MANAV RACHNA UNIVERSITY

SUPERVISED LEARNING

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⍰ Program 1

Write a python code to demonstrate commands for numpy and pandas.

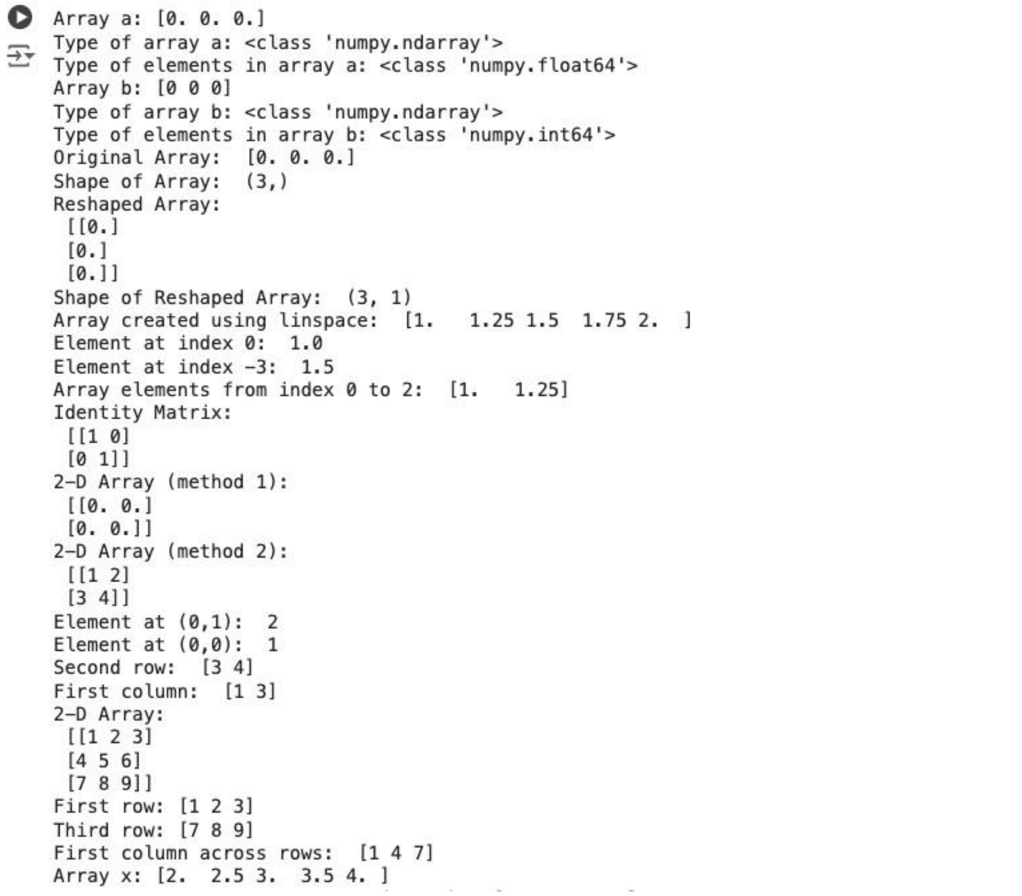
```
# Demonstrate numpy commands
# Import necessary libraries
import numpy as np

# Creating arrays with zeros a = np.zeros(3)  #
1D array of zeros print("Array a:", a)
print("Type of array a:", type(a)) print("Type of
elements in array a:", type(a[0]))

b = np.zeros(3, dtype=int)  # 1D array of zeros with integer type
print("Array b:", b) print("Type of array b:", type(b))
print("Type of elements in array b:", type(b[0]))

# Reshape example z = np.zeros(3)
print("Original Array: ", z)
print("Shape of Array: ", z.shape)
z.shape = (3, 1)  # Reshape array to 5x1
print("Reshaped Array:\n", z) print("Shape
of Reshaped Array: ", z.shape)

# Creating an array using linspace z =
np.linspace(1, 2, 5) print("Array created
using linspace: ", z)

# Accessing array elements with positive and negative indexing
print("Element at index 0: ", z[0]) print("Element at index -
3: ", z[-3])  print("Array elements from index 0 to 2: ",
z[0:2])

# Identity matrix i =
np.identity(2, dtype=int)
print("Identity Matrix:\n", i)

# Creating a 2D matrix in two different ways
z = np.zeros((2, 2))  # 2D array of zeros
print("2-D Array (method 1):\n", z)

y = np.array([[1, 2], [3, 4]])  # Manually defined 2D array
print("2-D Array (method 2):\n", y)

# Accessing elements with index
print("Element at (0,1): ", y[0, 1])
print("Element at (0,0): ", y[0, 0])

# Slicing in 2D arrays
print("Second row: ", y[1, :])
print("First column: ", y[:, 0])

H = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])
print("2-D Array:\n", H) print("First row:",
H[0, :]) print("Third row:", H[2, :])
print("First column across rows: ", H[:, 0])

# Access elements at specified indices x = np.linspace(2,
4, 5) indices = np.array((0, 2, 3)) print("Array x:", x)
print("Elements at specified indices(0,2,3): ", x[indices])

# Boolean array d = np.array([0, 1, 2, 0, 0], dtype=bool)  # Every non-zero is
True, 0 is False print("Boolean Array d:", d)

# Sorting and basic array statistics a = np.array([17,
11, 15, 19, 24, 28, 26, 37, 35, 40])
a.sort() print("Original
Array:", a) print("Sorted
Array:", a) print("Sum:",
a.sum()) print("Min:",
a.min()) print("Max:",
a.max()) print("Argmin
(index of min):",
a.argmin()) print("Argmax
(index of max):",
a.argmax())
print("Cumulative Sum:",
a.cumsum())
print("Cumulative
Product:", a.cumprod())
print("Mean:", a.mean())
print("Median:",
np.median(a))
print("Variance:", a.var())
print("Standard
Deviation:", a.std())
print("Searchsorted (insert
position for 25):",
a.searchsorted(25))

# Array arithmetic operations
a = np.array([1, 2, 3, 4]) b
= np.array([5, 6, 7, 8])
print("a + b:", a + b)
print("a * b:", a * b)
print("a + 10:", a + 10)
print("a * 10:", a * 10)

# Matrix operations
X = np.array([[1, 2, 3], [4, 5, 6], [5, 6, 7]]) Y
= np.array([[7, 8, 9], [4, 8, 9], [6, 3, 5]])
print("X:\n", X) print("Y:\n", Y) print("X +
Y:\n", X + Y) print("X + 10:\n", X + 10) print("X
* Y:\n", X @ Y)  # Matrix multiplication
print("Transpose of X:\n", X.T)

# Comparison and modifying elements
Z = np.array([2, 3]) X =
np.array([2, 3])
print("X == Z:", X == Z)
X[0] = 5
print("X == Z after modifying X:", X == Z)
```

Show hidden output

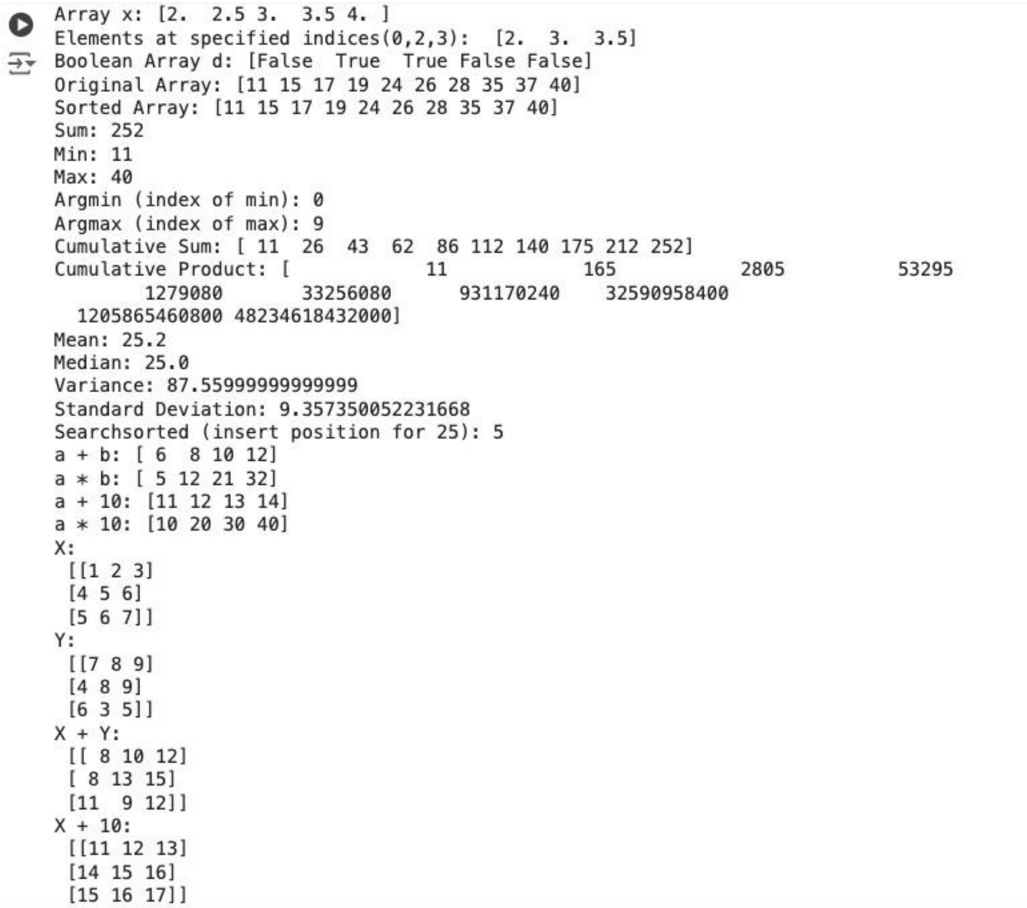
```
# Impoerneccessary libraries from pandas import DataFrame, Series  # Import Series
and DataFrame for convenience import pandas as pd import numpy as np

# Creating a Series with default index ser_1 = Series([1, 1, 2, -3, -5, 8, 13])
print("Series with default index:\n", ser_1) print("Values in series: ",
ser_1.values)  # Display only the values of the series

# Creating a Series with a custom index ser_2 = Series([1, 1, 2, -
3, -5], index=['a', 'b', 'c', 'd', 'e']) print("Series 2:\n",
ser_2)

# Accessing elements in a Series using index and labels
print("ser_2[1] == ser_2[b]", ser_2[1] == ser_2["b"])
print(ser_2[['c', 'a', 'b']])  # Filter Series for
values greater than 0 ser_2[ser_2 > 0]
# Apply an operation on Series elements
ser_2 * 2 np.exp(ser_2)

# Create a Series from a dictionary dict_1 = {'foo': 100, 'bar':
200, 'baz': 300} ser_3 = Series(dict_1) # Custom index on Series
index = ['foo', 'bar', 'baz', 'qux'] ser_4 = Series(dict_1,
index=index)  # Missing values become NaN

# Print Series print("Series
3:\n", ser_3) print("Series
4:\n", ser_4) # Check for null
values in Series
print("Null values in ser_4:\n", pd.isnull(ser_4)) # Arithmetic
operations between Series print("Sum of series 3 and 4:\n", ser_3 +
ser_4) # Setting names for the Series and index ser_4.name =
'foobarbaz' ser_4.index.name = 'label' print("Series 4 after setting
names for series and index:\n", ser_4)

# Create another Series with custom index ser = Series([10, 15,
18, 12, 20, 9], index=[5, 8, 12, 0, 1, 7]) # Access elements by
label or position using loc and iloc print("Accessing elements
by label or position: ") print(ser.loc[0:1])
print(ser.iloc[0:1]) print(ser.iloc[0]) print(ser.loc[0])

# Create a DataFrame with dictionaries data_1 =
{'state': ['VA', 'VA', 'VA', 'MD', 'MD'],
'year': [2012, 2013, 2014, 2015, 2016],
'pop': [5.0, 5.1, 5.2, 4.0, 4.1]} df_1 =
DataFrame(data_1)

# Access a column of the DataFrame
df_1['state']
```

```
# Find and print the series of prime numbers from 1 to 300
primes = []  fori in range(1, 301):
    if i> 1:
        for j in range(2, i // 2 + 1):
            if i % j == 0:
break
        else:
primes.append(i) primes_series =
pd.Series(primes)  print("Series of
Primes:\n", primes_series)

# Generate Fibonacci numbers up to 100
a, b = 0, 1 fibonacci_nums = [] while
a < 100:
fibonacci_nums.append(a)     a, b = b, a + b
fibonacci_series = Series(fibonacci_nums)
print("Fibonacci Series:\n", fibonacci_series)

# Prompt user for a list of 20 numbers l = [int(x) for x
in input("Enter 20 numbers: ").split()]

# Initialize min, max, and sum variables
min_val = l[0] max_val = l[0] sum_val =
0

# Calculate sum, min, and max manually
for i in l:
sum_val += i     if
i<min_val:
min_val = i
    if i>max_val:
max_val = i

print("Sum:", sum_val)
print("Min:", min_val)
print("Max:", max_val)

# Manually inputing values in a list one by one and finding the sum
l = []  sum_val = 0 for i in range(1, 21):
num = int(input("Enter number: "))
l.append(num)   sum_val
+= num print("Sum:",
sum_val)
```

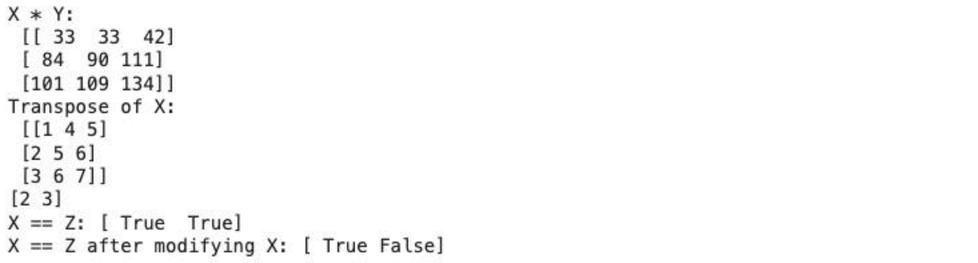
Show hidden output



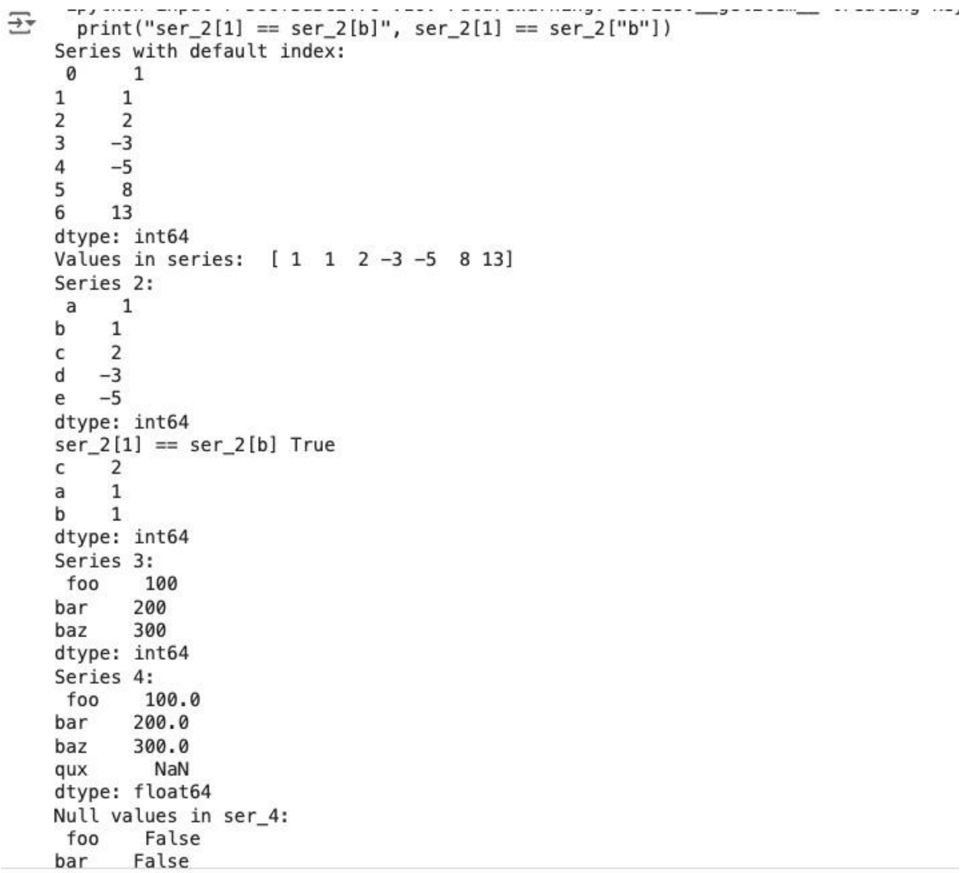
```
Array a: [0. 0. 0.]
Type of array a: <class 'numpy.ndarray'>
Type of elements in array a: <class 'numpy.float64'>
Array b: [0 0 0]
Type of array b: <class 'numpy.ndarray'>
Type of elements in array b: <class 'numpy.int64'>
Original Array:  [0. 0. 0.]
Shape of Array:  (3,)
Reshaped Array:
 [[0.]
 [0.]
 [0.]]
Shape of Reshaped Array:  (3, 1)
Array created using linspace:  [1.   1.25 1.5  1.75 2.  ]
Element at index 0:  1.0
Element at index -3:  1.5
Array elements from index 0 to 2:  [1.   1.25]
Identity Matrix:
 [[1 0]
 [0 1]]
2-D Array (method 1):
 [[0. 0.]
 [0. 0.]]
2-D Array (method 2):
 [[1 2]
 [3 4]]
Element at (0,1):  2
Element at (0,0):  1
Second row:  [3 4]
First column:  [1 3]
2-D Array:
 [[1 2 3]
 [4 5 6]
 [7 8 9]]
First row: [1 2 3]
Third row: [7 8 9]
First column across rows:  [1 4 7]
Array x: [2.  2.5 3.  3.5 4. ]
```



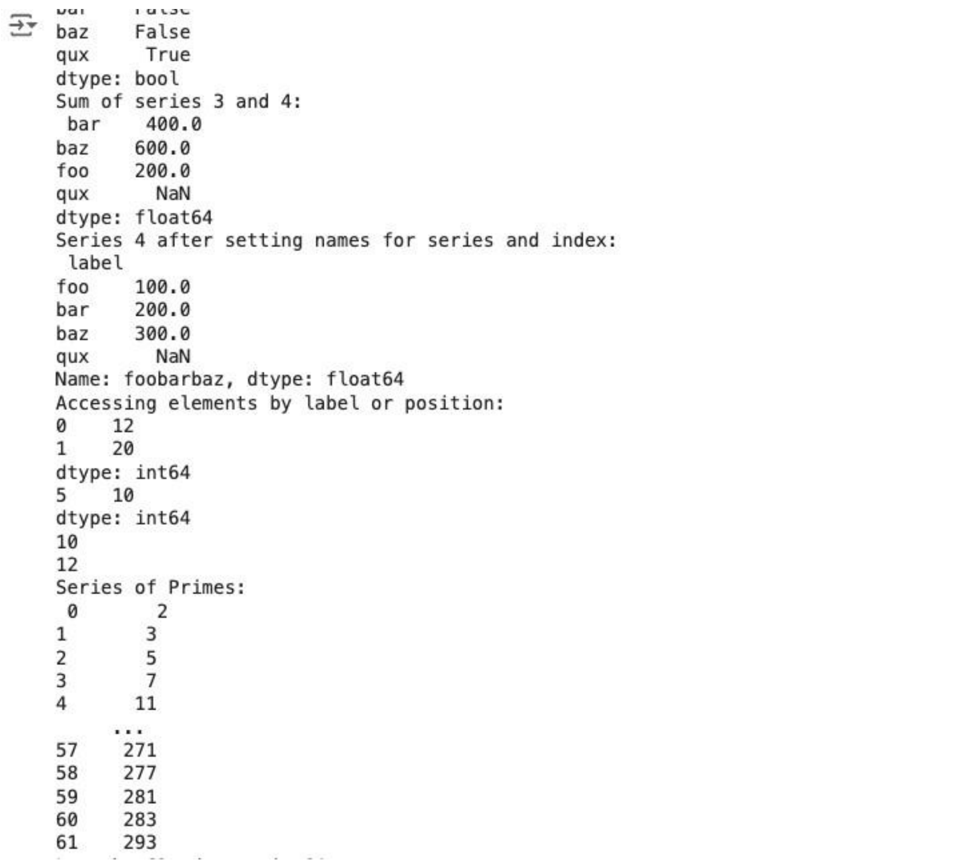
```
Array x: [2.  2.5 3.  3.5 4. ]
Elements at specified indices(0,2,3):  [2.  3.  3.5]
Boolean Array d: [False  True  True False False]
Original Array: [11 15 17 19 24 26 28 35 37 40]
Sorted Array: [11 15 17 19 24 26 28 35 37 40]
Sum: 252
Min: 11
Max: 40
Argmin (index of min): 0
Argmax (index of max): 9
Cumulative Sum: [ 11  26  43  62  86 112 140 175 212 252]
Cumulative Product: [            11            165           2805          53295
        1279080       33256080      931170240    32590958400
  1205865460800 48234618432000]
Mean: 25.2
Median: 25.0
Variance: 87.55999999999999
Standard Deviation: 9.357350052231668
Searchsorted (insert position for 25): 5
a + b: [ 6  8 10 12]
a * b: [ 5 12 21 32]
a + 10: [11 12 13 14]
a * 10: [10 20 30 40]
X:
 [[1 2 3]
 [4 5 6]
 [5 6 7]]
Y:
 [[7 8 9]
 [4 8 9]
 [6 3 5]]
X + Y:
 [[ 8 10 12]
 [ 8 13 15]
 [11  9 12]]
X + 10:
 [[11 12 13]
 [14 15 16]
 [15 16 17]]
```



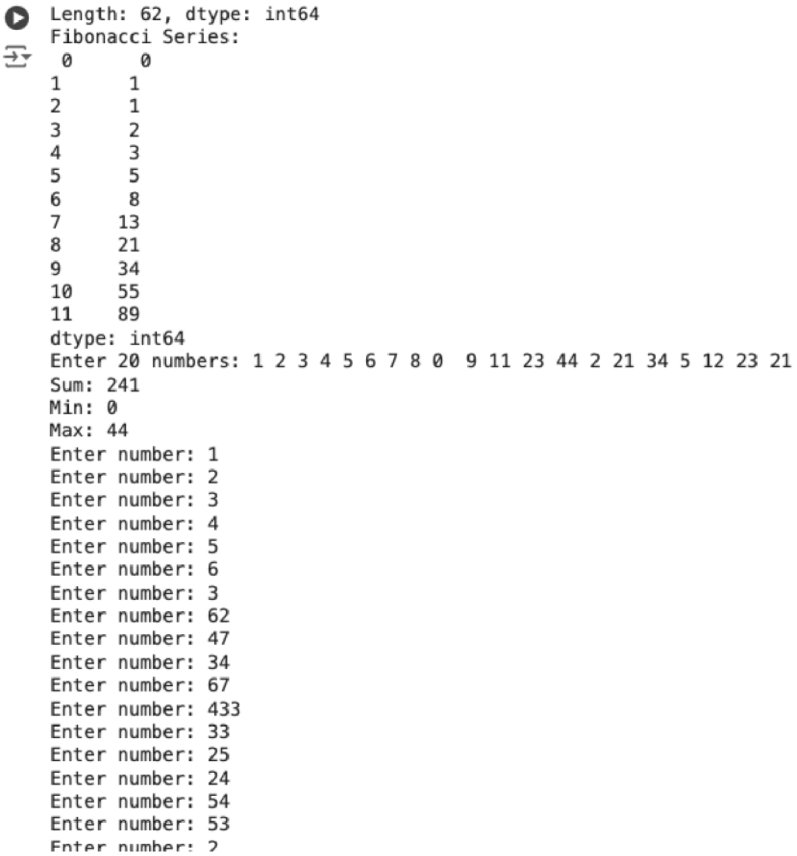
```
X * Y:
 [[ 33  33  42]
 [ 84  90 111]
 [101 109 134]]
Transpose of X:
 [[1 4 5]
 [2 5 6]
 [3 6 7]]
[2 3]
X == Z: [ True  True]
X == Z after modifying X: [ True False]
```



```
  print("ser_2[1] == ser_2[b]", ser_2[1] == ser_2["b"])
Series with default index:
 0     1
1     1
2     2
3    -3
4    -5
5     8
6    13
dtype: int64
Values in series:  [ 1  1  2 -3 -5  8 13]
Series 2:
 a    1
b    1
c    2
d   -3
e   -5
dtype: int64
ser_2[1] == ser_2[b] True
c    2
a    1
b    1
dtype: int64
Series 3:
 foo    100
bar    200
baz    300
dtype: int64
Series 4:
 foo    100.0
bar    200.0
baz    300.0
qux      NaN
dtype: float64
Null values in ser_4:
 foo    False
bar    False
```



```
baz    False
qux     True
dtype: bool
Sum of series 3 and 4:
 bar    400.0
baz    600.0
foo    200.0
qux      NaN
dtype: float64
Series 4 after setting names for series and index:
 label
foo    100.0
bar    200.0
baz    300.0
qux      NaN
Name: foobarbaz, dtype: float64
Accessing elements by label or position:
0    12
1    20
dtype: int64
5    10
dtype: int64
10
12
Series of Primes:
 0      2
1      3
2      5
3      7
4     11
     ...
57    271
58    277
59    281
60    283
61    293
```



```
Length: 62, dtype: int64
Fibonacci Series:
 0      0
1      1
2      1
3      2
4      3
5      5
6      8
7     13
8     21
9     34
10    55
11    89
dtype: int64
Enter 20 numbers: 1 2 3 4 5 6 7 8 0  9 11 23 44 2 21 34 5 12 23 21
Sum: 241
Min: 0
Max: 44
Enter number: 1
Enter number: 2
Enter number: 3
Enter number: 4
Enter number: 5
Enter number: 6
Enter number: 3
Enter number: 62
Enter number: 47
Enter number: 34
Enter number: 67
Enter number: 433
Enter number: 33
Enter number: 25
Enter number: 24
Enter number: 54
Enter number: 53
Enter number: 2
```

⍰ Program 2

Write a python program to calculate mean absolute error and mean square error.

```
#function to calculate the predicted values
def predicted_output(x,w,b):
y_hat=[]
    for i in range(len(x)):
y_hat.append(w*x[i]+b)
    return y_hat

#function to calculate mean absolute error
def MAE(y, y_hat):
    sum=0
    for i in range(len(y)):
        sum+=abs(y_hat[i]-y[i])
    return sum/len(y)

#function to calculate mean square error
def MSE(y, y_hat):
sq_sum=0
    for i in range(len(y)):
sq_sum+=(y_hat[i]-y[i])**2
    return sq_sum/len(y)

#taking inputs x=[eval(x) for x in input("Enter the values of x(input) separated by ',':
").split(",")] y=[eval(x) for x in input("Enter the values of y(output) separated by ',':
").split(",")] w=eval(input("Enter the value of w: ")) b=eval(input("Enter the value of
b: "))
#calling functions
y_hat=predicted_output(x, w, b)
MAE_value=MAE(y, y_hat)
MSE_value=MSE(y, y_hat) #printing the
values print("Predicted Output: ",y_hat)
print("Mean Absolute Error: ",MAE_value)
print("Mean Square Error: ",MSE_value)
```

```
Enter the values of x(input) separated by ',': 3, 6, 9, 12, 15, 18, 20
 Enter the values of y(output) separated by ',': 15, 28, 63, 90, 120, 152, 190
 Enter the value of w: 2.5
 Enter the value of b: 0
 Predicted Output:  [7.5, 15.0, 22.5, 30.0, 37.5, 45.0, 50.0]
 Mean Absolute Error:  64.35714285714286
 Mean Square Error:  6188.678571428572
```

⍰

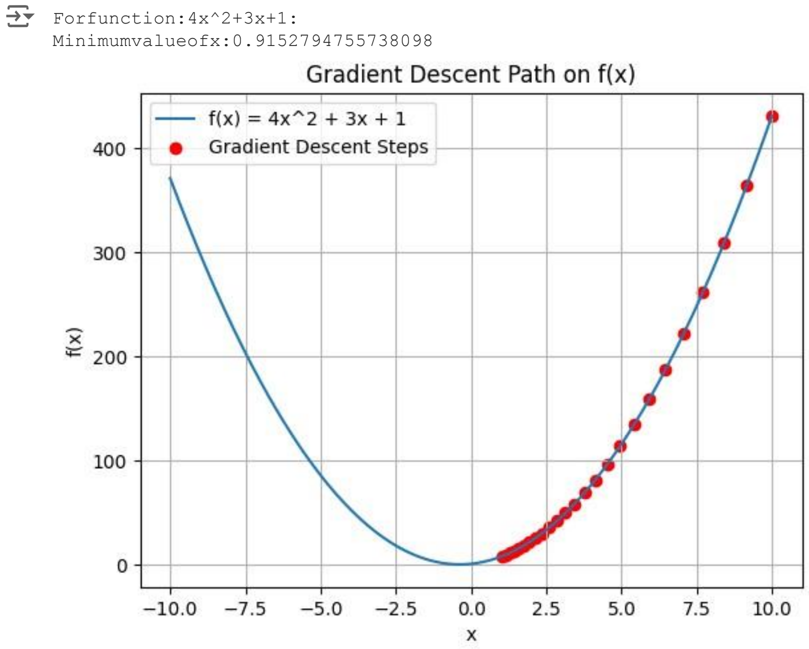
Write a python program to calculate gradient descent of a machine learning model.

Program 3

```
# Import neccessary libraries
import numpy as np import
matplotlib.pyplot as plt

# Function to perform gradient descent def
gradient_descent(func, x, learning_rate, num_iterations):
x_values=[]
for i in range(num_iterations):
        gradient=func(x)
x_values.append(x)
        x-=(learning_rate*gradient)
    return x,x_values

# Define the original function def
function(x):
    return 4*x**2+3*x+1
    # Define the derivative of the
function def derivative_f(x):
return 8*x+3

# Plotting the gradient descent steps on the function curve def
plot_gradient_descent(func, x, learning_rate, num_iterations, x_values):
x_range = np.linspace(-10, 10, 400)
y_range = func(x_range)
plt.plot(x_range, y_range, label="f(x) = 4x^2 + 3x + 1")
plt.scatter(x_values, [func(x) for x in x_values], color='red', label="Gradient Descent Steps")
plt.xlabel("x")
plt.ylabel("f(x)")
plt.legend()
plt.grid(True)
plt.title("Gradient Descent Path on f(x)")
plt.show()

# Set parameters for gradient descent initial_x=10 learning_rate=0.01 num_iterations=25
# Perform gradient descent min_x, x_values=gradient_descent(derivative_f, initial_x,
learning_rate, num_iterations)
# Print results print("For
function: 4x^2+3x+1: ")
print("Minimum value of x:", min_x)
# Call the plot function to visualize gradient descent
plot_gradient_descent(function, x, learning_rate, num_iterations, x_values)
```

Prepare a linear regression model for predicting the salary of user based on number of years of experience.

```
# importing neccessary libraries
import numpy as np import pandas
as pd import matplotlib.pyplot
as plt import seaborn as sns

# loading the dataset df =
pd.read_csv('Salary_Data.csv')
```

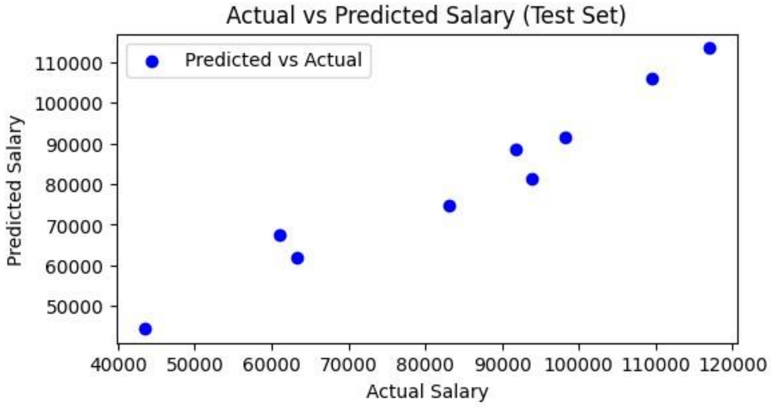


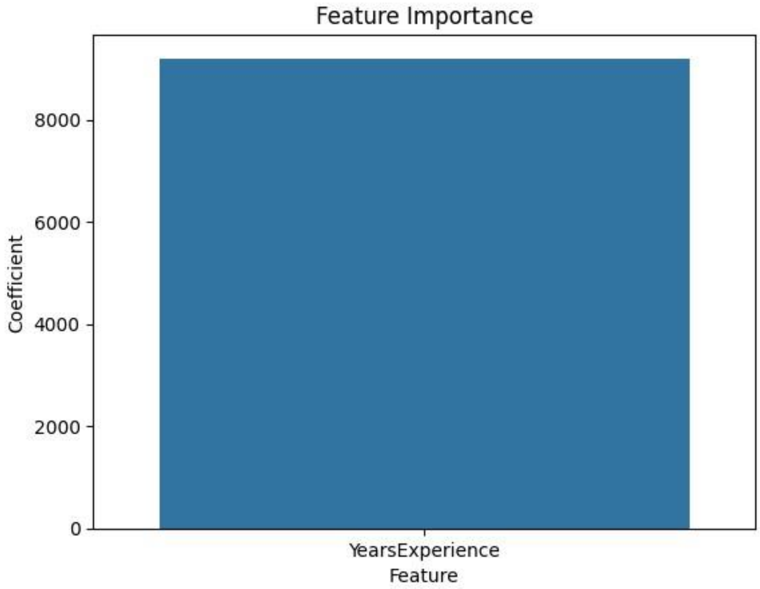
```
Forfunction:4x^2+3x+1:
Minimumvalueofx:0.9152794755738098
```

Program 4

```
# defining the feature variable 'x' by dropping Salary and target variable 'y' as the Salary column
x = df.drop('Salary', axis=1) y = df['Salary']

# split the dataset into training and testing sets from sklearn.model_selection import
train_test_splitx_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,
random_state=1)

# initialize and train the Linear Regression model on the training data
from sklearn.linear_model import LinearRegression model =
LinearRegression() model.fit(x_train, y_train)

# Predict the target variable for the test set
y_test_predict = model.predict(x_test)

# Display the model's coefficient and intercept print("Model
coefficient(s):", model.coef_) print("Model intercept:",
model.intercept_) print("Model R^2 score on test set:",
model.score(x_test, y_test))

# scatter plot to visualize the relationship between predicted and actual values in the test set
plt.figure(figsize=(6, 3)) plt.scatter(y_test, y_test_predict, color='blue', label="Predicted vs
Actual") plt.xlabel("Actual Salary") plt.ylabel("Predicted Salary") plt.title("Actual vs
Predicted Salary (Test Set)") plt.legend() plt.show()

# bar plot to display the importance of each feature based on model coefficients
imp=pd.DataFrame(list(zip(x_test.columns,np.abs(model.coef_))),columns=['Feature','Coefficient'])
sns.barplot(x='Feature', y='Coefficient', data=imp) plt.title("Feature Importance") plt.show()
```

```
Modelcoefficient(s):[9202.23359825]
Modelintercept:26049.577715443353
ModelR^2scoreontestset:0.9248580247217075
```





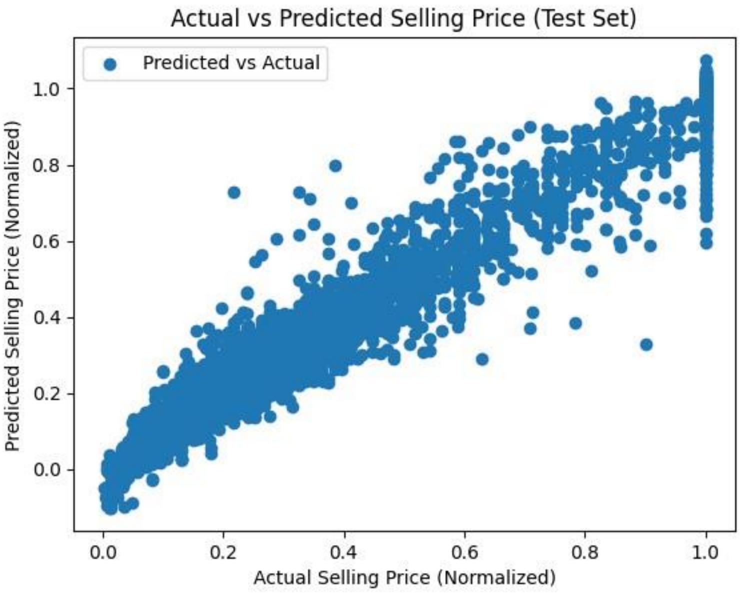
Program 5

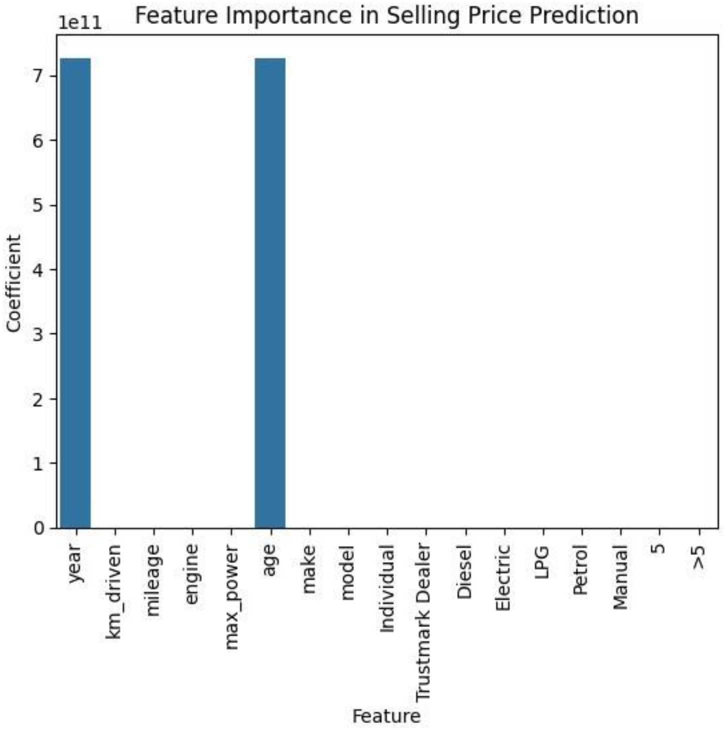
Prepare a linear regression model for prediction of resale car price.

```
# import necessary libraries
import numpy as np import
pandas as pd import
matplotlib.pyplot as plt
import seaborn as sns

# load the dataset df = pd.read_csv('cars24-car-
price-cleaned.csv')

# replace 'make' and 'model' columns with the mean selling price for each group
df['make'] = df.groupby('make')['selling_price'].transform('mean') df['model']
= df.groupby('model')['selling_price'].transform('mean')

# normalize the dataset using MinMaxScaler to scale features between 0 and 1
from sklearn.preprocessing import MinMaxScaler scaler = MinMaxScaler()
df_normalized = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)

# define target variable 'y' as the selling price and features 'x' by dropping the selling price
y = df_normalized['selling_price'] x = df_normalized.drop('selling_price', axis=1)

# split the dataset into training and testing sets from sklearn.model_selection import
train_test_splitx_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,
random_state=1)

# initialize and train the Linear Regression model on the training data
from sklearn.linear_model import LinearRegression model =
LinearRegression() model.fit(x_train, y_train)
```

```
# predict the target variable for the test set
y_test_predict = model.predict(x_test)

# Display model's coefficient, intercept, and R^2 score on test set
print("Model coefficients:", model.coef_) print("Model intercept:",
model.intercept_) print("Model R^2 score on test set:",
model.score(x_test, y_test))

# Scatter plot to visualize the relationship between predicted and actual values in the test set
#plt.figure(figsize=(8, 6)) plt.scatter(y_test, y_test_predict, label="Predicted vs Actual")
plt.xlabel("Actual Selling Price (Normalized)") plt.ylabel("Predicted Selling Price
(Normalized)") plt.title("Actual vs Predicted Selling Price (Test Set)") plt.legend() plt.show()

# Bar plot to display the importance of each feature based on model coefficients imp =
pd.DataFrame(list(zip(x_test.columns, np.abs(model.coef_))), columns=['Feature', 'Coefficient'])
#plt.figure(figsize=(8, 6))  sns.barplot(x='Feature',
y='Coefficient', data=imp) plt.xticks(rotation=90)
plt.title("Feature Importance in Selling Price Prediction")
plt.show()
```

```
Model coefficients: [ 7.26831852e+11 -2.50610352e-01 -2.32537818e-01  7.38776447e-02
  4.70141495e-02  7.26831852e+11  6.62815814e-02  8.59178586e-01  -
7.22882618e-03 -7.02099753e-03  7.03528760e-03  1.32983308e-01
  1.49877118e-02 -6.86552095e-03 -3.59124005e-03 -1.61993065e-02  -
2.35818239e-02]
Model intercept: -726831852169.8219
Model R^2 score on test set: 0.9459835819294395
```





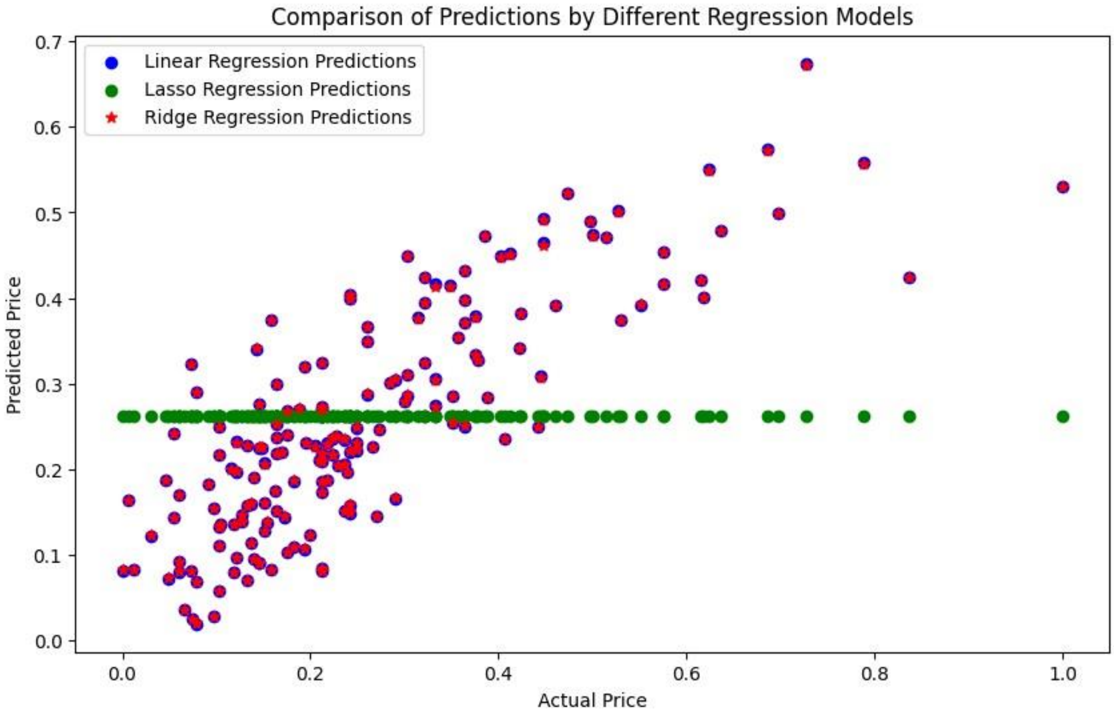
Program 6

Prepare a Lasso and Ridge regression model for prediction of house price and compare it with linear regression model.

```
# Import necessary libraries import numpy as np import pandas
as pd import matplotlib.pyplot as plt from sklearn.linear_model
import LinearRegression, Lasso, Ridge from
sklearn.model_selection import train_test_split from
sklearn.metrics import mean_squared_error from
sklearn.preprocessing import MinMaxScaler

# Load the housing dataset df =
pd.read_csv('Housing.csv')

# convert categorical variables into numerical features that can be used by the model (target variable encoding)
df['mainroad']=df.groupby('mainroad')['price'].transform('mean')
df['guestroom']=df.groupby('guestroom')['price'].transform('mean')
df['basement']=df.groupby('basement')['price'].transform('mean')
df['hotwaterheating']=df.groupby('hotwaterheating')['price'].transform('mean')
df['airconditioning']=df.groupby('airconditioning')['price'].transform('mean')
df['prefarea']=df.groupby('prefarea')['price'].transform('mean')
df['furnishingstatus']=df.groupby('furnishingstatus')['price'].transform('mean')
```

```
# Normalize the dataset to bring all features to the same scale scaler =
MinMaxScaler() df_normalized = pd.DataFrame(scaler.fit_transform(df),
columns=df.columns)

# Define the target variable 'y' as 'median_house_value' and features 'x' by dropping the target column
y = df_normalized['price'] x = df_normalized.drop('price', axis=1)

# Split the dataset into training and testing sets x_train, x_test, y_train, y_test =
train_test_split(x, y, test_size=0.3, random_state=1)

# Initialize models: Linear Regression, Lasso Regression, and Ridge Regression
model = LinearRegression() lasso_model = Lasso(alpha=0.1) ridge_model =
Ridge(alpha=0.1)

# Fit each model to the training data
model.fit(x_train, y_train)
lasso_model.fit(x_train, y_train)
ridge_model.fit(x_train, y_train)

# Display model coefficients, intercepts and R^2 scores
print("Linear Regression Coefficients:", model.coef_)
print("Lasso Regression Coefficients:", lasso_model.coef_)
print("Ridge Regression Coefficients:", ridge_model.coef_)

print("Linear Regression Intercept:", model.intercept_)
print("Lasso Regression Intercept:", lasso_model.intercept_)
print("Ridge Regression Intercept:", ridge_model.intercept_)

print("Linear Regression R^2 Score (Train):", model.score(x_train, y_train))
print("Lasso Regression R^2 Score (Train):", lasso_model.score(x_train, y_train))
print("Ridge Regression R^2 Score (Train):", ridge_model.score(x_train, y_train))

# Predict the target values on the test set using each model
y_pred = model.predict(x_test) y_pred_lasso =
lasso_model.predict(x_test) y_pred_ridge =
ridge_model.predict(x_test)

# Calculate Mean Squared Error (MSE) for each model on the test set
mse = mean_squared_error(y_test, y_pred) mse_lasso =
mean_squared_error(y_test, y_pred_lasso) mse_ridge =
mean_squared_error(y_test, y_pred_ridge)

# Display the MSE results to compare model performance, with lower MSE indicating better fit
print('MSE without regularization (Linear Regression):', mse) print('MSE with Lasso
regularization:', mse_lasso) print('MSE with Ridge regularization:', mse_ridge)

# Visualize the comparison of actual vs predicted values for each model
plt.figure(figsize=(10, 6)) plt.scatter(y_test, y_pred, color='blue', label="Linear
Regression Predictions") plt.scatter(y_test, y_pred_lasso, color='green', label="Lasso
Regression Predictions") plt.scatter(y_test, y_pred_ridge, color='red', label="Ridge
Regression Predictions", marker='*') plt.xlabel("Actual Price") plt.ylabel("Predicted
Price") plt.title("Comparison of Predictions by Different Regression Models")
plt.legend() plt.show()
```

```
Linear Regression Coefficients: [0.31039697 0.01959006 0.26477477 0.13658528 0.04098972 0.02376751
 0.04792801 0.07098812 0.05282266 0.07096655 0.04358941 0.03623753]
Lasso Regression Coefficients: [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
Ridge Regression Coefficients: [0.30639084 0.02106921 0.26241647 0.13615958 0.04133038 0.02401481
 0.04774817 0.07051319 0.0530351  0.0713936  0.04377635 0.03640865]
Linear Regression Intercept: -0.0050427725675667445
Lasso Regression Intercept: 0.26192224608287595
Ridge Regression Intercept: -0.0048457449783638196
Linear Regression R^2 Score (Train): 0.6806547764599723
Lasso Regression R^2 Score (Train): 0.0
Ridge Regression R^2 Score (Train): 0.6806349211986238
MSE without regularization (Linear Regression): 0.010274158458096141
MSE with Lasso regularization: 0.03051838551799671
MSE with Ridge regularization: 0.010266744866035897
```

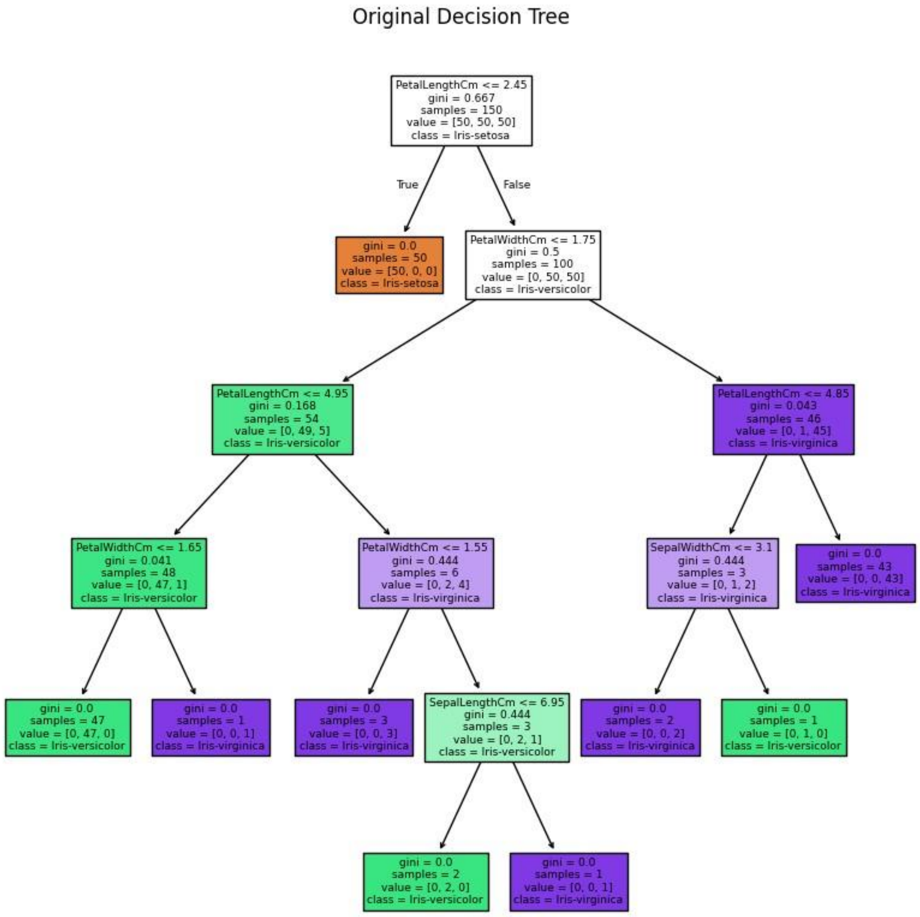

Comparison of Predictions by Different Regression Models
Linear Regression Predictions
Lasso Regression Predictions
Ridge Regression Predictions
Predicted Price
Actual Price
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.0
0.2
0.4
0.6
0.8
1.0

Program 7

Prepare a decision tree model for Iris Dataset using Gini Index.

```
# Import necessary libraries
from sklearn import datasets
from sklearn.tree import DecisionTreeClassifier,
plot_tree from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt import pandas as pd

# Load the Iris dataset df
= pd.read_csv("Iris.csv")

# Define feature matrix 'x' by dropping 'Species' and 'Id' columns and target variable 'y' as
'Species' x = df.drop(['Species', 'Id'], axis=1) y = df['Species']

# Initialize DecisionTreeClassifier with Gini impurity criterion
model = DecisionTreeClassifier(criterion='gini')

# Dictionary to store Gini impurity for each feature
gini_impurities = {}

#loop through each feature
for i in range(x.shape[1]):
#fit classifier with only the current feature
model.fit(x.iloc[:, i].values.reshape(-1, 1), y)
    prob=model.predict_proba(x.iloc[:, i].values.reshape(-1,1))
gini_impurities[i] = 1 - (prob[:, 0]**2 + prob[:, 1]**2 + prob[:, 2]**2).sum()


# Find the feature with the lowest Gini impurity (best
feature) best_feature = min(gini_impurities,
key=gini_impurities.get) print(f"Best feature:
{x.columns[best_feature]}") model.fit(x, y)

#plot original tree plt.figure(figsize=(10, 10)) plot_tree(model, filled=True,
feature_names=x.columns, class_names=model.classes_) plt.title("Original
Decision Tree")
plt.show()
```

```
Bestfeature:PetalLengthCm
```

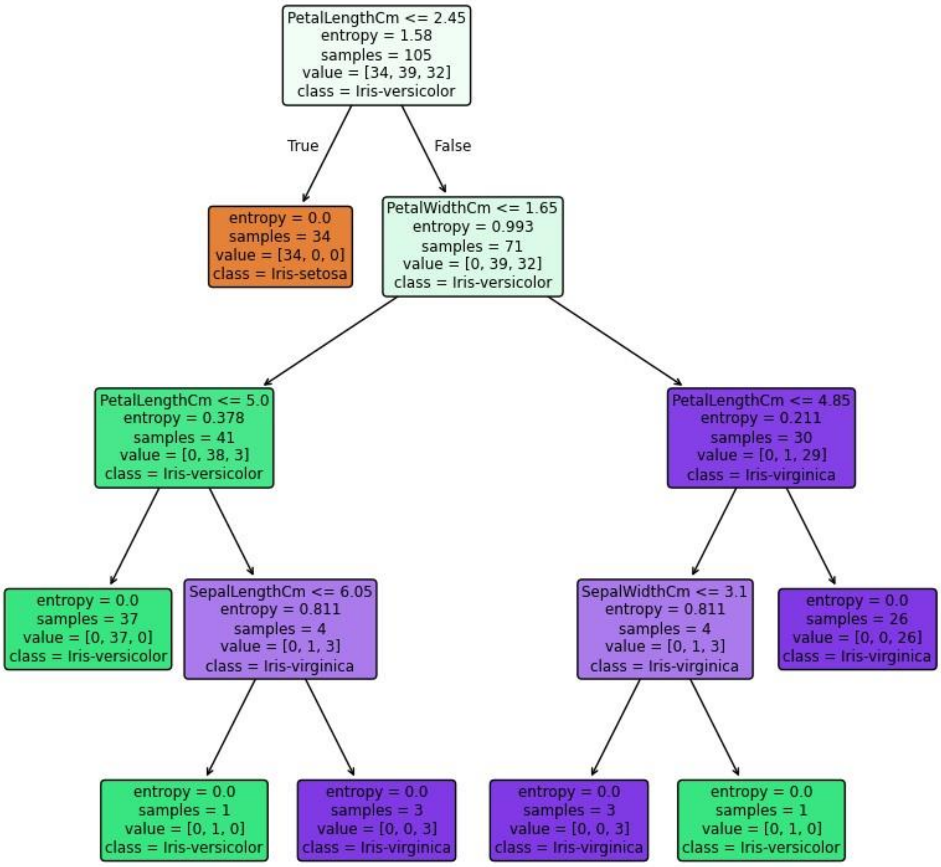


Program 8

Prepare a decision tree model for Iris Dataset using entropy.

```
# Import necessary libraries import numpy as np import
pandas as pd from sklearn.metrics import confusion_matrix,
accuracy_score from sklearn.model_selection import
train_test_split from sklearn.tree import
DecisionTreeClassifier, plot_tree import matplotlib.pyplot
as plt from sklearn import tree

# Load the Iris dataset
df=pd.read_csv("Iris.csv")

# Define feature matrix 'x' by dropping 'Species' and 'Id' columns and target variable 'y' as 'Species'
x=df.drop(["Species", "Id"], axis=1) y=df["Species"]

# Splitting the dataset into train and test x_train, x_test, y_train, y_test =
train_test_split(x, y, test_size=0.3, random_state=100)

# Build decision tree
model = tree.DecisionTreeClassifier(criterion='entropy', max_depth=4)

# Fit the tree to iris dataset
model.fit(x_train, y_train)

# Find the accuracy of the model
y_pred = model.predict(x_test)
print("Accuracy: ", accuracy_score(y_test, y_pred)*100)

# Function to plot the decision tree def
plot_decision_tree(model, feature_names, class_names):
plt.figure(figsize=(10, 10))
plot_tree(model, filled=True, feature_names=feature_names, class_names=class_names, rounded=True)
plt.show() plot_decision_tree(model, ["SepalLengthCm", "SepalWidthCm", "PetalLengthCm",
"PetalWidthCm"],
                                 ["Iris-setosa", "Iris-versicolor", "Iris-virginica"])
```

```
Accuracy:95.55555555555556
```

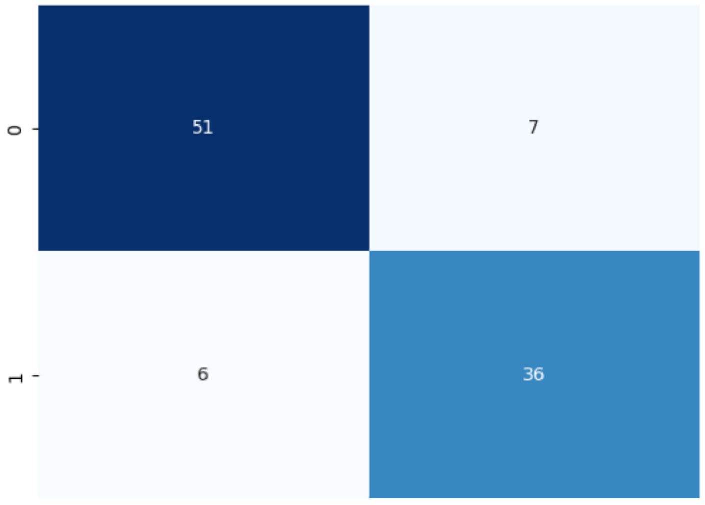


⍰ Program 9

Prepare a naïve bayes classification model for prediction of purchase power of a user.

```
# Import libraries import pandas as pd import numpy as np import matplotlib.pyplot as plt from matplotlib.colors
import ListedColormap import seaborn as sns from sklearn.preprocessing import LabelEncoder, StandardScaler from
sklearn.model_selection import train_test_split from sklearn.naive_bayes import GaussianNB from sklearn import
metrics from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, precision_recall_curve,
f1_score

# Load User_Data dataset df =
pd.read_csv('User_Data.csv')

# Drop User ID column as it does not contribute towards prediction purpose
df.drop(['User ID'], axis=1, inplace=True)

# Label Encoding le=LabelEncoder()
df['Gender']=le.fit_transform(df['Gender'])

# Split data into dependent/independent variables
x = df.iloc[:, :-1].values y = df.iloc[:, -
1].values

# Split the dataset into training and testing sets x_train, x_test, y_train, y_test =
train_test_split(x, y, test_size=0.25, random_state=True)

# Scale dataset sc =
StandardScaler() x_train =
sc.fit_transform(x_train) x_test =
sc.transform(x_test)

# Create naive-bayes classifier model
classifier=GaussianNB()
classifier.fit(x_train, y_train)

# Predict the values y_pred=classifier.predict(x_test) # Print
accuracy of classifier print("Accuracy of classifier: ",
accuracy_score(y_test, y_pred))

# Print the classification report print(f'Classification
report:\n{classification_report(y_test, y_pred)}')

# Print the confusion matrix cf_matrix=confusion_matrix(y_test,
y_pred) sns.heatmap(cf_matrix, annot=True, fmt='d', cmap='Blues',
cbar=False)
```

```
Accuracy of classifier:  0.87
Classification report:                     precision
recall   f1-score   support

          0       0.89      0.88      0.89        58
       1       0.84      0.86      0.85        42

    accuracy                           0.87       100
macro avg       0.87       0.87       0.87        100
weighted avg       0.87      0.87      0.87       100

<Axes: >
```

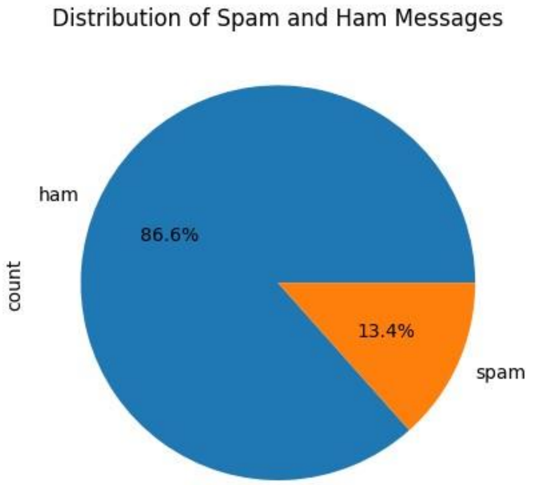


Program 10

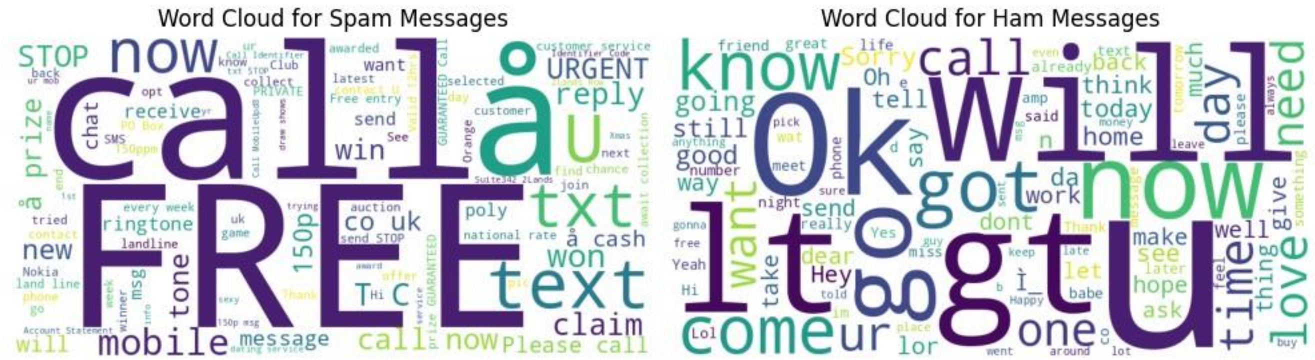
Prepare a naïve bayes classification model for classification of email messages into spam or not spam.

```
# Import libraries import pandas as pd from
sklearn.model_selection import train_test_split from
sklearn.naive_bayes import MultinomialNB, GaussianNB from
sklearn.feature_extraction.text import CountVectorizer from
sklearn.metrics import accuracy_score, f1_score import
matplotlib.pyplot as plt from wordcloud import WordCloud

# Load the dataset into a DataFrame with 'latin-1' encoding to avoid encoding issues
df = pd.read_csv('spam.csv', encoding='latin-1')

# Select only the relevant columns ('v1' as labels and 'v2' as messages) and rename them
df = df[['v1', 'v2']] df = df.rename(columns={'v1': 'label', 'v2': 'text'})

# Define feature matrix 'x' as 'text' and target variable 'y' as 'label'
x=df['text'] y=df['label']

# Split the dataset into training and testing sets x_train, x_test, y_train, y_test =
train_test_split(x, y, test_size=0.2, random_state=42)

# Find and plot the distribution of spam and ham messages
distribution = y.value_counts() print("Distribution of spam and
ham messages:\n", distribution) distribution.plot(kind='pie',
autopct='%1.1f%%') plt.title("Distribution of Spam and Ham
Messages") plt.show()

# Generate a Wordcloud for the Spam emails spam_text = ' '.join(df[df['label'] == 'spam']['text']) spam_wordcloud =
WordCloud(width=800, height=400, max_words=100, background_color='white', random_state=42).generate(spam_tex

# Generate a Wordcloud for the Ham emails ham_text = ' '.join(df[df['label'] == 'ham']['text']) ham_wordcloud =
WordCloud(width=800, height=400, max_words=100, background_color='white', random_state=42).generate(ham_text)

# Plot the word clouds for spam messages
plt.figure(figsize=(10, 4))
plt.subplot(1, 2, 1)
plt.imshow(spam_wordcloud)
plt.title('Word Cloud for Spam Messages')
plt.axis('off')
# Plot the wordcloud for ham messages
plt.subplot(1, 2, 2)
plt.imshow(ham_wordcloud)
plt.title('Word Cloud for Ham Messages')
plt.axis('off')
# Show both plots side by side
plt.tight_layout() plt.show()

# Vectorize the text data to convert it into numerical features
vectorizer = CountVectorizer() x_train =
vectorizer.fit_transform(x_train) x_test =
vectorizer.transform(x_test)

# Train a Multinomial Naive Bayes classifier on the vectorized data
model_multinomial = MultinomialNB(alpha = 0.8, fit_prior = True, force_alpha = True)
model_multinomial.fit(x_train, y_train)

# Train a Gaussian Naive Bayes classifier on the vectorized data
model_gaussian = GaussianNB()
model_gaussian.fit(x_train.toarray(), y_train)

# Calculate and print the accuracy of both models on the test data
y_pred_multinomial = model_multinomial.predict(x_test) accuracy_multinomial
= accuracy_score(y_test, y_pred_multinomial) print("Accuracy for
Multinomial Naive Bayes Model: ", accuracy_multinomial)

y_pred_gaussian = model_gaussian.predict(x_test.toarray())
accuracy_gaussian = accuracy_score(y_test, y_pred_gaussian)
print("Accuracy for Gaussian Naive Bayes Model: ", accuracy_gaussian) #
Plot a comparison of the accuracy scores for the two classification
methods methods = ["Multinomial Naive Bayes", "Gaussian Naive Bayes"]
scores = [accuracy_multinomial, accuracy_gaussian] plt.bar(methods,
scores) plt.xlabel("Classification Methods") plt.ylabel("Accuracy")
plt.title("Comparison of Classification Methods") plt.show()
```

```
Distribution of spam and ham messages:
 label ham     4825 spam     747 Name:
 count, dtype: int64
```



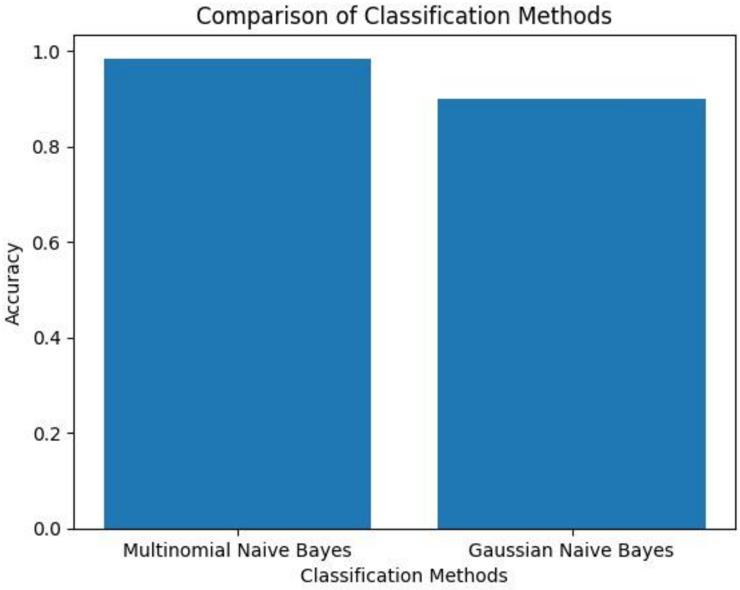
Distribution of Spam and Ham Messages



Word Cloud for Spam Messages

Word Cloud for Ham Messages

```
Accuracy for Multinomial Naive Bayes Model:  0.9838565022421525
Accuracy for Gaussian Naive Bayes Model:  0.9004484304932735
```



Comparison of Classification Methods

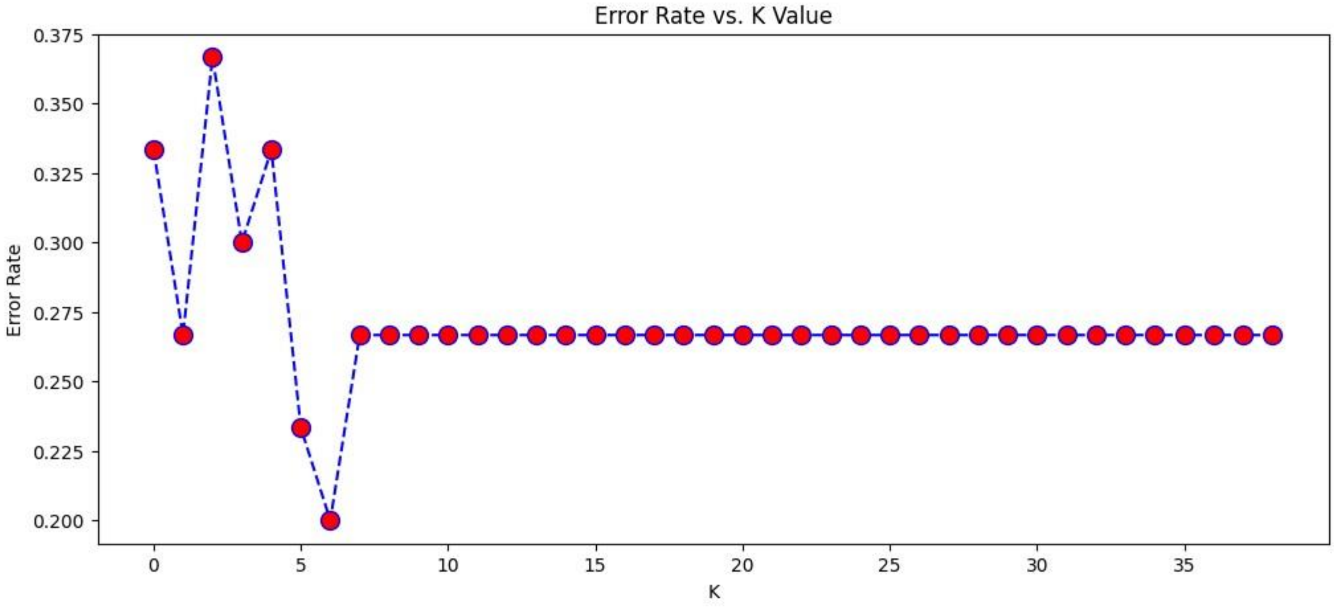
Program 11

Prepare a model for prediction of prostate cancer using KNN Classifier.

```
# Import necessary libraries import pandas as pd import numpy as np
import matplotlib.pyplot as plt import seaborn as sns from
sklearn.preprocessing import StandardScaler from sklearn.metrics
import classification_report, confusion_matrix from
sklearn.neighbors import KNeighborsClassifier from
sklearn.model_selection import train_test_split
```

```
# Load the dataset df =
pd.read_csv('prostate.csv')

# Define feature matrix 'x' and target vector 'y'
x=df.drop('Target', axis = 1) y=df['Target']

# Feature scaling using StandardScaler scaler=StandardScaler()
df1=pd.DataFrame(scaler.fit_transform(x),columns=x.columns[::-1])

# Split data into training and testing sets
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=1)

# Initialize K-Nearest Neighbors classifier with 1 neighborknn_model
= KNeighborsClassifier(n_neighbors=1) knn_model.fit(x_train,y_train)

# Make predictions on the test set
y_pred = knn_model.predict(x_test)

# Display the confusion matrix to evaluate model performance
print("Confusion Matrix:\n", confusion_matrix(y_test,y_pred))

# Display classification report with precision, recall, F1-score, and accuracy
print("Classification Report:\n", classification_report(y_test,y_pred))

# Elbow method for determining the optimal number of neighbors 'K'
error_rate = [] for i in range(1,40):
knn = KNeighborsClassifier(n_neighbors=i)
knn.fit(x_train,y_train)
new_y_pred = knn.predict(x_test)
error_rate.append(np.mean(new_y_pred != y_test))

# Plot the error rate for different values of K
plt.figure(figsize=(12,5)) plt.plot(error_rate,color='blue',
linestyle='dashed', marker='o',
markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K') plt.ylabel('Error Rate')
plt.show()
```

```
Confusion Matrix:
 [[18  4]
 [ 6  2]]
Classification  Report:                          precision
recall  f1-score   support

           0       0.75      0.82      0.78        22
       1       0.33      0.25      0.29          8

    accuracy                           0.67        30
macro avg        0.54       0.53       0.53         30
weighted avg       0.64      0.67      0.65        30
```



Program 12

Prepare a model for prediction of survival from Titanic Ship using Random Forest and compare the accuracy with other classiers also.

```
# Import necessary libraries import pandas as pd from sklearn.model_selection
import train_test_split from sklearn.ensemble import RandomForestClassifier from
sklearn.metrics import accuracy_score, classification_report, confusion_matrix from
sklearn.preprocessing import LabelEncoder from sklearn.neighbors import
KNeighborsClassifier from sklearn.naive_bayes import GaussianNB from sklearn.tree
import DecisionTreeClassifier import warnings warnings.filterwarnings('ignore')

# Load the dataset df =
pd.read_csv("titanic.csv")

# Drop rows where the target variable is missing
df = df.dropna(subset=['Survived'])

# Select features 'x' and target variable 'y' x =
df[['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare']] y =
df["Survived"]

# Encode categorical feature 'Sex' to numeric
le = LabelEncoder() x['Sex'] =
le.fit_transform(x['Sex'])

# Fill missing values in 'Age' with the mean
x['Age'] = x['Age'].fillna(x['Age'].mean())

# Split the dataset into training and testing sets x_train, x_test, y_train, y_test =
train_test_split(x, y, test_size=0.2, random_state=42)

# Create a Random Forest Classifier with 100 decision trees rf_model
= RandomForestClassifier(n_estimators=100, random_state=42)

# Train the Random Forest Classifier
rf_model.fit(x_train, y_train)

# Make predictions using the Random Forest Classifier
y_pred_rf = rf_model.predict(x_test)

# Evaluate the Random Forest Classifier rf_accuracy =
accuracy_score(y_test, y_pred_rf) rf_classification_report =
classification_report(y_test, y_pred_rf)

print("Accuracy of Random Forest Classifier: ", rf_accuracy)
print("Classification Report:\n", rf_classification_report)

# Comparison with other Models

# Initialize models model1 =
KNeighborsClassifier(n_neighbors=9) model2 =
GaussianNB() model3 =
DecisionTreeClassifier(criterion='entropy') model4 =
RandomForestClassifier(n_estimators=100)
# List of models for comparison modellist =
[model1, model2, model3, model4]

# Evaluate each model print("\n=== Model
Comparison Results ===") for model in
modellist:     model.fit(x_train, y_train)
y_pred = model.predict(x_test)
    # Calculate performance metrics
model_accuracy = accuracy_score(y_test, y_pred)
model_confusion_matrix = confusion_matrix(y_test, y_pred)
model_classification_report = classification_report(y_test, y_pred)
    # Display results for each model
print(f"\nModel: {model.__class__.__name__}")
print("Confusion Matrix:")
    print(model_confusion_matrix)
print(f"Accuracy: {model_accuracy:.2f}")
print("Classification Report:")
    print(model_classification_report)
```

```
 Classification Report:               precision
 recall  f1-score   support

                0       0.71      0.81      0.76       105
           1       0.67      0.54      0.60        74
```

```
    accuracy                           0.70       179
macro avg       0.69       0.68       0.68        179
weighted avg       0.69      0.70      0.69       179


Model: GaussianNB
Confusion Matrix:
[[85 20]
 [21 53]]
Accuracy: 0.77
Classification Report:               precision
recall  f1-score   support

           0       0.80      0.81      0.81       105
      1       0.73      0.72      0.72        74

    accuracy                           0.77       179
macro avg       0.76       0.76       0.76        179
weighted avg       0.77      0.77      0.77       179


Model: DecisionTreeClassifier
Confusion Matrix:
[[83 22]
 [21 53]]
Accuracy: 0.76
Classification Report:               precision
recall  f1-score   support

           0       0.80      0.79      0.79       105
      1       0.71      0.72      0.71        74

    accuracy                           0.76       179
macro avg       0.75       0.75       0.75        179
weighted avg       0.76      0.76      0.76       179


Model: RandomForestClassifier
Confusion Matrix:
[[91 14]
 [20 54]]
Accuracy: 0.81
Classification Report:               precision
recall  f1-score   support

           0       0.82      0.87      0.84       105
      1       0.79      0.73      0.76        74

    accuracy                           0.81       179
macro avg       0.81       0.80       0.80        179
weighted avg       0.81      0.81      0.81       179
```