VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

Maria Sayeema (1BM22CS151)

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

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "Machine Learning (23CS6PCMAL)" carried out by **Maria Sayeema (1BM22CS151),** 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 an Machine Learning (23CS6PCMAL) work prescribed for the said degree.

Lab faculty Incharge Name Assistant Professor Department of CSE, BMSCE	Dr. Kavitha Sooda Professor & HOD Department of CSE, BMSCE

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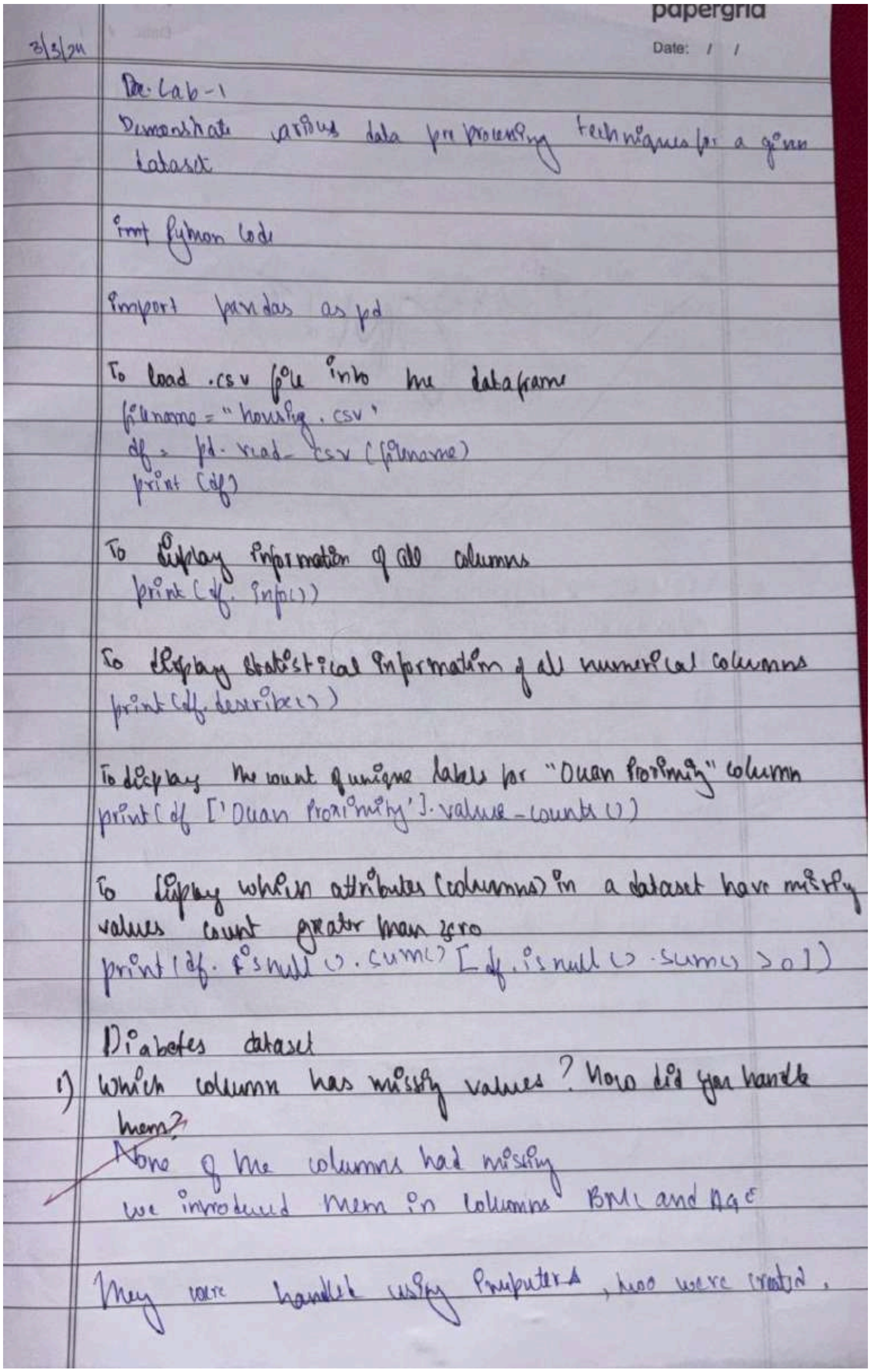
Github Link:
https://github.com/mariasayeema/ML-LAB

Program 1

Demonstrate various data pre-processing techniques for a given dataset

Screenshot



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De Lab-1

Demonstrate various data pre processing techniques for a given dataset

Imp python code

import pandas as pd

To load .csv file into the dataframe

filename = "housing.csv"
df = pd.read_csv(filename)
print(df)

To display information of all columns

print(df.info())

To display statistical information of all numerical columns

print(df.describe())

To display the count of unique labels for "Ocean Proximity" column

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

To display which attributes (columns) in a dataset have missing values count greater than zero

print(df.isnull().sum()[df.isnull().sum() > 0])

Diabetes dataset

1) Which column has missing values? How did you handle them?

~~None of the columns had missing~~

we introduced them in columns BMI and Age

They were handled using imputers, two were created.

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one that substituted median to handle missing values in AGE column
and another that substituted mean to handle missing values in BMI column

2) Which categorical columns did you identify in the dataset? How did you encode them?

Two categorical columns are present: Gender, CLASS
Gender was encoded using OrdinalEncoder with 'F' as 0 and 'M' as 1
CLASS was encoded as OneHotEncoder in which each value in the column became a row
i.e CLASS_N, CLASS_P, CLASS_Y

3) What is the difference between Min-Max Scaling and Standardization? When would you use one over the other

It was done on TG column, which forces all the values between 0 and 1

Standardization was applied for AGE column

Min-Max Scaling	Standardization
keeps all the data between 0 and 1, ideal for distance based models	works well for normally distributed data, suitable for many models : $x-\mu/\sigma$
can distort data distribution especially with extreme outliers	sensitive to outliers mean=0 and SD=1

Min-Max: distance-based models (evenly spread data and you want fixed bounds)

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Standardization:

normally distributed data & regression based models or PCA where feature distribution affects output

Use standardization when there are more outliers

Adult Income data set

1) which columns in the dataset had missing values? how did you handle them

No missing values in any columns. we introduced missing values in educational-num and age

to handle these, we used two imputers, one that substitutes median to handle missing values in educational-num

and another one to handle missing values in age by substituting mean.

2) which categorical column did you identify in the dataset? how did you encode them?

workclass, fnlwgt, education, marital status, occupation, relationships, race, gender, capital-gain, native-country

we encoded them using two schemes:

eg: gender: Female = 0 Male = 1 OrdinalEncoder

race: OneHotEncoder, each value i.e black white etc became a column

What is the difference between Min-Max scaling and standardization? When would you choose one over the other

MinMax was applied to hours per week in which all values were forced between 0 to 1. can distort data distribution

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with extreme values

Standardization was applied to age, using the formula $\frac{x-\mu}{\sigma}$, it tries to force mean as 0 and standard deviation as 1

use minmax: distance based models, less outliers, need fixed bounds, evenly spread data.

use standardization: normally distributed data, regression models, PCA, more no. of outliers.

Code:

Data Processing :**1 Dataset of Diabetes**

from google.colab import files

uploaded = files.upload()

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.impute import SimpleImputer

from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder

from sklearn.preprocessing import StandardScaler, MinMaxScaler

from scipy import stats

import pandas as pd

df = pd.read_csv('Dataset of Diabetes .csv')

df.head()

df.head(10)

df.shape

print(df.describe())

missing_values = df.isnull().sum()

print(missing_values[missing_values > 0])

import numpy as np

df.loc[5, 'AGE'] = np.nan

df.loc[10, 'BMI'] = np.nan  # Set missing value for 'BMI' at row index 10

print(df.head(10))

df

print(df.describe())

missing_values = df.isnull().sum()

print(missing_values[missing_values > 0])
```

```
imputer1 = SimpleImputer(strategy="median")

imputer2 = SimpleImputer(strategy="mean")

df_copy=df

imputer1.fit(df_copy[["AGE"]])

imputer2.fit(df_copy[["BMI"]])

df_copy["AGE"] = imputer1.transform(df[["AGE"]])

df_copy["BMI"] = imputer2.transform(df[["BMI"]])

print(df_copy["AGE"].isnull().sum())

print(df_copy["BMI"].isnull().sum())

import pandas as pd

from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder

df['Gender'] = df['Gender'].str.upper()  # Convert to uppercase

df['CLASS'] = df['CLASS'].str.upper()

ordinal_encoder = OrdinalEncoder(categories=[["F", "M"]])  # Encoding 'F' as 0, 'M' as 1

df["Gender_Encoded"] = ordinal_encoder.fit_transform(df[["Gender"]])

onehot_encoder = OneHotEncoder()

if 'CLASS' in df.columns:

    encoded_data = onehot_encoder.fit_transform(df[["CLASS"]])

    encoded_array = encoded_data.toarray()

    encoded_df = pd.DataFrame(encoded_array,
columns=onehot_encoder.get_feature_names_out(["CLASS"]))

    df_encoded = pd.concat([df, encoded_df], axis=1)

    df_encoded.drop("CLASS", axis=1, inplace=True)

else:

    df_encoded = df.copy()
```

```
df_encoded.drop("Gender", axis=1, inplace=True)
print(df_encoded.head())
df_encoded
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
normalizer = MinMaxScaler()
df_encoded[['AGE']] = normalizer.fit_transform(df_encoded[['AGE']])
print(df_encoded.head())
df_encoded
normalizer = MinMaxScaler()
df_encoded[['TG']] = normalizer.fit_transform(df_encoded[['TG']])
df_encoded.head()
scaler = StandardScaler()
df_encoded[['AGE']] = scaler.fit_transform(df_encoded[['AGE']])
df_encoded.head()
df_encoded_copy1=df_encoded
df_encoded_copy2=df_encoded
df_encoded_copy3=df_encoded
Q1 = df_encoded_copy1['Chol'].quantile(0.25)
Q3 = df_encoded_copy1['Chol'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
df_encoded_copy1['Chol'] = np.where(df_encoded_copy1['Chol'] > upper_bound, upper_bound,
```

```
                    np.where(df_encoded_copy1['Chol'] < lower_bound, lower_bound,
df_encoded_copy1['Chol']))

print(df_encoded_copy1.head())

df_encoded_copy2['Chol_zscore'] = stats.zscore(df_encoded_copy2['Chol'])

df_encoded_copy2['Chol'] = np.where(df_encoded_copy2['Chol_zscore'].abs() > 3, np.nan,
df_encoded_copy2['Chol'])

print(df_encoded_copy2.head())

df_encoded_copy3['Chol_zscore'] = stats.zscore(df_encoded_copy3['Chol'])

median_salary = df_encoded_copy3['Chol'].median()

df_encoded_copy3['Chol'] = np.where(df_encoded_copy3['Chol'].abs() > 3, median_salary,
df_encoded_copy3['Chol'])

print(df_encoded_copy3.head())
```

2 Adult:

```
from google.colab import files

uploaded = files.upload()

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.impute import SimpleImputer

from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder

from sklearn.preprocessing import StandardScaler, MinMaxScaler

from scipy import stats

import pandas as pd


df = pd.read_csv('adult.csv')
```

```
df.head()

df.head(10)

df.shape

print(df.describe())

missing_values = df.isnull().sum()

print(missing_values[missing_values > 0])

import numpy as np

df.loc[5, 'educational-num'] = np.nan

df.loc[7, 'age'] = np.nan

print(df.head(10))

df

print(df.describe())

missing_values = df.isnull().sum()

print(missing_values[missing_values > 0])

imputer1 = SimpleImputer(strategy="median")

imputer2 = SimpleImputer(strategy="mean")

df_copy = df

imputer1.fit(df_copy[["educational-num"]])

imputer2.fit(df_copy[["age"]])

df_copy["educational-num"] = imputer1.transform(df[["educational-num"]])

df_copy["age"] = imputer2.transform(df[["age"]])

print(df_copy["educational-num"].isnull().sum())

print(df_copy["age"].isnull().sum())
```

```
import pandas as pd

from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder

df['gender'] = df['gender'].str.upper()

df['race'] = df['race'].str.upper()

ordinal_encoder = OrdinalEncoder(categories=[["FEMALE", "MALE"]])

df["gender_Encoded"] = ordinal_encoder.fit_transform(df[["gender"]])

onehot_encoder = OneHotEncoder()

if 'race' in df.columns:

    encoded_data = onehot_encoder.fit_transform(df[["race"]])

    encoded_array = encoded_data.toarray()

    encoded_df = pd.DataFrame(encoded_array,
columns=onehot_encoder.get_feature_names_out(["race"]))

    df_encoded = pd.concat([df, encoded_df], axis=1)

    df_encoded.drop("race", axis=1, inplace=True)

else:

    df_encoded = df.copy()

df_encoded.drop("gender", axis=1, inplace=True)

print(df_encoded.head())

df_encoded

import pandas as pd

from sklearn.preprocessing import MinMaxScaler

normalizer = MinMaxScaler()

df_encoded[['hours-per-week']] = normalizer.fit_transform(df_encoded[['hours-per-week']])

print(df_encoded.head())

df_encoded
```

```
scaler = StandardScaler()

df_encoded[['age']] = scaler.fit_transform(df_encoded[['age']])

df_encoded.head()

df_encoded_copy1 = df_encoded

df_encoded_copy2 = df_encoded

df_encoded_copy3 = df_encoded

Q1 = df_encoded_copy1['fnlwgt'].quantile(0.25)

Q3 = df_encoded_copy1['fnlwgt'].quantile(0.75)

IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR

upper_bound = Q3 + 1.5 * IQR

df_encoded_copy1['fnlwgt'] = np.where(

    df_encoded_copy1['fnlwgt'] > upper_bound,

    upper_bound,

    np.where(df_encoded_copy1['fnlwgt'] < lower_bound, lower_bound, df_encoded_copy1['fnlwgt'])

)

print(df_encoded_copy1.head())

df_encoded_copy2['fnlwgt_zscore'] = stats.zscore(df_encoded_copy2['fnlwgt'])

df_encoded_copy2['fnlwgt'] = np.where(df_encoded_copy2['fnlwgt_zscore'].abs() > 3, np.nan,
df_encoded_copy2['fnlwgt'])

print(df_encoded_copy2.head())

df_encoded_copy3['fnlwgt_zscore'] = stats.zscore(df_encoded_copy3['fnlwgt'])

median_salary = df_encoded_copy3['fnlwgt'].median()

df_encoded_copy3['fnlwgt'] = np.where(df_encoded_copy3['fnlwgt_zscore'].abs() > 3,
median_salary, df_encoded_copy3['fnlwgt'])
```

```
print(df_encoded_copy3.head())
```

Preprocessing:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from scipy import stats
def createdata():
    data = {
        'Age': np.random.randint(18, 70, size=20),
        'Salary': np.random.randint(30000, 120000, size=20),
        'Purchased': np.random.choice([0, 1], size=20),
        'Gender': np.random.choice(['Male', 'Female'], size=20),
        'City': np.random.choice(['New York', 'San Francisco', 'Los Angeles'], size=20)
    }
    df = pd.DataFrame(data)
    return df
df = createdata()
df.head(10)
df.shape
```

```
df.loc[5, 'Age'] = np.nan

df.loc[10, 'Salary'] = np.nan

df.head(10)

print(df.info())

print(df.describe())

missing_values = df.isnull().sum()

print(missing_values[missing_values > 0])

imputer1 = SimpleImputer(strategy="median")

imputer2 = SimpleImputer(strategy="mean")

df_copy = df

imputer1.fit(df_copy[["Age"]])

imputer2.fit(df_copy[["Salary"]])

df_copy["Age"] = imputer1.transform(df[["Age"]])

df_copy["Salary"] = imputer2.transform(df[["Salary"]])

print(df_copy["Age"].isnull().sum())

print(df_copy["Salary"].isnull().sum())

ordinal_encoder = OrdinalEncoder(categories=[["Male", "Female"]])

df_copy["Gender_Encoded"] = ordinal_encoder.fit_transform(df_copy[["Gender"]])

onehot_encoder = OneHotEncoder()

encoded_data = onehot_encoder.fit_transform(df[["City"]])

encoded_array = encoded_data.toarray()

encoded_df = pd.DataFrame(encoded_array,
columns=onehot_encoder.get_feature_names_out(["City"]))

df_encoded = pd.concat([df_copy, encoded_df], axis=1)

df_encoded.drop("Gender", axis=1, inplace=True)
```

```
df_encoded.drop("City", axis=1, inplace=True)
print(df_encoded.head())
normalizer = MinMaxScaler()
df_encoded[['Salary']] = normalizer.fit_transform(df_encoded[['Salary']])
df_encoded.head()
scaler = StandardScaler()
df_encoded[['Age']] = scaler.fit_transform(df_encoded[['Age']])
df_encoded.head()
df_encoded_copy1 = df_encoded
df_encoded_copy2 = df_encoded
df_encoded_copy3 = df_encoded
Q1 = df_encoded_copy1['Salary'].quantile(0.25)
Q3 = df_encoded_copy1['Salary'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
df_encoded_copy1['Salary'] = np.where(
    df_encoded_copy1['Salary'] > upper_bound,
    upper_bound,
    np.where(df_encoded_copy1['Salary'] < lower_bound, lower_bound, df_encoded_copy1['Salary'])
)
print(df_encoded_copy1.head())


df_encoded_copy2['Salary_zscore'] = stats.zscore(df_encoded_copy2['Salary'])
```

```
df_encoded_copy2['Salary'] = np.where(df_encoded_copy2['Salary_zscore'].abs() > 3, np.nan,
df_encoded_copy2['Salary'])

print(df_encoded_copy2.head())

df_encoded_copy3['Salary_zscore'] = stats.zscore(df_encoded_copy3['Salary'])

median_salary = df_encoded_copy3['Salary'].median()

df_encoded_copy3['Salary'] = np.where(df_encoded_copy3['Salary_zscore'].abs() > 3,
median_salary, df_encoded_copy3['Salary'])

print(df_encoded_copy3.head())
```

Preprocessing:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.impute import SimpleImputer

from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder

from sklearn.preprocessing import StandardScaler, MinMaxScaler

from scipy import stats

def createdata():

   data = {

       'Age': np.random.randint(18, 70, size=20),

       'Salary': np.random.randint(30000, 120000, size=20),

       'Purchased': np.random.choice([0, 1], size=20),

       'Gender': np.random.choice(['Male', 'Female'], size=20),

       'City': np.random.choice(['New York', 'San Francisco', 'Los Angeles'], size=20)

   }
```

```
    df = pd.DataFrame(data)

    return df

df = createdata()

df.shape

df.loc[5, 'Age'] = np.nan

df.loc[10, 'Salary'] = np.nan

df.head(10)

print(df.info())

print(df.describe())

missing_values = df.isnull().sum()

print(missing_values[missing_values > 0])

imputer1 = SimpleImputer(strategy="median")

imputer2 = SimpleImputer(strategy="mean")

df_copy = df

imputer1.fit(df_copy[["Age"]])

imputer2.fit(df_copy[["Salary"]])

df_copy["Age"] = imputer1.transform(df[["Age"]])

df_copy["Salary"] = imputer2.transform(df[["Salary"]])

print(df_copy["Age"].isnull().sum())

print(df_copy["Salary"].isnull().sum())

ordinal_encoder = OrdinalEncoder(categories=[["Male", "Female"]])

df_copy["Gender_Encoded"] = ordinal_encoder.fit_transform(df_copy[["Gender"]])


onehot_encoder = OneHotEncoder()
```

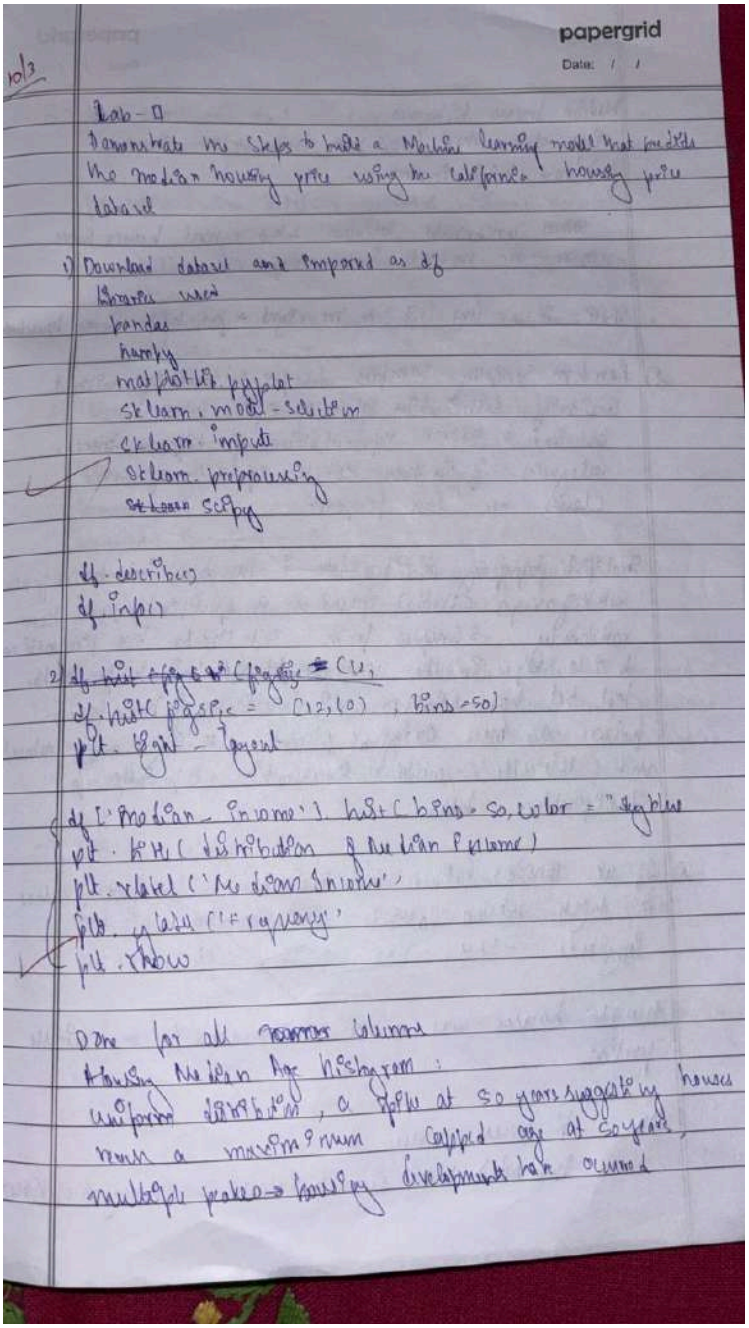
```
encoded_data = onehot_encoder.fit_transform(df[["City"]])

encoded_array = encoded_data.toarray()

encoded_df = pd.DataFrame(encoded_array,
columns=onehot_encoder.get_feature_names_out(["City"]))

df_encoded = pd.concat([df_copy, encoded_df], axis=1)

df_encoded.drop("Gender", axis=1, inplace=True)

df_encoded.drop("City", axis=1, inplace=True)

print(df_encoded.head())

normalizer = MinMaxScaler()

df_encoded[['Salary']] = normalizer.fit_transform(df_encoded[['Salary']])

df_encoded.head()

scaler = StandardScaler()

df_encoded[['Age']] = scaler.fit_transform(df_encoded[['Age']])

df_encoded.head()

df_encoded_copy1 = df_encoded

df_encoded_copy2 = df_encoded

df_encoded_copy3 = df_encoded

Q1 = df_encoded_copy1['Salary'].quantile(0.25)

Q3 = df_encoded_copy1['Salary'].quantile(0.75)

IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR

upper_bound = Q3 + 1.5 * IQR

df_encoded_copy1['Salary'] = np.where(df_encoded_copy1['Salary'] > upper_bound, upper_bound,

                                np.where(df_encoded_copy1['Salary'] < lower_bound, lower_bound,
df_encoded_copy1['Salary']))
```

```
print(df_encoded_copy1.head())

df_encoded_copy2['Salary_zscore'] = stats.zscore(df_encoded_copy2['Salary'])

df_encoded_copy2['Salary'] = np.where(df_encoded_copy2['Salary_zscore'].abs() > 3, np.nan,
df_encoded_copy2['Salary'])

print(df_encoded_copy2.head())

df_encoded_copy3['Salary_zscore'] = stats.zscore(df_encoded_copy3['Salary'])

median_salary = df_encoded_copy3['Salary'].median()

df_encoded_copy3['Salary'] = np.where(df_encoded_copy3['Salary_zscore'].abs() > 3,
median_salary, df_encoded_copy3['Salary'])

print(df_encoded_copy3.head())
```

Program 2

Demonstrate the steps to build a machine-learning model that predicts the median housing price using the California housing price dataset.

Screenshot:



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Lab - II

Demonstrate the steps to build a Machine learning model that predicts the median housing price using the California housing price dataset

1) Download dataset and imported as df

Libraries used

pandas

numpy

matplotlib.pyplot

sklearn.model_selection

sklearn.impute

sklearn.preprocessing

sklearn scipy

df.describe()

df.info()

2) ~~df.hist(figsize=(12,~~

df.hist(figsize = (12,10), bins=50)

plt.tight_layout

df['median_income'].hist(bins=50, color='skyblue'

plt.title(Distribution of Median Income)

plt.xlabel('Median Income')

plt.ylabel('Frequency'

plt.show

Done for all numeric columns

Housing Median Age histogram:

uniform distribution, a spike at 50 years suggesting houses with a maximum capped age at 50 years, multiple peaks → housing development had occurred

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Median Income histogram:
Right skew: most houses have lower median income
few have high income

values concentrated between 2 to 6 : most houses have
lower - to moderate income range

There is a long tail on the right + few higher income households

3) Random Sampling: samples data points randomly without
considering distribution of a specific feature
can lead to uneven representation of different classes or
categories in the test set especially if some
classes are less frequent

Stratified Sampling: divides ~~data~~ the data into homogeneous
subgroups (strata) based on a specific feature then
randomly samples from each strata proportionally
to its size in the overall dataset. this helps the
test set has similar distribution of the chosen
feature as the original dataset. leading to more robust
and reliable model evaluation especially for
classification tasks

4) If we consider latitude and longitude: median house value
is high between latitude ~~[illegible]~~. 34, 36, 38 and
longitude -124, -122, ~~[illegible]~~, -120, -118

most houses are ~~[illegible]~~ concentrated in the middle
portion

the ~~[illegible]~~ house value is
Inland > near ocean > island > near bay > <1 hocean

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5) total rooms ~~and total~~ bedrooms with
total bedrooms, population, household.

population with total_rooms, total_bedrooms, household

household with total_rooms, total_bedrooms, population

most correlated with housing price = median_income
correlation = 0.688

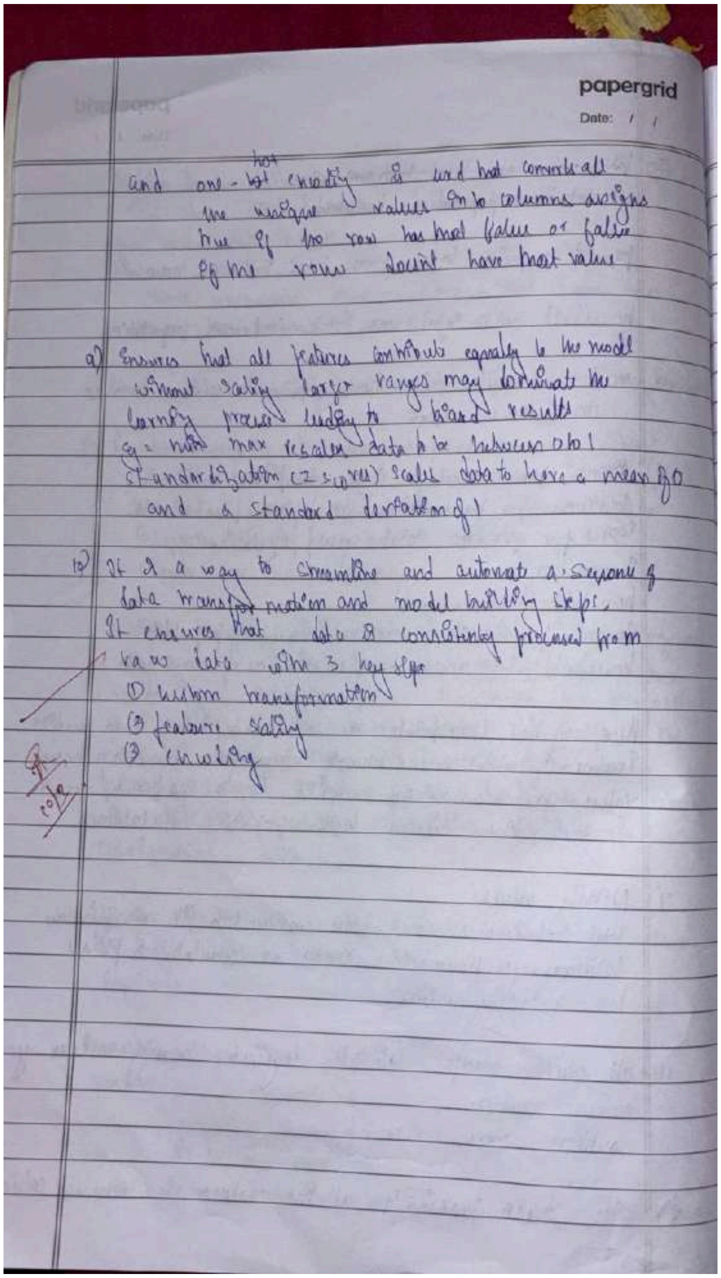
6) Rooms per household = total_rooms / households
bedrooms per household = total_bedrooms / households
rooms per person = total_rooms / population
~~Income per~~
~~household income = medi~~
income per person = median_income / population
household_income = median_income * households

Most of the data points are concentrated below 8 as median income which means most ~~house price~~ median house values are associated with low to moderate median income, there is a loose positive correlation

7) Missing values:
total_bedrooms → median was used to fill missing values
bedrooms_per_household: mean was calculated to fill all the missing values

all columns except latitude, longitude, housing_median_age have outliers.
outliers were removed

8) Yes ocean proximity all the values are taken as column



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and one-hot encoding is used that converts all the unique values into columns assigns true if the row has that value or false if the row doesn't have that value

9) Ensures that all features contribute equally to the model without scaling larger ranges may dominate the learning process leading to biased results
eg = min max rescales data to be between 0 to 1
Standardization (Z score) scales data to have a mean of 0 and a standard deviation of 1

10) It is a way to streamline and automate a sequence of data transformation and model building steps.
It ensures that data is consistently processed from raw data with 3 key steps
① custom transformation
② feature scaling
③ encoding

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Code:

import pandas as pd

from sklearn.base import BaseEstimator, TransformerMixin

from sklearn.compose import ColumnTransformer

from sklearn.preprocessing import StandardScaler, OneHotEncoder

from sklearn.pipeline import Pipeline

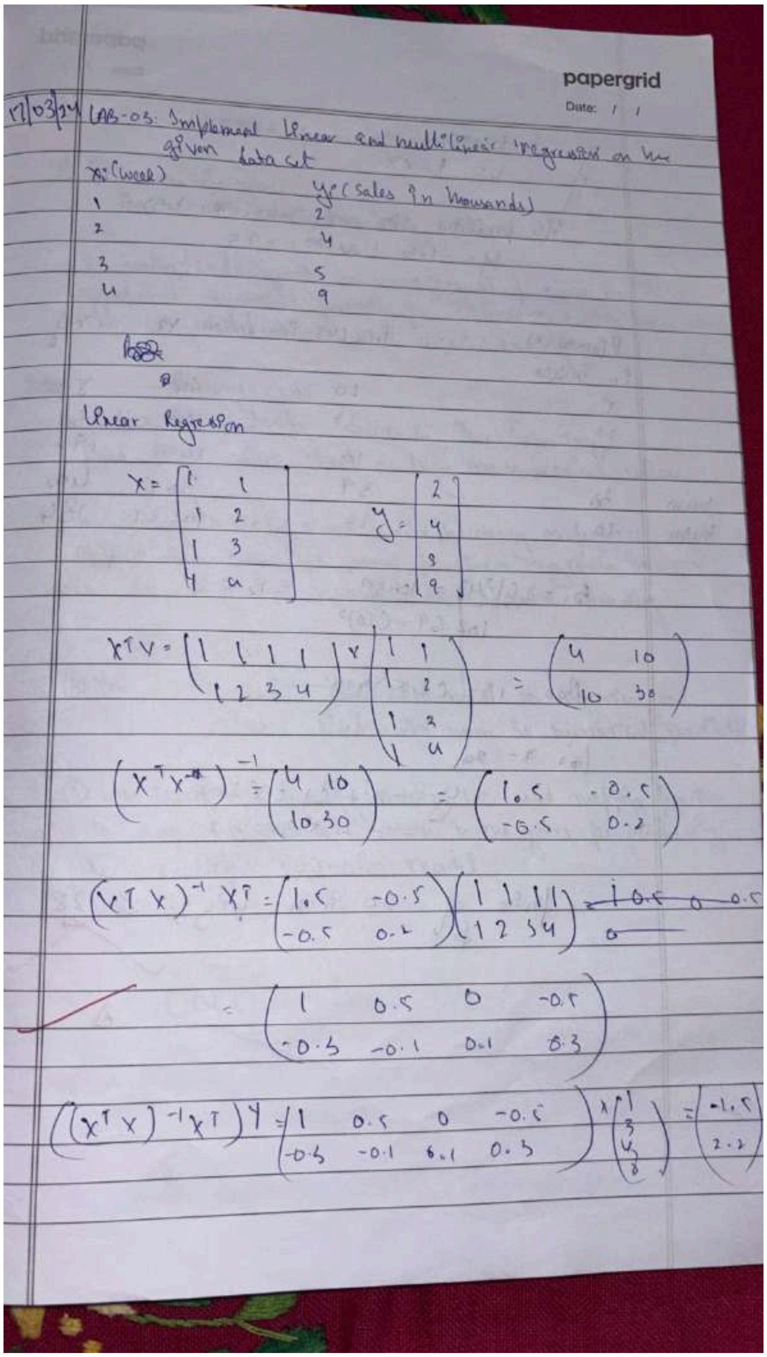
```
from sklearn.impute import SimpleImputer

df.columns = df.columns.str.strip()

class CustomFeatureTransformer(BaseEstimator, TransformerMixin):

    def fit(self, X, y=None):

        return self

    def transform(self, X):

        X['rooms_per_household'] = X['total_rooms'] / X['households']

        return X

numerical_features = ['housing_median_age', 'total_rooms', 'total_bedrooms', 'population',
'households', 'median_income', 'median_house_value']

categorical_features = ['ocean_proximity']

preprocessor = ColumnTransformer([

    ('num', Pipeline([

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

        ('scaler', StandardScaler())

    ]), numerical_features),

    ('cat', Pipeline([

        ('imputer', SimpleImputer(strategy='most_frequent')),

        ('encoder', OneHotEncoder(handle_unknown='ignore'))

    ]), categorical_features)

])

pipeline = Pipeline([

    ('custom', CustomFeatureTransformer()),

    ('preprocessor', preprocessor)

])
```

```
processed_data = pipeline.fit_transform(df)

num_cols = numerical_features + ['rooms_per_household']

cat_cols =
pipeline.named_steps['preprocessor'].transformers_[1][1].named_steps['encoder'].get_feature_names
_out(categorical_features)

all_columns = num_cols + list(cat_cols)

if processed_data.shape[1] == len(all_columns):

    processed_df = pd.DataFrame(processed_data, columns=all_columns)

else:

    print(f"Mismatch in number of columns: processed data has {processed_data.shape[1]} columns,
expected {len(all_columns)}.")

    print("Adjusted column names:", all_columns)
```

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshot



17/03/24 LAB-03: Implement linear and multi-linear regression on the given data set

x: (week)	y: (Sales in thousands)
1	2
2	4
3	5
4	9

Linear Regression

$$X = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{bmatrix} \quad y = \begin{bmatrix} 2 \\ 4 \\ 5 \\ 9 \end{bmatrix}$$

$$X^T X = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 \end{pmatrix} \times \begin{pmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{pmatrix} = \begin{pmatrix} 4 & 10 \\ 10 & 30 \end{pmatrix}$$

$$(X^T X)^{-1} = \begin{pmatrix} 4 & 10 \\ 10 & 30 \end{pmatrix}^{-1} = \begin{pmatrix} 1.5 & -0.5 \\ -0.5 & 0.2 \end{pmatrix}$$

$$(X^T X)^{-1} X^T = \begin{pmatrix} 1.5 & -0.5 \\ -0.5 & 0.2 \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 \end{pmatrix}$$

$$= \begin{pmatrix} 1 & 0.5 & 0 & -0.5 \\ -0.3 & -0.1 & 0.1 & 0.3 \end{pmatrix}$$

$$((X^T X)^{-1} X^T) Y = \begin{pmatrix} 1 & 0.5 & 0 & -0.5 \\ -0.3 & -0.1 & 0.1 & 0.3 \end{pmatrix} \times \begin{pmatrix} 1 \\ 3 \\ 4 \\ 8 \end{pmatrix} = \begin{pmatrix} -1.5 \\ 2.2 \end{pmatrix}$$

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$y = a_0 + a_1 x$

$y = -1.5 + 2.2x$

The predicted sun cool sales (when $x=5$) is

$y = -1.5 + 2.2 x = 9.5$

	Diameter (x) in inches	Price (y) in dollars	x^2	xy
	8	10	64	80
	10	13	100	130
	12	16	144	192
Sum	30	39	308	402
mean	10	13	102.67	134

$$b_1 = \frac{(134) - 10 \times 39}{102.69 - (10)^2} = 1.5$$

$b_0 = 13 - (1.5) \times 10 = -2$

for $x = 20$

$y = -2 + (1.5 \times 20)$

$= -2 + 30 = 28$

price of 20 inch pizza is \$28

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1) CANADA - per - CAPITAL - income.csv

① No missing values
no need for handling missing values

② Scaling / encoding → not necessary as features are in appropriate numerical formats for linear regression. there were No categorical variables that required encoding

Salary.csv:
① Yes : 2 missing values in Years Experience, filled them with mean as they are numerical values

② Scaling / encoding → not needed / necessary as features are in appropriate numerical format for linear regression. there are were no categorical variables that required encoding

Hiring.csv
① Yes, experience → filled with mode as categorical and testscore → filled with mean as numerical (quantitative)

② ~~We tried~~ to scaling / encoding: we used mapping function to map numerical notations to the years for producing the multiple regression model.

OMIT THIS SPACE

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2) Positive regression line as the year increases, per capita income in US dollars also increases

3) $64629.25

4) Yes State: so one-hot encoding was used. ~~Yes~~ rest of the features were scaled so that the stability of the model and the prediction ~~total~~ could be obtained as State is a categorical variable and rest of the features were numerical variables such as R&D Spend, Administration and Marketing Spend

Code:

Linear Regression:

HOUSING:

```
import pandas as pd
import numpy as np
from sklearn import linear_model
import matplotlib.pyplot as plt
from google.colab import files
uploaded = files.upload()
import pandas as pd
df = pd.read_csv('housing_area_price.csv')
df.head()
plt.xlabel('area')
plt.ylabel('price')
plt.scatter(df.area, df.price, color='red', marker='+')
new_df = df.drop('price', axis='columns')
new_df
price = df.price
price
reg = linear_model.LinearRegression()
reg.fit(new_df, price)
reg.predict([[3300]])
reg.coef_
reg.intercept_
reg = linear_model.LinearRegression()
reg.fit(new_df, price)
reg.predict([[3300]])
```

```
reg.coef_

reg.intercept_

3300 * 135.78767123 + 180616.43835616432

reg.predict([[5000]])
```

SALARY

```
import pandas as pd

import numpy as np

from sklearn import linear_model

import matplotlib.pyplot as plt

from sklearn.linear_model import LinearRegression

from sklearn.model_selection import train_test_split

from google.colab import files

uploaded = files.upload()

df_salary = pd.read_csv('salary.csv')

print(df_salary.head())

print(df_salary.isnull().sum())

mean_years_experience = df_salary['YearsExperience'].mean()

df_salary['YearsExperience'].fillna(mean_years_experience, inplace=True)

print(df_salary.isnull().sum())

plt.scatter(df_salary['YearsExperience'], df_salary['Salary'], color='blue')

plt.xlabel('Years of Experience')

plt.ylabel('Salary')

plt.title('Years of Experience vs Salary')
```

```
plt.show()

X_salary = df_salary['YearsExperience'].values.reshape(-1, 1)  # Independent variable (Years of
Experience)

y_salary = df_salary['Salary'].values  # Dependent variable (Salary)

X_train, X_test, y_train, y_test = train_test_split(X_salary, y_salary, test_size=0.2,
random_state=42)

salary_model = LinearRegression()

salary_model.fit(X_train, y_train)

predicted_salary_12_years = salary_model.predict([[12]])

print(f"Predicted salary for 12 years of experience: ${predicted_salary_12_years[0]:.2f}")

plt.scatter(df_salary['YearsExperience'], df_salary['Salary'], color='blue')

plt.plot(df_salary['YearsExperience'], salary_model.predict(X_salary), color='red')  # Regression line

plt.xlabel('Years of Experience')

plt.ylabel('Salary')

plt.title('Years of Experience vs Salary with Regression Line')

plt.show()
```

CANADA_PER_CAPITA_INCOME:

```
import pandas as pd

import numpy as np

from sklearn import linear_model

import matplotlib.pyplot as plt

from sklearn.linear_model import LinearRegression

from sklearn.model_selection import train_test_split

from google.colab import files
```

```
uploaded = files.upload()

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

print(df.head())

print(df.isnull().sum())

df.dropna(inplace=True)

df.shape

plt.scatter(df['year'], df['per capita income (US$)'], color='blue')

plt.xlabel('Year')

plt.ylabel('Per Capita Income (US$)')

plt.title('Year vs Per Capita Income')

plt.show()

X = df['year'].values.reshape(-1, 1)

y = df['per capita income (US$)'].values

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

model = LinearRegression()

model.fit(X_train, y_train)

predicted_income_2020 = model.predict([[2020]])

print(f"Predicted per capita income for 2020: ${predicted_income_2020[0]:.2f}")

plt.scatter(df['year'], df['per capita income (US$)'], color='blue')

plt.plot(df['year'], model.predict(X), color='red')

plt.xlabel('Year')

plt.ylabel('Per Capita Income (US$)')

plt.title('Year vs Per Capita Income with Regression Line')

plt.show()
```

Multilinear Regression:

HIRING:

```
import pandas as pd

import numpy as np

from sklearn import linear_model

import matplotlib.pyplot as plt

from sklearn.linear_model import LinearRegression

from sklearn.model_selection import train_test_split

from google.colab import files

uploaded = files.upload()

df_hiring = pd.read_csv('hiring.csv')

print("Missing values in the dataset:")

print(df_hiring.isnull().sum())

df_hiring['experience'].fillna(df_hiring['experience'].mode()[0], inplace=True)

df_hiring['test_score(out of 10)'].fillna(df_hiring['test_score(out of 10)'].mean(), inplace=True)

print("Missing values in the dataset:")

print(df_hiring.isnull().sum())

experience_mapping = {

    'two': 2,

    'three': 3,

    'five': 5,

    'seven': 7,

    'eight': 8,

    'ten': 10,
```

```
    'eleven': 11

}

df_hiring['experience'] = df_hiring['experience'].replace(experience_mapping)

X_hiring = df_hiring[['experience', 'test_score(out of 10)', 'interview_score(out of 10)']]

y_hiring = df_hiring['salary($)']

X_train_hiring, X_test_hiring, y_train_hiring, y_test_hiring = train_test_split(

    X_hiring, y_hiring, test_size=0.2, random_state=42)

hiring_model = LinearRegression()

hiring_model.fit(X_train_hiring, y_train_hiring)

predicted_salary_12_10_10 = hiring_model.predict([[12, 10, 10]])

print(f"\nPredicted salary for a candidate with 12 years of experience, 10 test score, and 10 interview score: ${predicted_salary_12_10_10[0]:.2f}")

predicted_salary_2_9_6 = hiring_model.predict([[2, 9, 6]])

print(f"Predicted salary for a candidate with 2 years of experience, 9 test score, and 6 interview score: ${predicted_salary_2_9_6[0]:.2f}")
```

1000_COMPANIES:

```
import pandas as pd

from sklearn.linear_model import LinearRegression

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import OneHotEncoder

from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline

from sklearn.preprocessing import StandardScaler

from google.colab import files

uploaded = files.upload()
```

```
df = pd.read_csv('1000_Companies.csv')
missing_values = df.isnull().sum()
print(f"Missing values in each column:\n{missing_values}")
X = df[['R&D Spend', 'Administration', 'Marketing Spend', 'State']]
y = df['Profit']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
preprocessor = ColumnTransformer(
    transformers=[
        ('state', OneHotEncoder(), ['State']),
        ('num', 'passthrough', ['R&D Spend', 'Administration', 'Marketing Spend'])
    ])
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('scaler', StandardScaler()),
    ('regressor', LinearRegression())
])
pipeline.fit(X_train, y_train)
new_data = pd.DataFrame({
    'R&D Spend': [91694.48],
    'Administration': [515841.3],
    'Marketing Spend': [11931.24],
    'State': ['Florida']
})
predicted_profit = pipeline.predict(new_data)
```

```
print(f"Predicted Profit: {predicted_profit[0]}")
```

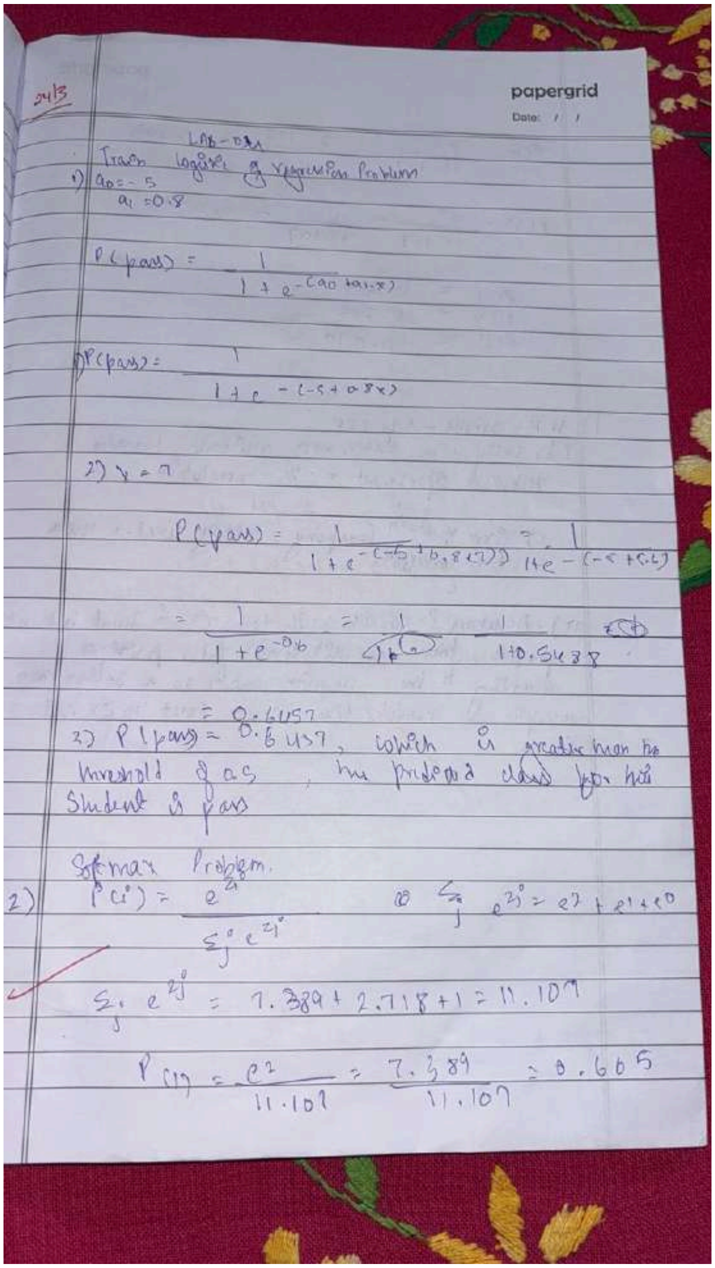
HOME_PRICES_MULTIPLE_LR:

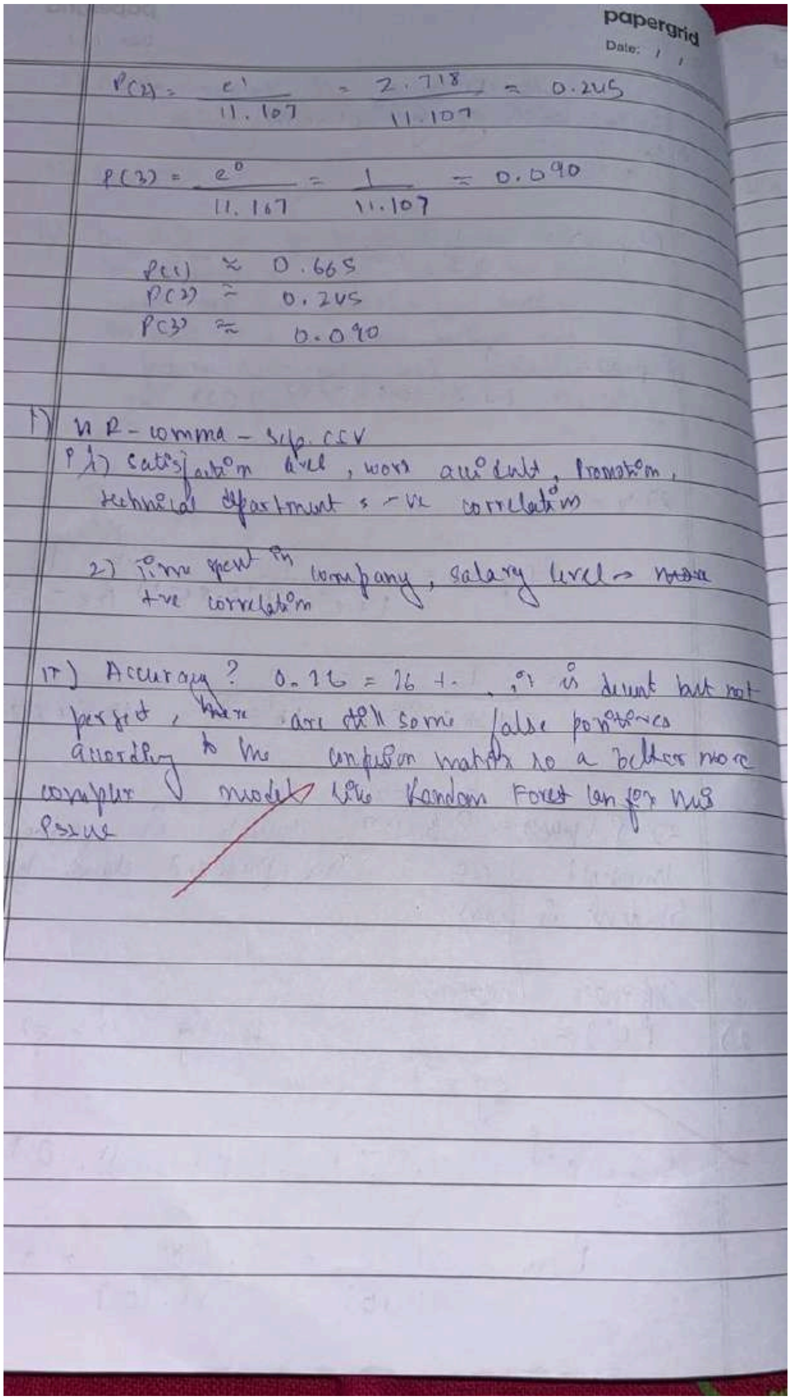
```
import pandas as pd

import numpy as np

from sklearn import linear_model

import matplotlib.pyplot as plt

from google.colab import files

uploaded = files.upload()

import pandas as pd

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

df.head()

df.bedrooms.median()

df.bedrooms = df.bedrooms.fillna(df.bedrooms.median())

dfreg = linear_model.LinearRegression()

reg.fit(df.drop('price', axis='columns'), df.price)

reg.coef_

reg.intercept_

reg.predict([[3000, 3, 40]])

112.06244194*3000 + 23388.88007794*3 + -3231.71790863*40 + 221323.00186540384
```

Program 4

Build Logistic Regression Model for a given dataset

Screenshot





$P(2) = \frac{e^1}{11.107} = \frac{2.718}{11.107} \approx 0.245$

$P(3) = \frac{e^0}{11.107} = \frac{1}{11.107} \approx 0.090$

$P(1) \approx 0.665$
$P(2) \approx 0.245$
$P(3) \approx 0.090$

1) HR-comma-sep.csv
P 1) satisfaction level, work accident, promotion, technical department : -ve correlation

2) time spent in company, salary level → more +ve correlation

1r) Accuracy? 0.76 = 76 %. it is decent but not perfect, there are still some false positives according to the confusion matrix so a better more complex model like Random Forest can fix this issue

Code:

HR_COMMA_SEPARATED.CSV:

```
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.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('HR_comma_sep.csv')
df
df.info()
df.isnull().sum()
label_enc = LabelEncoder()
df["salary"] = label_enc.fit_transform(df["salary"])
plt.figure(figsize=(12, 6))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Feature Correlation Heatmap")
plt.show()
correlation = df.corr()["left"].sort_values(ascending=False)
print("Correlation with Employee Retention:\n", correlation)
plt.figure(figsize=(8, 5))
sns.countplot(x="salary", hue="left", data=df, palette="coolwarm")
plt.xlabel("Salary Level")
plt.ylabel("Number of Employees")
plt.title("Impact of Salary on Employee Retention")
```

```
plt.xticks(ticks=[0, 1, 2], labels=["Low", "Medium", "High"])
plt.legend(["Stayed", "Left"])
plt.show()
plt.figure(figsize=(12, 6))
dept_retention = df.groupby("left")[df.columns[df.columns.str.startswith("Department_")]].sum().T
dept_retention.plot(kind="bar", figsize=(12, 6), colormap="coolwarm", edgecolor="black")
plt.xlabel("Department")
plt.ylabel("Number of Employees")
plt.title("Department-wise Employee Retention")
plt.xticks(rotation=45)
plt.legend(["Stayed", "Left"], title="Employee Status")
plt.show()
features = ["satisfaction_level", "last_evaluation", "number_project",
            "average_montly_hours", "time_spend_company", "salary"]
features += [col for col in df.columns if "Department_" in col]
X = df[features]
y = df["left"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = LogisticRegression(max_iter=500)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy:.2f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(6, 4))

sns.heatmap(cm, annot=True, fmt="d", cmap="coolwarm", xticklabels=["Stayed", "Left"],
yticklabels=["Stayed", "Left"])

plt.xlabel("Predicted")

plt.ylabel("Actual")

plt.title("Confusion Matrix")

plt.show()
```

INSURANCE:

```
import pandas as pd

from sklearn.linear_model import LinearRegression

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import OneHotEncoder

from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline

from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score

from matplotlib import pyplot as plt

from google.colab import files

uploaded = files.upload()

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

df
```

```
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=0.9,
random_state=10)

X_train.shape

X_test

from sklearn.linear_model import LogisticRegression

model = LogisticRegression()

model.fit(X_train, y_train)

X_test

y_test

y_predicted = model.predict(X_test)

y_predicted

model.score(X_test, y_test)

model.predict_proba(X_test)

y_predicted = model.predict([[60]])

y_predicted

model.coef_

model.intercept_

import math

def sigmoid(x):

    return 1 / (1 + math.exp(-x))

def prediction_function(age):

    z = 0.127 * age - 4.973
```

```
    y = sigmoid(z)
    return y
age = 35
prediction_function(age)
```

MULTICLASS:

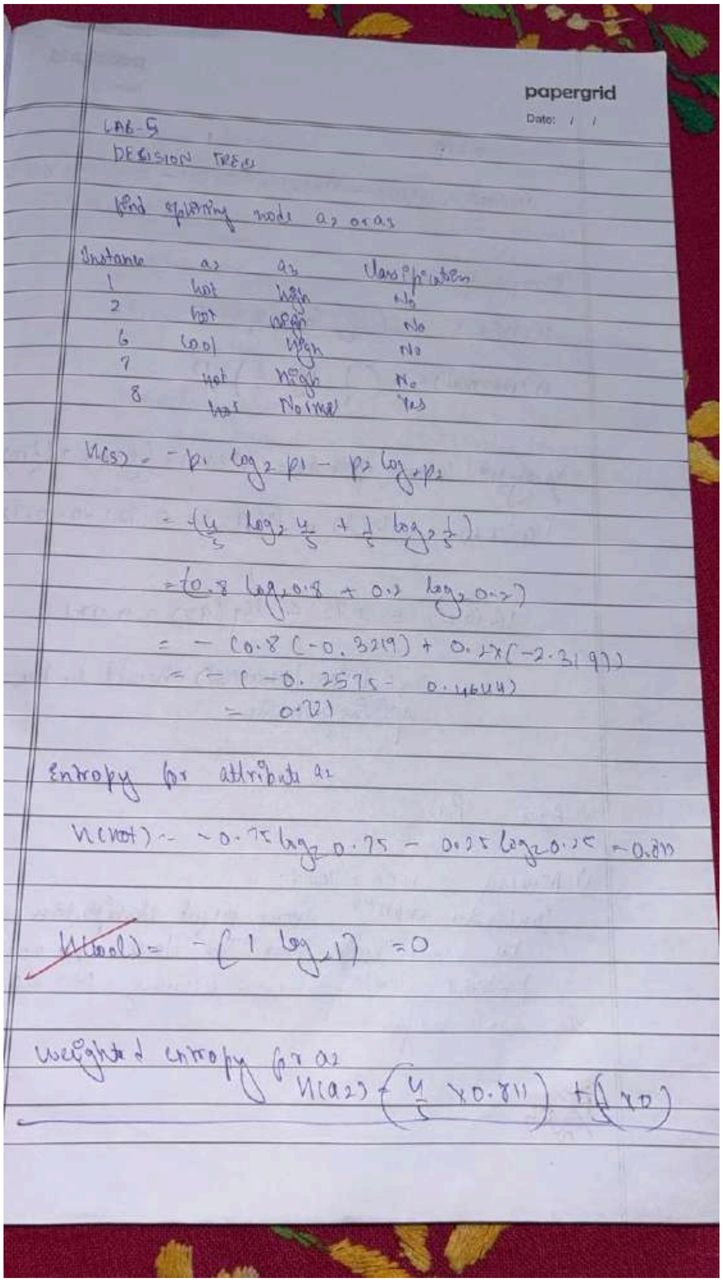
```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn import metrics
import matplotlib.pyplot as plt
iris =  pd.read_csv("/content/drive/MyDrive/Colab Notebooks/ML-Course-6thSem-Feb-2025/Unit-2/iris.csv")
iris.head()
X = iris.drop('species', axis='columns')
y = iris.species  # Target labels (0: Setosa, 1: Versicolor, 2: Virginica)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = LogisticRegression(multi_class='multinomial')
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the Multinomial Logistic Regression model on the test set: {accuracy:.2f}")

confusion_matrix = metrics.confusion_matrix(y_test, y_pred)
```

```
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix,
display_labels=["Setosa", "Versicolor", "Virginica"])

cm_display.plot()

plt.show()
```

Program 5

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

Screenshot:



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LAB-5

DECISION TREE

Find splitting node a_2 or a_3

Instance	a_2	a_3	Classification
1	hot	high	No
2	hot	high	No
6	cool	high	No
7	hot	high	No
8	hot	Normal	Yes

$H(S) = -p_1 \log_2 p_1 - p_2 \log_2 p_2$

$= -(\frac{4}{5} \log_2 \frac{4}{5} + \frac{1}{5} \log_2 \frac{1}{5})$

$= -(0.8 \log_2 0.8 + 0.2 \log_2 0.2)$

$= -(0.8(-0.3219) + 0.2 \times (-2.3197))$

$= -(-0.2575 - 0.4644)$

$= 0.721$

Entropy for attribute a_2

$H(hot) = -0.75 \log_2 0.75 - 0.25 \log_2 0.25 = 0.811$

$H(cool) = -(1 \log_2 1) = 0$

Weighted entropy for a_2

$H(a_2) = (\frac{4}{5} \times 0.811) + (\frac{1}{5} \times 0)$

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$= 0.649$

$IG(a_2) = H(S) - H(a_2) - 0.721 - 0.649 = 0.0$

Entropy for a3

$H(High) = -\left(\frac{4}{4} \log_2 \frac{4}{4}\right) = 0$

$H(Normal) = -\left(\frac{1}{1} \log_2 \frac{1}{1}\right) = 0$

weighted entropy for $a_3 = H(a_3) = \left(\frac{4}{5} \times 0\right) + \left(\frac{1}{5} \times 0\right) = 0$

$IG(a_3) = H(S) - H(a_3) = 0.721 - 0 = 0.721$

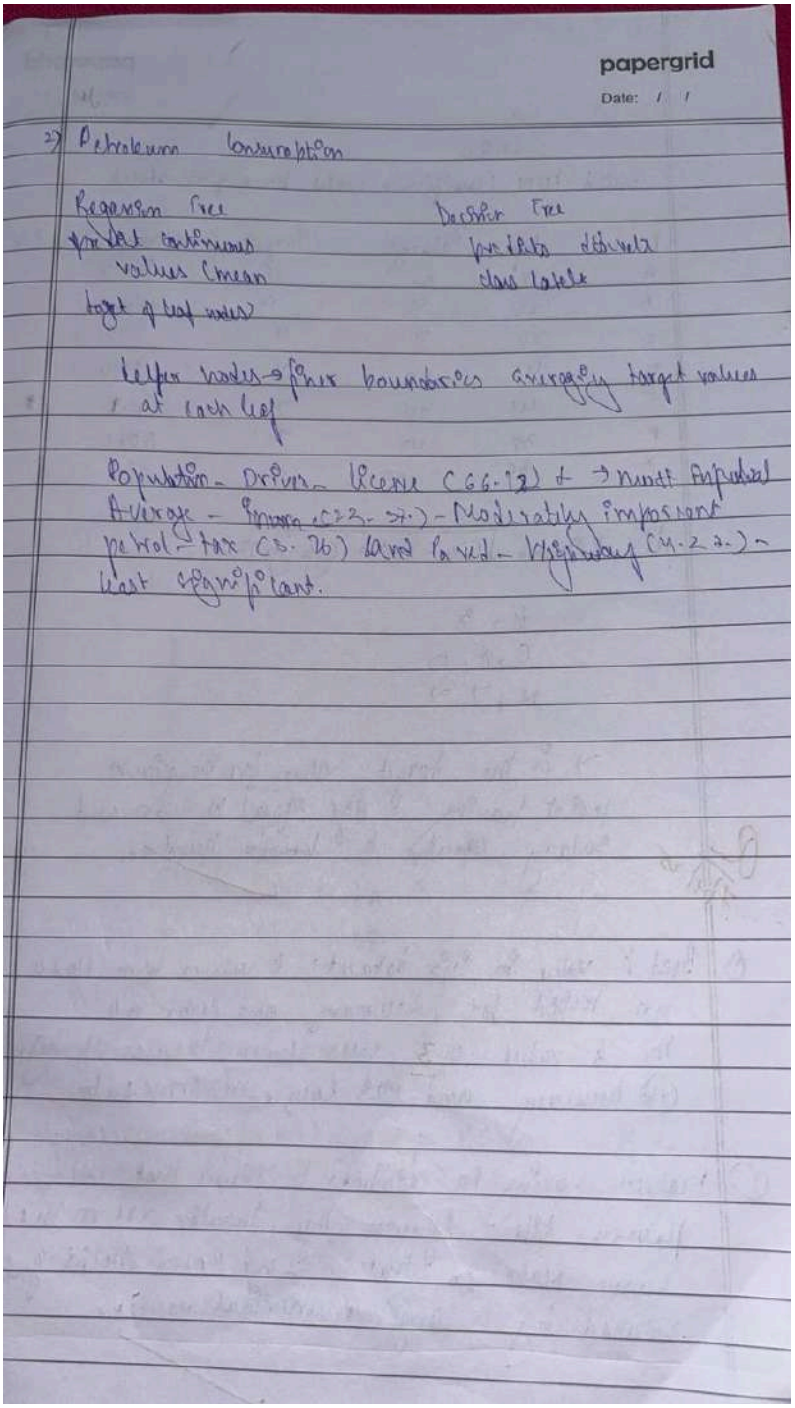
$IG(a_2) = 0.072 < IG(a_3) = 0.721$

a3 (High / Normal) should be the splitting Node

1) ~~Att~~ IRIS

1) Accuracy - 1.00 = 100%.
confusion matrix shows perfect classification with no misclassifications. All classes were correctly predicted, leading to 100% accuracy. No classes were confused

2/3



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Date: / /

2) Petroleum Consumption

Regression Tree
predict continuous
values (mean
target of leaf nodes)

Decision Tree
predicts discrete
class labels

Leaf nodes → their boundaries averaging target values at each leaf

Population - Drivers - license (66.12) & → most important
Average - Income (22.57) - Moderately important
petrol - tax (3.76) and paved - highways (4.22) - least significant.

Code:

PETROLEUM_CONSUMPTION:

```
import pandas as pd

import numpy as np
```

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
from google.colab import files
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree
uploaded = files.upload()
df = pd.read_csv('petrol_consumption.csv')
X = df.drop(columns=['Petrol_Consumption'])
y = df['Petrol_Consumption']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = DecisionTreeRegressor()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
feature_importance = model.feature_importances_
features = X.columns
print("\nFeature Importance:")
for feature, importance in zip(features, feature_importance):
```

```
    print(f"{feature}: {importance:.4f}")
plt.figure(figsize=(8, 5))
plt.barh(features, feature_importance, color='skyblue')
plt.xlabel("Feature Importance Score")
plt.ylabel("Features")
plt.title("Feature Importance for Petrol Consumption Prediction")
plt.show()
plt.figure(figsize=(12, 6))
plot_tree(model, feature_names=features, filled=True, rounded=True)
plt.show()
```

DRUG_TEST:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('drug.csv')
df['Sex'] = df['Sex'].map({'F': 0, 'M': 1})
df['BP'] = df['BP'].map({'LOW': 0, 'NORMAL': 1, 'HIGH': 2})
df['Cholesterol'] = df['Cholesterol'].map({'NORMAL': 0, 'HIGH': 1})
X = df.drop(columns=['Drug'])
y = df['Drug']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = DecisionTreeClassifier()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
print(f"Accuracy Score: {accuracy:.4f}")
print("Confusion Matrix:")
print(conf_matrix)
```

IRIS:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from google.colab import files
uploaded = files.upload()
iris = pd.read_csv('iris.csv')
X = iris.iloc[:, :-1]
y = iris.iloc[:, -1]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
print("Confusion Matrix:")
print(conf_matrix)
```

DECISION TREE CODE:

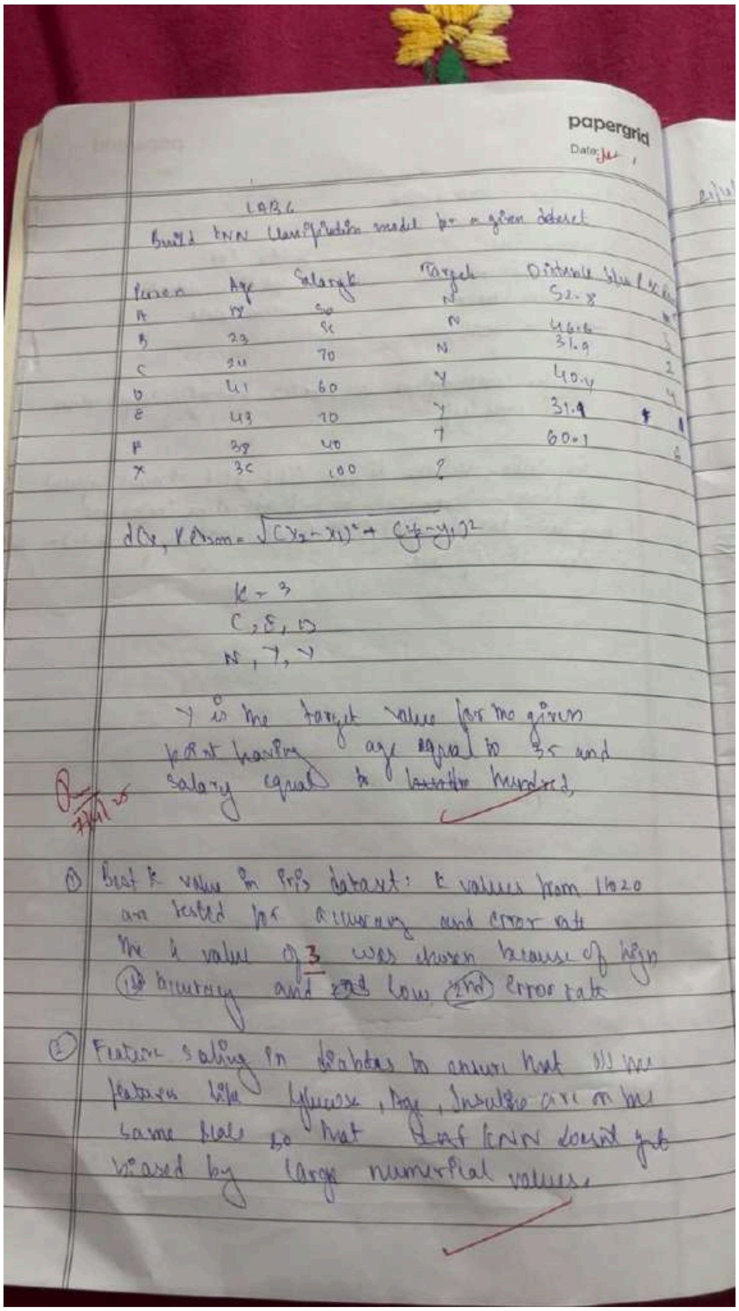
```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt
data = {
    'a1': [True, True, False, False, False, True, True, True, False, False],
    'a2': ['Hot', 'Hot', 'Hot', 'Cool', 'Cool', 'Cool', 'Hot', 'Hot', 'Cool', 'Cool'],
    'a3': ['High', 'High', 'High', 'Normal', 'Normal', 'High', 'High', 'Normal', 'Normal', 'High'],
    'Classification': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'No', 'Yes', 'Yes', 'Yes']
}
df = pd.DataFrame(data)
label_encoders = {}
for column in df.columns:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
```

```
    label_encoders[column] = le
X = df.drop('Classification', axis=1)
y = df['Classification']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
clf = DecisionTreeClassifier(criterion='entropy')
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
print(classification_report(y_test, y_pred, target_names=['No', 'Yes']))
plt.figure(figsize=(12,8))
plot_tree(clf, filled=True, feature_names=X.columns, class_names=['No', 'Yes'])
plt.show()
```

Program 6

Build KNN Classification model for a given dataset.

Screenshot:



LAB 6

Build KNN Classification model for a given dataset

Person	Age	Salary(k)	Target	Distance
A	18	50	N	52.8
B	23	56	N	46.6
C	30	70	N	31.9
D	41	60	Y	40.4
E	43	70	Y	31.4
F	38	40	Y	60.1
x	35	100	?	

$d(x, P) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$

$k = 3$

C, E, D

N, Y, Y

Y is the target value for the given point having age equal to 35 and salary equal to hundred.

① Best k value for this dataset: k values from 1 to 20 are tested for accuracy and error rate. The k value of 3 was chosen because of high (1st) accuracy and low (2nd) error rate.

② Feature scaling in diabetes to ensure that all the features like Glucose, Age, Insulin are on the same scale so that KNN doesn't get biased by large numerical values.

Code:

DIABETES:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('diabetes.csv')
X = df.drop('Outcome', axis=1)
y = df['Outcome']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
print("Accuracy Score:", accuracy)
print("Confusion Matrix:\n", conf_matrix)
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
plt.figure(figsize=(6,4))

sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No Diabetes', 'Diabetes'], yticklabels=['No Diabetes', 'Diabetes'])

plt.xlabel('Predicted')

plt.ylabel('Actual')

plt.title('Confusion Matrix')

plt.show()
```

HEART.CSV:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, ConfusionMatrixDisplay

from google.colab import files

uploaded = files.upload()

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

X = df.drop("target", axis=1)

y = df["target"]

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

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
```

```
X_test_scaled = scaler.transform(X_test)
scores = []
k_values = range(1, 21)
for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_scaled, y_train)
    score = knn.score(X_test_scaled, y_test)
    scores.append(score)
plt.figure(figsize=(10, 6))
plt.plot(k_values, scores, marker='o', linestyle='--')
plt.title('KNN Accuracy for different k values')
plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()
best_k = k_values[np.argmax(scores)]
print(f"Best k: {best_k} with accuracy: {max(scores):.4f}")
best_knn = KNeighborsClassifier(n_neighbors=best_k)
best_knn.fit(X_train_scaled, y_train)
y_pred = best_knn.predict(X_test_scaled)
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=best_knn.classes_)
disp.plot(cmap='Blues')
plt.title('Confusion Matrix')
```

```
plt.show()
report = classification_report(y_test, y_pred, output_dict=False)
print("Classification Report:")
print(report)
```

IRIS.CSV:

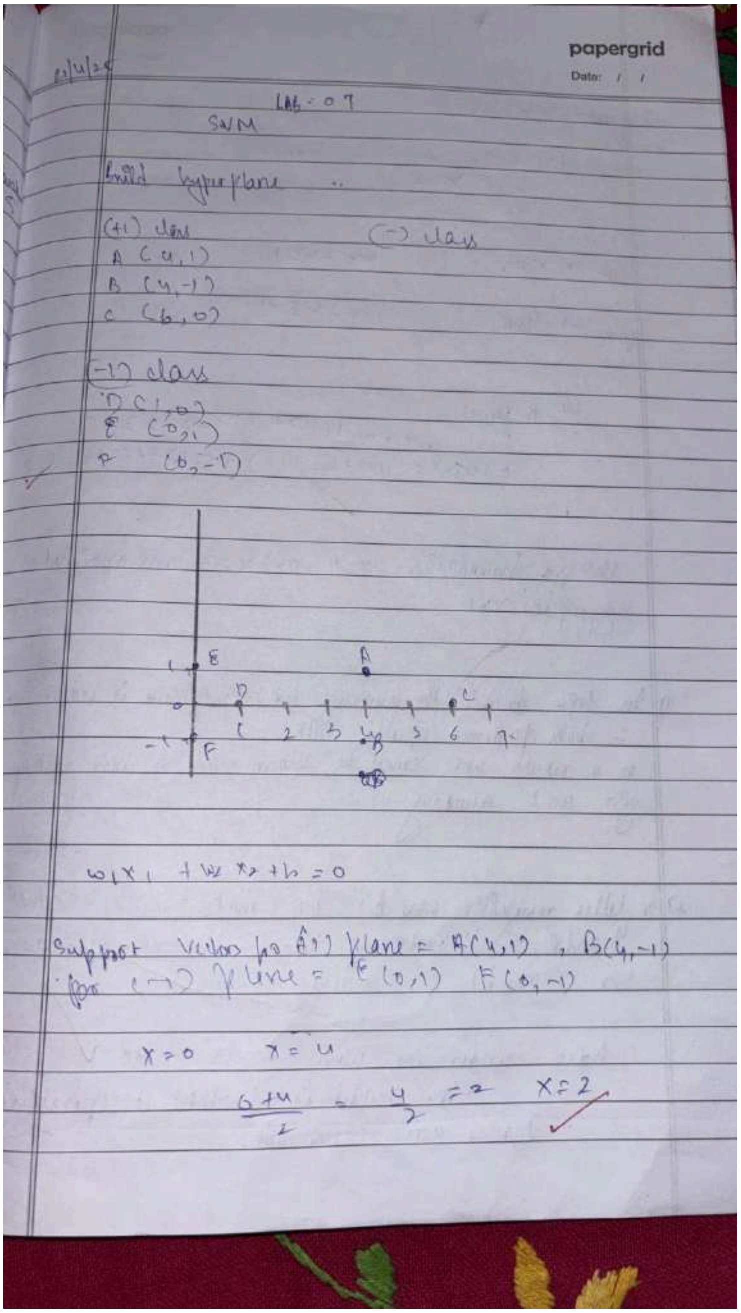
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('iris.csv')
df['species'] = df['species'].astype('category').cat.codes
X = df.drop('species', axis=1)
y = df['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
param_grid = {'n_neighbors': list(range(1, 21))}
knn = KNeighborsClassifier()
grid = GridSearchCV(knn, param_grid, cv=5)
grid.fit(X_train, y_train)
```

```
best_k = grid.best_params_['n_neighbors']
print(f"Best k value: {best_k}")
knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy Score: {accuracy:.2f}")
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(classification_report(y_test, y_pred))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

Program 7

Build Support vector machine model for a given dataset

Screenshot



papergrid

Date: / /

$w = (1, 0)$

$1x_1 + 0x_2 - 2 = 0$ $x_1 = 2$

$x_1 = 2$

for +1 class $wx + b \geq 1$

for -1 class $wx + b \leq -1$

so $A(4, 1)$

$= wx + b = 1(4) + 0(1) - 2 = 2 \geq 1$

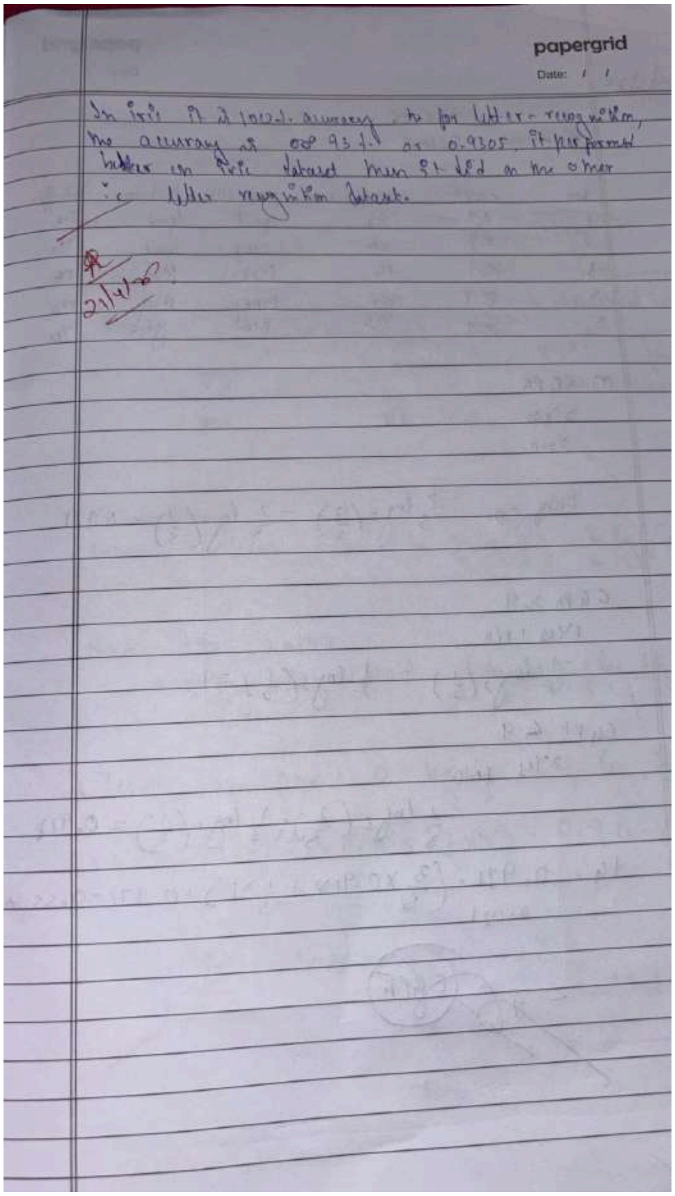
$E(0, 1) = wx + b = 1(0) + 0(1) - 2 = -2 \leq -1$

margin boundaries $x = 1$ and $x = 3$ and optimal hyperplane $x = 2$

1) In Iris dataset: the accuracy for both of them is 100%.
∴ both performed equally well
as a result one cannot be chosen over the other as they both give 100% accuracy

2) In letter recognition.csv: Y vs F and P, S and Z, V and W, Y and R, K and R as some of the examples where the model is getting confused

Area under the curve = 0.99 > 0.95
∴ the model is excellent at separating the classes across thresholds.



papergrid

Date: / /

In iris it is 100% accuracy, but for letter-recognition, the accuracy is ~~of~~ 93% or 0.9305. it performed better on iris dataset than it did on the other i.e. letter recognition dataset.

21/4/2

Code:

IRIS.CSV:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import LabelEncoder
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('iris.csv')
le = LabelEncoder()
df['species'] = le.fit_transform(df['species'])
X = df.drop('species', axis=1)
y = df['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
svm_linear = SVC(kernel='linear')
svm_linear.fit(X_train, y_train)
y_pred_linear = svm_linear.predict(X_test)
print("Linear Kernel SVM:")
print("Accuracy:", accuracy_score(y_test, y_pred_linear))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_linear))
svm_rbf = SVC(kernel='rbf')
svm_rbf.fit(X_train, y_train)
y_pred_rbf = svm_rbf.predict(X_test)
print("\nRBF Kernel SVM:")
print("Accuracy:", accuracy_score(y_test, y_pred_rbf))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rbf))
def plot_confusion_matrix(y_true, y_pred, kernel_name):
```

```
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(5, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=le.classes_, yticklabels=le.classes_)
    plt.title(f'Confusion Matrix - {kernel_name} Kernel')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()
plot_confusion_matrix(y_test, y_pred_linear, "Linear")
plot_confusion_matrix(y_test, y_pred_rbf, "RBF")
```

LETTER_RECOGNITION.CSV:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelBinarizer
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score, roc_curve
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('letter-recognition.csv')
X = df.drop('letter', axis=1)
y = df['letter']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
svm_model = SVC(kernel='rbf', probability=True)
svm_model.fit(X_train, y_train)
y_pred = svm_model.predict(X_test)
acc = accuracy_score(y_test, y_pred)
print("Accuracy:", acc)
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(14, 10))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=sorted(df['letter'].unique()),
            yticklabels=sorted(df['letter'].unique()))
plt.title("Confusion Matrix - SVM on Letter Recognition")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
lb = LabelBinarizer()
y_test_bin = lb.fit_transform(y_test)
y_score = svm_model.predict_proba(X_test)
auc = roc_auc_score(y_test_bin, y_score, average="macro", multi_class="ovr")
print("AUC Score (macro-averaged):", auc)
fpr = {}
tpr = {}
plt.figure(figsize=(10, 7))
for i, letter in enumerate(lb.classes_[:5]):
```

```
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    plt.plot(fpr[i], tpr[i], label=f'ROC curve for {letter}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves (First 5 Letters)')
plt.legend()
plt.grid(True)
plt.show()
```

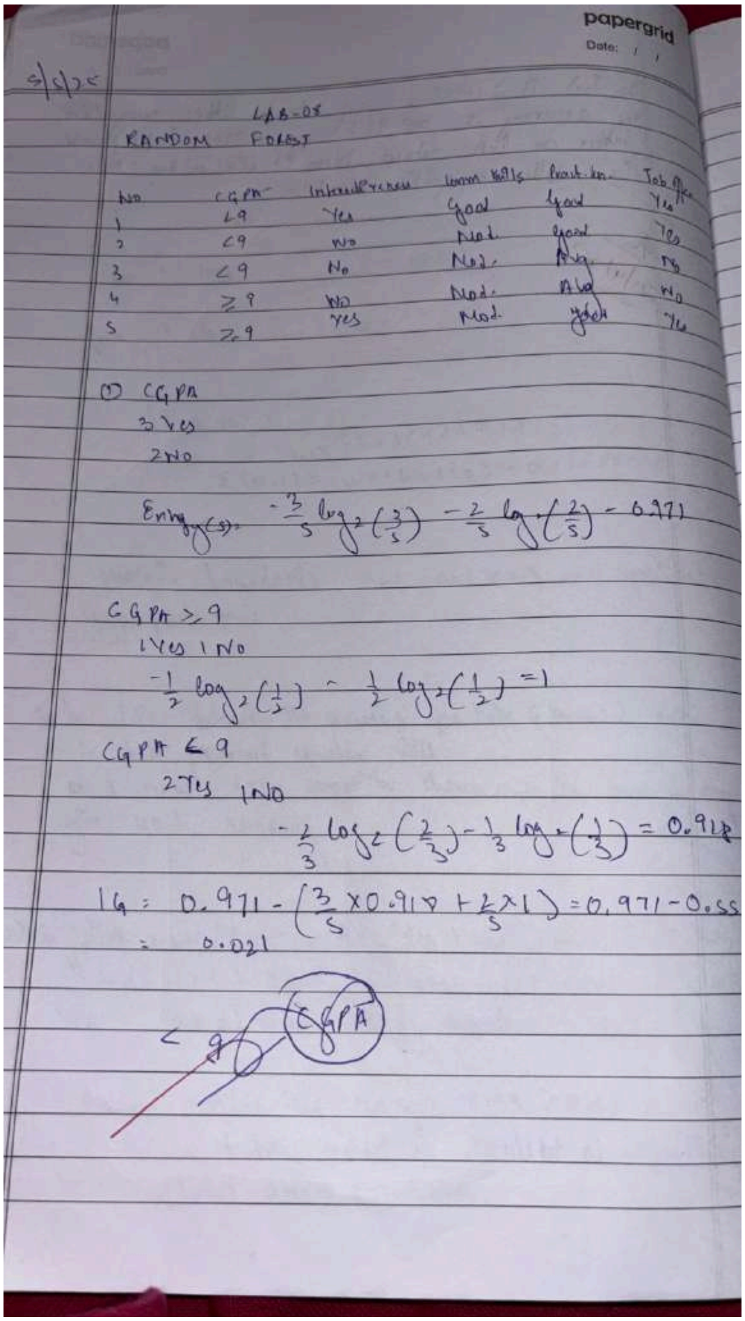
SVM,BASICS,CSV:

```
import pandas as pd
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
digits = load_digits()
df = pd.DataFrame(digits.data, digits.target)
df['target'] = digits.target
X_train, X_test, y_train, y_test = train_test_split(df.drop('target', axis='columns'), df['target'],
test_size=0.3)
rbf_model = SVC(kernel='rbf')
rbf_model.fit(X_train, y_train)
print("RBF Kernel Accuracy:", rbf_model.score(X_test, y_test))
linear_model = SVC(kernel='linear')
linear_model.fit(X_train, y_train)
print("Linear Kernel Accuracy:", linear_model.score(X_test, y_test))
```

Program 8

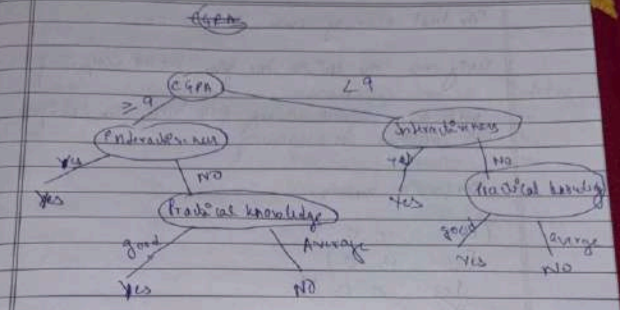
Implement Random forest ensemble method on a given dataset

Screenshot



papergrid

Date: / /



2) Interactiveness

Entropy 3Yes 2No $= -\frac{3}{5}\log_2\left(\frac{3}{5}\right) - \frac{2}{5}\log_2\left(\frac{2}{5}\right) = 0.971$

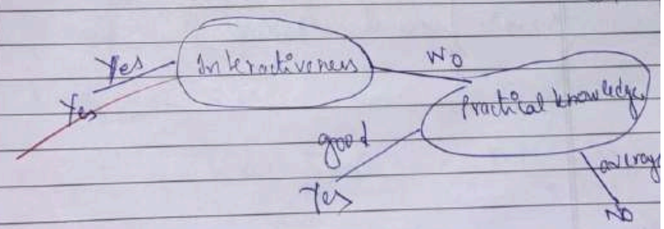
No ⇒ (1Yes, 2No)

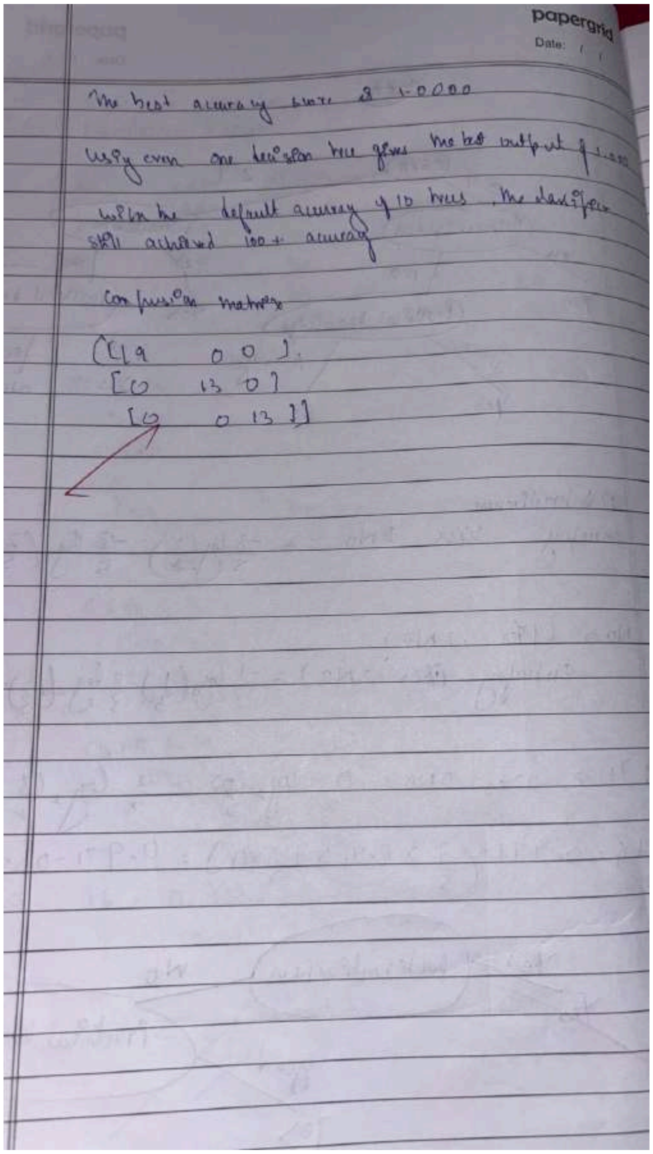
Entropy (1Yes 2No) $= -\frac{1}{3}\log_2\left(\frac{1}{3}\right) - \frac{2}{3}\log_2\left(\frac{2}{3}\right) = 0.918$

Yes ⇒ 2Yes 0No $= \frac{0}{2} - \log_2\left(\frac{0}{2}\right) - \frac{2}{2}\log_2\left(\frac{2}{2}\right) = 0$

$IG = 0.971 - \left(\frac{3}{5} \times 0.918 + \frac{2}{5} \times 0\right) = 0.971 - 0.550 = \cancel{0.420}$

0.421




The best accuracy score is 1.0000
Using even one decision tree gives the best output of 1.000
With the default accuracy of 10 trees, the classifier still achieved 100% accuracy
Confusion matrix
[[19 0 0].
[0 13 0]
[0 0 13]]

Code:

IRIS.CSV:

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.ensemble import RandomForestClassifier

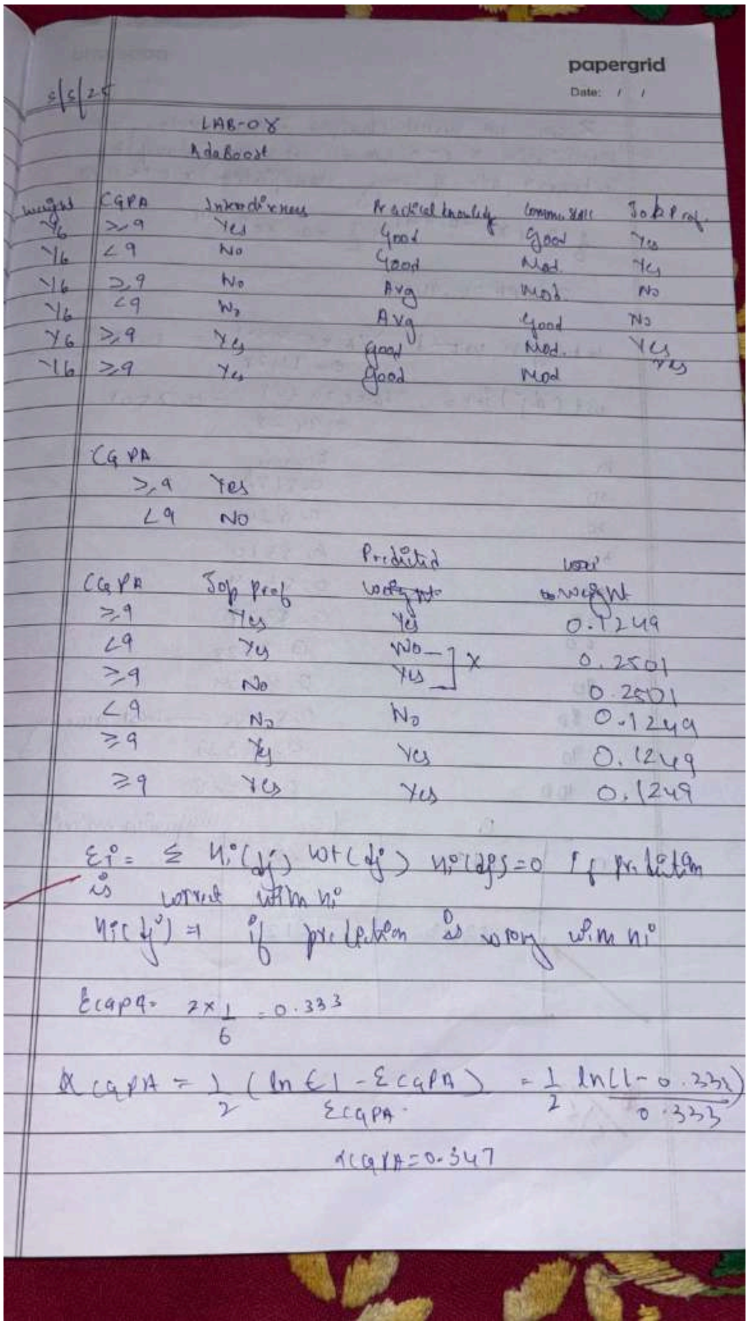
```
from sklearn.metrics import accuracy_score, confusion_matrix
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('iris.csv')
X = df.drop('species', axis=1)
y = df['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
rf_default = RandomForestClassifier(n_estimators=10, random_state=42)
rf_default.fit(X_train, y_train)
y_pred_default = rf_default.predict(X_test)
default_score = accuracy_score(y_test, y_pred_default)
print(f"Default RF Accuracy (n_estimators=10): {default_score:.4f}")
scores = []
tree_range = range(1, 101)
for n in tree_range:
    rf = RandomForestClassifier(n_estimators=n, random_state=42)
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    scores.append(acc)
best_score = max(scores)
best_n = tree_range[scores.index(best_score)]
print(f"Best Accuracy: {best_score:.4f} with {best_n} trees")
plt.figure(figsize=(10, 5))
```

```
plt.plot(tree_range, scores, marker='o')

plt.title('Random Forest Accuracy vs Number of Trees')

plt.xlabel('Number of Trees')

plt.ylabel('Accuracy')

plt.grid(True)

plt.show()

rf_best = RandomForestClassifier(n_estimators=1, random_state=42)

rf_best.fit(X_train, y_train)

y_pred_best = rf_best.predict(X_test)

cm = confusion_matrix(y_test, y_pred_best)

print("Confusion Matrix:\n", cm)

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=rf_best.classes_,
yticklabels=rf_best.classes_)

plt.title("Confusion Matrix")

plt.xlabel("Predicted Label")

plt.ylabel("True Label")

plt.show()
```

Program 9

Implement Boosting ensemble method on a given dataset.

Screenshot



papergrid

Date: / /

5/5/25

LAB-08

AdaBoost

weight	CGPA	Interactiveness	Practical knowledge	Commu. skill	Job Prof.
1/6	>,9	Yes	Good	Good	Yes
1/6	<9	No	Good	Mod.	Yes
1/6	>,9	No	Avg	Mod.	No
1/6	<9	No	Avg	Good	No
1/6	>,9	Yes	Good	Mod.	Yes
1/6	>,9	Yes	Good	Mod	Yes

CGPA

>,9 Yes

<9 No

CGPA	Job Prof	Predicted weight	New weight
>,9	Yes	Yes	0.1249
<9	Yes	No	0.2501
>,9	No	Yes	0.2501
<9	No	No	0.1249
>,9	Yes	Yes	0.1249
>,9	Yes	Yes	0.1249

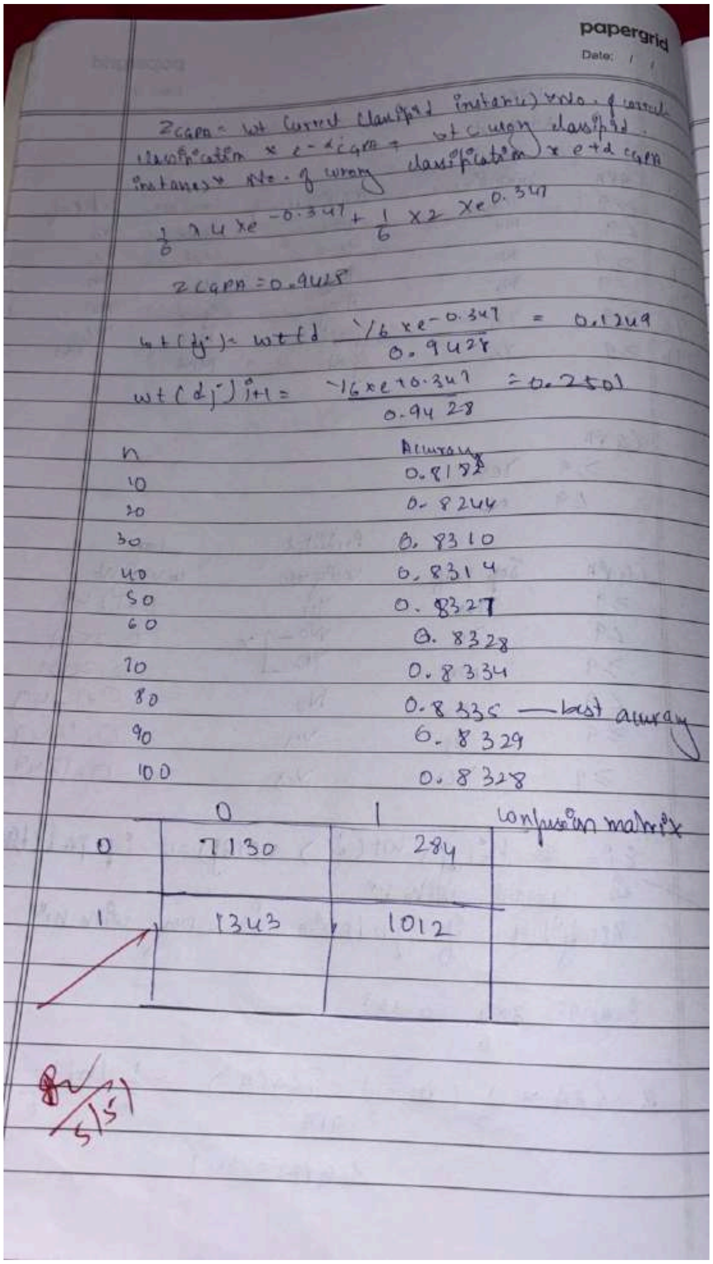
$\varepsilon_i = \sum w_i(x_j)\, wt(x_j)$ $w_i(x_j) = 0$ if prediction is correct with h_i

$w_i(x_j) = 1$ if prediction is wrong with h_i

$\varepsilon_{CGPA} = 2 \times \frac{1}{6} = 0.333$

$\alpha_{CGPA} = \frac{1}{2}\left(\ln \frac{1 - \varepsilon_{CGPA}}{\varepsilon_{CGPA}}\right) = \frac{1}{2} \ln \frac{(1 - 0.333)}{0.333}$

$\alpha_{CGPA} = 0.347$



Z_{CAPA} = wt correct classified instances × No. of correct classification × $e^{-\alpha_{CAPA}}$ + wt of wrong classified instances × No. of wrong classification × $e^{+\alpha_{CAPA}}$

$\frac{1}{6} \times 4 \times e^{-0.347} + \frac{1}{6} \times 2 \times e^{0.347}$

$Z_{CAPA} = 0.9428$

$wt(d_j) = wt(d_j) \; \frac{1/6 \times e^{-0.347}}{0.9428} = 0.1249$

$wt(d_j)_{i+1} = \frac{1/6 \times e^{+0.347}}{0.9428} = 0.2501$

n	Accuracy
10	0.8182
20	0.8244
30	0.8310
40	0.8314
50	0.8327
60	0.8328
70	0.8334
80	0.8335 — best accuracy
90	0.8329
100	0.8328

confusion matrix

	0	1
0	7130	284
1	1343	1012

5/5

Code:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.ensemble import AdaBoostClassifier
```

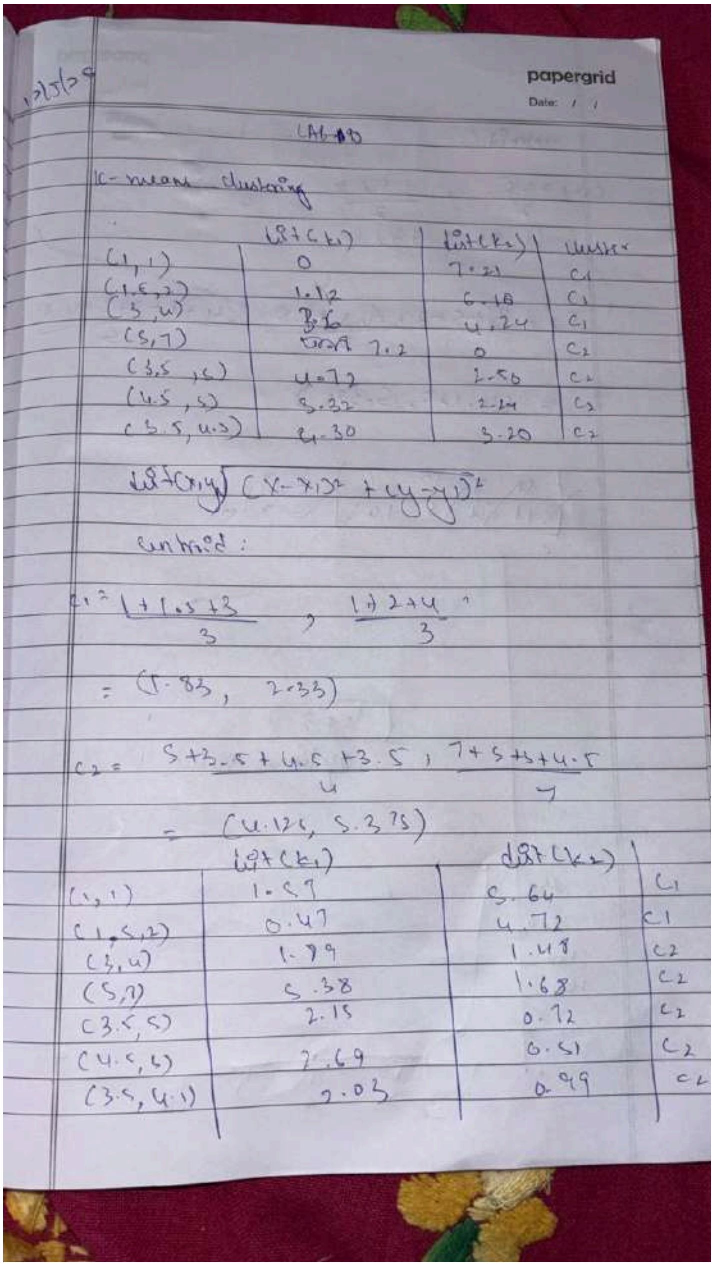
```
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('income.csv')
X = df.drop("income_level", axis=1)
y = df["income_level"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model_10 = AdaBoostClassifier(n_estimators=10, random_state=42)
model_10.fit(X_train, y_train)
y_pred_10 = model_10.predict(X_test)
score_10 = accuracy_score(y_test, y_pred_10)
print(f"Accuracy with 10 estimators: {score_10:.4f}")
estimator_range = range(10, 101, 10)
scores = []
for n in estimator_range:
    model = AdaBoostClassifier(n_estimators=n, random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    scores.append(acc)
    print(f"n_estimators={n}, Accuracy={acc:.4f}")
plt.figure(figsize=(10, 6))
plt.plot(estimator_range, scores, marker='o')
plt.title("AdaBoost Accuracy vs Number of Estimators")
```

```
plt.xlabel("Number of Estimators")
plt.ylabel("Accuracy")
plt.grid(True)
plt.show()
best_n = estimator_range[scores.index(max(scores))]
best_score = max(scores)
print(f"\nBest Accuracy: {best_score:.4f} with n_estimators={best_n}")
best_model = AdaBoostClassifier(n_estimators=best_n, random_state=42)
best_model.fit(X_train, y_train)
y_best_pred = best_model.predict(X_test)
cm = confusion_matrix(y_test, y_best_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.title(f"Confusion Matrix (n_estimators = {best_n})")
plt.show()
```

Program 10

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

Screenshot



papergrid

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LAB 10

k-means clustering

	dist (k1)	dist (k2)	cluster
(1, 1)	0	7.21	C1
(1.5, 2)	1.12	6.10	C1
(3, 4)	3.6	4.24	C1
(5, 7)	7.2	0	C2
(3.5, 5)	4.72	2.50	C2
(4.5, 5)	5.32	2.24	C2
(3.5, 4.5)	4.30	3.20	C2

dist(x,y) $\sqrt{(x-x_1)^2 + (y-y_1)^2}$

centroid :

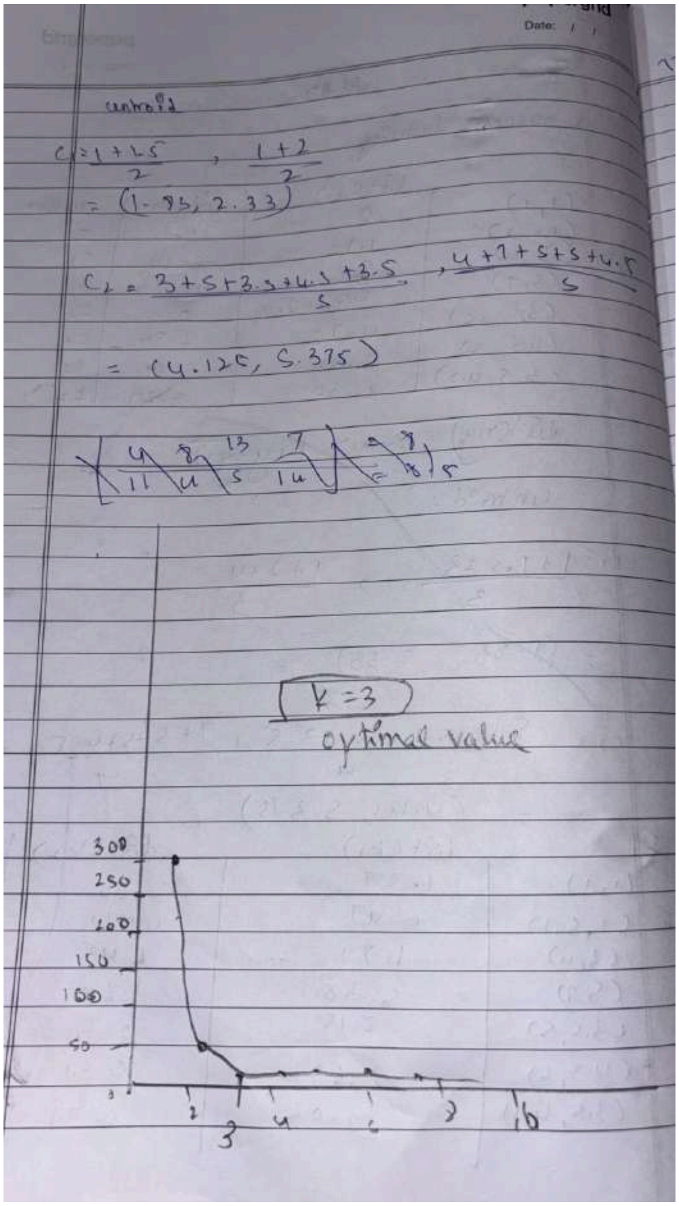
$c_1 = \frac{1+1.5+3}{3}, \frac{1+2+4}{3}$

$= (1.83, 2.33)$

$c_2 = \frac{5+3.5+4.5+3.5}{4}, \frac{7+5+5+4.5}{4}$

$= (4.125, 5.375)$

	dist (k1)	dist (k2)	
(1, 1)	1.57	5.64	C1
(1.5, 2)	0.47	4.72	C1
(3, 4)	1.79	1.48	C2
(5, 7)	5.38	1.68	C2
(3.5, 5)	2.15	0.72	C2
(4.5, 5)	2.69	0.51	C2
(3.5, 4.5)	2.03	0.99	C2



Code:

IRIS.:

import pandas as pd

import matplotlib.pyplot as plt

from sklearn.cluster import KMeans

from sklearn.preprocessing import StandardScaler

from google.colab import files

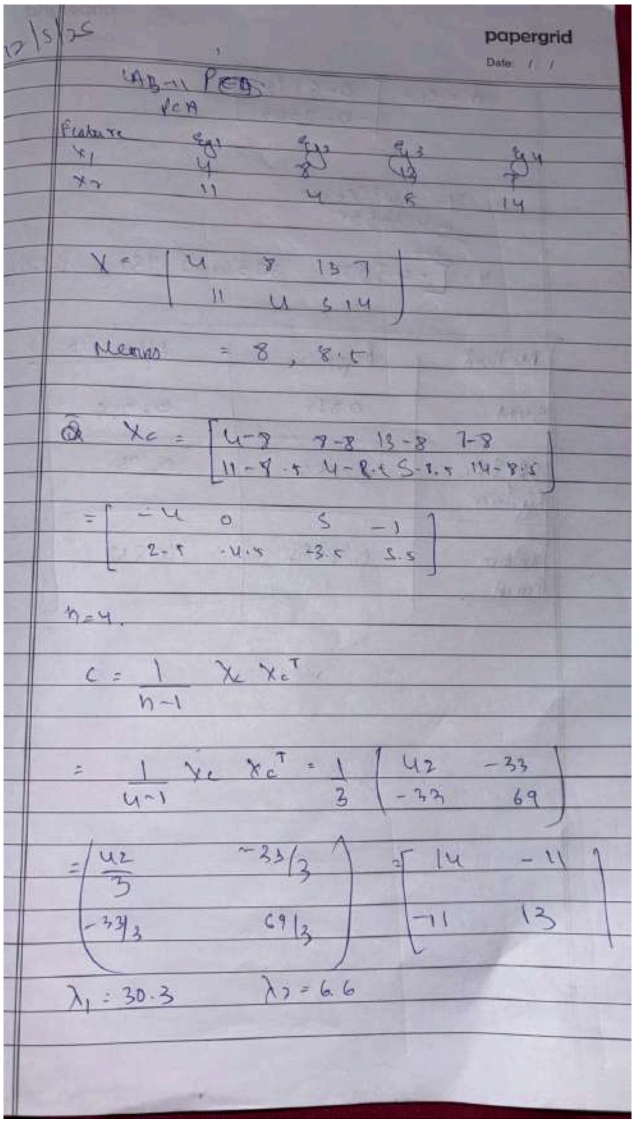
```
uploaded = files.upload()

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

X = df[['petal_length', 'petal_width']]

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)

inertia = []

k_range = range(1, 11)

for k in k_range:

    kmeans = KMeans(n_clusters=k, random_state=42)

    kmeans.fit(X_scaled)

    inertia.append(kmeans.inertia_)

plt.figure(figsize=(8, 5))

plt.plot(k_range, inertia, marker='o')

plt.title("Elbow Method for Optimal k")

plt.xlabel("Number of Clusters (k)")

plt.ylabel("Inertia")

plt.grid(True)

plt.show()

optimal_k = 3

kmeans = KMeans(n_clusters=optimal_k, random_state=42)

clusters = kmeans.fit_predict(X_scaled)

df['cluster'] = clusters

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],

            s=200, c='black', marker='X', label='Centroids')
```

```python
plt.title("K-Means Clusters on Petal Features")
plt.xlabel("Petal Length (scaled)")
plt.ylabel("Petal Width (scaled)")
plt.legend()
plt.grid(True)
plt.show()
```

Program 11

Implement Dimensionality reduction using Principal Component Analysis (PCA) method.

Screenshot



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LAB-11 PCA

PCA

Feature	Eg1	Eg2	Eg3	Eg4
x_1	4	8	13	7
x_2	11	4	5	14

$$X = \begin{bmatrix} 4 & 8 & 13 & 7 \\ 11 & 4 & 5 & 14 \end{bmatrix}$$

Means = 8, 8.5

$$X_c = \begin{bmatrix} 4-8 & 8-8 & 13-8 & 7-8 \\ 11-8.5 & 4-8.5 & 5-8.5 & 14-8.5 \end{bmatrix}$$

$$= \begin{bmatrix} -4 & 0 & 5 & -1 \\ 2.5 & -4.5 & -3.5 & 5.5 \end{bmatrix}$$

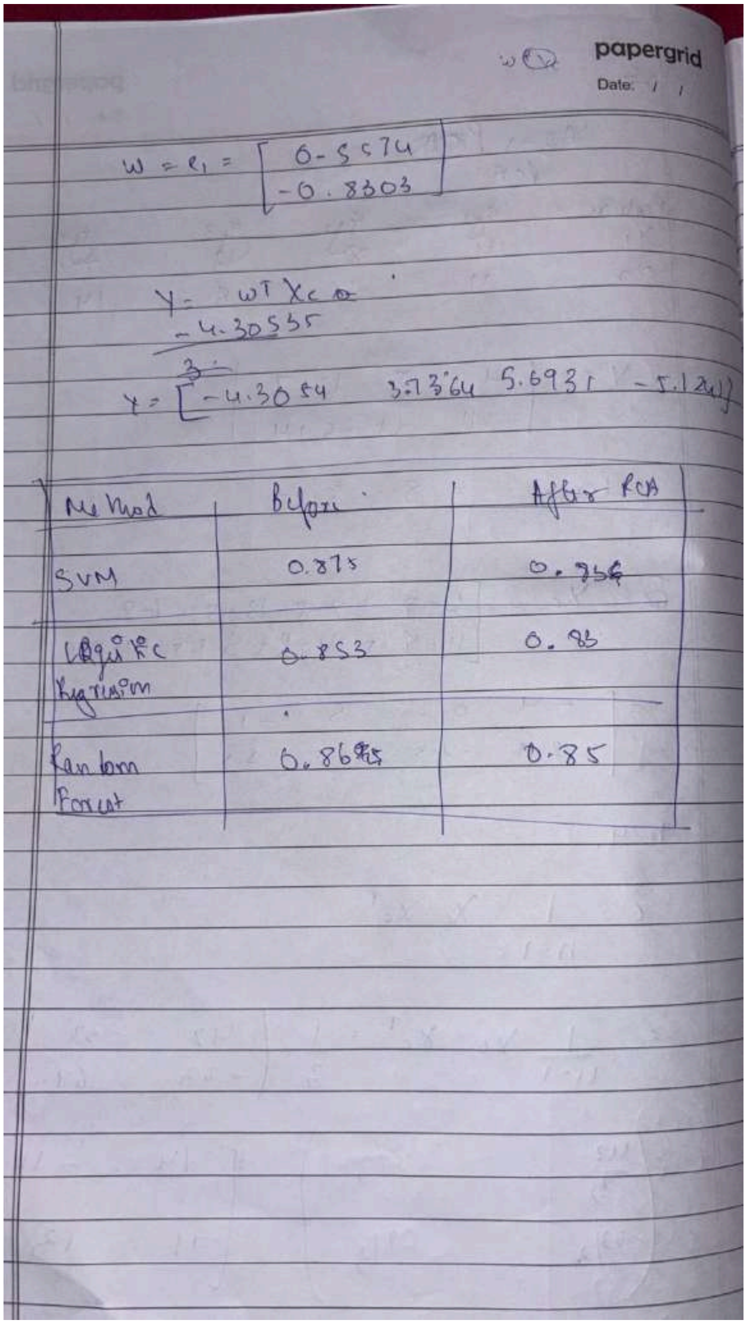
$n = 4.$

$$C = \frac{1}{n-1} X_c X_c^T$$

$$= \frac{1}{4-1} X_c X_c^T = \frac{1}{3} \begin{pmatrix} 42 & -33 \\ -33 & 69 \end{pmatrix}$$

$$= \begin{pmatrix} \frac{42}{3} & -33/3 \\ -33/3 & 69/3 \end{pmatrix} = \begin{bmatrix} 14 & -11 \\ -11 & 13 \end{bmatrix}$$

$\lambda_1 = 30.3 \qquad \lambda_2 = 6.6$



$$w = e_1 = \begin{bmatrix} 0.5574 \\ -0.8303 \end{bmatrix}$$

$$Y = w^T X_c$$

$$-4.30535$$

$$Y = [-4.3054 \quad 3.7364 \quad 5.6931 \quad -5.1241]$$

Method	Before	After PCA
SVM	0.875	0.756
Logistic Regression	0.853	0.85
Random Forest	0.865	0.85

Code:

HEART.

```
import pandas as pd

import numpy as np

from sklearn.preprocessing import LabelEncoder, StandardScaler

from sklearn.model_selection import train_test_split
```

```
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('heart.csv')
label_encoder = LabelEncoder()
df['Sex'] = label_encoder.fit_transform(df['Sex'])
df['FastingBS'] = label_encoder.fit_transform(df['FastingBS'])
df['ExerciseAngina'] = label_encoder.fit_transform(df['ExerciseAngina'])
df['HeartDisease'] = label_encoder.fit_transform(df['HeartDisease'])
print(df.head())
df = pd.get_dummies(df, columns=['ChestPainType', 'RestingECG', 'ST_Slope'], drop_first=True)
print(df.head())
X = df.drop('HeartDisease', axis=1)
y = df['HeartDisease']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
print(X_scaled[:5])
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

```
svm_model = SVC()

svm_model.fit(X_train, y_train)

y_pred_svm = svm_model.predict(X_test)

accuracy_svm = accuracy_score(y_test, y_pred_svm)

print(f"SVM Accuracy: {accuracy_svm}")

log_reg_model = LogisticRegression()

log_reg_model.fit(X_train, y_train)

y_pred_log_reg = log_reg_model.predict(X_test)

accuracy_log_reg = accuracy_score(y_test, y_pred_log_reg)

print(f"Logistic Regression Accuracy: {accuracy_log_reg}")

rf_model = RandomForestClassifier()

rf_model.fit(X_train, y_train)

y_pred_rf = rf_model.predict(X_test)

accuracy_rf = accuracy_score(y_test, y_pred_rf)

print(f"Random Forest Accuracy: {accuracy_rf}")

pca = PCA(n_components=5)

X_train_pca = pca.fit_transform(X_train)

X_test_pca = pca.transform(X_test)

print(f"Explained variance ratio by PCA: {pca.explained_variance_ratio_}")

svm_model_pca = SVC()

svm_model_pca.fit(X_train_pca, y_train)

y_pred_svm_pca = svm_model_pca.predict(X_test_pca)

accuracy_svm_pca = accuracy_score(y_test, y_pred_svm_pca)

print(f"SVM Accuracy with PCA: {accuracy_svm_pca}")
```

```
log_reg_model_pca = LogisticRegression()
log_reg_model_pca.fit(X_train_pca, y_train)
y_pred_log_reg_pca = log_reg_model_pca.predict(X_test_pca)
accuracy_log_reg_pca = accuracy_score(y_test, y_pred_log_reg_pca)
print(f"Logistic Regression Accuracy with PCA: {accuracy_log_reg_pca}")
rf_model_pca = RandomForestClassifier()
rf_model_pca.fit(X_train_pca, y_train)
y_pred_rf_pca = rf_model_pca.predict(X_test_pca)
accuracy_rf_pca = accuracy_score(y_test, y_pred_rf_pca)
print(f"Random Forest Accuracy with PCA: {accuracy_rf_pca}")
print("\nAccuracy Comparison:")
print(f"SVM Accuracy: {accuracy_svm}")
print(f"Logistic Regression Accuracy: {accuracy_log_reg}")
print(f"Random Forest Accuracy: {accuracy_rf}")
print(f"SVM Accuracy with PCA: {accuracy_svm_pca}")
print(f"Logistic Regression Accuracy with PCA: {accuracy_log_reg_pca}")
print(f"Random Forest Accuracy with PCA: {accuracy_rf_pca}")
```