

A decorative banner featuring five large, stylized letters in red with a black outline: 'I', 'N', 'D', 'E', and 'X'. The letters are arranged horizontally and have a three-dimensional, layered effect.

NAME: SREEJA KATTA STD.: SEC.: D ROLL NO.: 1BM21CS267 SUB.: ML LAB

Program-1 : Import and Export using Pandas

Importing Data

```
import pandas as pd
```

```
housing_data = pd.read_csv("/content/sample-data/california-housing-test.csv")
```

```
housing_data.head()
```

works fine for 1-gate

works with housing

	longitude	latitude	housing-median-age	total-rooms	total-bedrooms	population
0	-122.05	37.37	27.0	3885.0	661.0	15370961
1	-118.30	34.26	43.0	1510.0	810.0	809.0
2	-117.81	33.94	27.0	3599.0	507.0	1484.0

"http://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"

Reading data from URL

```
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
col_names = ["sepal-length-in-cm", "sepal-width-in-cm", "petal-length-in-cm", "petal-width-in-cm", "class"]
iris_data = pd.read_csv(url, names=col_names)
iris_data.head()
```

	sepal-length-in-cm	sepal-width-in-cm	petal-length-in-cm	petal-width-in-cm	class
0	5.1	3.5	1.4	0.2	Iris-setosa

by reading file

One
2/15/21

(17.17 - 14.00) * 100 = 21.5% error

(17.17 - 14.00) * 100 = 21.5% error

(17.17 - 14.00) * 100 = 21.5% error

the last mark at 17.17 will be 17.17

so first last 17.17

first class to be 17.17 - 14.00 = 3.17 miltiply it by last 17.17 - 14.00

optimal value = 17.17 - 14.00 = 3.17

28/3/24

Program - 2 : hands-on-machine-learning

Step-1 : Get the data

(by executing from command line or by double clicking the file)

Download the data

```
import os
import tarfile
import urllib
```

```
DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master/"
HOUSING_PATH = os.path.join("data", "01")
HOUSING_URL = DOWNLOAD_ROOT + "datasets/housing/housing.tgz"
```

```
def fetch_housing_data(housing_url=HOUSING_URL, housing_path=HOUSING_PATH):
    os.makedirs(name=housing_path, exist_ok=True)
    tgz_path = os.path.join(housing_path, "housing.tgz")
    urllib.request.urlretrieve(url=housing_url, filename=tgz_path)
    housing_tgz = tarfile.open(name=tgz_path)
    housing_tgz.extractall(path=housing_path)
    housing_tgz.close()
```

fetch_housing_data()

```
import pandas as pd
```

```
def load_housing_data(housing_path=HOUSING_PATH):
    data_path = os.path.join(housing_path, "housing.csv")
    return pd.read_csv(data_path)
```

Step 2: Discover & Visualize the Data to Gain Insights

strat_train_set.shape, strat_test_set.shape

strat_test_set.reset_index().to_feather(fname='data/01/strat-test-set.f')

housing = strat_train_set.copy(); housing.shape

Visualizing Geographical Data

```
housing.plot(kind='scatter', x='longitude', y='latitude')
plt.show()
```

```
housing.plot(kind='scatter', x='longitude', y='latitude', alpha=0.1)
plt.show()
```

```
housing[['population', 'median_house_value']].corr()
```

3. Prepare the Data for Machine Learning Algorithms

Data Cleaning

```
from sklearn.impute import SimpleImputer
```

```
imputer = SimpleImputer(strategy='median')
```

```
housing_num = housing.drop(['ocean_proximity'], axis=1)
```

Feature Transformation Pipelines

```
num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='median')),
    ('atributes_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler())
])
```

```
housing_num_tr = num_pipeline.fit_transform(housing_num)
```

```
housing_num_tr.shape
```

4. Select and Train a Model

```
lin_reg = LinearRegression()
```

```
lin_reg.fit(X=housing_prepared, y=housing_labels)
```

```
some_data = housing.iloc[:5]
```

```
some_labels = housing_labels.iloc[:5]
```

```
some_data_prepared = full_pipeline.transform(some_data)
```

```
some_data_prepared
```

housing_predictions = lin_regr.predict(housing_prepared)

lin_mse = mean_squared_error(housing_labels, housing_predictions)

lin_rmse = np.sqrt(lin_mse)

lin_rmse

5. Fine-Tune Your Model

param_grid = [

{'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},

{'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]}

]

forest_regr = RandomForestRegressor()

grid_search = GridSearchCV(estimator=forest_regr, param_grid=param_grid, scoring='neg_mean_squared_error', cv=5, return_train_score=True, n_jobs=-1)

grid_search.fit(x=housing_prepared, y=housing_labels)

grid_search.best_params_

grid_search.best_estimator_

*Date
28/3/24*

import pandas as pd

def load_housing_data(housing_path="Housing.csv"):

data_pandas = pd.read_csv(housing_path, header=None)

Is there a way to do this?

(read_csv) = pd.read_csv

(label_price = y, longitude_longitude = X) if you do

[y] = pd.DataFrame = data_mse

[y] = pd.Series = data_mse

(label_mse) = mean_squared_error(y_true = housing_labels, y_pred = housing_predictions)

1.007 - 0.1512 * 0.0001

Linear Regression

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from pandas.core.common import random_state
from sklearn.linear_model import LinearRegression

df_sal = pd.read_csv('content/sample_data/salary.csv')
df_sal.head()           ('vergnekti tashqari' ) bosh -tara -ja
df_sal.describe()       ('bosh -tara -ja' )
plt.title('Salary Distribution Plot')
sns.distplot(df_sal['Salary'])
plt.show()               ('tara -tara -ja' )

plt.scatter(df_sal['Years Experience'], df_sal['Salary'], color='lightcoral')
plt.title('Salary vs Experience')          ('tara -tara -ja' )
plt.box(False)
plt.show()               ('tara -tara -ja' )

x = df_sal.iloc[:, :-1]
y = df_sal.iloc[:, -1]

regressor = LinearRegression()
regressor.fit(x_train, y_train)           ('tara -tara -ja' )

y_pred_test = regressor.predict(x_test)
y_pred_train = regressor.predict(x_train)

plt.scatter(x_test, y_test, color='lightcoral')
plt.plot(x_train, y_pred_train, color='firebrick')      ('tara -tara -ja' )
plt.title('Salary vs Experience')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')                         ('tara -tara -ja' )
plt.box(False)
plt.show()

print(f'Coefficient: {regressor.coef_[0]}')
print(f'Intercept: {regressor.intercept_}')        ('tara -tara -ja' )

```

Multiple Regression

0012233079 : 6 মাসী

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LinearRegression

df_start = pd.read_csv('content/sample_data/50_Startups.csv')
df_start.head()
df_start.describe()

plt.title('Profit Distribution Plot')
sns.distplot(df_start['Profit'])
plt.show()

plt.scatter(df_start['R&D spend'], df_start['Profit'], color='lightcoral')
plt.xlabel('R&D spend')
plt.ylabel('Profit')
plt.box(False)
plt.show()

X = df_start.iloc[:, :-1].values
y = df_start.iloc[:, -1].values
X = np.array(ct.fit_transform(X))

regressor = LinearRegression()
regressor.fit(X_train, y_train)
y_pred = regressor.predict(X_test)

np.set_printoptions(precision=2)
result = np.concatenate((y_pred.reshape(len(y_pred), 1), y_test.reshape(len(y_test), 1)), axis=1)

Sneha 12/12/24

```

```

import pandas as pd
# This code is based on a dataset from the UCI Machine Learning Repository
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
("iris dataset is available at https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data")
# dataset
iris_data = load_iris()
iris_df = pd.DataFrame(data=iris_data.data, columns=iris_data.feature_names)
iris_df['target'] = iris_data.target
print(iris_df.head())
X = iris_df.drop('target', axis=1)
y = iris_df['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
clf = DecisionTreeClassifier(criterion="gini", random_state=100, max_depth=4, min_samples_leaf=8)
clf.fit(X_train, y_train)
accuracy = clf.score(X_test, y_test)
print("Accuracy: ", accuracy)

plt.figure(figsize=(12, 8))
tree.plot_tree(clf, feature_names=iris_data.feature_names, class_names=iris_data.target_names,
               filled=True)
plt.show()

```

OUTPUT

Accuracy: 80.98

petal width (cm) ≤ 0.8
 $gini = 0.667$
 samples = 120
 value = [40, 41, 39]
 class = versicolor

petal width (cm) > 0.8
 $gini = 0.0$
 samples = 40
 value = [40, 0, 0]
 class = setosa

petal length (cm) ≤ 1.75
 $gini = 0.5$
 samples = 80
 value = [0, 41, 39]
 class = versicolor

petal length (cm) > 1.75
 $gini = 0.0$
 samples = 40
 value = [0, 0, 0]
 class = virginica

Date
18/07/23EP = 0.25
(1 - 0.808) * 0.25
(1 - 0.792) * 0.25
(1 - 0.792) * 0.25

Predicting if a person would buy life insurance based on his age using logistic regression

```

import pandas as pd
import matplotlib import pyplot as plt
%matplotlib inline

df = pd.read_csv ("content/sample_data/insurance-data.csv")
df.head()
plt.scatter (df.age, df.bought_insurance, marker = '+', color = 'red')

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split (df[['age']], df.bought_insurance, train_size = 0.8)

from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model.fit (X_train, y_train)
y_predicted = model.predict (X_test)
model.predict_proba (X_test)
model.score (X_test, y_test)

print ("Coefficient: ", model.coef_)
print ("Intercept: ", model.intercept_)

import math

def sigmoid (x):
    return 1 / (1 + math.exp (-x))

def prediction_function (age):
    z = 0.042 * age - 1.53
    y = sigmoid (z)
    return y

age_1 = 35
prediction_1 = prediction_function (age_1)

age_2 = 43
prediction_2 = prediction_function (age_2)

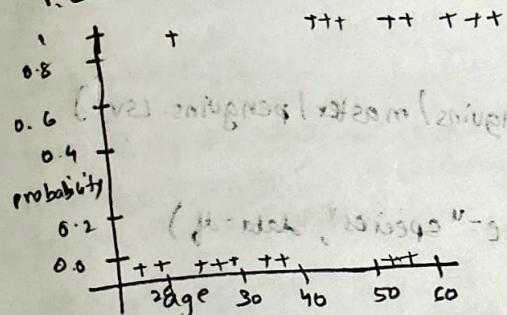
print (prediction_1)
print (prediction_2)

```

accuracy = 0.6666666666
coefficient : [0.16265891]
Intercept : [-6.81930256]

$$\begin{aligned} \text{accuracy} &= 0.66666666 \\ \text{coefficient} &: [0.16265891] \\ \text{Intercept} &: [-6.81930256] \end{aligned}$$

Prediction 1 is 0.4850044983
Prediction 2 is 0.5685652990



($w_{\text{PT}} = \text{weight}$) $\text{work} \cdot \text{fb}$
[if 'p-heat-phob' (or -heat-resist)] $\text{fb} = X$
 $(\text{lossage}) / h = C$
(in state $\text{initial} \leq 0 = \text{work_test}, V(X)$) $\text{tip2_test_work} = \text{test_p_heat-phob} \cdot \text{test_X_heat_X}$
(Excess power) $\text{excess_producing} = \text{work}$
 $(\text{heat_p_heat_X}) \text{ tip_work}$
 $(\text{test_X}) \text{ tip_work} = \text{heat_p}$
 $(\text{heat_p_heat_X}) \text{ work_process} = \text{work}$
 $(\text{process}) \cdot (\text{product}) / h$

09/05/24

Program 6 : KNN classification model

```

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

df = pd.read_csv("https://raw.githubusercontent.com/palmerpenguins/master/penguins.csv")
print(df.head())

sns.scatterplot(x="flipper-length-mm", y="body-mass-g", hue="species", data=df)
plt.title("Penguin Species Classification")
plt.xlabel("Flipper Length (mm)")
plt.ylabel("Body Mass (g)")
plt.show()

df.dropna(inplace=True)

X = df[['flipper-length-mm', 'body-mass-g']]
y = df['species']

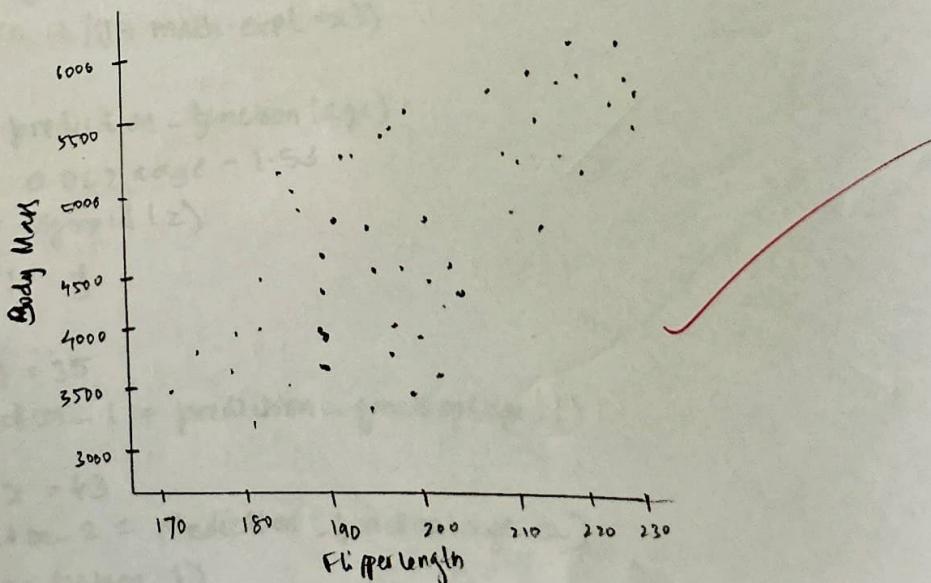
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

knn = KNeighborsClassifier(n_neighbors=3)

knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: ", accuracy)

```



Accuracy: 0.686567164

Program 7: Support Vector Machine model

09/25/24

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score

iris = load_iris()

iris_df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
iris_df['target'] = iris.target
print(iris_df.head())

plt.figure(figsize=(10, 6))
plt.scatter(iris_df['sepal length (cm)'], iris_df['sepal width (cm)'],
            c=iris_df['target'], cmap='viridis')

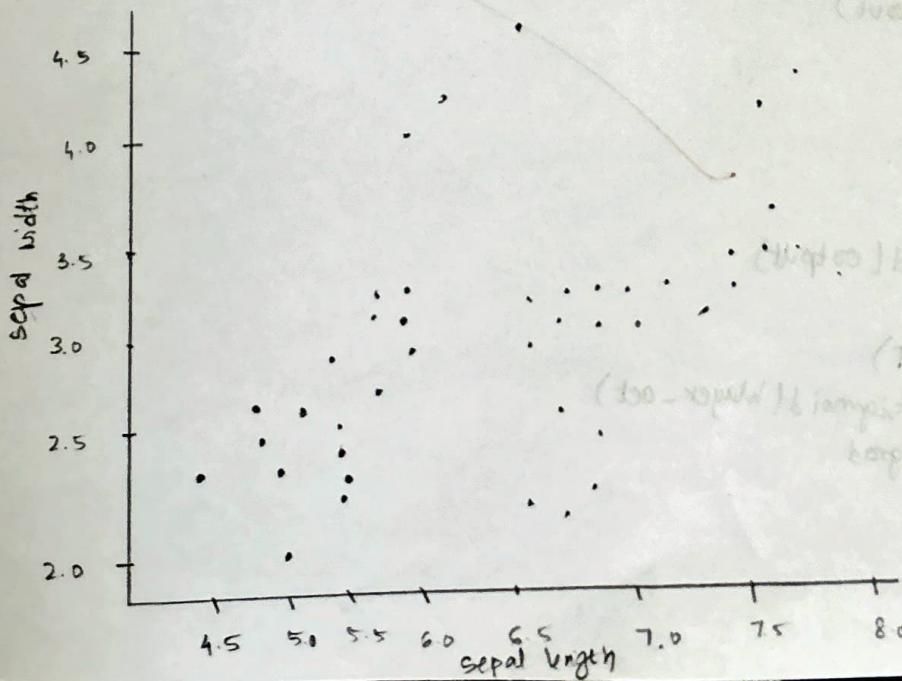
plt.xlabel('Sepal length (cm)')
plt.ylabel('Sepal width (cm)')
plt.colorbar(label='species')
plt.show()
```

```
x_train, x_test, y_train, y_test = train_test_split(iris.data, iris.target, test_size=0.6,
                                                    random_state=32)
```

```
svm_classifier = SVC(kernel='linear')
svm_classifier.fit(x_train, y_train)

y_pred = svm_classifier.predict(x_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy of SVM classifier:", accuracy)
```



Accuracy: 0.97777

Program 8 : Artificial Neural Networks

```
import numpy as np
x = np.array([[2, 9], [1, 5], [3, 6]], dtype=float)
y = np.array([[92], [86], [89]], dtype=float)
```

```
x = x / np.amax(x, axis=0)
```

```
y = y / 100
```

```
epoch = 5000
```

```
lr = 0.1
```

```
inputlayer_neurons = 2
```

```
hiddenlayer_neurons = 3
```

```
output_neurons = 1
```

```
wh = np.random.uniform(size=(inputlayer_neurons, hiddenlayer_neurons))
```

```
bh = np.random.uniform(size=(1, hiddenlayer_neurons))
```

```
wout = np.random.uniform(size=(hiddenlayer_neurons, output_neurons))
```

```
bout = np.random.uniform(size=(1, output_neurons))
```

```
def sigmoid(x):
```

```
return 1 / (1 + np.exp(-x))
```

```
def derivatives_sigmoid(x):
```

```
return x * (1 - x)
```

```
for i in range(epoch):
```

```
hinpl = np.dot(x, wh)
```

```
hinp = hinpl + bh
```

```
hlayer_act = sigmoid(hinp)
```

```
outinp1 = np.dot(hlayer_act, wout)
```

```
outinp = outinp1 + bout
```

```
output = sigmoid(outinp)
```

EO = y - output

outgrad = derivatives_sigmoid(output)

d_output = EO * outgrad

EH = d_output . dot(wout.T)

hidengrad = derivatives_sigmoid(hlayer_act)

d_hiddenlayer = EH * hidengrad

FFFFP.C.POLYU

wout += hlayer_act.T.dot(d_output) * lr
wh += x.T.dot(d_hiddenlayer) * lr

```
print("Input : \n" + str(x))  
print("Actual Output: \n" + str(y))  
print("Predicted output: \n", output)
```

Input:

```
[[0.666667 1. ]  
 [0.333333 0.555556]  
 [1. 0.666667]]
```

Actual output:

```
[0.92]  
[0.86]  
[0.89]
```

Predicted output:

~~```
[0.76787301]
[0.75248028]
[0.77506492]
```~~

| target | max off | losses | min loss | single |
|--------|---------|--------|----------|--------|
| 0.2    | 0.0     | 0.0    | 0.0      | 0.0    |
| 1.5    | 0.0     | 0.0    | 0.0      | 0.0    |
| 0.8    | 0.0     | 0.0    | 0.0      | 0.0    |
| 0.2    | 0.0     | 0.0    | 0.0      | 0.0    |
| 2.5    | 0.0     | 0.0    | 0.0      | 0.0    |
| 2.5    | 0.0     | 0.0    | 0.0      | 0.0    |
| 2.5    | 0.0     | 0.0    | 0.0      | 0.0    |

23/05/24

## Program 9(a): Random Forest Algorithm

```

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

iris = load_iris()
X = iris.data
y = iris.target

```

```

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=32)
rf_classifier = RandomForestClassifier()
rf_classifier.fit(X_train, y_train)
y_pred = rf_classifier.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: ", accuracy)

```

## OUTPUT

Accuracy : 0.933333

## Classification Report

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 1.00      | 1.00   | 1.00     | 30      |
|              | 0.81      | 1.00   | 0.89     | 21      |
|              | 1.00      | 0.79   | 0.88     | 24      |
| accuracy     |           |        | 0.93     | 75      |
| macro avg    | 0.94      | 0.93   | 0.93     | 75      |
| weighted avg | 0.95      | 0.93   | 0.93     | 75      |

```

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score

iris = load_iris()
X = iris.data
y = iris.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=42)
adaBoost_clf = AdaBoostClassifier(n_estimators=30, learning_rate=1.0, random_state=42)
adaBoost_clf.fit(X_train, y_train)

y_pred = adaBoost_clf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: ", accuracy)

```

OUTPUT

Accuracy: 0.966667

*Solve  
23/5/24*

30/05/24

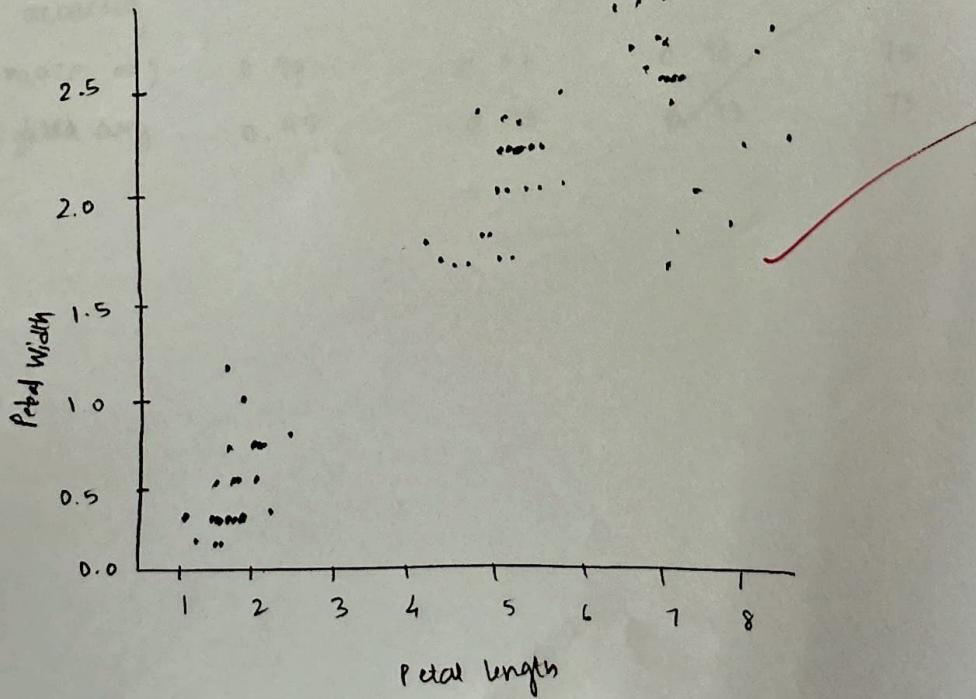
## Program 10: K-Means clustering

```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import pandas as pd
import numpy as np

iris = datasets.load_iris()
X = pd.DataFrame(iris.data)
X.columns = ['Sepal-length', 'Sepal-Width', 'Petal-length', 'Petal-Width']
y = pd.DataFrame(iris.target)
y.columns = ['Targets']

model = KMeans(n_clusters=3)
model.fit(X)

plt.figure(figsize=(14, 14))
color_map = np.array(['red', 'lime', 'black'])
plt.subplot(2, 2, 1)
plt.scatter(X.Petal-length, X.Petal-Width, c=color_map[model.labels_], s=40)
plt.title('K-Means clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
```



```

import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
%matplotlib inline

from sklearn.datasets import load_breast_cancer
cancer = load_breast_cancer()
cancer.keys()
print(cancer['DESCR'])
df = pd.DataFrame(cancer['data'], columns=cancer['feature_names'])
df.head(1)

```

```

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(df)
scaled_data = scaler.transform(df)

```

```

from sklearn.decomposition import PCA
pca = PCA(n_components=2)
pca.fit(scaled_data)
x_pca = pca.transform(scaled_data)
scaled_data.shape

```

x\_pca.shape  
plt.figure(figsize=(8, 6))  
plt.scatter(x\_pca[:, 0], x\_pca[:, 1], c=cancer['target'], cmap='plasma')  
plt.xlabel('First Principal Component')  
plt.ylabel('Second Principal Component')

