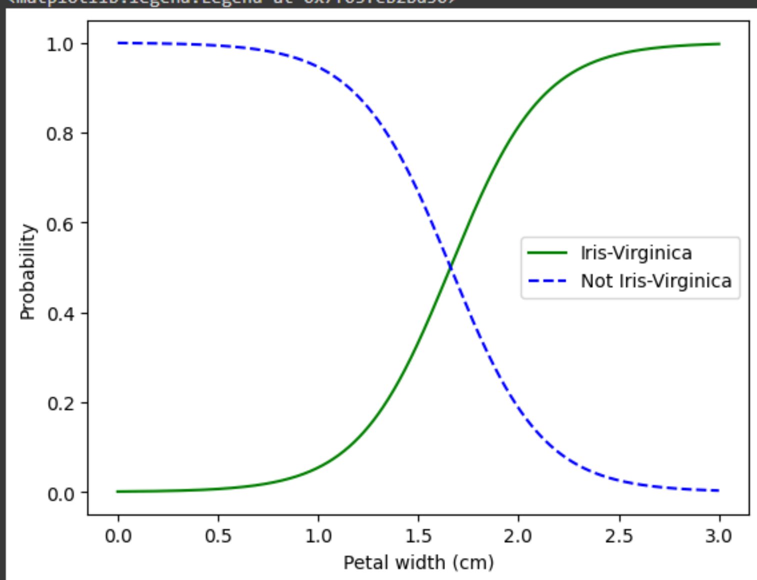
Training the Logistic Regression Model

```
[ ] from sklearn.linear_model import LogisticRegression

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

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

```
[ ]  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>
```



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

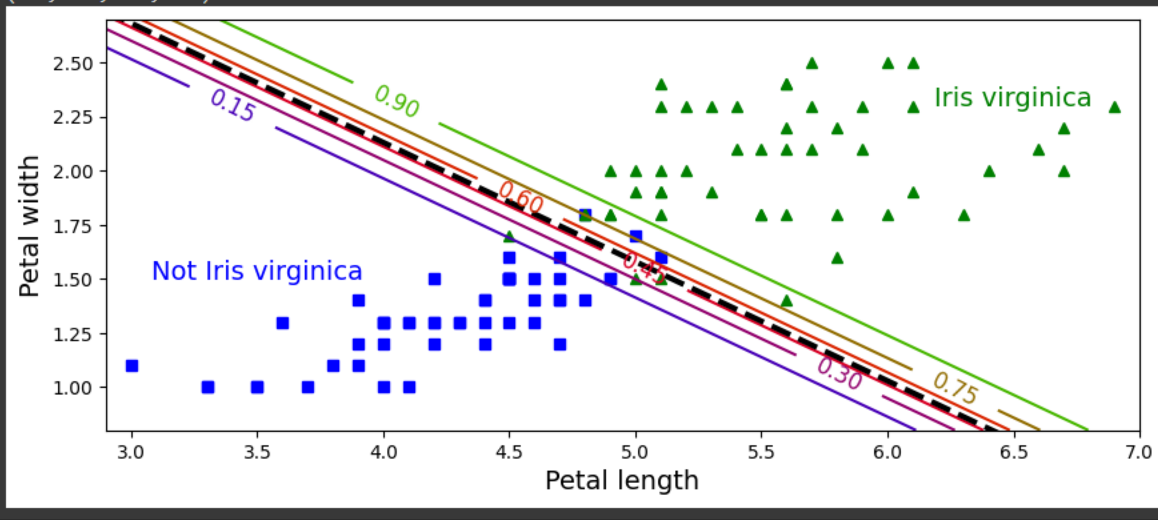
Below we use the same dataset but use two features: petal width and petal length to train the Logistic Regression model to estimate the probability that a new flower is an Iris-Virginica based on these two features.

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.

```
[ ]  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)
```



4) Multi-Class Classification using k-Nearest Neighbours

```
[ ]  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']))
```

```
.. _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 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 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))
```

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

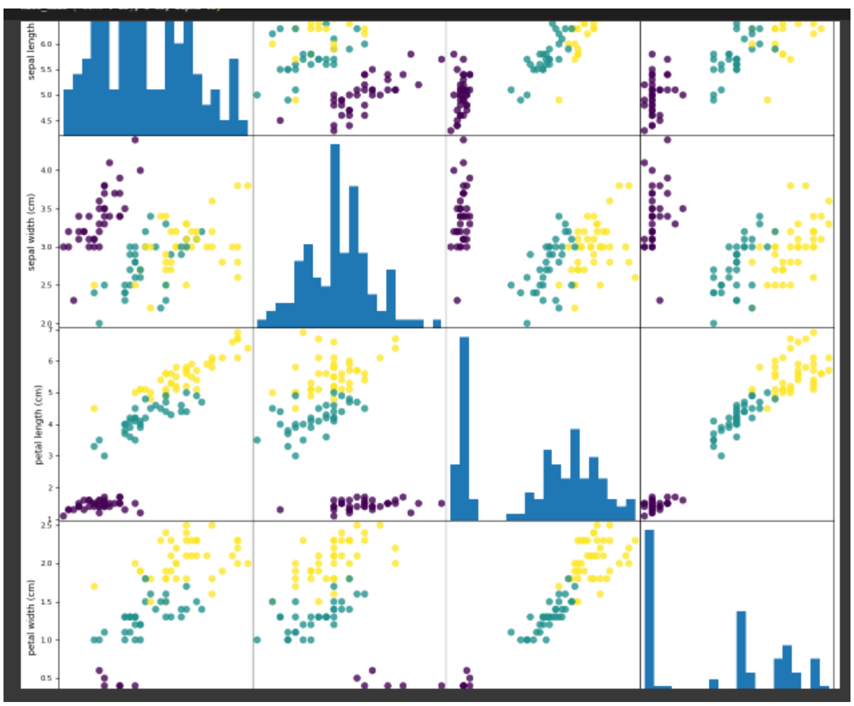
Knowing Your Data

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)
```



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)
```

```
[ ] 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 prediction for 97% of the irises in the test set. Under some mathematical assumptions, this means that we can expect our model to be correct 97% of the time for new irises.

5) Linear and Non-Linear SVM Classification

Problem Statement 1 - Linear SVM Classification:

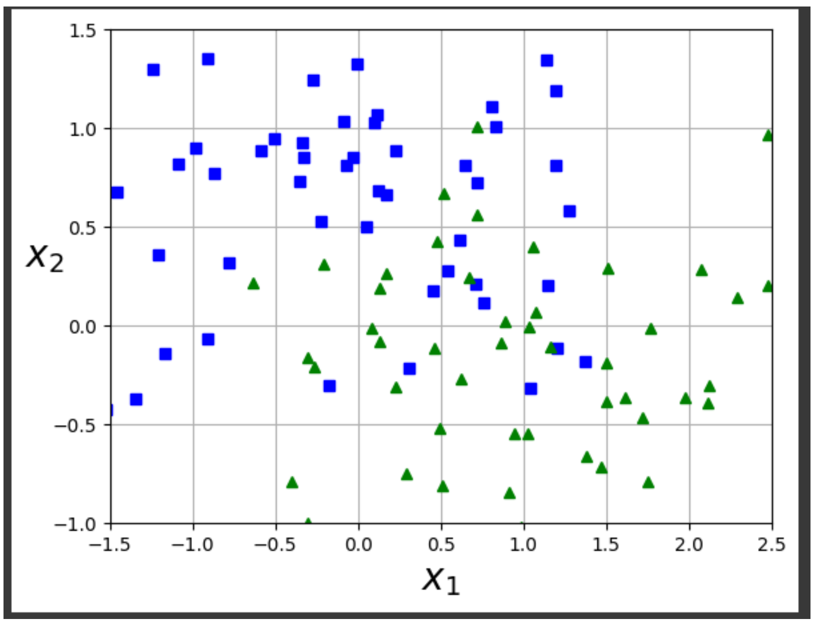
Load the iris dataset, scale the petal-width and petal-length features and then train a linear SVM model to detect Iris-Virginica flowers. Use the petal length and petal width features to train the model. Scale the features before training the model. Use the resulting model to do the detection on some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

```
[ ] 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]
```

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

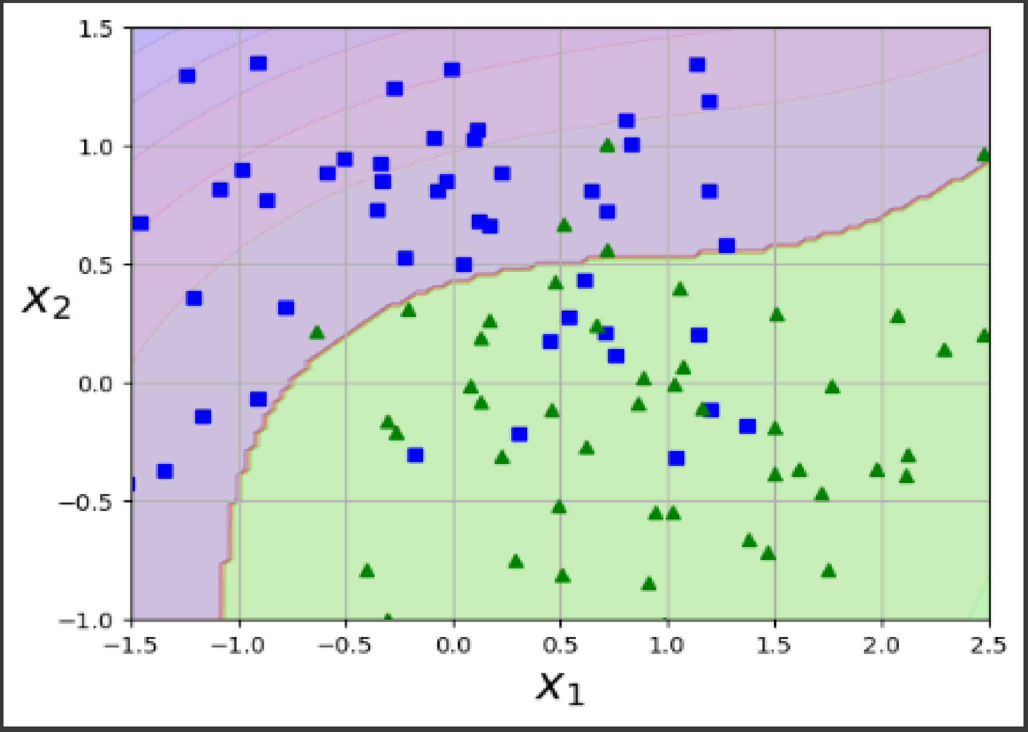
```python
# Plotting Moons data to illustrate its linear inseparability
import matplotlib.pyplot as plt
from sklearn.datasets import make_moons

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

```python
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])
```



Visualizing the Non Linear SVM Classification Decision Boundary

```
[ ] 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])
```



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.

```
[ ] # 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)
```

Step 1 - Training and Visualizing a Decision Tree

```
[ ] 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

Suppose you have found a flower whose petals are 5 cm long and 1.5 cms wide. The corresponding leaf node is the depth-2 left node, so the decision tree should predict the class as Iris-Versicolor (class 1).

```
# 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])
```

If you ask it to predict the class probabilities instead, for the same flower, then it should output the following probabilities: 0 % for Iris-Setosa (0/54), 90.7 % for Iris-Versicolor (49/54), and 9.3 % for Iris-Virginica (class 1).

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

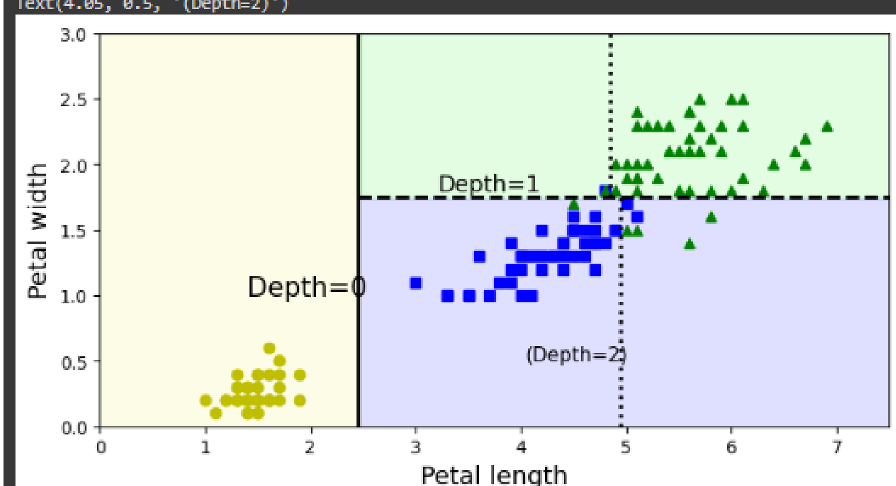
```
array([[0.        , 0.90740741, 0.09259259]])
```

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.

(***Note:*** *A Decision Stump is a Decision Tree with max_depth = 1 - in other words, a tree composed of a single decision node plus two leaf nodes.*)

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

```
[ ] 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

```
[ ] 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)
```

```
▸ AdaBoostClassifier
▸ estimator: DecisionTreeClassifier
  ▸ DecisionTreeClassifier
```

```
[ ] 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 trained DecisionStump
    # 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
```

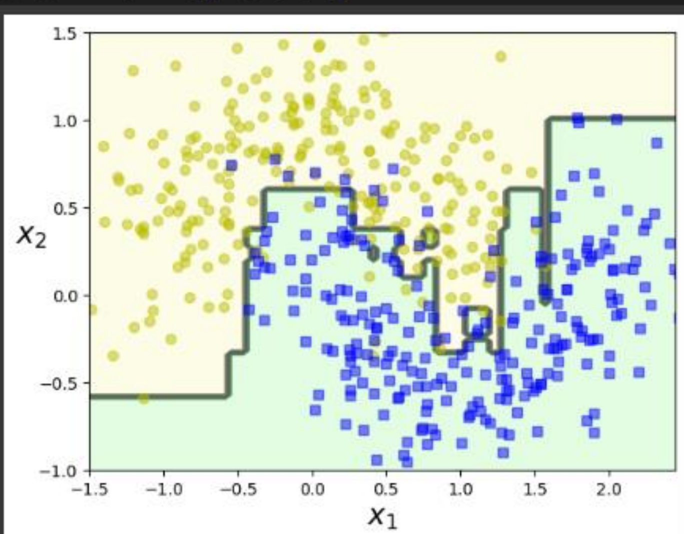
Step 4 : Visualizing the Decision Boundary of our AdaBoost Model

We define a function named *plot_decision_boundary* for the purpose and then invoke it passing our AdaBoost 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)
```

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



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 clustering model. Finally, visualize the formed clusters along with their respective centroids.

```
[ ] 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()
```