VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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B.M.S. College of Engineering,
Bull Temple Road, Bangalore 560019
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Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "Machine Learning (23CS6PCMAL)" carried out by **Navneeth K S (1BM22CS174),** who is Bonafide student of **B.M.S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements in respect of a Machine Learning (23CS6PCMAL) work prescribed for the said degree.

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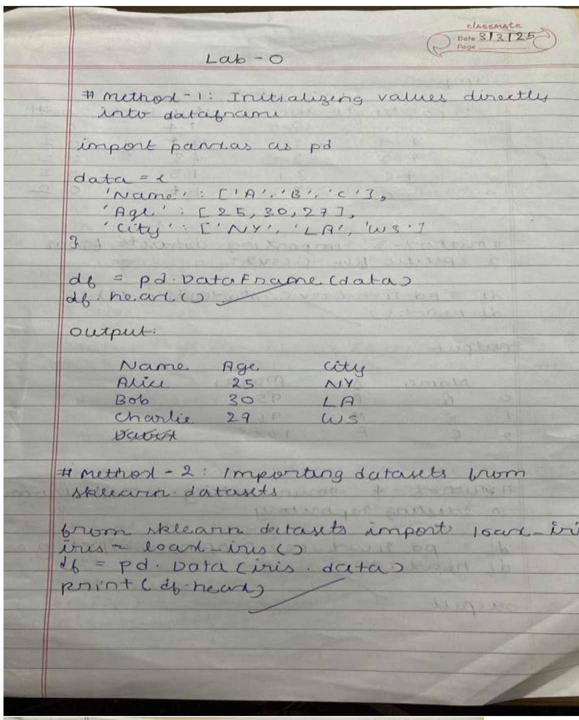
Program 1

Write a python program to import and export data using Panda's library functions

Screenshot



Lab - O

Date 3/3/25

method - 1 : Initializing values directly into dataframe

import pandas as pd

data = {
'Name' : ['A', 'B', 'C'],
'Age' : [25, 30, 27],
'City' : ['NY', 'LA', 'WS']
}

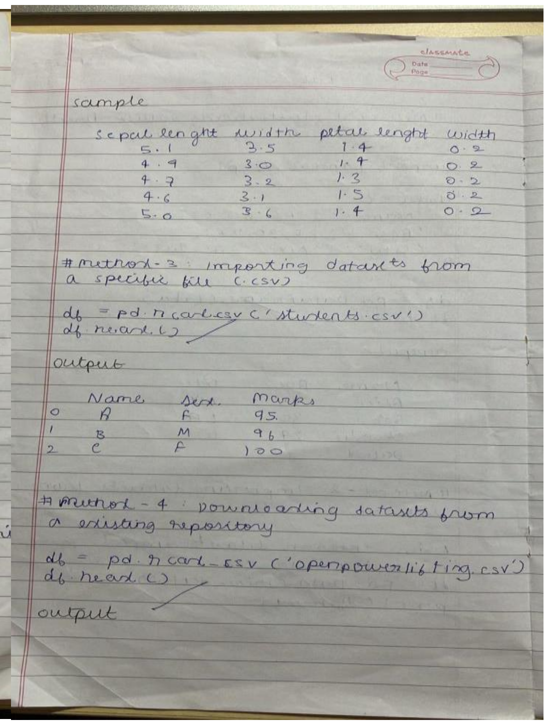
df = pd.DataFrame(data)
df.head()

output:

Name	Age	City
Alice	25	NY
Bob	30	LA
Charlie	27	WS
~~David~~		

method - 2 : Importing datasets from sklearn datasets

from sklearn.datasets import load_iris
iris = load_iris()
df = pd.DataFrame(iris.data)
print(df.head)



sample

sepal lenght	width	petal lenght	width
5.1	3.5	1.4	0.2
4.9	3.0	1.4	0.2
4.7	3.2	1.3	0.2
4.6	3.1	1.5	0.2
5.0	3.6	1.4	0.2

method - 3 : importing datasets from a specific file (.csv)

df = pd.read_csv('students.csv')
df.head()

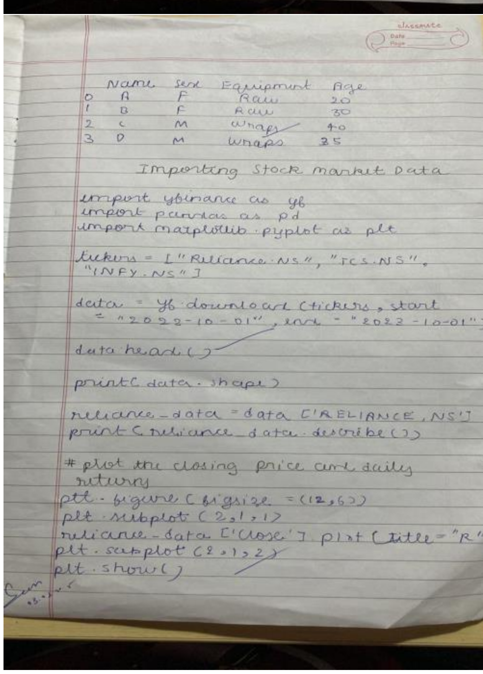
output

	Name	Sex	Marks
0	A	F	95
1	B	M	96
2	C	F	100

method - 4 : Downloading datasets from a existing repository

df = pd.read_csv('openpowerlifting.csv')
df.head()

output



	Name	Sex	Equipment	Age
0	A	F	Raw	20
1	B	F	Raw	30
2	C	M	Wraps	40
3	D	M	Wraps	35

Importing Stock market Data

import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt

tickers = ["Reliance.NS", "TCS.NS", "INFY.NS"]

data = yf.download(tickers, start = "2022-10-01", end = "2023-10-01")

data.head()

print(data.shape)

reliance_data = data['RELIANCE.NS']
print(reliance_data.describe())

# plot the closing price and daily returns
plt.figure(figsize = (12,6))
plt.subplot(2,1,1)
reliance_data['Close'].plot(title = "R"
plt.subplot(2,1,2)
plt.show()

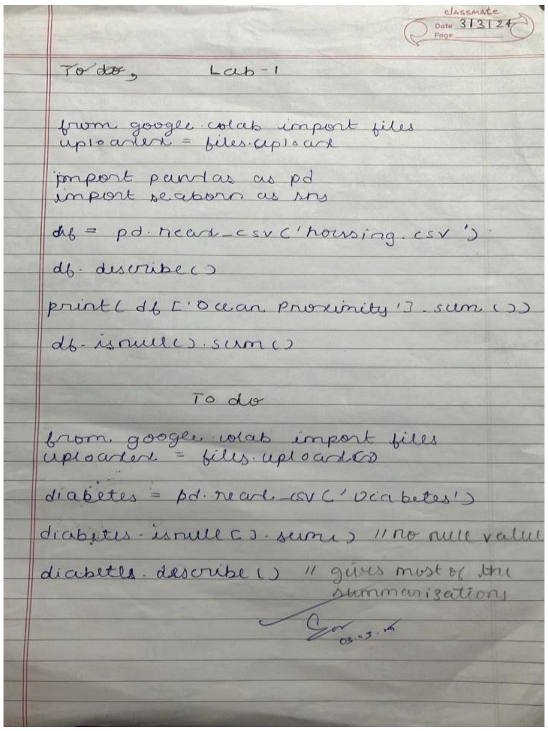
Code:

```
import pandas as pd
try:
    df = pd.read_csv('input.csv')
    print("Data imported successfully!\n")
    print(df)
except FileNotFoundError:
    print("The file 'input.csv' was not found.")
df["Processed"] = True
df.to_csv('output.csv', index=False)
print("\nData exported successfully to 'output.csv'.")
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Screenshots


classmate
Date 3|3|24
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To do,   Lab-1

from google.colab import files
uploaded = files.upload

import pandas as pd
import seaborn as sns

df = pd.read_csv('housing.csv')

df.describe()

print(df['Ocean Proximity'].sum())

df.isnull().sum()

To do

from google.colab import files
uploaded = files.upload()

diabetes = pd.read_csv('Diabetes')

diabetes.isnull().sum() //no null value

diabetes.describe() // gives most of the summarizations

03.03.24

Code

```
import pandas as pd

import numpy as np

from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler


data = {

    'Name': ['Alice', 'Bob', 'Charlie', 'David', 'Eve', None],

    'Age': [25, 30, np.nan, 35, 29, 40],
```

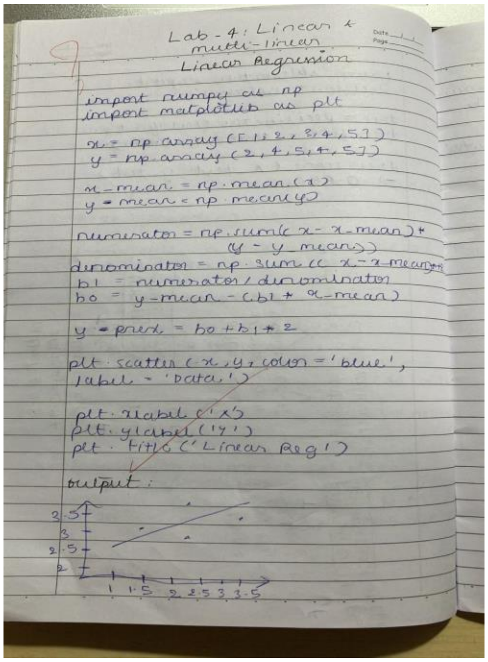
```
    'Department': ['HR', 'IT', 'Finance', 'IT', 'HR', 'Finance'],
    'Salary': [50000, 60000, 58000, 62000, np.nan, 52000]
}

df = pd.DataFrame(data)

print("Original DataFrame:\n", df)

df['Age'].fillna(df['Age'].mean(), inplace=True)
df['Salary'].fillna(df['Salary'].median(), inplace=True)
df['Name'].fillna('Unknown', inplace=True)

le = LabelEncoder()
df['Department_Encoded'] = le.fit_transform(df['Department'])

df.drop_duplicates(inplace=True)

df.rename(columns={'Salary': 'Monthly_Salary'}, inplace=True)

df['Age'] = df['Age'].astype(int)

scaler = MinMaxScaler()
df['Salary_Normalized'] = scaler.fit_transform(df[['Monthly_Salary']])

standard_scaler = StandardScaler()
```

```
df['Age_Standardized'] = standard_scaler.fit_transform(df[['Age']])

print("\nPreprocessed DataFrame:\n", df)
```

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshots



Code

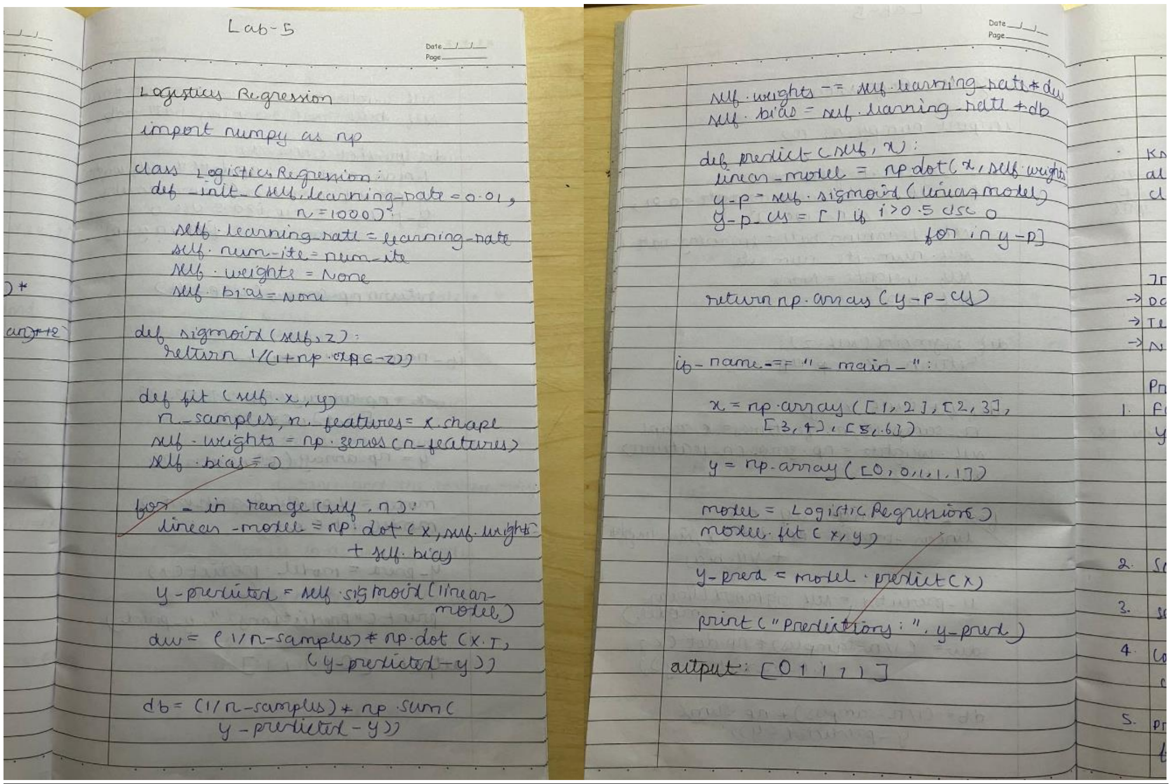
```
# Linear Regression

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_boston
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

# Load dataset
boston = load_boston()
df = pd.DataFrame(boston.data, columns=boston.feature_names)
df['PRICE'] = boston.target

# Use only one feature for simple linear regression (e.g., RM = average number of rooms)
X = df[['RM']]
y = df['PRICE']

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

# Train model
lr = LinearRegression()
lr.fit(X_train, y_train)
```

```
# Predict
y_pred = lr.predict(X_test)

# Output
print("Linear Regression Results")
print("Coefficients:", lr.coef_)
print("Intercept:", lr.intercept_)
print("MSE:", mean_squared_error(y_test, y_pred))
print("R² Score:", r2_score(y_test, y_pred))

# Plot
plt.scatter(X_test, y_test, color='blue')
plt.plot(X_test, y_pred, color='red')
plt.xlabel('Average Number of Rooms (RM)')
plt.ylabel('House Price')
plt.title('Simple Linear Regression')
plt.show()

# Multiple Linear Regression

# Use all features
X = df.drop('PRICE', axis=1)
y = df['PRICE']

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

# Train model
mlr = LinearRegression()
mlr.fit(X_train, y_train)

# Predict
y_pred = mlr.predict(X_test)

# Output
print("\nMultiple Linear Regression Results")
print("Coefficients:", mlr.coef_)
print("Intercept:", mlr.intercept_)
print("MSE:", mean_squared_error(y_test, y_pred))
print("R² Score:", r2_score(y_test, y_pred))
```

Program 4

Build Logistic Regression Model for a given dataset

Screenshot's


```
Lab-5

Logistics Regression

import numpy as np

class LogisticsRegression:
    def _init_(self, learning_rate=0.01,
               n=1000):
        self.learning_rate = learning_rate
        self.num_ite = num_ite
        self.weights = None
        self.bias = None

    def sigmoid(self, z):
        return 1/(1+np.exp(-z))

    def fit(self, x, y)
        n_samples, n_features = x.shape
        self.weights = np.zeros(n_features)
        self.bias = 0

    for _ in range(self, n):
        linear_model = np.dot(x, self.weights)
                       + self.bias

        y_predicted = self.sigmoid(linear_
                                   model)
        dw = (1/n_samples) * np.dot(x.T,
                                    (y_predicted - y))

        db = (1/n_samples) * np.sum(
              y_predicted - y))

        self.weights -= self.learning_rate * dw
        self.bias = self.learning_rate * db

    def predict(self, x):
        linear_model = np.dot(x, self.weights)
        y_p = self.sigmoid(linear_model)
        y_p_cls = [1 if i>0.5 else 0
                   for i in y_p]

        return np.array(y_p_cls)

if _name_ == "_main_":

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

    y = np.array([0,0,1,1])

    model = LogisticRegression()
    model.fit(x, y)

    y_pred = model.predict(x)

    print("Predictions:", y_pred)
output: [0 1 1 1]
```

Code

import pandas as pd

from sklearn.datasets import load_iris

from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import train_test_split

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

iris = load_iris()

df = pd.DataFrame(iris.data, columns=iris.feature_names)

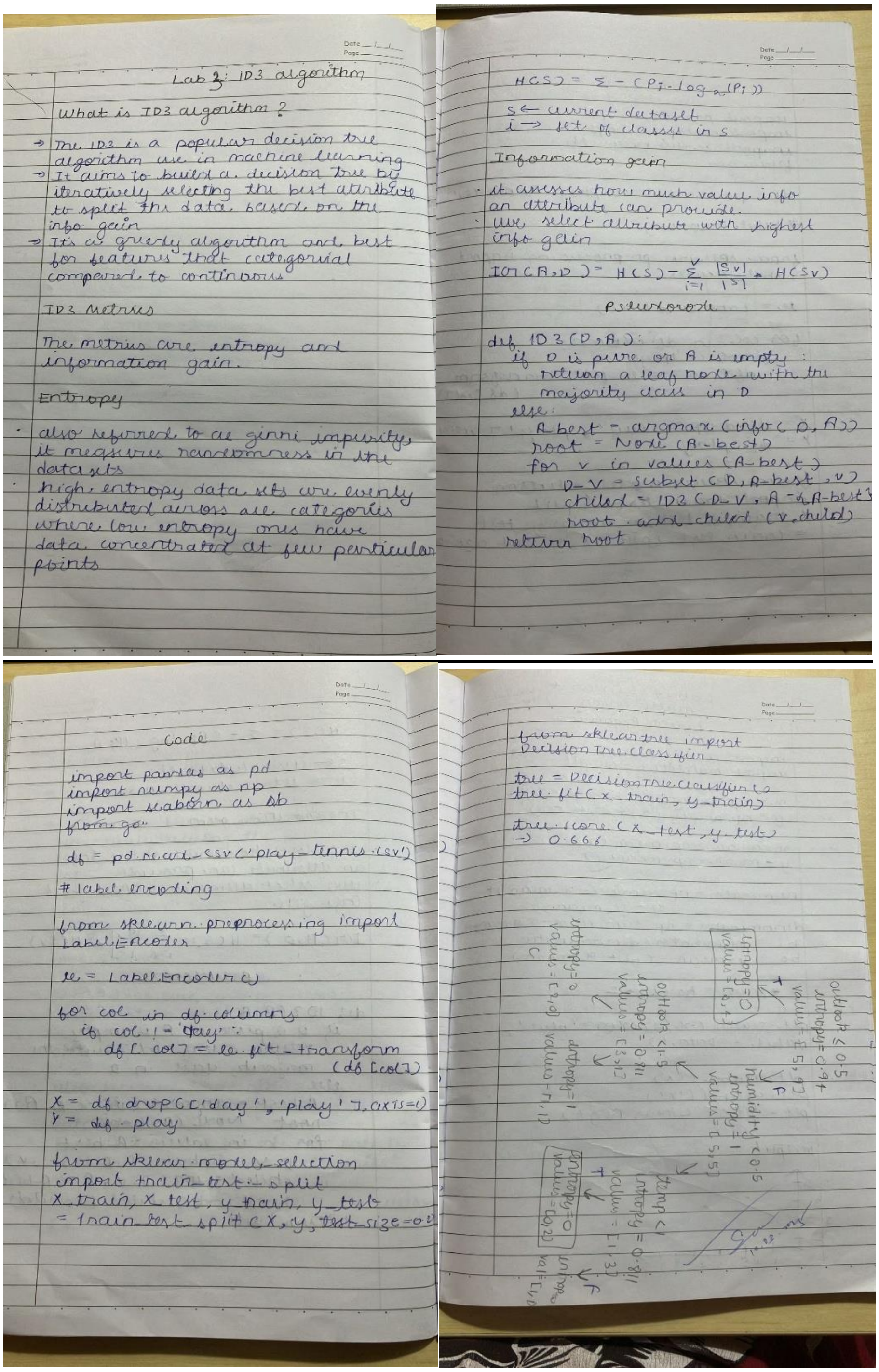
df['species'] = iris.target

```python
df_binary = df[df['species'] != 2]  # Remove class 2 (Virginica)

X = df_binary.iloc[:, :-1]   # Features
y = df_binary['species']     # Target (0 or 1)

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

model = LogisticRegression()
model.fit(X_train, y_train)

# Step 5: Predict and evaluate
y_pred = model.predict(X_test)

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nAccuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

Program 5

Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample

Screenshots



Lab 3: ID3 algorithm

What is ID3 algorithm ?

→ The ID3 is a popular decision tree algorithm use in machine learning
→ It aims to build a decision tree by iteratively selecting the best attribute to split the data based on the info gain
→ It's a greedy algorithm and best for features that categorical compared to continuous

ID3 Metrics

The metrics are entropy and information gain.

Entropy

- also referred to as ginni impurity, it measures randomness in the data sets
- high entropy data sets are evenly distributed across all categories where low entropy ones have data concentrated at few particular points

$H(S) = \Sigma - (P_i \cdot \log_2 (P_i))$

S ← current dataset
i → set of classes in S

Information gain

- it assesses how much value info an attribute can provide.
- we select attribute with highest info gain

$IG(A, D) = H(S) - \sum_{i=1}^{v} \frac{|S_v|}{|S|} * H(S_v)$

Pseudocode

```
def ID3(D, A):
    if D is pure or A is empty:
        return a leaf node with the majority class in D
    else:
        A best = argmax(info(D, A))
        root = Node(A-best)
        for v in values(A-best)
            D-V = subset(D, A-best, v)
            child = ID3(D-V, A - {A-best}
            root.add_child(v, child)
    return root
```

Code

```
import pandas as pd
import numpy as np
import seaborn as sb
from go..

df = pd.read_csv('play_tennis.csv')

# label encoding

from sklearn.preprocessing import
LabelEncoder

le = LabelEncoder()

for col in df.columns
    if col != 'day':
        df[col] = le.fit_transform
                         (df[col])

X = df.drop(['day', 'play'], axis=1)
Y = df.play

from sklearn.model_selection
import train_test_split
X_train, X_test, y_train, y_test
= train_test_split(X, y, test_size=0.2

from sklearn.tree import
DecisionTreeClassifier

tree = DecisionTreeClassifier()
tree.fit(X_train, y_train)

tree.score(X_test, y_test)
→ 0.666
```

outlook ≤ 0.5
entropy = 0.94
values = [5, 9]

entropy = 0
values = [0, 4]

humidity < 0.5
entropy = 1
values = [5, 5]

outlook < 1.5
entropy = 0.811
values = [3, 1]

temp < 1
entropy = 0.811
values = [1, 3]

entropy = 0
values = [2, 0]

entropy = 1
values = [1, 1]

entropy = 0
values = [0, 2]

Code

import pandas as pd

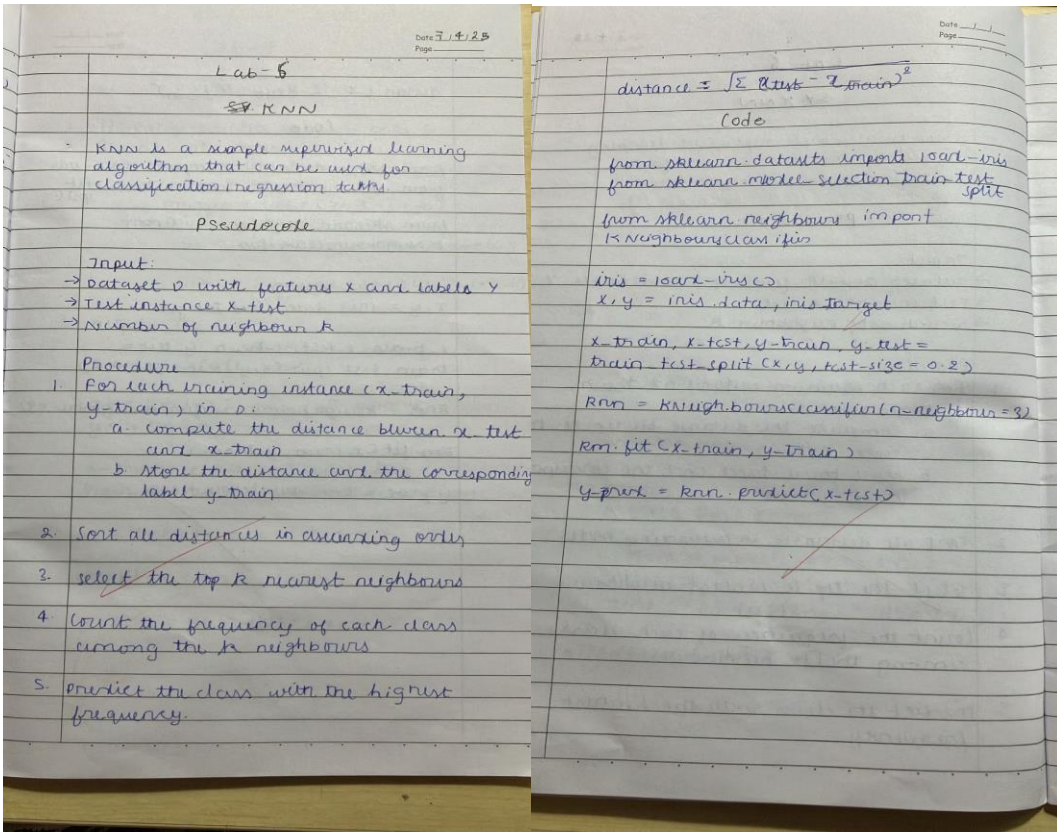
```
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
data = {
    'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rain', 'Rain', 'Rain', 'Overcast',
                'Sunny', 'Sunny', 'Rain', 'Sunny', 'Overcast', 'Overcast', 'Rain'],
    'Temperature': ['Hot', 'Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool',
                    'Mild', 'Cool', 'Mild', 'Mild', 'Mild', 'Hot', 'Mild'],
    'Humidity': ['High', 'High', 'High', 'High', 'Normal', 'Normal', 'Normal',
                 'High', 'Normal', 'Normal', 'Normal', 'High', 'Normal', 'High'],
    'Wind': ['Weak', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong',
             'Weak', 'Weak', 'Weak', 'Strong', 'Strong', 'Weak', 'Strong'],
    'PlayTennis': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes',
                   'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']
}

df = pd.DataFrame(data)
le = LabelEncoder()
for column in df.columns:
    df[column] = le.fit_transform(df[column])

# Step 3: Separate features and label
X = df.drop('PlayTennis', axis=1)
y = df['PlayTennis']
clf = DecisionTreeClassifier(criterion='entropy')  # ID3 uses 'entropy'
```

```
clf = clf.fit(X, y)

print("\nDecision Tree Rules:")

tree_text = tree.export_text(clf, feature_names=X.columns.tolist())

print(tree_text)

# Example: Outlook=Rain, Temperature=Mild, Humidity=High, Wind=Weak

# Encode input sample with same label encoding order used earlier

sample = pd.DataFrame({

    'Outlook': [le.transform(['Rain'])[0]],

    'Temperature': [le.transform(['Mild'])[0]],

    'Humidity': [le.transform(['High'])[0]],

    'Wind': [le.transform(['Weak'])[0]]

})


# Predict

prediction = clf.predict(sample)

result = 'Yes' if prediction[0] == 1 else 'No'

print(f"\nPrediction for new sample (Rain, Mild, High, Weak): {result}")
```

Program 6

Build KNN Classification model for a given dataset

Screenshots



Date 7/4/25

Lab-5

KNN

• KNN is a simple supervised learning algorithm that can be used for classification/regression tasks.

Pseudocode

Input:

→ Dataset D with features X and labels Y

→ Test instance x_test

→ Number of neighbours k

Procedure

1. For each training instance (x_train, y_train) in D:
   a. compute the distance btwn x_test and x_train
   b. Store the distance and the corresponding label y_train
2. Sort all distances in ascending order
3. Select the top k nearest neighbours
4. Count the frequency of each class among the k neighbours
5. Predict the class with the highest frequency.

distance = $\sqrt{\sum (x_{test} - x_{train})^2}$

Code

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.neighbours import KNeighboursClassifier

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

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

knn = KNeighboursClassifier(n_neighbours = 3)

knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
```

Code

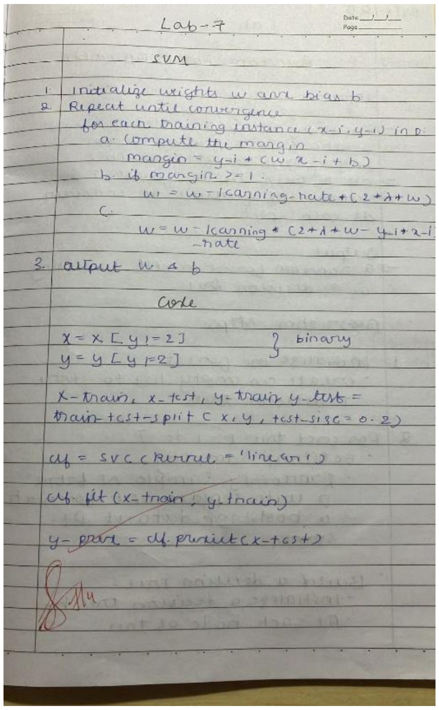
```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Step 1: Load the Iris dataset
iris = load_iris()
X = pd.DataFrame(iris.data, columns=iris.feature_names)
```

```
y = pd.Series(iris.target)

# Step 2: Split the data (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 3: Build KNN model (k = 3)
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)

# Step 4: Predict and evaluate
y_pred = knn.predict(X_test)

# Results
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("Accuracy Score:", accuracy_score(y_test, y_pred))
```

Program 7

Build Support vector machine model for a given dataset

Screenshots



Lab-7

SVM

1. initialize weights w and bias b
2. Repeat until convergence
   for each training instance (x-i, y-i) in D:
   a. compute the margin
      margin = y-i * (w. x-i + b)
   b. if margin >= 1:
      w = w - learning-rate * (2 * λ * w)
   c.
      w = w - learning-rate * (2 * λ * w - y-i * x-i)
3. output w & b

Code

```
x = x[y != 2]     } binary
y = y[y != 2]

X-train, x-test, y-train, y-test =
train-test-split(x, y, test-size = 0.2)

clf = SVC(kernel = 'linear')
clf.fit(x-train, y-train)
y-pred = clf.predict(x-test)
```

Code

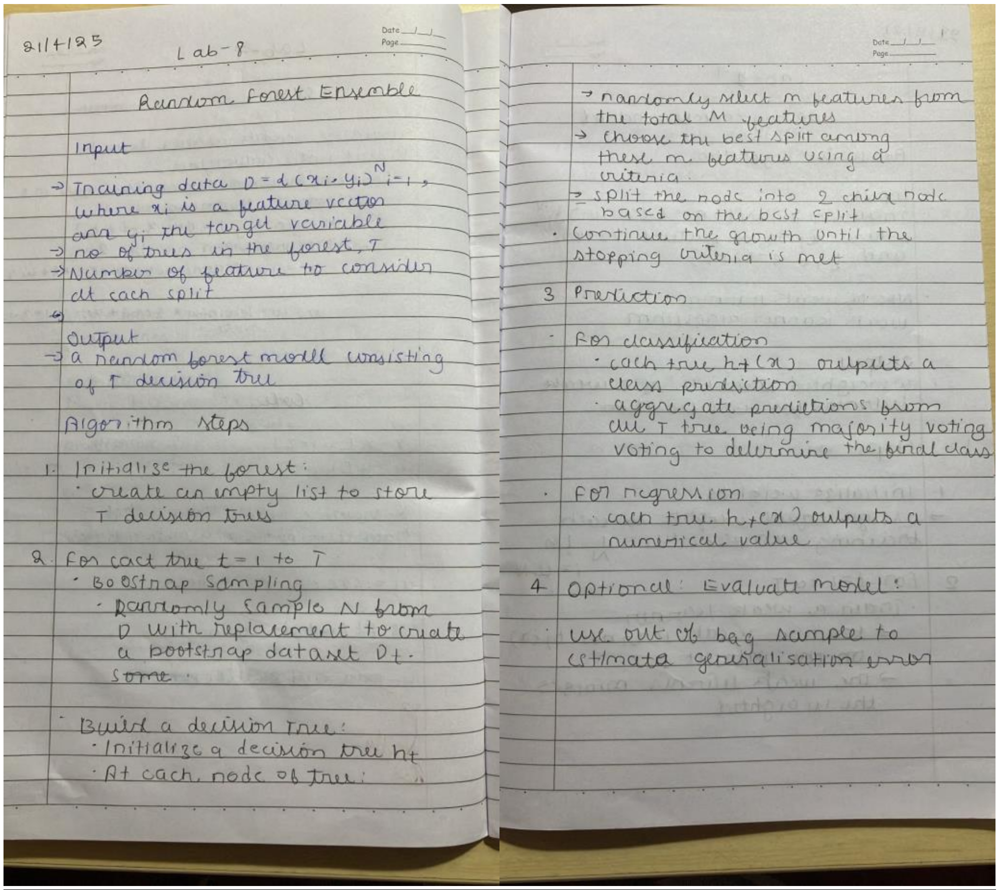
```
import pandas as pd

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

from sklearn.svm import SVC

from sklearn.metrics import confusion_matrix, classification_report, accuracy_score


# Step 1: Load the Iris dataset

iris = load_iris()

X = pd.DataFrame(iris.data, columns=iris.feature_names)

y = pd.Series(iris.target)


# Step 2: Split the data into train and test sets (80% train, 20% test)
```

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


# Step 3: Build and train the SVM model (linear kernel)
svm_model = SVC(kernel='linear')
svm_model.fit(X_train, y_train)


# Step 4: Predict and evaluate
y_pred = svm_model.predict(X_test)


# Output results
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("Accuracy Score:", accuracy_score(y_test, y_pred))
```

Program 8

Implement Random Forest ensemble method on a given dataset

Screenshots



21/1/25 Lab-8

Random Forest Ensemble

Input

→ Training data $D = \{(x_i, y_i)\}_{i=1}^{N}$, where x_i is a feature vector and y_i the target variable
→ no of trees in the forest, T
→ Number of feature to consider at each split

Output
→ a random forest model consisting of T decision tree

Algorithm steps

1. Initialise the forest:
   · create an empty list to store T decision trees
2. For each tree t = 1 to T
   · Bootstrap Sampling
   · Randomly sample N from D with replacement to create a bootstrap dataset D_t.
   ~~some~~
   · Build a decision tree:
   · Initialize a decision tree h_t
   · At each node of tree:
   → randomly select m features from the total M features
   → choose the best split among these m features using a criteria
   → split the node into 2 child node based on the best split
   · continue the growth until the stopping criteria is met
3. Prediction
   · For classification
   · each tree $h_t(x)$ outputs a class prediction
   · aggregate predictions from all T tree using majority voting voting to determine the final class
   · For regression
   · each tree $h_t(x)$ outputs a numerical value
4. Optional: Evaluate model:
   · use out of bag sample to estimate generalisation error

Code

```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

# Step 1: Load Iris dataset
iris = load_iris()
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = pd.Series(iris.target)
```

```
# Step 2: Split into train and test sets (80% train, 20% test)

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


# Step 3: Train Random Forest model

rf = RandomForestClassifier(n_estimators=100, random_state=42)  # 100 trees

rf.fit(X_train, y_train)


# Step 4: Predict and evaluate

y_pred = rf.predict(X_test)


print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

print("\nClassification Report:\n", classification_report(y_test, y_pred))

print("Accuracy Score:", accuracy_score(y_test, y_pred))
```

Program 9

Implement Boosting ensemble method on a given dataset

Screenshots

~~24~~ 21/5/25

Lab-~~8~~ 9

Boosting ensemble method

AdaBoost Algorithm

Input
· Training dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$ where x_i is a feature vector and $y_i \in \{-1, +1\}$

· No of weak learners
· weak learner algorithm

Output
· a weighted ensemble of T weak learners for classification

Steps:

1. Initialize weights:
→ assign equal weights to each training sample: $w_i = \frac{1}{N}$ for $i = 1, 2, \dots N$

2. For $t = 1$ to T
· Train a weak learner
→ train a weak learner $h_t(x)$ on the dataset D
→ the weak learner minimizes the weighted

· Compute weak learner weight

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$$

· update sample weights:

$$w_i \leftarrow w_i * \exp(-\alpha_t \cdot y_i \cdot h_t(x_i))$$

$$w_i \leftarrow \frac{w_i}{\sum_{j=1}^{N} w_j}$$

3. Prediction

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t \cdot h_t(x)\right)$$

output the class lable: -1 or $+1$

Code

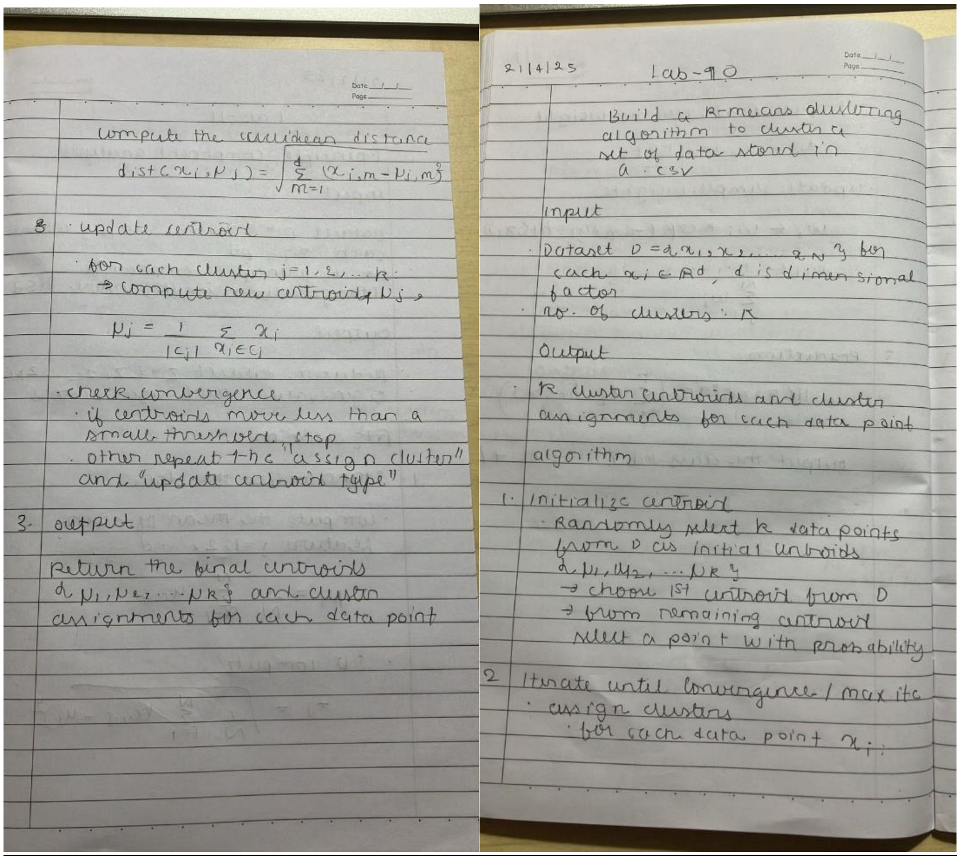
```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.tree import DecisionTreeClassifier

# Step 1: Load the Iris dataset
iris = load_iris()
```

```
X = pd.DataFrame(iris.data, columns=iris.feature_names)

y = pd.Series(iris.target)


# Step 2: Split into train and test sets (80% train, 20% test)

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


# Step 3: Build AdaBoost model with DecisionTreeClassifier as base estimator

base_estimator = DecisionTreeClassifier(max_depth=1)

model = AdaBoostClassifier(base_estimator=base_estimator, n_estimators=50, learning_rate=1.0,
random_state=42)

model.fit(X_train, y_train)


# Step 5: Predict and evaluate

y_pred = model.predict(X_test)

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

print("\nClassification Report:\n", classification_report(y_test, y_pred))

print("Accuracy Score:", accuracy_score(y_test, y_pred))
```

Program 10

Build k-Means algorithm to cluster a set of data stored in a .CSV file

Screenshots


compute the euclidean distance

$$dist(x_i, \mu_j) = \sqrt{\sum_{m=1}^{d} (x_{i,m} - \mu_{j,m})^2}$$

8 · update centroid

· for each cluster $j = 1, 2, \ldots k$:

→ compute new centroid μ_j,

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i$$

· check convergence

· if centroids move less than a small threshold, stop

· other repeat the "assign cluster" and "update centroid type"

3. output

Return the final centroids $\{\mu_1, \mu_2, \ldots \mu_k\}$ and cluster assignments for each data point

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Build a k-means clustering algorithm to cluster a set of data stored in a .csv

input

· Dataset $D = \{x_1, x_2, \ldots x_N\}$ for each $x_i \in R^d$, d is dimensional factor

· no. of clusters: k

Output

: k cluster centroids and cluster assignments for each data point

algorithm

1. initialize centroid

· Randomly select k data points from D as initial centroids $\{\mu_1, \mu_2, \ldots \mu_k\}$

→ choose 1st centroid from D

→ from remaining centroid select a point with probability

2 Iterate until convergence / max itr

· assign clusters

· for each data point x_i:

Code

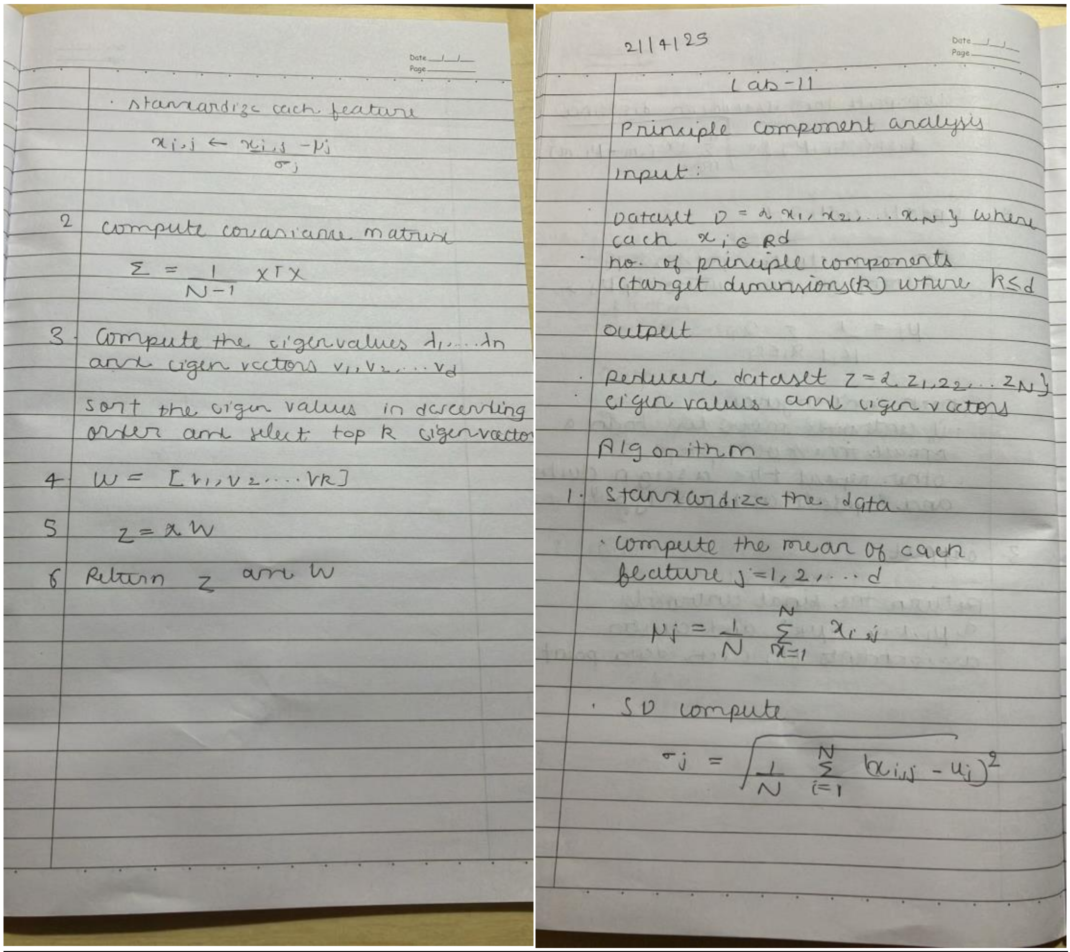
```
import pandas as pd
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler


# Step 1: Load dataset from CSV
df = pd.read_csv('your_dataset.csv')  # Replace with your file path


# Optional: View first few rows
print("Data Preview:\n", df.head())
```

```
# Step 2: Select relevant numeric columns for clustering
# You can specify specific columns like: df[['column1', 'column2']]
X = df.select_dtypes(include='number')

# Step 3: Scale the data (important for K-Means)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 4: Apply K-Means clustering (e.g., 3 clusters)
kmeans = KMeans(n_clusters=3, random_state=42)
df['Cluster'] = kmeans.fit_predict(X_scaled)

# Step 5: Print cluster centers
print("Cluster Centers:\n", kmeans.cluster_centers_)

# Optional Step 6: Visualize (works well for 2D or PCA-reduced data)
if X.shape[1] >= 2:
    plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=df['Cluster'], cmap='viridis')
    plt.title("K-Means Clustering")
    plt.xlabel("Feature 1")
    plt.ylabel("Feature 2")
    plt.show()
```

Program 11

Implement Dimensionality reduction using Principal Component Analysis (PCA) method

Screenshots



21/4/25

Lab-11

Principle component analysis

Input:

Dataset $D = \{x_1, x_2, \ldots x_N\}$ where each $x_i \in R^d$

no. of principle components (target dimensions(k)) where $k \le d$

Output

Reduced dataset $Z = \{z_1, z_2, \ldots z_N\}$

eigen values and eigen vectors

Algorithm

1. Standardize the data

· compute the mean of each feature $j = 1, 2, \ldots d$

$$\mu_j = \frac{1}{N} \sum_{i=1}^{N} x_{i,j}$$

· SD compute

$$\sigma_j = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_{i,j} - \mu_j)^2}$$

· standardize each feature

$$x_{i,j} \leftarrow \frac{x_{i,j} - \mu_j}{\sigma_j}$$

2 compute covariance matrix

$$\Sigma = \frac{1}{N-1} X^T X$$

3. Compute the eigenvalues $\lambda_1, \ldots \lambda_n$ and eigen vectors $v_1, v_2, \ldots v_d$

sort the eigen values in descending order and select top k eigenvectors

4 $W = [v_1, v_2 \ldots v_k]$

5 $Z = xW$

6 Return Z and W

Code

```
import pandas as pd

from sklearn.datasets import load_iris

from sklearn.preprocessing import StandardScaler

from sklearn.decomposition import PCA

import matplotlib.pyplot as plt


# Step 1: Load the Iris dataset

iris = load_iris()

X = iris.data
```

```
y = iris.target
feature_names = iris.feature_names

# Step 2: Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 3: Apply PCA (reduce to 2 components for visualization)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Step 4: Plot the 2D PCA result
plt.figure(figsize=(8, 6))
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis', edgecolor='k', s=60)
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.title("PCA - Iris Dataset")
plt.legend(handles=scatter.legend_elements()[0], labels=iris.target_names)
plt.grid(True)
plt.show()

# Explained variance
print("Explained variance ratio:", pca.explained_variance_ratio_)
```