# SRM VALLIAMMAI ENGINEERING COLLEGE

## (An Autonomous Institution)

SRM Nagar, Kattankulathur-603203

**DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE**

ACADEMIC YEAR: 2023-2024

EVEN SEMESTER

# LAB MANUAL

**(REGULATION - 2019)**

# 1922405 – DATA SCIENCE LABORATORY

FOURTH SEMSTER

B. Tech – Artificial Intelligence and Data Science

**Prepared By**

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# PROGRAMME EDUCATIONAL OBJECTIVES (PEOs)

1. To afford the necessary background in the field of Information Technology to deal with engineering problems to excel as engineering professionals in industries.
2. To improve the qualities like creativity, leadership, teamwork and skill thus contributing towards the growth and development of society.
3. To develop ability among students towards innovation and entrepreneurship that caters to the needs of Industry and society.
4. To inculcate and attitude for life-long learning process through the use of information technology sources.
5. To prepare then to be innovative and ethical leaders, both in their chosen profession and in other activities.

# PROGRAMME OUTCOMES (POs)

After going through the four years of study, Information Technology Graduates will exhibit ability to:

| PO# | Graduate Attribute | Programme Outcome |
|---|---|---|
| 1 | Engineering knowledge | Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization for the solution of complex engineering problems. |
| 2 | Problem analysis | Identify, formulate, research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences. |
| 3 | Design/development of solutions | Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for public health and safety, and cultural, societal, and environmental considerations. |
| 4 | Conduct investigations of complex problems | Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and |

| | | |
|---|---|---|
| | | synthesis of the information to provide valid conclusions |
| 5 | Modern tool usage | Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools, including prediction and modeling to complex engineering activities, with an understanding of the limitations. |
| 6 | The engineer and society | Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice |
| 7 | Environment and sustainability | Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development. |
| 8 | Ethics | Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice |
| 9 | Individual and team work | Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings |
| 10 | Communication | Communicate effectively on complex engineering activities with the engineering community and with the society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions |
| 11 | Project management and finance | Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments |
| 12 | Life-long learning | Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change |

# PROGRAMME SPECIFIC OUTCOMES (PSOs)

After the completion of Bachelor of Technology in Artificial Intelligence and Data Science programme the student will have following Program specific outcomes

1. Design and develop secured database applications with data analytical approaches of data preprocessing, optimization, visualization techniques and maintenance using state of the art methodologies based on ethical values.
2. Design and develop intelligent systems using computational principles, methods and systems for extracting knowledge from data to solve real time problems using advanced technologies and tools.
3. Design, plan and setting up the network that is helpful for contemporary business environments using latest software and hardware.
4. Planning and defining test activities by preparing test cases that can predict and correct errors ensuring a socially transformed product catering all technological needs.

| 1922405 | DATA SCIENCE LABORATORY | L T P C |
|---|---|---|
| | | 0 0 4 2 |

**OBJECTIVES:**

**This course will enable students to**

- Develop a basic understanding of import data sets for various analytical purposes.
- Utilize the various packages available visualization, reporting, data manipulation, and statistical analysis.
- Create interactive business applications that allow for data querying and data exploration.
- Collect, explore, clean, munge and manipulate data.
- Build data science applications using Python based toolkits.

**LIST OF EXPERIMENTS:**

1. Write a program in Python to predict the class of the flower based on available attributes.
2. Write a program in Python to predict if a loan will get approved or not.
3. Write a program in Python to predict the traffic on a new mode of transport.
4. Write a program in Python to predict the class of user.
5. Write a program in Python to identify the tweets which are hate tweets and which are not.
6. Write a program in Python to predict the age of the actors.
7. Introduction to Python Libraries-Numpy, Pandas, Matplotlib, Scikit
8. Perform Data exploration and preprocessing in Python
9. Implement regularized Linear regression
10. Mini project to predict the time taken to solve a problem given the current status of the user.

**Total: 60 Periods**

# LIST OF EQUIPMENTS FOR A BATCH OF 30 STUDENTS

**SOFTWARE:**

Standalone desktops with Python 3 interpreter for Windows / Linux 30 Nos. (or) Server with Python 3 interpreter for Windows/Linux supporting 30 terminals or more.

**HARDWARE:**

Standalone Desktops: 30 Nos.

**COURSE OUTCOMES**

| | |
|---|---|
| 1922405.1 | Import data sets for various analytical purposes. |
| 1922405.2 | Suggest Develop an interactive business application that allow for data querying and data exploration. |
| 1922405.3 | Collect, explore, clean, munge and manipulate data. |
| 1922405.4 | Develop data science applications using Python based toolkits. |
| 1922405.5 | Implement models such as k-nearest Neighbours, Naive Bayes, linear and logistic regression, decision trees, neural networks and clustering |

**CO- PO-PSO MATRIX**

| CO | PO | | | | | | | | | | | | PSO | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **1** | **2** | **3** | **4** |
| **1** | - | 2 | 3 | - | 3 | - | - | - | - | - | - | - | 2 | - | - | - |
| **2** | - | 2 | 3 | - | 3 | - | - | - | - | - | - | 2 | 2 | - | - | - |
| **3** | - | 2 | 3 | - | 3 | - | - | - | - | - | - | - | 3 | - | - | - |
| **4** | 2 | 2 | 3 | - | 3 | - | - | - | - | - | 2 | - | 3 | - | 2 | 2 |
| **5** | 2 | 2 | 3 | - | 3 | - | - | - | - | - | 2 | - | 3 | - | - | 2 |

## EVALUATION PROCEDURE FOR EACH EXPERIMENT

| S. No | Description | Mark |
|---|---|---|
| 1. | Aim & Procedure | 20 |
| 2. | Observation | 30 |
| 3. | Conduction and Execution | 30 |
| 4. | Output & Result | 10 |
| 5. | Viva | 10 |
| **Total** | | **100** |

## INTERNAL ASSESSMENT FOR LABORATORY

| S. No | Description | Mark |
|---|---|---|
| 1. | Conduction & Execution of Experiment | 25 |
| 2. | Record | 10 |
| 3. | Model Test | 15 |
| **Total** | | **50** |

**Ex. No: 1 PREDICT THE CLASS OF THE FLOWER BASED ON AVAILABLE ATTRIBUTES**

**AIM**

To write a Python program to predict the class of the flower based on available attributes using K-Nearest Neighbor.

**PROCEDURE**

1. Importing the necessary libraries, including **'pandas'** for data manipulation, and **'numpy'** for numerical operations.
2. Load the dataset containing flower attributes. For Example, iris dataset.
3. Explore the dataset to understand its structure and features. Preprocess the data if needed, such as handling missing values or encoding categorical variables.
4. Split the dataset into features (x) and target variable (y).
5. Further split the dataset into training and testing sets using 'train_test_split' from **'sklearn.model_selection'**.
6. Initialize a K-Nearest Neighbors model with a specified number of neighbors **('n_neighbors')** from '**sklearn. Neighbors'.**
7. Train the K-Nearest Neighbor model using the training data with the **'fit'** method.
8. Use the trained KNN model to make predictions on the testing data with the **'predict'** method.
9. Evaluate the performance of the model using **metrics** such as accuracy, precision, recall, F1_Score, or others based on the requirements.
10. Finally, predict the flower class for new data using the trained model.

**PROGRAM**

```
# Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings. Simplefilter ("ignore")

# Load the Dataset
df = pd. read_csv("C:\\Users\\Documents\\iris.csv")
df. head ()
```

**Output**

| | sepal_length | sepal_width | petal_length | petal_width | species |
|---|---|---|---|---|---|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | setosa |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | setosa |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | setosa |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | setosa |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | setosa |

df.info ()

**Output**

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

df. describe ()

**Output**

| | sepal_length | sepal_width | petal_length | petal_width |
|---|---|---|---|---|
| count | 150.000000 | 150.000000 | 150.000000 | 150.000000 |
| mean | 5.843333 | 3.054000 | 3.758667 | 1.198667 |
| std | 0.828066 | 0.433594 | 1.764420 | 0.763161 |
| min | 4.300000 | 2.000000 | 1.000000 | 0.100000 |
| 25% | 5.100000 | 2.800000 | 1.600000 | 0.300000 |
| 50% | 5.800000 | 3.000000 | 4.350000 | 1.300000 |
| 75% | 6.400000 | 3.300000 | 5.100000 | 1.800000 |
| max | 7.900000 | 4.400000 | 6.900000 | 2.500000 |

**# Explore and preprocess the data**
df. isnull (). sum ()

**Output**

```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
```

**# Split the data into features (x)**
x = df. iloc [: , :-1]
x

**Output**

| | sepal_length | sepal_width | petal_length | petal_width |
|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 |
| **...** | ... | ... | ... | ... |
| **145** | 6.7 | 3.0 | 5.2 | 2.3 |
| **146** | 6.3 | 2.5 | 5.0 | 1.9 |
| **147** | 6.5 | 3.0 | 5.2 | 2.0 |
| **148** | 6.2 | 3.4 | 5.4 | 2.3 |
| **149** | 5.9 | 3.0 | 5.1 | 1.8 |

150 rows × 4 columns

**# Split the data into target variable (y)**
y = df. iloc [: , -1]

**Output**

```
0         setosa
1         setosa
2         setosa
3         setosa
4         setosa
        ...
145    virginica
146    virginica
147    virginica
148    virginica
149    virginica
Name: species, Length: 150, dtype: object
```

**# Further split the dataset into training and testing sets**
**from** sklearn. model_selection **import** train_test_split
x_train, x_test, y_train, y_test=train_test_split (x, y, random_state=0)

**# Intialize the KNN model**
**from** sklearn. neighbors **import** KNeighborsClassifier
model = KNeighborsClassifier(n_neighbors=3)

**# Train the KNN model**
model.fit (x_train, y_train)

**Output**
KNeighborsClassifier(n_neighbors=3)

**# Make predictions**
y_pred=model. predict(x_test)
y_pred

**Output**

```
array(['virginica', 'versicolor', 'setosa', 'virginica', 'setosa',
       'virginica', 'setosa', 'versicolor', 'versicolor', 'versicolor',
       'virginica', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'setosa', 'versicolor', 'versicolor', 'setosa',
       'setosa', 'virginica', 'versicolor', 'setosa', 'setosa',
       'virginica', 'setosa', 'setosa', 'versicolor', 'versicolor',
       'setosa', 'virginica', 'versicolor', 'setosa', 'virginica',
       'virginica', 'versicolor', 'setosa', 'virginica'], dtype=object)
```

**# Evaluate the model**
**from** sklearn. metrics **import** accuracy_score, confusion_matrix
confusion_matrix (y_test, y_pred)

**Output**

```
array([[13,  0,  0],
       [ 0, 15,  1],
       [ 0,  0,  9]], dtype=int64)
```

accuracy=accuracy_score (y_test, y_pred) *****100
print ("Accuracy of the model is {:.2f}". format(accuracy))

**Output**
Accuracy of the model is 97.37

**from** sklearn. metrics **import** classification_report
class_report = classification_report (y_test, y_pred)
print (f"\nClassification Report:\n{class_report}")

**Output**

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

      setosa       1.00      1.00      1.00        13
  versicolor       1.00      0.94      0.97        16
   virginica       0.90      1.00      0.95         9

    accuracy                           0.97        38
   macro avg       0.97      0.98      0.97        38
weighted avg       0.98      0.97      0.97        38
```

**# Predict for new data**
new_flower = [[5.1, 3.5, 1.4, 0.2]]
predicted_class = model**.** predict(new_flower)
predicted_class

**Output**
array(['setosa'], dtype=object)

**RESULT**

Thus, the python program to predict the class of the flower based on available attributes was completed successfully using K-Nearest Neighbor model.

## Ex. No: 2 PREDICT IF A LOAN WILL GET APPROVED OR NOT

**AIM**

To write a Python program to predict if a loan will get approved or not using Logistic Regression.

**PROCEDURE**

1. Importing the necessary libraries, including **'pandas'** for data manipulation, and **'numpy'** for numerical operations and warnings.
2. Load the dataset containing loan details. For Example, loan dataset.
3. Explore the dataset to understand its structure and features. Preprocess the data if needed, such as handling missing values.
4. Use **'LabelEncoder'** to encode categorical columns like 'Gender', 'Married', 'Education', 'Self_employed', etc.
5. Use **'SimpleImputer'** to replace null values in numeric columns with the most frequent values.
6. Split the dataset into features (x) and target variable (y).
7. Replace '$3^{+}$' with 3 and convert the column to float using **'df['Dependents'] = df['Dependents']. replace ('$3^{+}$', 3). astype(float)**.
8. Further split the dataset into training and testing sets using 'train_test_split' from **'sklearn. model_selection'**.
9. Standardize the features using **'StandardScaler'** from **'sklearn. preprocessing'**.
10. Initialize a Logistic Regression model from '**sklearn. linear_model'.**
11. Train the Logistic Regression model using the training data with the **'fit'** method.
12. Use the trained Logistic Regression model to make predictions on the testing data with the **'predict'** method.
13. Evaluate the performance of the model using **metrics** such as accuracy, precision, recall, F1_Score, or others based on the requirements.
14. Finally, use the trained model to predict the outcome for the new data.

**PROGRAM**

```
# Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings. Simplefilter ("ignore")

# Load the Dataset
df = pd. read_csv("C:\\Users\\Documents\\loan.csv")
df. head ()
```

## Output

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | LP001002 | Male | No | 0 | Graduate | No | 5849 | 0.0 | NaN | 360.0 | 1.0 |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | 128.0 | 360.0 | 1.0 |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | 66.0 | 360.0 | 1.0 |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | 120.0 | 360.0 | 1.0 |
| 4 | LP001008 | Male | No | 0 | Graduate | No | 6000 | 0.0 | 141.0 | 360.0 | 1.0 |

df. info ()

## Output

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

df. describe ()

## Output

| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History |
|---|---|---|---|---|---|
| **count** | 614.000000 | 614.000000 | 592.000000 | 600.00000 | 564.000000 |
| **mean** | 5403.459283 | 1621.245798 | 146.412162 | 342.00000 | 0.842199 |
| **std** | 6109.041673 | 2926.248369 | 85.587325 | 65.12041 | 0.364878 |
| **min** | 150.000000 | 0.000000 | 9.000000 | 12.00000 | 0.000000 |
| **25%** | 2877.500000 | 0.000000 | 100.000000 | 360.00000 | 1.000000 |
| **50%** | 3812.500000 | 1188.500000 | 128.000000 | 360.00000 | 1.000000 |
| **75%** | 5795.000000 | 2297.250000 | 168.000000 | 360.00000 | 1.000000 |
| **max** | 81000.000000 | 41667.000000 | 700.000000 | 480.00000 | 1.000000 |

**# Explore and preprocess the data**

df. isnull (). Sum ()

**Output**

```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

**# Drop the null values**

df = df. drop ('Loan_ID', axis =1)

df. head ()

**Output**

| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | Property_Ai |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Male | No | 0 | Graduate | No | 5849 | 0.0 | NaN | 360.0 | 1.0 | Urt |
| **1** | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | 128.0 | 360.0 | 1.0 | Ru |
| **2** | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | 66.0 | 360.0 | 1.0 | Urt |
| **3** | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | 120.0 | 360.0 | 1.0 | Urt |
| **4** | Male | No | 0 | Graduate | No | 6000 | 0.0 | 141.0 | 360.0 | 1.0 | Urt |

**# Encoding the categorical values**

from sklearn. preprocessing import LabelEncoder

label_encoder = LabelEncoder ()

categorical_columns = ['Gender', 'Married', 'Education', 'Self_Employed', 'Property_Area', 'Loan_Status']

df[categorical_columns] = df[categorical_columns]. apply(label_encoder.fit_transform)

df[categorical_columns]

**Output**

| | Gender | Married | Education | Self_Employed | Property_Area | Loan_Status |
|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 0 | 0 | 2 | 1 |
| **1** | 1 | 1 | 0 | 0 | 0 | 0 |
| **2** | 1 | 1 | 0 | 1 | 2 | 1 |
| **3** | 1 | 1 | 1 | 0 | 2 | 1 |
| **4** | 1 | 0 | 0 | 0 | 2 | 1 |
| **...** | ... | ... | ... | ... | ... | ... |
| **609** | 0 | 0 | 0 | 0 | 0 | 1 |
| **610** | 1 | 1 | 0 | 0 | 0 | 1 |
| **611** | 1 | 1 | 0 | 0 | 2 | 1 |
| **612** | 1 | 1 | 0 | 0 | 2 | 1 |
| **613** | 0 | 0 | 0 | 1 | 1 | 0 |

614 rows × 6 columns

**# Replace the null value**

from sklearn. impute import SimpleImputer

numeric_columns = ['Gender', 'Married','Dependents', 'Self_Employed', 'LoanAmount', 'Loan_Amount_Term', 'Credit_History']

df[numeric_columns] = SimpleImputer(strategy='most_frequent'). fit_transform(df[numeric_columns])

df[numeric_columns]

**Output**

| | Gender | Married | Dependents | Self_Employed | LoanAmount | Loan_Amount_Term | Credit_History |
|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 0 | 0 | 120.0 | 360.0 | 1.0 |
| **1** | 1 | 1 | 1 | 0 | 128.0 | 360.0 | 1.0 |
| **2** | 1 | 1 | 0 | 1 | 66.0 | 360.0 | 1.0 |
| **3** | 1 | 1 | 0 | 0 | 120.0 | 360.0 | 1.0 |
| **4** | 1 | 0 | 0 | 0 | 141.0 | 360.0 | 1.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **609** | 0 | 0 | 0 | 0 | 71.0 | 360.0 | 1.0 |
| **610** | 1 | 1 | 3+ | 0 | 40.0 | 180.0 | 1.0 |
| **611** | 1 | 1 | 1 | 0 | 253.0 | 360.0 | 1.0 |
| **612** | 1 | 1 | 2 | 0 | 187.0 | 360.0 | 1.0 |
| **613** | 0 | 0 | 0 | 1 | 133.0 | 360.0 | 0.0 |

614 rows × 7 columns

**# Handle special case in 'Dependents' column**

df['Dependents'] = df['Dependents']. replace ('3+', 3). astype(float)

df['Dependents']

**Output**

```
0      0.0
1      1.0
2      0.0
3      0.0
4      0.0
      ...
609    0.0
610    3.0
611    1.0
612    2.0
613    0.0
Name: Dependents, Length: 614, dtype: float64
```

**# Split the data into features (x)**

x = df. iloc [: , :-1]

x

**Output**

| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | Property_ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 0.0 | 0 | 0 | 5849 | 0.0 | 120.0 | 360.0 | 1.0 | |
| **1** | 1 | 1 | 1.0 | 0 | 0 | 4583 | 1508.0 | 128.0 | 360.0 | 1.0 | |
| **2** | 1 | 1 | 0.0 | 0 | 1 | 3000 | 0.0 | 66.0 | 360.0 | 1.0 | |
| **3** | 1 | 1 | 0.0 | 1 | 0 | 2583 | 2358.0 | 120.0 | 360.0 | 1.0 | |
| **4** | 1 | 0 | 0.0 | 0 | 0 | 6000 | 0.0 | 141.0 | 360.0 | 1.0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **609** | 0 | 0 | 0.0 | 0 | 0 | 2900 | 0.0 | 71.0 | 360.0 | 1.0 | |
| **610** | 1 | 1 | 3.0 | 0 | 0 | 4106 | 0.0 | 40.0 | 180.0 | 1.0 | |
| **611** | 1 | 1 | 1.0 | 0 | 0 | 8072 | 240.0 | 253.0 | 360.0 | 1.0 | |
| **612** | 1 | 1 | 2.0 | 0 | 0 | 7583 | 0.0 | 187.0 | 360.0 | 1.0 | |
| **613** | 0 | 0 | 0.0 | 0 | 1 | 4583 | 0.0 | 133.0 | 360.0 | 0.0 | |

614 rows × 11 columns

**# Split the data into target variable (y)**

y = df. iloc [: , -1]

**Output**

```
0      1
1      0
2      1
3      1
4      1
      ..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status, Length: 614, dtype: int32
```

**# Further split the dataset into training and testing sets**
**from** sklearn. model_selection **import** train_test_split
x_train, x_test, y_train, y_test=train_test_split (x, y, random_state=0)

**# Feature scaling using StandardScaler**
from sklearn. preprocessing import StandardScaler
scaler = StandardScaler ()
x_train = scaler.fit_transform(x_train)
x_test = scaler. transform(x_test)
x_train

**Output**

```
array([[ 0.36547961,  0.6622422 ,  0.20631248, ...,  0.27778225,
         0.41649656,  1.20186498],
       [ 0.36547961, -1.42427431, -0.77207659, ...,  0.27778225,
         0.41649656, -1.31684978],
       [ 0.36547961, -1.42427431,  1.18470154, ...,  0.27778225,
         0.41649656, -1.31684978],
       ...,
       [ 0.36547961,  0.6622422 ,  2.1630906 , ...,  0.27778225,
         0.41649656, -0.0574924 ],
       [ 0.36547961,  0.6622422 , -0.77207659, ...,  0.27778225,
         0.41649656,  1.20186498],
       [-2.00241646,  0.6622422 , -0.77207659, ...,  0.27778225,
         0.41649656, -0.0574924 ]])
```

x_test

**Output**

```
array([[ 0.36547961, -1.42427431, -0.77207659, ...,  0.27778225,
         0.41649656, -0.0574924 ],
       [-2.00241646, -1.42427431, -0.77207659, ...,  0.27778225,
         0.41649656, -0.0574924 ],
       [ 0.36547961,  0.6622422 , -0.77207659, ...,  0.27778225,
         0.41649656,  1.20186498],
       ...,
       [ 0.36547961,  0.6622422 , -0.77207659, ...,  0.27778225,
         0.41649656,  1.20186498],
       [ 0.36547961, -1.42427431, -0.77207659, ...,  0.27778225,
         0.41649656, -0.0574924 ],
       [ 0.36547961,  0.6622422 ,  0.20631248, ...,  0.27778225,
        -2.40098019, -0.0574924 ]])
```

**# Intialize the Logistic Regression model**
from sklearn. linear_model import LogisticRegression
model = LogisticRegression ()

**# Train the Logistic Regression model**
model.fit (x_train, y_train)

**Output**
LogisticRegression ()

**# Make predictions**
y_pred=model. predict(x_test)
y_pred

**Output**

```
array([1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0])
```

**# Evaluate the model**
**from** sklearn. metrics **import** accuracy_score,  classification_report
accuracy = accuracy_score (y_test, y_pred) * 100
print ("Accuracy of the model is {:.2f}". format(accuracy))

**Output**
Accuracy: 84%

**from** sklearn. metrics **import** classification_report
class_report = classification_report (y_test, y_pred)
print (f"\nClassification Report:\n{class_report}")

**Output**

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

           0       0.91      0.47      0.62        43
           1       0.83      0.98      0.90       111

    accuracy                           0.84       154
   macro avg       0.87      0.72      0.76       154
weighted avg       0.85      0.84      0.82       154
```

# Predict for new data
```
new_data = [1, 1, 2, 1, 1, 4106.0, 240.0, 253.0, 360.0, 1, 2]
predictions = model. predict([new_data])
print(predictions)
```

**Output**
```
[1]
```

# Assuming a label encoder for decoding categorical predictions
```
decoded_predictions = label_encoder. inverse_transform(predictions)
print(decoded_predictions)
```

**Output**
```
['Y']
```

**RESULT**

Thus, the program to predict if a loan will get approved or not was completed successfully using Logistic Regression.

**Ex. No:3 PREDICT THE TRAFFIC ON A NEW MODE OF TRANSPORT**

**AIM**

To write a Python program to predict the traffic on a new mode of transport using Support Vector Machine.

**PROCEDURE**

1. Importing the necessary libraries, including **'pandas'** for data manipulation, and **'numpy'** for numerical operations and warnings.
2. Load the dataset containing traffic data. For Example, traffic dataset.
3. Explore the dataset to understand its structure and features. Preprocess the data if needed, such as handling missing values.
4. Use **'LabelEncoder'** to encode categorical columns like 'Day of the week', and 'Traffic Situation'.
5. Split the dataset into features (x) and target variable (y).
6. Further split the dataset into training and testing sets using 'train_test_split' from **'sklearn. model_selection'**.
7. Standardize the features using **'StandardScaler'** from **'sklearn. preprocessing'**.
8. Initialize a Support Vector Machine model from '**sklearn.svm'.**
9. Train the Support Vector Machine model using the training data with the **'fit'** method.
10. Use the trained Support Vector Machine model to make predictions on the testing data with the **'predict'** method.
11. Evaluate the performance of the model using **metrics** such as accuracy, precision, recall, F1_Score, or others based on the requirements.
12. Finally, use the trained model to predict the outcome for the new data.

**PROGRAM**

```
# Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings. Simplefilter ("ignore")

# Load the Dataset
df = pd. read_csv("C:\\Users\\Documents\\Traffic.csv")
df. head()
```

**Output**

| | Time | Date | Day of the week | CarCount | BikeCount | BusCount | TruckCount | Total | Traffic Situation |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 12:00:00 AM | 10 | Tuesday | 31 | 0 | 4 | 4 | 39 | low |
| **1** | 12:15:00 AM | 10 | Tuesday | 49 | 0 | 3 | 3 | 55 | low |
| **2** | 12:30:00 AM | 10 | Tuesday | 46 | 0 | 3 | 6 | 55 | low |
| **3** | 12:45:00 AM | 10 | Tuesday | 51 | 0 | 2 | 5 | 58 | low |
| **4** | 1:00:00 AM | 10 | Tuesday | 57 | 6 | 15 | 16 | 94 | normal |

df.info ()

**Output**

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2976 entries, 0 to 2975
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Time               2976 non-null   object
 1   Date               2976 non-null   int64
 2   Day of the week    2976 non-null   object
 3   CarCount           2976 non-null   int64
 4   BikeCount          2976 non-null   int64
 5   BusCount           2976 non-null   int64
 6   TruckCount         2976 non-null   int64
 7   Total              2976 non-null   int64
 8   Traffic Situation  2976 non-null   object
dtypes: int64(6), object(3)
memory usage: 209.4+ KB
```

df. describe ()

**Output**

| | Date | CarCount | BikeCount | BusCount | TruckCount | Total |
|---|---|---|---|---|---|---|
| **count** | 2976.000000 | 2976.000000 | 2976.000000 | 2976.000000 | 2976.000000 | 2976.000000 |
| **mean** | 16.000000 | 68.696573 | 14.917339 | 15.279570 | 15.324933 | 114.218414 |
| **std** | 8.945775 | 45.850693 | 12.847518 | 14.341986 | 10.603833 | 60.190627 |
| **min** | 1.000000 | 6.000000 | 0.000000 | 0.000000 | 0.000000 | 21.000000 |
| **25%** | 8.000000 | 19.000000 | 5.000000 | 1.000000 | 6.000000 | 55.000000 |
| **50%** | 16.000000 | 64.000000 | 12.000000 | 12.000000 | 14.000000 | 109.000000 |
| **75%** | 24.000000 | 107.000000 | 22.000000 | 25.000000 | 23.000000 | 164.000000 |
| **max** | 31.000000 | 180.000000 | 70.000000 | 50.000000 | 40.000000 | 279.000000 |

**# Explore and preprocess the data**

df. isnull (). sum ()

**Output**

```
Time                 0
Date                 0
Day of the week      0
CarCount             0
BikeCount            0
BusCount             0
TruckCount           0
Total                0
Traffic Situation    0
dtype: int64
```

**# Drop the null values**

df = df. drop ('Time', axis =1)

df. head ()

**Output**

| | Date | Day of the week | CarCount | BikeCount | BusCount | TruckCount | Total | Traffic Situation |
|---|---|---|---|---|---|---|---|---|
| **0** | 10 | Tuesday | 31 | 0 | 4 | 4 | 39 | low |
| **1** | 10 | Tuesday | 49 | 0 | 3 | 3 | 55 | low |
| **2** | 10 | Tuesday | 46 | 0 | 3 | 6 | 55 | low |
| **3** | 10 | Tuesday | 51 | 0 | 2 | 5 | 58 | low |
| **4** | 10 | Tuesday | 57 | 6 | 15 | 16 | 94 | normal |

**# Encoding the categorical values**

from sklearn. preprocessing import LabelEncoder

label_encoder = LabelEncoder ()

categorical_columns = ['Day of the week', 'Traffic Situation']

df[categorical_columns] = df[categorical_columns]. apply(label_encoder.fit_transform)

df[categorical_columns]

**Output**

| | Day of the week | Traffic Situation |
|---|---|---|
| **0** | 5 | 2 |
| **1** | 5 | 2 |
| **2** | 5 | 2 |
| **3** | 5 | 2 |
| **4** | 5 | 3 |
| **...** | ... | ... |
| **2971** | 4 | 3 |
| **2972** | 4 | 3 |
| **2973** | 4 | 3 |
| **2974** | 4 | 3 |
| **2975** | 4 | 3 |

2976 rows × 2 columns

**# Split the data into features (x)**

x = df. iloc [: , :-1]

x

**Output**

| | Date | Day of the week | CarCount | BikeCount | BusCount | TruckCount | Total |
|---|---|---|---|---|---|---|---|
| **0** | 10 | 5 | 31 | 0 | 4 | 4 | 39 |
| **1** | 10 | 5 | 49 | 0 | 3 | 3 | 55 |
| **2** | 10 | 5 | 46 | 0 | 3 | 6 | 55 |
| **3** | 10 | 5 | 51 | 0 | 2 | 5 | 58 |
| **4** | 10 | 5 | 57 | 6 | 15 | 16 | 94 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **2971** | 9 | 4 | 16 | 3 | 1 | 36 | 56 |
| **2972** | 9 | 4 | 11 | 0 | 1 | 30 | 42 |
| **2973** | 9 | 4 | 15 | 4 | 1 | 25 | 45 |
| **2974** | 9 | 4 | 16 | 5 | 0 | 27 | 48 |
| **2975** | 9 | 4 | 14 | 3 | 1 | 15 | 33 |

2976 rows × 7 columns

**# Split the data into target variable (y)**
y = df. iloc [: , -1]

**Output**

```
0       2
1       2
2       2
3       2
4       3
       ..
2971    3
2972    3
2973    3
2974    3
2975    3
Name: Traffic Situation, Length: 2976, dtype: int32
```

**# Further split the dataset into training and testing sets**
**from** sklearn. model_selection **import** train_test_split
x_train, x_test, y_train, y_test=train_test_split (x, y, random_state=0)

**# Feature scaling using StandardScaler**
from sklearn. preprocessing import StandardScaler
scaler = StandardScaler ()
x_train = scaler.fit_transform(x_train)
x_test = scaler. transform(x_test)
x_train

**Output**

```
array([[-0.33600687, -1.59798223,  1.98010887, ...,  1.00899718,
        -1.1633432 ,  2.0733575 ],
       [ 0.43635908, -1.59798223,  2.30697357, ..., -0.31203497,
        -1.1633432 ,  2.20601196],
       [ 1.42940101, -0.10771914,  1.10846967, ...,  0.66135714,
        -0.68866549,  0.8628855 ],
       ...,
       [ 1.20872503, -1.59798223, -0.351526  , ..., -0.590147  ,
        -0.02411669, -0.48024096],
       [-1.10837282, -1.10122786, -1.15779226, ..., -1.07684306,
         0.83030319, -1.1766769 ],
       [-0.99803483,  0.88578959,  0.01892066, ..., -0.72920302,
         1.30498091, -0.09885937]])
```

x_test

**Output**

```
array([[-0.99803483,  0.88578959, -1.24495618, ..., -1.07684306,
         1.21004537, -1.19325871],
       [-1.66006278,  1.38254396,  0.38936732, ...,  0.17466108,
         1.39991645,  0.43175849],
       [-1.32904881, -0.6044735 , -0.22078012, ...,  1.2175812 ,
         0.92523874,  0.21619498],
       ...,
       [ 1.31906302, -0.6044735 , -1.07062834, ..., -0.17297896,
         0.64043211, -0.91136797],
       [ 0.32602109,  0.38903523, -1.13600128, ..., -1.00731505,
         0.45056102, -1.20984052],
       [-1.4393868 , -1.59798223, -0.351526  , ..., -0.79873103,
        -0.02411669, -0.57973181]])
```

**# Intialize the Support Vector Machine model**

from sklearn.svm import SVC

model = SVC (kernel = 'linear', random_state = 0)

**# Train the Support Vector Machine model**

model.fit (x_train, y_train)

**Output**

SVC (kernel='linear', random_state=0)

**# Make predictions**

y_pred=model. predict(x_test)

y_pred

**Output**

```
array([3, 1, 1, 0, 3, 3, 3, 0, 0, 3, 0, 3, 0, 3, 3, 0, 1, 0, 2, 3, 3, 1,
       3, 2, 3, 0, 3, 3, 2, 0, 0, 3, 3, 3, 0, 0, 3, 0, 0, 3, 0, 0, 2, 3,
       0, 3, 3, 0, 3, 3, 3, 0, 3, 0, 3, 0, 3, 0, 3, 3, 3, 0, 3, 3, 2, 0,
       3, 3, 2, 0, 1, 0, 2, 3, 3, 2, 3, 0, 3, 3, 3, 0, 0, 3, 3, 0, 2, 3,
       3, 0, 0, 3, 2, 3, 3, 0, 3, 1, 1, 3, 0, 0, 3, 3, 3, 0, 3, 3, 3, 3,
       3, 0, 3, 1, 3, 3, 0, 3, 3, 0, 3, 3, 0, 3, 3, 3, 2, 3, 0, 3, 0, 3,
       0, 0, 3, 3, 3, 0, 3, 3, 0, 3, 1, 3, 2, 2, 3, 0, 3, 3, 0, 3, 3, 2,
       3, 2, 2, 0, 3, 3, 2, 3, 0, 3, 3, 3, 3, 3, 1, 3, 3, 2, 3, 2, 0, 3,
       0, 3, 3, 0, 3, 3, 0, 3, 0, 1, 1, 3, 0, 0, 3, 3, 2, 0, 0, 0, 2, 3,
       0, 3, 3, 1, 1, 1, 3, 3, 3, 1, 3, 3, 3, 1, 0, 0, 1, 2, 2, 1, 3, 0,
       3, 3, 3, 3, 0, 3, 1, 3, 3, 0, 3, 3, 3, 0, 3, 2, 2, 3, 0, 3, 3, 1,
       3, 3, 3, 1, 1, 1, 1, 3, 0, 3, 3, 3, 3, 0, 3, 3, 0, 3, 0, 3, 3, 0,
       3, 3, 3, 1, 0, 1, 2, 3, 3, 2, 0, 3, 3, 3, 0, 1, 0, 3, 3, 3, 1, 3,
       0, 3, 1, 3, 0, 3, 3, 3, 3, 3, 3, 0, 0, 2, 0, 0, 3, 2, 2, 3, 0, 3,
       3, 0, 3, 3, 3, 3, 1, 0, 3, 1, 0, 2, 1, 2, 0, 3, 3, 3, 0, 3, 3, 0,
       3, 1, 3, 3, 0, 0, 0, 0, 3, 3, 3, 3, 0, 3, 3, 3, 3, 3, 1, 3, 3, 0,
       3, 3, 3, 2, 3, 3, 3, 0, 0, 3, 0, 3, 3, 3, 3, 3, 3, 0, 3, 0, 3, 3,
       0, 3, 3, 0, 3, 3, 1, 0, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 0, 3,
       0, 3, 3, 2, 3, 2, 0, 3, 3, 3, 0, 0, 3, 3, 3, 1, 3, 3, 3, 3, 2, 3,
       3, 3, 3, 3, 2, 2, 2, 3, 0, 3, 3, 1, 1, 0, 2, 3, 3, 2, 3, 3, 0, 3,
       1, 3, 3, 3, 3, 0, 1, 3, 3, 2, 3, 0, 3, 1, 3, 0, 3, 3, 3, 2, 3, 3,
       3, 2, 2, 3, 3, 3, 1, 0, 3, 3, 2, 3, 1, 3, 0, 3, 2, 3, 3, 3, 3, 0,
       2, 3, 3, 3, 2, 3, 3, 3, 3, 3, 3, 0, 1, 3, 0, 1, 0, 3, 3, 1, 3, 3,
       0, 3, 3, 2, 3, 3, 1, 3, 0, 3, 1, 2, 3, 3, 3, 3, 0, 3, 3, 3, 1, 3,
       0, 3, 3, 3, 3, 3, 0, 2, 2, 0, 2, 0, 0, 3, 0, 1, 0, 3, 3, 0, 0, 3,
       3, 3, 3, 1, 0, 3, 3, 3, 0, 0, 0, 0, 3, 1, 3, 0, 3, 3, 3, 3, 3, 1,
       3, 2, 3, 0, 3, 3, 0, 3, 3, 3, 0, 0, 0, 3, 3, 3, 2, 2, 3, 3, 3, 3,
       1, 3, 2, 3, 3, 3, 3, 3, 3, 0, 0, 3, 2, 1, 0, 1, 3, 3, 0, 3, 3, 3,
       1, 0, 3, 3, 3, 2, 0, 3, 0, 2, 3, 0, 3, 3, 3, 3, 0, 3, 1, 3, 3, 0,
       0, 3, 3, 0, 3, 1, 3, 3, 3, 1, 0, 3, 3, 3, 3, 3, 3, 3, 3, 3, 0, 3,
       2, 3, 1, 3, 3, 3, 0, 1, 3, 0, 3, 3, 3, 0, 3, 3, 3, 1, 2, 3, 3, 0,
       3, 3, 3, 3, 3, 0, 2, 0, 3, 3, 0, 0, 3, 3, 3, 1, 2, 3, 3, 3, 0, 1,
       3, 2, 1, 3, 3, 2, 3, 3, 3, 1, 3, 0, 1, 3, 1, 3, 3, 3, 1, 2, 3, 0,
       0, 3, 0, 3, 3, 2, 3, 3, 0, 3, 3, 3, 0, 3, 0, 3, 3, 3])
```

# Evaluate the model
**from** sklearn. metrics **import** accuracy_score,  classification_report
accuracy = accuracy_score (y_test, y_pred) * 100
print ("Accuracy of the model is {:.2f}”. format(accuracy))

**Output**
Accuracy: 89%

**from** sklearn. metrics **import** classification_report
class_report **=** classification_report (y_test, y_pred)
print (f"\nClassification Report:\n{class_report}")

**Output**

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

           0       0.95      0.99      0.97       168
           1       0.85      0.75      0.79        80
           2       0.72      0.68      0.70        73
           3       0.90      0.92      0.91       423

    accuracy                           0.89       744
   macro avg       0.86      0.84      0.84       744
weighted avg       0.89      0.89      0.89       744
```

# Predict for new data
new_data = [9, 5, 6, 3, 2, 5, 45]
predictions = model. predict([new_data])
print(predictions)

**Output**
[0]

# Assuming a label encoder for decoding categorical predictions
decoded_predictions = label_encoder.inverse_transform(predictions)
print(decoded_predictions)

**Output**
['heavy']

**RESULT**

Thus, the program to predict the traffic on a new mode of transport was executed successfully using Support Vector Machine model.

**Ex. No: 4 PREDICT THE CLASS OF USER**

**AIM**

To write a Python program to predict the class of user using Decision Tree.

**PROCEDURE**

1. Importing the necessary libraries, including **'pandas'** for data manipulation, and **'numpy'** for numerical operations and warnings.
2. Load the dataset containing trip history data. For Example, Trip dataset.
3. Explore the dataset to understand its structure and features. Preprocess the data if needed, such as handling missing values.
4. Use **'LabelEncoder'** to encode categorical columns like 'Start date', 'End station', 'Bike number' and 'Member type'.
5. Split the dataset into features (x) and target variable (y).
6. Further split the dataset into training and testing sets using 'train_test_split' from **'sklearn. model_selection'**.
7. Standardize the features using **'StandardScaler'** from **'sklearn. preprocessing'**.
8. Initialize a Decision Tree Classifier model from '**sklearn. tree'.**
9. Train the Decision Tree Classifier model using the training data with the **'fit'** method.
10. Use the trained Decision Tree Classifier model to make predictions on the testing data with the **'predict'** method.
11. Evaluate the performance of the model using **metrics** such as accuracy, precision, recall, F1_Score, or others based on the requirements.
12. Finally, use the trained model to predict the outcome for the new data.

**PROGRAM**

```
# Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings. Simplefilter ("ignore")

# Load the Dataset
df = pd. read_csv("C:\\Users\\Documents\\Trip.csv")
df. head ()
```

## Output

| | Duration | Start date | End date | Start station number | Start station | End station number | End station | Bike number | Member type |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1012 | 20-09-2010 11:27 | 20-09-2010 11:43 | 31208 | M St & New Jersey Ave SE | 31108 | 4th & M St SW | W00742 | Member |
| **1** | 61 | 20-09-2010 11:41 | 20-09-2010 11:42 | 31209 | 1st & N St SE | 31209 | 1st & N St SE | W00032 | Member |
| **2** | 2690 | 20-09-2010 12:05 | 20-09-2010 12:50 | 31600 | 5th & K St NW | 31100 | 19th St & Pennsylvania Ave NW | W00993 | Member |
| **3** | 1406 | 20-09-2010 12:06 | 20-09-2010 12:29 | 31600 | 5th & K St NW | 31602 | Park Rd & Holmead Pl NW | W00344 | Member |
| **4** | 1413 | 20-09-2010 12:10 | 20-09-2010 12:34 | 31100 | 19th St & Pennsylvania Ave NW | 31201 | 15th & P St NW | W00883 | Member |

df.info ()

## Output

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 115597 entries, 0 to 115596
Data columns (total 9 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   Duration              115597 non-null  int64
 1   Start date            115597 non-null  object
 2   End date              115597 non-null  object
 3   Start station number  115597 non-null  int64
 4   Start station         115597 non-null  object
 5   End station number    115597 non-null  int64
 6   End station           115597 non-null  object
 7   Bike number           115597 non-null  object
 8   Member type           115597 non-null  object
dtypes: int64(3), object(6)
memory usage: 7.9+ MB
```

df. describe ()

## Output

| | Duration | Start station number | End station number |
|---|---|---|---|
| **count** | 115597.000000 | 115597.000000 | 115597.000000 |
| **mean** | 1254.649956 | 31266.213431 | 31268.042250 |
| **std** | 2914.317998 | 187.645048 | 186.194316 |
| **min** | 60.000000 | 31000.000000 | 31000.000000 |
| **25%** | 403.000000 | 31110.000000 | 31111.000000 |
| **50%** | 665.000000 | 31213.000000 | 31214.000000 |
| **75%** | 1120.000000 | 31301.000000 | 31238.000000 |
| **max** | 85644.000000 | 31805.000000 | 31805.000000 |

# Explore and preprocess the data
df. isnull (). sum ()

**Output**

```
Duration                0
Start date              0
End date                0
Start station number    0
Start station           0
End station number      0
End station             0
Bike number             0
Member type             0
dtype: int64
```

# Drop the null values
df = df. drop (['Start date', 'End date'], axis =1)
df. head ()

**Output**

| | Duration | Start station number | Start station | End station number | End station | Bike number | Member type |
|---|---|---|---|---|---|---|---|
| **0** | 1012 | 31208 | M St & New Jersey Ave SE | 31108 | 4th & M St SW | W00742 | Member |
| **1** | 61 | 31209 | 1st & N St SE | 31209 | 1st & N St SE | W00032 | Member |
| **2** | 2690 | 31600 | 5th & K St NW | 31100 | 19th St & Pennsylvania Ave NW | W00993 | Member |
| **3** | 1406 | 31600 | 5th & K St NW | 31602 | Park Rd & Holmead Pl NW | W00344 | Member |
| **4** | 1413 | 31100 | 19th St & Pennsylvania Ave NW | 31201 | 15th & P St NW | W00883 | Member |

# Encoding the categorical values
from sklearn. preprocessing import LabelEncoder
label_encoder = LabelEncoder ()
categorical_columns = ['Start station', 'End station', 'Bike number', 'Member type']
df[categorical_columns] = df[categorical_columns]. apply(label_encoder.fit_transform)
df[categorical_columns]

**Output**

| | Start station | End station | Bike number | Member type |
|---|---|---|---|---|
| **0** | 85 | 50 | 614 | 1 |
| **1** | 32 | 33 | 41 | 1 |
| **2** | 52 | 31 | 836 | 1 |
| **3** | 52 | 94 | 282 | 1 |
| **4** | 30 | 21 | 734 | 1 |
| **...** | ... | ... | ... | ... |
| **115592** | 35 | 65 | 716 | 0 |
| **115593** | 63 | 18 | 764 | 1 |
| **115594** | 93 | 18 | 819 | 1 |
| **115595** | 1 | 14 | 946 | 1 |
| **115596** | 1 | 1 | 636 | 0 |

115597 rows × 4 columns

```
# Split the data into features (x)
x = df. iloc [: , :-1]
x
```

**Output**

| | Duration | Start station number | Start station | End station number | End station | Bike number |
|---|---|---|---|---|---|---|
| **0** | 1012 | 31208 | 85 | 31108 | 50 | 614 |
| **1** | 61 | 31209 | 32 | 31209 | 33 | 41 |
| **2** | 2690 | 31600 | 52 | 31100 | 31 | 836 |
| **3** | 1406 | 31600 | 52 | 31602 | 94 | 282 |
| **4** | 1413 | 31100 | 30 | 31201 | 21 | 734 |
| **...** | ... | ... | ... | ... | ... | ... |
| **115592** | 2179 | 31110 | 35 | 31623 | 65 | 716 |
| **115593** | 953 | 31106 | 63 | 31401 | 18 | 764 |
| **115594** | 737 | 31602 | 93 | 31401 | 18 | 819 |
| **115595** | 514 | 31111 | 1 | 31202 | 14 | 946 |
| **115596** | 51962 | 31111 | 1 | 31111 | 1 | 636 |

115597 rows × 6 columns

**# Split the data into target variable (y)**

y = df. iloc [: , -1]

**Output**

```
0         1
1         1
2         1
3         1
4         1
         ..
115592    0
115593    1
115594    1
115595    1
115596    0
Name: Member type, Length: 115597, dtype: int32
```

**# Further split the dataset into training and testing sets**

**from** sklearn. model_selection **import** train_test_split

x_train, x_test, y_train, y_test=train_test_split (x, y, random_state=0)

**# Feature scaling using StandardScaler**

from sklearn. preprocessing import StandardScaler

scaler = StandardScaler ()

x_train = scaler.fit_transform(x_train)

x_test = scaler. transform(x_test)

x_train

**Output**

```
array([[ 0.54640202, -1.40804138, -0.50762432,  1.8909801 ,  0.11621975,
        -1.36635173],
       [-0.32533639, -1.41337456, -0.81044688, -1.36975376,  0.69092124,
        -1.47913197],
       [-0.14892163, -0.28274243, -0.84409383, -0.89702793, -1.10079519,
         1.07843294],
       ...,
       [-0.21022131, -0.16007951, -0.13750786, -0.30074876, -0.35706384,
        -1.51915077],
       [-0.18028425,  1.85052573,  0.77095983,  1.86949256, -0.05281011,
         0.57637894],
       [-0.35277869, -0.35207365,  1.30931104, -0.35983949, -0.93176534,
         0.82740594]])
```

x_test

**Output**

```
array([[-0.36026295, -0.82672581, -1.58432676, -0.20942672,  1.43465259,
        -0.78789821],
       [ 0.00682231, -0.84272532,  0.0307269 , -0.2524018 , -0.76273549,
         0.74736835],
       [-0.28648951, -0.35207365,  1.30931104, -0.88091228,  0.2852496 ,
        -0.93705918],
       ...,
       [-0.12254851, -0.83205898, -0.44033042, -0.26314557, -1.57407878,
         1.63141995],
       [-0.2815    , -0.32540779, -0.40668346, -0.34909572, -1.13460116,
        -1.46457968],
       [-0.16887966, -0.85872483, -1.21421029, -0.29000499, -0.8641534 ,
        -1.01709678]])
```

**# Intialize the Decision Tree model**

from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier ()

**# Train the Decision Tree model**

model.fit (x_train, y_train)

**Output**

DecisionTreeClassifier ()

**# Make predictions**

y_pred=model. predict(x_test)
y_pred

**Output**

array ([1, 1, 1, ..., 1, 1, 0])

**# Evaluate the model**

**from** sklearn. metrics **import** accuracy_score,  classification_report
accuracy = accuracy_score (y_test, y_pred) * 100
print ("Accuracy of the model is {:.2f}". format(accuracy))

**Output**

Accuracy: 80%

```
from sklearn. metrics import classification_report
class_report = classification_report (y_test, y_pred)
print (f"\nClassification Report:\n{class_report}")
```

**Output**

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

           0       0.52      0.54      0.53      6089
           1       0.88      0.87      0.87     22811

    accuracy                           0.80     28900
   macro avg       0.70      0.70      0.70     28900
weighted avg       0.80      0.80      0.80     28900
```

```
# Predict for new data
new_data = [737, 31110, 63, 31623, 18, 636]
predictions = model. predict([new_data])
print(predictions)
```

**Output**

[1]

```
# Assuming a label encoder for decoding categorical predictions
    decoded_predictions = label_encoder. inverse_transform(predictions)
print(decoded_predictions)
```

**Output**

['Member']

**RESULT**

Thus, the program to predict the class of user was completed successfully using Decision Tree Classifier.

**Ex. No: 5 IDENTIFY THE TWEETS WHICH ARE HATE TWEETS AND WHICH ARE NOT.**

**AIM**

To write a Python program to identify the tweets which are hate tweets and which are not using Multinomial Naïve Bayes model.

**PROCEDURE**

1. Importing the necessary libraries, including **'pandas'** for data manipulation, and **'numpy'** for numerical operations and warnings.
2. Load the dataset containing twitter data. For Example, Twitter dataset.
3. Explore the dataset to understand its structure and features. Preprocess the data if needed, such as handling missing values.
4. Split the dataset into features (x) and target variable (y).
5. Further split the dataset into training and testing sets using 'train_test_split' from **'sklearn. model_selection'**.
6. Use CountVectorizer from sklearn to convert the text features in the training data into a matrix of token counts and apply the same CountVectorizer to transform the text feature in the test data.
7. Initialize a Multinomial Naïve Bayes model from '**sklearn. naive_bayes'.**
8. Train the Multinomial Naïve Bayes model using the training data with the **'fit'** method.
9. Use the trained Multinomial Naïve Bayes model to make predictions on the testing data with the **'predict'** method.
10. Evaluate the performance of the model using **metrics** such as accuracy, precision, recall, F1_Score, or others based on the requirements.
11. Finally, use the trained model to predict the outcome for the new data.

**PROGRAM**

```
# Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings. Simplefilter ("ignore")

# Load the Dataset
df = pd. read_csv("C:\\Users\\Documents\\Twitter.csv")
df. head ()
```

## Output

| | status_id | text | created_at | favorite_count | retweet_count | location | followers_count | friends_count | statuses_count | category |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1046207313588236290 | Entitled, obnoxious, defensive, lying weasel. ... | 2018-09-30T01:17:15Z | 5 | 1 | McAllen, TX | 2253 | 2303 | 23856 | 0 |
| 1 | 1046207328113086464 | Thank you and for what you did for the women... | 2018-09-30T01:17:19Z | 5 | 2 | Tampa, FL | 2559 | 4989 | 19889 | 0 |
| 2 | 1046207329589493760 | Knitting (s) & getting ready for January 1... | 2018-09-30T01:17:19Z | 0 | 0 | St Cloud, MN | 16 | 300 | 9 | 0 |
| 3 | 1046207341283168256 | Yep just like triffeling women weaponized thei... | 2018-09-30T01:17:22Z | 1 | 0 | flyover country | 3573 | 3732 | 38361 | 1 |
| 4 | 1046207347016826880 | No, the President wants to end movement posin... | 2018-09-30T01:17:23Z | 0 | 0 | World | 294 | 312 | 7635 | 0 |

df.info ()

## Output

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 807174 entries, 0 to 807173
Data columns (total 10 columns):
 #   Column           Non-Null Count   Dtype 
---  ------           --------------   ----- 
 0   status_id        807174 non-null  int64 
 1   text             803638 non-null  object
 2   created_at       807174 non-null  object
 3   favorite_count   807174 non-null  int64 
 4   retweet_count    807174 non-null  int64 
 5   location         616394 non-null  object
 6   followers_count  807174 non-null  int64 
 7   friends_count    807174 non-null  int64 
 8   statuses_count   807174 non-null  int64 
 9   category         807174 non-null  int64 
dtypes: int64(7), object(3)
memory usage: 61.6+ MB
```

df. describe ()

## Output

| | status_id | favorite_count | retweet_count | followers_count | friends_count | statuses_count | category |
|---|---|---|---|---|---|---|---|
| count | 8.071740e+05 | 807174.000000 | 807174.000000 | 8.071740e+05 | 807174.000000 | 8.071740e+05 | 807174.000000 |
| mean | 1.061411e+18 | 6.466671 | 2.557508 | 4.663755e+04 | 6306.597207 | 4.793559e+04 | 0.118108 |
| std | 1.428176e+16 | 159.865656 | 50.724140 | 6.111813e+05 | 40549.763583 | 1.646474e+05 | 0.322737 |
| min | 1.046207e+18 | 0.000000 | 0.000000 | 0.000000e+00 | 0.000000 | 1.000000e+00 | 0.000000 |
| 25% | 1.050184e+18 | 0.000000 | 0.000000 | 1.070000e+02 | 160.000000 | 1.663250e+03 | 0.000000 |
| 50% | 1.054643e+18 | 0.000000 | 0.000000 | 5.390000e+02 | 528.000000 | 8.007000e+03 | 0.000000 |
| 75% | 1.071177e+18 | 1.000000 | 0.000000 | 2.844000e+03 | 1756.000000 | 3.317500e+04 | 0.000000 |
| max | 1.097647e+18 | 70385.000000 | 17484.000000 | 5.457643e+07 | 899383.000000 | 9.565126e+06 | 1.000000 |

# Explore and preprocess the data
df. isnull (). sum ()

**Output**

```
status_id               0
text                 3536
created_at              0
favorite_count          0
retweet_count           0
location           190780
followers_count         0
friends_count           0
statuses_count          0
category                0
dtype: int64
```

# Replace the null value
df['text']. fillna ('', inplace=True)

df['text']

**Output**

```
0         Entitled, obnoxious, defensive, lying weasel. ...
1         Thank you  and  for what you did for the women...
2         Knitting (s) &amp; getting ready for January 1...
3         Yep just like triffeling women weaponized thei...
4         No, the President wants to end  movement posin...
                                ...
807169    Let’s not forget that this “iconic kiss” was u...
807170    DEFINITELY....the only one any of us should su...
807171    Did the  movement count the dollars of Erin An...
807172    This is one of my all time fav songs &amp; vid...
807173     I watched your news on the death of the sailo...
Name: text, Length: 807174, dtype: object
```

df['location']. fillna ('', inplace=True)

df['location']

**Output**

```
0                McAllen, TX
1                  Tampa, FL
2               St Cloud, MN
3            flyover country
4                      World
                 ...
807169         South Florida
807170
807171                Philly
807172    Berlin, Deutschland
807173     Massachusetts, USA
Name: location, Length: 807174, dtype: object
```

# Drop the null values

```
df = df. drop (['status_id', 'created_at'], axis =1)
df. head ()
```

**Output**

| | text | favorite_count | retweet_count | location | followers_count | friends_count | statuses_count | category |
|---|---|---|---|---|---|---|---|---|
| **0** | Entitled, obnoxious, defensive, lying weasel. ... | 5 | 1 | McAllen, TX | 2253 | 2303 | 23856 | 0 |
| **1** | Thank you and for what you did for the women... | 5 | 2 | Tampa, FL | 2559 | 4989 | 19889 | 0 |
| **2** | Knitting (s) & getting ready for January 1... | 0 | 0 | St Cloud, MN | 16 | 300 | 9 | 0 |
| **3** | Yep just like triffeling women weaponized thei... | 1 | 0 | flyover country | 3573 | 3732 | 38361 | 1 |
| **4** | No, the President wants to end movement posin... | 0 | 0 | World | 294 | 312 | 7635 | 0 |

# Split the data into features (x)

```
x = df. iloc [: , :-1]
x
```

**Output**

| | text | favorite_count | retweet_count | location | followers_count | friends_count | statuses_count |
|---|---|---|---|---|---|---|---|
| **0** | Entitled, obnoxious, defensive, lying weasel. ... | 5 | 1 | McAllen, TX | 2253 | 2303 | 23856 |
| **1** | Thank you and for what you did for the women... | 5 | 2 | Tampa, FL | 2559 | 4989 | 19889 |
| **2** | Knitting (s) & getting ready for January 1... | 0 | 0 | St Cloud, MN | 16 | 300 | 9 |
| **3** | Yep just like triffeling women weaponized thei... | 1 | 0 | flyover country | 3573 | 3732 | 38361 |
| **4** | No, the President wants to end movement posin... | 0 | 0 | World | 294 | 312 | 7635 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **807169** | Let's not forget that this "iconic kiss" was u... | 2 | 0 | South Florida | 206 | 412 | 1247 |
| **807170** | DEFINITELY....the only one any of us should su... | 3 | 0 | | 63 | 6 | 137 |
| **807171** | Did the movement count the dollars of Erin An... | 0 | 0 | Philly | 2721 | 3509 | 66966 |
| **807172** | This is one of my all time fav songs & vid... | 1 | 1 | Berlin, Deutschland | 2683 | 1011 | 15455 |
| **807173** | I watched your news on the death of the sailo... | 1 | 0 | Massachusetts, USA | 237 | 741 | 789 |

807174 rows × 7 columns

# Split the data into target variable (y)

```
y = df. iloc [: , -1]
```

**Output**

```
0         0
1         0
2         0
3         1
4         0
         ..
807169    0
807170    0
807171    0
807172    1
807173    0
Name: category, Length: 807174, dtype: int64
```

**# Further split the dataset into training and testing sets**

```
from sklearn. model_selection import train_test_split
x_train, x_test, y_train, y_test=train_test_split (x, y, random_state=0)
```

**# Use CountVectorizer for text feature on training data**

```
from sklearn. feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer ()
x_train_text = vectorizer.fit_transform(x_train['text'])
x_train_text
```

**Output**

```
<605380x119250 sparse matrix of type '<class 'numpy.int64'>'
	with 10994435 stored elements in Compressed Sparse Row format>
```

**# Apply the same CountVectorizer to transform the text feature in the test data**

```
x_test_text = vectorizer. transform(x_test['text'])
x_test_text
```

**Output**

```
<201794x119250 sparse matrix of type '<class 'numpy.int64'>'
	with 3641705 stored elements in Compressed Sparse Row format>
```

**# Intialize the Naïve Bayes model**

```
from sklearn. naive_bayes import MultinomialNB
model = MultinomialNB ()
```

**# Train the Naïve Bayes model**

```
model.fit (x_train, y_train)
```

**Output**

```
MultinomialNB ()
```

**# Make predictions**

```
y_pred = model. predict(x_test_text)
y_pred
```

**Output**

```
array ([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

**# Evaluate the model**

```
from sklearn. metrics import accuracy_score,  classification_report
accuracy = accuracy_score (y_test, y_pred) * 100
print ("Accuracy of the model is {:.2f}”. format(accuracy))
```

**Output**

Accuracy: 93%

```
from sklearn. metrics import classification_report
class_report = classification_report (y_test, y_pred)
print (f"\nClassification Report:\n{class_report}")
```

**Output**

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

           0       0.96      0.96      0.96    178149
           1       0.70      0.71      0.71     23645

    accuracy                           0.93    201794
   macro avg       0.83      0.84      0.83    201794
weighted avg       0.93      0.93      0.93    201794
```

**RESULT**

Thus, the program to identify the tweets which are hate tweets and which are not was completed successfully using Multinomial Naïve Bayes model.

**Ex. No: 6** **PREDICT THE AGE OF THE ACTORS**

**AIM**

To write a Python program to predict the age of the actors using Linear Regression.

**PROCEDURE**

1. Importing the necessary libraries, including **‘pandas’** for data manipulation, and **‘numpy’** for numerical operations and warnings.
2. Load the dataset containing age of actor’s data. For Example, age dataset.
3. Explore the dataset to understand its structure and features. Preprocess the data if needed, such as handling missing values.
4. In the preprocessing, convert the ‘birthday’ column to a datetime format and also extract the birth year from the ‘birth year’ from the ‘birthday’ column to create a new ‘birth_year’ column.
5. Use **‘LabelEncoder’** to encode categorical columns like ‘name’, and ‘Character_gender’.
6. Use ‘SimpleImputer’ fro, sklearn to replace null values in numerical columns (‘birth_year’, ‘actor_age’) with the most frequent values.
7. Split the dataset into features (x) and target variable (y).
8. Further split the dataset into training and testing sets using ‘train_test_split’ from **‘sklearn. model_selection’**.
9. Initialize a Linear Regression model from ‘**sklearn. linear_model’.**
10. Train the Linear Regression model using the training data with the **‘fit’** method.
11. Use the trained Linear Regression model to make predictions on the testing data with the **‘predict’** method.
12. Evaluate the performance of the model using **metrics** such as mean_squared_error, or others based on the requirements.
13. Finally, use the trained model to predict the outcome for the new data.

**PROGRAM**

```
# Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings. Simplefilter ("ignore")

# Load the Dataset
df = pd. read_csv("C:\\Users\\Documents\\age.csv")
df. head ()
```

### Output

| | name | birthday | title | character_name | character_year | characterage | character_gender | love_interest | release_date | actor_age |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Ben Platt | 24-09-1993 | The Politician | Payton Hobart | hs senior | NaN | M | Alice Charles, Astrid Sloan, River Barkley | 27-09-2019 | 26.0 |
| 1 | Zoey Deutch | 10-11-1994 | The Politician | Infinity Jackson | hs senior | NaN | F | NaN | 27-09-2019 | 24.0 |
| 2 | Lucy Boynton | 17-01-1994 | The Politician | Astrid Sloan | hs senior | NaN | F | Payton Hobart, River Barkley | 27-09-2019 | 25.0 |
| 3 | Julia Schlaepfer | 03-03-1995 | The Politician | Alice Charles | hs senior | NaN | F | Payton Hobart, James Sullivan | 27-09-2019 | 24.0 |
| 4 | Laura Dreyfuss | 22-08-1988 | The Politician | McAfee Westbrook | hs senior | NaN | F | Skye Leighton | 27-09-2019 | 31.0 |

df.info ()

### Output

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243 entries, 0 to 242
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   name              243 non-null    object
 1   birthday          227 non-null    object
 2   title             243 non-null    object
 3   character_name    243 non-null    object
 4   character_year    111 non-null    object
 5   characterage      131 non-null    float64
 6   character_gender  243 non-null    object
 7   love_interest     132 non-null    object
 8   release_date      243 non-null    object
 9   actor_age         227 non-null    float64
dtypes: float64(2), object(8)
memory usage: 19.1+ KB
```

df. describe ()

### Output

| | characterage | actor_age |
|---|---|---|
| count | 131.000000 | 227.000000 |
| mean | 16.580153 | 21.977974 |
| std | 1.518877 | 3.908743 |
| min | 10.000000 | 11.000000 |
| 25% | 16.000000 | 20.000000 |
| 50% | 17.000000 | 22.000000 |
| 75% | 17.000000 | 24.000000 |
| max | 25.000000 | 32.000000 |

**# Explore and preprocess the data**

df. isnull (). sum ()

**Output**

```
name                 0
birthday            16
title                0
character_name       0
character_year     132
characterage       112
character_gender     0
love_interest      111
release_date         0
actor_age           16
dtype: int64
```

**# Preprocessing**

**# Extract year from birthday**

df['birthday'] = pd.to_datetime(df['birthday'])

df['birthday']

**Output**

```
0      1993-09-24
1      1994-11-10
2      1994-01-17
3      1995-03-03
4      1988-08-22
          ...
238           NaT
239    1991-10-19
240    1994-11-09
241    1998-04-20
242           NaT
Name: birthday, Length: 243, dtype: datetime64[ns]
```

df['birth_year'] = df['birthday'].dt. year

df['birth_year']

**Output**

```
0      1993.0
1      1994.0
2      1994.0
3      1995.0
4      1988.0
        ...
238       NaN
239    1991.0
240    1994.0
241    1998.0
242       NaN
Name: birth_year, Length: 243, dtype: float64
```

# Drop the null values

```
df = df. drop (['birthday', 'title','character_name', 'character_year', 'characterage', 'love_interest', 'release_date'], axis=1)
df
```

**Output**

| | name | character_gender | actor_age | birth_year |
|---|---|---|---|---|
| **0** | Ben Platt | M | 26.0 | 1993.0 |
| **1** | Zoey Deutch | F | 24.0 | 1994.0 |
| **2** | Lucy Boynton | F | 25.0 | 1994.0 |
| **3** | Julia Schlaepfer | F | 24.0 | 1995.0 |
| **4** | Laura Dreyfuss | F | 31.0 | 1988.0 |
| **...** | ... | ... | ... | ... |
| **238** | Thomas Mitchell Barnet | M | NaN | NaN |
| **239** | Kevin Alves | M | 28.0 | 1991.0 |
| **240** | Asha Bromfield | F | 25.0 | 1994.0 |
| **241** | Felix Mallard | M | 21.0 | 1998.0 |
| **242** | Hallea Jones | F | NaN | NaN |

243 rows × 4 columns

# Encoding the categorical values

```
from sklearn. preprocessing import LabelEncoder
label_encoder = LabelEncoder ()
categorical_columns = ['name', 'character_gender']
df[categorical_columns] = df[categorical_columns]. apply(label_encoder.fit_transform)
df[categorical_columns]
```

**Output**

| | name | character_gender |
|---|---|---|
| **0** | 24 | 1 |
| **1** | 239 | 0 |
| **2** | 151 | 0 |
| **3** | 126 | 0 |
| **4** | 142 | 0 |
| **...** | ... | ... |
| **238** | 229 | 1 |
| **239** | 135 | 1 |
| **240** | 18 | 0 |
| **241** | 80 | 1 |
| **242** | 94 | 0 |

243 rows × 2 columns

**# Explore the null values in the data**
df**.** isnull ()**.** sum ()

**Output**

```
name                0
character_gender    0
actor_age          16
birth_year         16
dtype: int64
```

**# Replace the null values**
from sklearn. impute import SimpleImputer
numeric_columns = ['birth_year','actor_age']
df[numeric_columns] = SimpleImputer(strategy='most_frequent'). fit_transform(df[numeric_columns])
df[numeric_columns]

**Output**

| | birth_year | actor_age |
|---|---|---|
| **0** | 1993.0 | 26.0 |
| **1** | 1994.0 | 24.0 |
| **2** | 1994.0 | 25.0 |
| **3** | 1995.0 | 24.0 |
| **4** | 1988.0 | 31.0 |
| **...** | ... | ... |
| **238** | 1996.0 | 22.0 |
| **239** | 1991.0 | 28.0 |
| **240** | 1994.0 | 25.0 |
| **241** | 1998.0 | 21.0 |
| **242** | 1996.0 | 22.0 |

243 rows × 2 columns

**# Split the data into features (x)**
x = df[['name', 'character_gender', 'birth_year']]
x

**Output**

| | name | character_gender | birth_year |
|---|---|---|---|
| **0** | 24 | 1 | 1993.0 |
| **1** | 239 | 0 | 1994.0 |
| **2** | 151 | 0 | 1994.0 |
| **3** | 126 | 0 | 1995.0 |
| **4** | 142 | 0 | 1988.0 |
| **...** | ... | ... | ... |
| **238** | 229 | 1 | 1996.0 |
| **239** | 135 | 1 | 1991.0 |
| **240** | 18 | 0 | 1994.0 |
| **241** | 80 | 1 | 1998.0 |
| **242** | 94 | 0 | 1996.0 |

243 rows × 3 columns

**# Split the data into target variable (y)**

y = df['actor_age']

y

**Output**

```
0      26.0
1      24.0
2      25.0
3      24.0
4      31.0
       ...
238    22.0
239    28.0
240    25.0
241    21.0
242    22.0
Name: actor_age, Length: 243, dtype: float64
```

**# Further split the dataset into training and testing sets**

from sklearn. model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split (x, y, test_size=0.2, random_state=42)

**# Intialize the Linear Regression model**

from sklearn. linear_model import LinearRegression

model = LinearRegression ()

**# Train the Linear Regression model**
model.fit (x_train, y_train)

**Output**
LinearRegression ()

**# Make predictions**
y_pred = model. predict(x_test)
y_pred

**Output**
```
array([20.09904337, 23.90720926, 20.81859233, 17.27447575, 20.69497398,
       19.17478424, 20.17372696, 19.32125732, 26.15894389, 20.06672071,
       23.63164979, 26.99190733, 23.06216532, 20.95792124, 21.86855069,
       20.60029112, 21.8311261 , 26.20693847, 19.70247812, 20.88760364,
       21.86063193, 21.31628731, 21.96911008, 20.55001143, 19.37308618,
       20.47177507, 28.29322551, 20.24192505, 20.99893724, 20.76190441,
       21.17414158, 20.93918962, 20.9083775 , 22.36906249, 21.07435678,
       21.26959902, 23.92308542, 20.81785638, 23.86149981, 21.93115378,
       22.94291295, 20.06312931, 20.71599071, 21.13390016, 20.34685042,
       22.32955702, 20.15422076, 20.61032939, 21.4240295 ])
```

**# Evaluate the model**
from sklearn. metrics import mean_squared_error
mse = mean_squared_error (y_test, y_pred)
print (f"Mean Squared Error: {mse}")

**Output**
Mean Squared Error: 9.760123797821025

**# Predict the new data**
new_data = pd. DataFrame ({"name": [142], "character_gender": [1], "birth_year": [1996.0]})
predicted_age = model. predict(new_data)
print (f"Predicted Actor Age: {predicted_age [0]}")

**Output**
Predicted Actor Age: 21.007426345958265

**RESULT**

Thus, the program to predict the age of the actors was completed successfully using Linear Regression.

## Ex. No: 7 INTRODUCTION TO PYTHON LIBRARIES - NUMPY, PANDAS, MATPLOTLIB, SCIKIT

### AIM

The aim to study the Python Libraries such as Numpy for numerical operations, Pandas for data manipulation and analysis, Matplotlib for data visualization, Scikit – Learn for machine learning tasks.

### PROCEDURE

1. **Numpy**
    - Numpy is used for numerical operations in Python.
    - It provides support for large, multi-dimensional arrays, along with mathematical functions to operate on these arrays.

    **Program**

    ```
    import numpy as np
    arr = np. array ([1, 2, 3, 4, 5])
    print ("Numpy Array:", arr)
    ```

    **Output**

    ```
    Numpy Array: [1 2 3 4 5]
    ```

2. **Pandas**
    - Pandas is a powerful library for data manipulation and analysis.
    - It introduces two primary data structures: Series (1D labeled array) and DataFrame (2D labeled table).
    - Procedures including loading data, exploring data using methods like info (), head (), and performing operations like dropping null values.

    **Program**

    ```
    import pandas as pd
    data = {'Name': ['Alice', 'Bob', 'Charlie'], 'Age': [25, 30, 35]}
    df = pd. DataFrame(data)
    print ("Pandas DataFrame:")
    print(df)
    ```

    **Output**

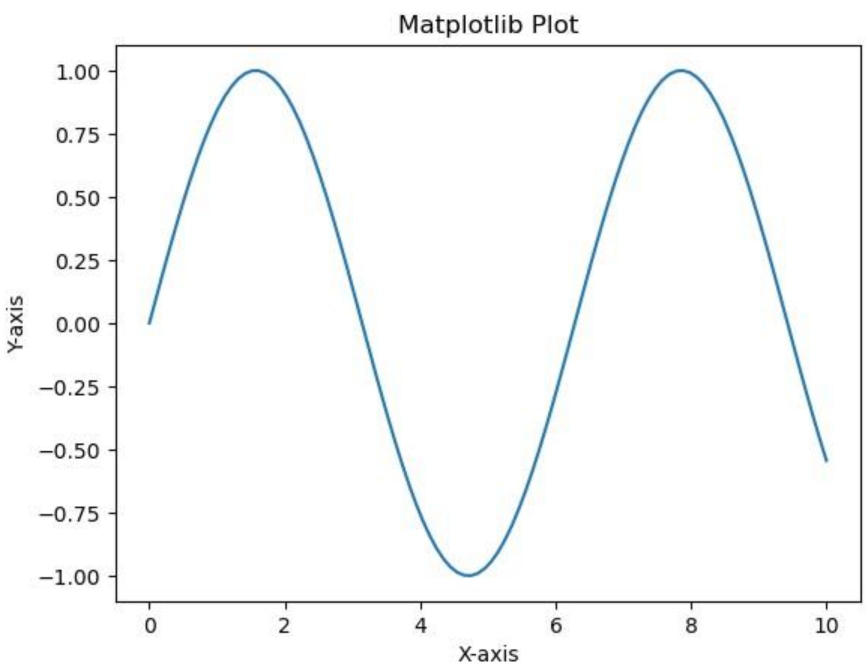
    ```
    Pandas DataFrame:
          Name  Age
    0    Alice   25
    1      Bob   30
    2  Charlie   35
    ```

3. **Matplotlib**
    - Matplotlib is a popular plotting library for creating static, interactive, and animated visualizations.
    - The focus is on using Matplotlib to create basic plots like line plots, scatter plots, and bar plots.

**Program**

```
import numpy as np
import matplotlib. pyplot as plt
x = np. linspace (0, 10, 100)
y = np. sin (x)
plt. plot (x, y)
plt. title (“Matplotlib Plot”)
plt. xlabel (“X-axis”)
plt. ylabel (“Y-axis”)
plt. show ()
```

**Output**




4. **Scikit-Learn**
    - Scikit-Learn is a machine learning library that provides simple and efficient tools for data analysis and modeling.
    - Procedures involve splitting data into training and testing sets using **train_test_split,** initializing and training a machine learning model (e.g., Linear regression), making predictions, and evaluating model performance.

**Program**

**# Dataset**

```
x = np. array ([1, 2, 3, 4, 5]). reshape (-1, 1)
y = np. array ([2, 4, 5, 4, 5])
```

**# Split the training and testing sets**

```
from sklearn. model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split (x, y, test_size = 0.2, random_state = 42)
```

**# Initialize the Linear Regression Model**

```
from sklearn. linear_model import LinearRegression
model = LinearRegression ()
```

**# Train the Linear regression Model**

```
model.fit (x_train, y_train)
```

**Output**

LinearRegression ()

**# Make Predictions**

```
prediction = model. predict(x_test)
print (“Scikit-Learn Prediction:”, prediction)
```

**# Evaluate the model**

```
from sklearn. metrics import mean_absolute_error, mean_squared_error, root_mean_sqerr, R_squared
mae = mean_absolute_error (y_test, y_pred)
print (f'Mean Absolute Error: {mae}')

mse = mean_squared_error (y_test, y_pred)
print (f'Mean Squared Error: {mse}')
```

**Output**

Mean Absolute Error: 85.71428571428572
Mean Squared Error: 73.46938775510206

**Result**

Thus, the basic usage of Numpy, Pandas, Matplotlib, and Scikit-Lear for machine learning tasks was studied successfully.

## Ex. No: 8 PERFORM DATA EXPLORATION AND PREPROCESSING IN PYTHON

### AIM

The aim is to perform the data exploration and preprocessing techniques in Python using a real-world dataset.

### PROCEDURE

1. **Import necessary libraries**

   Importing the necessary libraries, including **‘pandas’** for data manipulation, and **‘numpy’** for numerical operations.

   **Program**

   ```
   import numpy as np
   import pandas as pd
   ```

2. **Load the dataset**

   Load the real-world sample dataset to explore and preprocess the data for better understanding. For Example, Data.CSV dataset.

   **Program**

   ```
   dataset = pd. read_csv ("C:\\Users\\HP\\Documents\\DSC LAB\\Dataset\\Data.csv")
   dataset
   ```

   **Output**

| | Country | Age | Salary | Purchased |
|---|---|---|---|---|
| 0 | France | 44.0 | 72000.0 | No |
| 1 | Spain | 27.0 | 48000.0 | Yes |
| 2 | Germany | 30.0 | 54000.0 | No |
| 3 | Spain | 38.0 | 61000.0 | No |
| 4 | Germany | 40.0 | NaN | Yes |
| 5 | France | 35.0 | 58000.0 | Yes |
| 6 | Spain | NaN | 52000.0 | No |
| 7 | France | 48.0 | 79000.0 | Yes |
| 8 | Germany | 50.0 | 83000.0 | No |
| 9 | France | 37.0 | 67000.0 | Yes |

3. **Display the few rows to understand the data structure**

Display the few rows to understand the data structure of the data using **head ()** method.

**Program**

dataset. head (10)

**Output**

| | Country | Age | Salary | Purchased |
|---|---|---|---|---|
| **0** | France | 44.0 | 72000.0 | No |
| **1** | Spain | 27.0 | 48000.0 | Yes |
| **2** | Germany | 30.0 | 54000.0 | No |
| **3** | Spain | 38.0 | 61000.0 | No |
| **4** | Germany | 40.0 | NaN | Yes |
| **5** | France | 35.0 | 58000.0 | Yes |
| **6** | Spain | NaN | 52000.0 | No |
| **7** | France | 48.0 | 79000.0 | Yes |
| **8** | Germany | 50.0 | 83000.0 | No |
| **9** | France | 37.0 | 67000.0 | Yes |

4. **Analyze and view the information in tha data**

To view the information of the data using **info ()** method.

**Program**

dataset.info ()

**Output**

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Country    10 non-null     object
 1   Age        9 non-null      float64
 2   Salary     9 non-null      float64
 3   Purchased  10 non-null     object
dtypes: float64(2), object(2)
memory usage: 452.0+ bytes
```

5. **Analyze and view the statistics information of the data**
   To view the statistics information of the data using **describe ()** method.

   **Program**
   dataset. describe ()

   **Output**

| | Age | Salary |
|---|---|---|
| **count** | 9.000000 | 9.000000 |
| **mean** | 38.777778 | 63777.777778 |
| **std** | 7.693793 | 12265.579662 |
| **min** | 27.000000 | 48000.000000 |
| **25%** | 35.000000 | 54000.000000 |
| **50%** | 38.000000 | 61000.000000 |
| **75%** | 44.000000 | 72000.000000 |
| **max** | 50.000000 | 83000.000000 |

6. **Split the dataset into features (x)**
   From the dataset, split the independent variable (x).

   **Program**
   x = dataset. iloc [:, :-1].values
   print(x)

   **Output**

```
[['France' 44.0 72000.0]
 ['Spain' 27.0 48000.0]
 ['Germany' 30.0 54000.0]
 ['Spain' 38.0 61000.0]
 ['Germany' 40.0 nan]
 ['France' 35.0 58000.0]
 ['Spain' nan 52000.0]
 ['France' 48.0 79000.0]
 ['Germany' 50.0 83000.0]
 ['France' 37.0 67000.0]]
```

7. **Split the dataset into target variable (y)**
   From the dataset, split the dependent variable (y).

   **Program**
   y = dataset. iloc [:, 3].values
   print(y)

   **Output**
   ['No' 'Yes' 'No' 'No' 'Yes' 'Yes' 'No' 'Yes' 'No' 'Yes']

## 8. Handling missing Data

Identify missing values using **'dataset. isnull (). sum ()'**.

**Program**

```
print (dataset. isnull (). sum ())
```

**Output**

```
Country      0
Age          1
Salary       1
Purchased    0
dtype: int64
```

## 9. Drop missing values

Drop missing values from the dataset using **'dataset. dropna ()'**.

**Program**

```
dataset. dropna (inplace = True)
print(dataset)
```

**Output**

```
   Country   Age   Salary Purchased
0   France  44.0  72000.0        No
1    Spain  27.0  48000.0       Yes
2  Germany  30.0  54000.0        No
3    Spain  38.0  61000.0        No
5   France  35.0  58000.0       Yes
7   France  48.0  79000.0       Yes
8  Germany  50.0  83000.0        No
9   France  37.0  67000.0       Yes
```

## 10. Replace missing values

Use **'SimpleImputer'** from scikit-learn to replace missing values with the mean of the respective columns.

**Program**

```
# Taking care of missing data (replacing with the mean)
from sklearn. impute import SimpleImputer
imputer = SimpleImputer (missing_values = np.nan, strategy = 'mean')

# Fitting the imputer object to the matrix of features X
imputer.fit(x[:,1:3])

# Replacing the missing data by the mean of the column
x[:,1:3] = imputer.transform(x[:,1:3])
print(x[:,1:3])
```

**Output**

```
[[44.0 72000.0]
 [27.0 48000.0]
 [30.0 54000.0]
 [38.0 61000.0]
 [40.0 63777.77777777778]
 [35.0 58000.0]
 [38.77777777777778 52000.0]
 [48.0 79000.0]
 [50.0 83000.0]
 [37.0 67000.0]]
```

**11. Encoding the categorical data**

- Apply one-hot encoding to the **'Country'** column using **'ColumnTransfomer'** and **'OneHotEncoder'**.

**Program**

```
from sklearn. compose import ColumnTransformer
from sklearn. preprocessing import OneHotEncoder
ct = ColumnTransformer (transformers = [('encoder', OneHotEncoder (), [0])], remainder =
"passthrough")
x = np. array(ct.fit_transform(x))
print(x)
```

**Output**

```
[[1.0 0.0 0.0 44.0 72000.0]
 [0.0 0.0 1.0 27.0 48000.0]
 [0.0 1.0 0.0 30.0 54000.0]
 [0.0 0.0 1.0 38.0 61000.0]
 [0.0 1.0 0.0 40.0 63777.77777777778]
 [1.0 0.0 0.0 35.0 58000.0]
 [0.0 0.0 1.0 38.77777777777778 52000.0]
 [1.0 0.0 0.0 48.0 79000.0]
 [0.0 1.0 0.0 50.0 83000.0]
 [1.0 0.0 0.0 37.0 67000.0]]
```

- Apply Label encode to the **'Purchased'** column using **'LabelEncoder'**.

**Program**

```
from sklearn. preprocessing import LabelEncoder
le = LabelEncoder ()
y=le.fit_transform(y)
print(y)
```

**Output**

```
[0 1 0 0 1 1 0 1 0 1]
```

**12. Splitting the Dataset**

Use **'train_test_split'** from scikit-learn to split the dataset into training and testing sets.

**Program**

```
from sklearn. model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split (x, y, test_size = 0.25, random_state = 1)
print(x_train)
```

**Output**

```
[[0.0 1.0 0.0 40.0 63777.77777777778]
 [1.0 0.0 0.0 44.0 72000.0]
 [0.0 0.0 1.0 38.0 61000.0]
 [0.0 0.0 1.0 27.0 48000.0]
 [1.0 0.0 0.0 48.0 79000.0]
 [0.0 1.0 0.0 50.0 83000.0]
 [1.0 0.0 0.0 35.0 58000.0]]
```

**Program**

```
print(x_test)
```

**Output**

```
[[0.0 1.0 0.0 30.0 54000.0]
 [1.0 0.0 0.0 37.0 67000.0]
 [0.0 0.0 1.0 38.77777777777778 52000.0]]
```

**Program**

```
print(y_train)
```

**Output**

```
[1 0 0 1 1 0 1]
```

**Program**

```
print(y_test)
```

**Output**

```
[0 1 0]
```

**13. Feature Scaling**

Standardize the numerical features using **'StandardScaler'** from scikit-learn.

**Program**

```
from sklearn. preprocessing import StandardScaler
scaler = StandardScaler ()
x_train[:,2:]=scaler.fit_transform(x_train[:,2:])
x_test[:,2:]=scaler.fit_transform(x_test[:,2:])
print(x_train)
print(x_test)
```

**Output**

```
[[0.0 1.0 -0.6324555320336758 -0.038910211282047996 -0.22960023388015188]
 [1.0 0.0 -0.6324555320336758 0.5058327466666259 0.49120534884662787]
 [0.0 0.0 1.5811388300841895 -0.3112816902563849 -0.4731156334500103]
 [0.0 0.0 1.5811388300841895 -1.809324824615238 -1.6127677034369463]
 [1.0 0.0 -0.6324555320336758 1.0505757046152997 1.1048641557626704]
 [0.0 1.0 -0.6324555320336758 1.3229471835896367 1.455526331143266]
 [1.0 0.0 -0.6324555320336758 -0.7198389087178904 -0.7361122649854577]]
[[0.0 1.0 -0.7071067811865475 -1.3880272079128577 -0.5513801778287937]
 [1.0 0.0 -0.7071067811865475 0.4594174561401711 1.40351317992784]
 [0.0 0.0 1.4142135623730951 0.9286097517726866 -0.8521330020990451]]
```

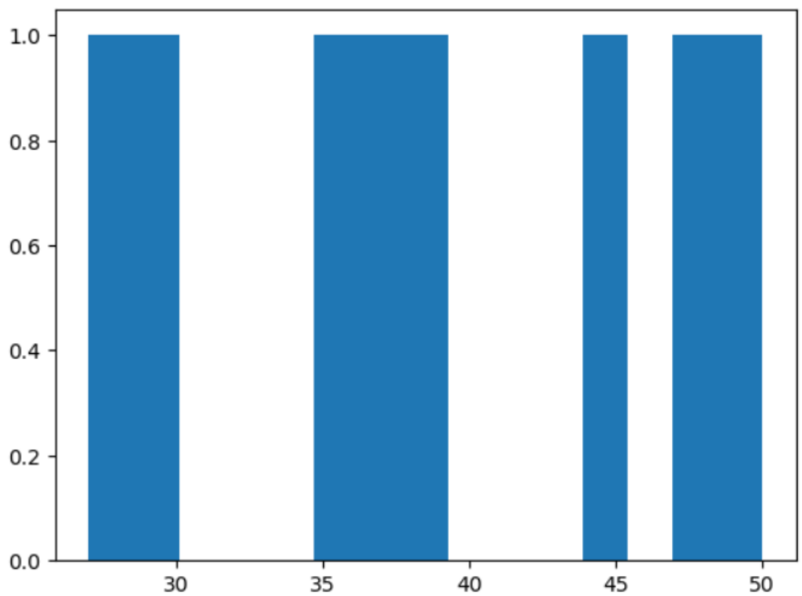
## 14. Data Visualization

Visualize the distribution of the 'Age' column using a histogram.

**Program**

```
import matplotlib. pyplot as plt
plt. hist(dataset['Age'], bins=15)
plt. show ()
```

**Output**




## 15. Identify outliers

Identify the outliers using the quantile method.

**Program**

```
lowerLimit=dataset['Age']. quantile (0.05)
print(lowerLimit)
```

**Output**

28.05

**Program**

```
print(dataset[dataset['Age’] <lowerLimit])
```

**Output**

```
  Country   Age   Salary Purchased
1   Spain  27.0  48000.0       Yes
```

**Program**

```
upperLimit=dataset['Age']. quantile (0.95)
print(upperLimit)
```

**Output**

49.3

**Program**

```
print(dataset[dataset['Age']>upperLimit])
```

**Output**

```
   Country   Age   Salary Purchased
8  Germany  50.0  83000.0        No
```

**16. Remove outliers from the dataset**

Remove the outliers from the dataset using quantile method.

**Program**

```
dataset = dataset[(dataset['Age']>lowerLimit) & (dataset['Age’] <upperLimit)]
print(dataset)
```

**Output**

```
   Country   Age   Salary Purchased
0   France  44.0  72000.0        No
2  Germany  30.0  54000.0        No
3    Spain  38.0  61000.0        No
5   France  35.0  58000.0       Yes
7   France  48.0  79000.0       Yes
9   France  37.0  67000.0       Yes
```

**Result**

Thus, the performance of the data exploration and preprocessing techniques in Python using a real-world dataset was successfully completed.

## Ex. No: 9 IMPLEMENTATION OF REGULARIZED LINEAR REGRESSION

**AIM**

To write a Python program to implement a regularized linear regression on housing dataset.

**PROCEDURE**

1. Importing the necessary libraries, including **'pandas'** for data manipulation, and **'numpy'** for numerical operations and warnings.
2. Load the dataset containing housing dataset from the specified file location.
3. Explore the dataset to understand its structure and features. Preprocess the data if needed, such as handling missing values.
4. Replace missing values in specific numeric columns with the mean using **'SimpleImputer'**.
5. Split the dataset into features (x) and target variable (y).
6. Further split the dataset into training and testing sets using 'train_test_split' from **'sklearn. model_selection'**.
7. Standardize the features using **'StandardScaler'** from **'sklearn. preprocessing'**.
8. Initialize a Ridge Regression model from '**sklearn. linear_model'.**
9. Train the Ridge Regression model using the training data with the **'fit'** method.
10. Use the trained Ridge Regression model to make predictions on the testing data with the **'predict'** method.
11. Evaluate the performance of the model using **metrics** such as mean_squared_error, or others based on the requirements.
12. Finally, use the trained model to predict the outcome for the new data.

**PROGRAM**

```
# Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings. Simplefilter ("ignore")

# Load the Dataset
df = pd. read_csv("C:\\Users\\Documents\\Housing.csv")
df
```

**Output**

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX | PTRATIO | B | LSTAT | MEDV |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.00632 | 18.0 | 2.31 | 0.0 | 0.538 | 6.575 | 65.2 | 4.0900 | 1 | 296 | 15.3 | 396.90 | 4.98 | 24.0 |
| **1** | 0.02731 | 0.0 | 7.07 | 0.0 | 0.469 | 6.421 | 78.9 | 4.9671 | 2 | 242 | 17.8 | 396.90 | 9.14 | 21.6 |
| **2** | 0.02729 | 0.0 | 7.07 | 0.0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2 | 242 | 17.8 | 392.83 | 4.03 | 34.7 |
| **3** | 0.03237 | 0.0 | 2.18 | 0.0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3 | 222 | 18.7 | 394.63 | 2.94 | 33.4 |
| **4** | 0.06905 | 0.0 | 2.18 | 0.0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3 | 222 | 18.7 | 396.90 | NaN | 36.2 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **501** | 0.06263 | 0.0 | 11.93 | 0.0 | 0.573 | 6.593 | 69.1 | 2.4786 | 1 | 273 | 21.0 | 391.99 | NaN | 22.4 |
| **502** | 0.04527 | 0.0 | 11.93 | 0.0 | 0.573 | 6.120 | 76.7 | 2.2875 | 1 | 273 | 21.0 | 396.90 | 9.08 | 20.6 |
| **503** | 0.06076 | 0.0 | 11.93 | 0.0 | 0.573 | 6.976 | 91.0 | 2.1675 | 1 | 273 | 21.0 | 396.90 | 5.64 | 23.9 |
| **504** | 0.10959 | 0.0 | 11.93 | 0.0 | 0.573 | 6.794 | 89.3 | 2.3889 | 1 | 273 | 21.0 | 393.45 | 6.48 | 22.0 |
| **505** | 0.04741 | 0.0 | 11.93 | 0.0 | 0.573 | 6.030 | NaN | 2.5050 | 1 | 273 | 21.0 | 396.90 | 7.88 | 11.9 |

506 rows × 14 columns

df.info ()

**Output**

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     486 non-null    float64
 1   ZN       486 non-null    float64
 2   INDUS    486 non-null    float64
 3   CHAS     486 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      486 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64  
 9   TAX      506 non-null    int64  
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    486 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

df. describe ()

**Output**

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX | PTRATIO | B | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 486.000000 | 486.000000 | 486.000000 | 486.000000 | 506.000000 | 506.000000 | 486.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 486.00 |
| **mean** | 3.611874 | 11.211934 | 11.083992 | 0.069959 | 0.554695 | 6.284634 | 68.518519 | 3.795043 | 9.549407 | 408.237154 | 18.455534 | 356.674032 | 12.71 |
| **std** | 8.720192 | 23.388876 | 6.835896 | 0.255340 | 0.115878 | 0.702617 | 27.999513 | 2.105710 | 8.707259 | 168.537116 | 2.164946 | 91.294864 | 7.15 |
| **min** | 0.006320 | 0.000000 | 0.460000 | 0.000000 | 0.385000 | 3.561000 | 2.900000 | 1.129600 | 1.000000 | 187.000000 | 12.600000 | 0.320000 | 1.73 |
| **25%** | 0.081900 | 0.000000 | 5.190000 | 0.000000 | 0.449000 | 5.885500 | 45.175000 | 2.100175 | 4.000000 | 279.000000 | 17.400000 | 375.377500 | 7.12 |
| **50%** | 0.253715 | 0.000000 | 9.690000 | 0.000000 | 0.538000 | 6.208500 | 76.800000 | 3.207450 | 5.000000 | 330.000000 | 19.050000 | 391.440000 | 11.43 |
| **75%** | 3.560263 | 12.500000 | 18.100000 | 0.000000 | 0.624000 | 6.623500 | 93.975000 | 5.188425 | 24.000000 | 666.000000 | 20.200000 | 396.225000 | 16.95 |
| **max** | 88.976200 | 100.000000 | 27.740000 | 1.000000 | 0.871000 | 8.780000 | 100.000000 | 12.126500 | 24.000000 | 711.000000 | 22.000000 | 396.900000 | 37.97 |

**# Explore and preprocess the data**

df. isnull (). sum ()

**Output**

```
CRIM       20
ZN         20
INDUS      20
CHAS       20
NOX         0
RM          0
AGE        20
DIS         0
RAD         0
TAX         0
PTRATIO     0
B           0
LSTAT      20
MEDV        0
dtype: int64
```

**# Replace the null values**

from sklearn. impute import SimpleImputer

numeric_columns = ['CRIM', 'ZN','INDUS', 'CHAS', 'AGE', 'LSTAT']

df[numeric_columns] = SimpleImputer(strategy='mean').fit_transform(df[numeric_columns])

df[numeric_columns]

**Output**

| | CRIM | ZN | INDUS | CHAS | AGE | LSTAT |
|---|---|---|---|---|---|---|
| **0** | 0.00632 | 18.0 | 2.31 | 0.0 | 65.200000 | 4.980000 |
| **1** | 0.02731 | 0.0 | 7.07 | 0.0 | 78.900000 | 9.140000 |
| **2** | 0.02729 | 0.0 | 7.07 | 0.0 | 61.100000 | 4.030000 |
| **3** | 0.03237 | 0.0 | 2.18 | 0.0 | 45.800000 | 2.940000 |
| **4** | 0.06905 | 0.0 | 2.18 | 0.0 | 54.200000 | 12.715432 |
| **...** | ... | ... | ... | ... | ... | ... |
| **501** | 0.06263 | 0.0 | 11.93 | 0.0 | 69.100000 | 12.715432 |
| **502** | 0.04527 | 0.0 | 11.93 | 0.0 | 76.700000 | 9.080000 |
| **503** | 0.06076 | 0.0 | 11.93 | 0.0 | 91.000000 | 5.640000 |
| **504** | 0.10959 | 0.0 | 11.93 | 0.0 | 89.300000 | 6.480000 |
| **505** | 0.04741 | 0.0 | 11.93 | 0.0 | 68.518519 | 7.880000 |

506 rows × 6 columns

**# Split the data into features (x)**

```
x = df. iloc [:,  :-1]
x
```

**Output**

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX | PTRATIO | B | LSTAT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.00632 | 18.0 | 2.31 | 0.0 | 0.538 | 6.575 | 65.200000 | 4.0900 | 1 | 296 | 15.3 | 396.90 | 4.980000 |
| **1** | 0.02731 | 0.0 | 7.07 | 0.0 | 0.469 | 6.421 | 78.900000 | 4.9671 | 2 | 242 | 17.8 | 396.90 | 9.140000 |
| **2** | 0.02729 | 0.0 | 7.07 | 0.0 | 0.469 | 7.185 | 61.100000 | 4.9671 | 2 | 242 | 17.8 | 392.83 | 4.030000 |
| **3** | 0.03237 | 0.0 | 2.18 | 0.0 | 0.458 | 6.998 | 45.800000 | 6.0622 | 3 | 222 | 18.7 | 394.63 | 2.940000 |
| **4** | 0.06905 | 0.0 | 2.18 | 0.0 | 0.458 | 7.147 | 54.200000 | 6.0622 | 3 | 222 | 18.7 | 396.90 | 12.715432 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **501** | 0.06263 | 0.0 | 11.93 | 0.0 | 0.573 | 6.593 | 69.100000 | 2.4786 | 1 | 273 | 21.0 | 391.99 | 12.715432 |
| **502** | 0.04527 | 0.0 | 11.93 | 0.0 | 0.573 | 6.120 | 76.700000 | 2.2875 | 1 | 273 | 21.0 | 396.90 | 9.080000 |
| **503** | 0.06076 | 0.0 | 11.93 | 0.0 | 0.573 | 6.976 | 91.000000 | 2.1675 | 1 | 273 | 21.0 | 396.90 | 5.640000 |
| **504** | 0.10959 | 0.0 | 11.93 | 0.0 | 0.573 | 6.794 | 89.300000 | 2.3889 | 1 | 273 | 21.0 | 393.45 | 6.480000 |
| **505** | 0.04741 | 0.0 | 11.93 | 0.0 | 0.573 | 6.030 | 68.518519 | 2.5050 | 1 | 273 | 21.0 | 396.90 | 7.880000 |

506 rows × 13 columns

**# Split the data into target variable (y)**

```
y = df. iloc[:,  -1]
y
```

**Output**

```
0      24.0
1      21.6
2      34.7
3      33.4
4      36.2
       ...
501    22.4
502    20.6
503    23.9
504    22.0
505    11.9
Name: MEDV, Length: 506, dtype: float64
```

**# Further split the dataset into training and testing sets**

```
from sklearn. model_selection import train_test_split
x_train, x_test, y_train, y_test=train_test_split (x, y, random_state=0)
```

**# Intialize the Regularized Linear Regression model**

```
from sklearn. linear_model import Ridge
```

**# Train a Ridge Regression model**

**# Regularization strength, adjust as needed**

```
alpha = 1.0
model = Ridge(alpha=alpha)
```

**# Train the Regularized Linear Regression model**

```
model.fit (x_train, y_train)
```

**Output**

```
Ridge ()
```

**# Make predictions**

```
y_pred = model. predict(x_test)
y_pred
```

**Output**

```
array([26.34156898, 22.20793785, 28.81921868, 11.47348568, 21.04408706,
       20.07024517, 19.92297674, 21.98467322, 19.4284628 , 19.78080258,
        4.16412665, 15.12289492, 17.09792351,  5.05900886, 38.91946091,
       32.92319545, 21.24037396, 36.10602752, 31.81994714, 23.86720827,
       25.23529707, 22.88616194, 20.79907381, 30.51097382, 22.69975385,
        7.89770805, 17.85693177, 18.79114443, 35.85644296, 20.64459013,
       17.22799563, 17.71776841, 19.12617187, 22.88297321, 28.53952139,
       19.82099868, 11.05567273, 23.90734107, 16.91704535, 14.40178292,
       25.90653761, 21.42101506, 23.7896341 , 13.97022376, 24.14528817,
       24.67733954, 19.26650784, 24.12468236, 11.09047876, 24.65867603,
       22.77081575, 19.26975343, 24.25327367, 31.6500543 , 12.84562266,
       22.28345771, 21.23812988, 16.08306186, 11.65101825, 22.23665653,
       18.60898999, 22.10455726, 32.35772086, 31.57758771, 17.12779565,
       32.87589474, 19.54848641, 19.28578883, 19.20291078, 24.09782582,
       21.94365685, 23.69076767, 30.63340076, 29.0446177 , 24.44329987,
        5.35195943, 37.02566061, 24.09822246, 27.67967687, 19.90269748,
       28.43908868, 18.85735312, 17.29445352, 37.82901475, 39.31585098,
       24.74164818, 25.00022374, 16.02274095, 26.54988516, 16.73956103,
       16.46269817, 13.41520098, 24.63687876, 30.64557876, 22.71383635,
       20.562259  ,  0.09343784, 25.64117227, 15.50351612, 17.61209673,
       25.92059772, 22.30531336, 32.48071611, 22.28998171, 27.57238428,
       23.45701196,  6.11176901, 14.10019865, 22.60348397, 29.02334184,
       31.92622327, 12.03657088, 19.53895825, 21.18421153, 12.1825899 ,
       23.82100592,  5.79235568, 19.29551109,  9.01036856, 45.15731178,
       30.5553796 , 17.34563703, 17.515943  , 22.17927199, 23.41151526,
       18.70788687, 34.97867185])
```

**# Evaluate the model**

```
from sklearn. metrics import mean_squared_error
mse = mean_squared_error (y_test, y_pred)
print (f'Mean Squared Error: {mse}')
```

**Output**

Mean Squared Error: 32.12855445696262

**# Predict the new data**

```
new_data = [0.02731, 0.0, 7.07, 0.0, 0.469, 6.421, 78.900000, 4.9671, 2, 242, 17.8, 396.90, 9.140000]
predictions = model. predict([new_data])
print(predictions)
```

**Output**

[24.67733954]

**RESULT**

Thus, the implementation of regularized linear regression was completed successfully.

**Ex. No: 10 MINI PROJECT TO PREDICT THE TIME TAKEN TO SOLVE A PROBLEM GIVEN THE CURRENT STATUS OF THE USER**

**AIM**

The Mini Project to predict the time taken to solve a problem given the current status of the user using Random Forest Regressor Model.

**PROCEDURE**

1. Importing the necessary libraries, including **'pandas'** for data manipulation, and **'numpy'** for numerical operations and warnings.
2. Load the user data from the specified file location.
3. Explore the dataset to understand its structure and features. Preprocess the data if needed, such as handling missing values.
4. Replace missing values in specific numeric columns with the mean using **'SimpleImputer'**.
5. Use **'LabelEncoder'** to encode categorical columns like 'Country', and 'rank'.
6. Drop null values from the dataset, specifically the 'user_id' column.
7. Split the dataset into features (x) and target variable (y).
8. Further split the dataset into training and testing sets using 'train_test_split' from **'sklearn. model_selection'**.
9. Initialize a Random Forest Regression model from '**sklearn. ensemble'.**
10. Train the Random Forest Regression model using the training data with the **'fit'** method.
11. Use the trained Random Forest Regression model to make predictions on the testing data with the **'predict'** method.
12. Evaluate the performance of the model using **metrics** such as mean_squared_error, Score, or others based on the requirements.
13. Finally, use the trained model to predict the outcome for the new data.

**PROGRAM**

```
# Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings. Simplefilter ("ignore")

# Load the Dataset
df = pd. read_csv("C:\\Users\\Documents\\user_data.csv")
df
```

## Output

| | user_id | submission_count | problem_solved | contribution | country | follower_count | last_online_time_seconds | max_rating | rating | rank | regis |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | user_3311 | 47 | 40 | 0 | NaN | 4 | 1504111645 | 348.337 | 330.849 | intermediate | |
| **1** | user_3028 | 63 | 52 | 0 | India | 17 | 1498998165 | 405.677 | 339.450 | intermediate | |
| **2** | user_2268 | 226 | 203 | -8 | Egypt | 24 | 1505566052 | 307.339 | 284.404 | beginner | |
| **3** | user_480 | 611 | 490 | 1 | Ukraine | 94 | 1505257499 | 525.803 | 471.330 | advanced | |
| **4** | user_650 | 504 | 479 | 12 | Russia | 4 | 1496613433 | 548.739 | 486.525 | advanced | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **3566** | user_2685 | 161 | 120 | 0 | Bangladesh | 42 | 1505409069 | 306.193 | 246.560 | beginner | |
| **3567** | user_1548 | 41 | 30 | 0 | NaN | 0 | 1504026868 | 331.135 | 218.463 | beginner | |
| **3568** | user_1929 | 58 | 51 | 0 | NaN | 0 | 1505552744 | 330.275 | 262.901 | beginner | |
| **3569** | user_2772 | 148 | 137 | 0 | NaN | 2 | 1496606504 | 409.977 | 345.757 | intermediate | |
| **3570** | user_2179 | 163 | 115 | 6 | South Korea | 40 | 1502074467 | 392.775 | 288.704 | beginner | |

3571 rows × 11 columns

df.info ()

## Output

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3571 entries, 0 to 3570
Data columns (total 11 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   user_id                   3571 non-null   object
 1   submission_count          3571 non-null   int64
 2   problem_solved            3571 non-null   int64
 3   contribution              3571 non-null   int64
 4   country                   2418 non-null   object
 5   follower_count            3571 non-null   int64
 6   last_online_time_seconds  3571 non-null   int64
 7   max_rating                3571 non-null   float64
 8   rating                    3571 non-null   float64
 9   rank                      3571 non-null   object
 10  registration_time_seconds 3571 non-null   int64
dtypes: float64(2), int64(6), object(3)
memory usage: 307.0+ KB
```

df. describe ()

## Output

| | submission_count | problem_solved | contribution | follower_count | last_online_time_seconds | max_rating | rating | registration_time_seconds |
|---|---|---|---|---|---|---|---|---|
| **count** | 3571.000000 | 3571.000000 | 3571.000000 | 3571.000000 | 3.571000e+03 | 3571.000000 | 3571.000000 | 3.571000e+03 |
| **mean** | 299.481098 | 267.894427 | 4.102492 | 46.690563 | 1.502680e+09 | 390.374392 | 350.165578 | 1.434961e+09 |
| **std** | 366.102887 | 344.139688 | 16.552256 | 211.494638 | 5.114850e+06 | 92.428788 | 106.592503 | 4.750758e+07 |
| **min** | 1.000000 | 0.000000 | -64.000000 | 0.000000 | 1.484237e+09 | 303.899000 | 0.000000 | 1.264761e+09 |
| **25%** | 66.500000 | 53.000000 | 0.000000 | 4.000000 | 1.502691e+09 | 317.661000 | 279.243000 | 1.416323e+09 |
| **50%** | 169.000000 | 146.000000 | 0.000000 | 13.000000 | 1.505054e+09 | 355.791000 | 329.702000 | 1.449085e+09 |
| **75%** | 390.000000 | 349.000000 | 0.000000 | 40.000000 | 1.505551e+09 | 444.954000 | 413.417500 | 1.470379e+09 |
| **max** | 4570.000000 | 4476.000000 | 171.000000 | 10575.000000 | 1.505595e+09 | 983.085000 | 911.124000 | 1.484236e+09 |

**# Explore and preprocess the data**

df. isnull (). sum ()

**Output**

```
user_id                         0
submission_count                0
problem_solved                  0
contribution                    0
country                      1153
follower_count                  0
last_online_time_seconds        0
max_rating                      0
rating                          0
rank                            0
registration_time_seconds       0
dtype: int64
```

**# Encoding the categorical values**

from sklearn. preprocessing import LabelEncoder

label_encoder = LabelEncoder ()

categorical_columns = ['country', 'rank']

df[categorical_columns] = df[categorical_columns].apply(label_encoder.fit_transform)

df[categorical_columns]

**Output**

| | country | rank |
|---|---|---|
| **0** | 79 | 3 |
| **1** | 31 | 3 |
| **2** | 21 | 1 |
| **3** | 73 | 0 |
| **4** | 57 | 0 |
| **...** | ... | ... |
| **3566** | 5 | 1 |
| **3567** | 79 | 1 |
| **3568** | 79 | 1 |
| **3569** | 79 | 3 |
| **3570** | 62 | 1 |

3571 rows × 2 columns

**# Replace the null values**

```
from sklearn. impute import SimpleImputer
numeric_columns = ['country']
df[numeric_columns] = SimpleImputer(strategy='mean'). fit_transform(df[numeric_columns])
df[numeric_columns]
```

**Output**

| | country |
|---|---|
| **0** | 79.0 |
| **1** | 31.0 |
| **2** | 21.0 |
| **3** | 73.0 |
| **4** | 57.0 |
| **...** | ... |
| **3566** | 5.0 |
| **3567** | 79.0 |
| **3568** | 79.0 |
| **3569** | 79.0 |
| **3570** | 62.0 |

3571 rows × 1 columns

**# Drop the null values**

```
df = df. drop ('user_id', axis =1)
df. head ()
```

**Output**

| | submission_count | problem_solved | contribution | country | follower_count | last_online_time_seconds | max_rating | rating | rank | registration_time_seconds |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 47 | 40 | 0 | 79.0 | 4 | 1504111645 | 348.337 | 330.849 | 3 | 1466686436 |
| **1** | 63 | 52 | 0 | 31.0 | 17 | 1498998165 | 405.677 | 339.450 | 3 | 1441893325 |
| **2** | 226 | 203 | -8 | 21.0 | 24 | 1505566052 | 307.339 | 284.404 | 1 | 1454267603 |
| **3** | 611 | 490 | 1 | 73.0 | 94 | 1505257499 | 525.803 | 471.330 | 0 | 1350720417 |
| **4** | 504 | 479 | 12 | 57.0 | 4 | 1496613433 | 548.739 | 486.525 | 0 | 1395560498 |

# Split the data into features (x)
x = df. iloc [:,  :-1]
x

**Output**

| | submission_count | problem_solved | contribution | country | follower_count | last_online_time_seconds | max_rating | rating | rank |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 47 | 40 | 0 | 79.0 | 4 | 1504111645 | 348.337 | 330.849 | 3 |
| **1** | 63 | 52 | 0 | 31.0 | 17 | 1498998165 | 405.677 | 339.450 | 3 |
| **2** | 226 | 203 | -8 | 21.0 | 24 | 1505566052 | 307.339 | 284.404 | 1 |
| **3** | 611 | 490 | 1 | 73.0 | 94 | 1505257499 | 525.803 | 471.330 | 0 |
| **4** | 504 | 479 | 12 | 57.0 | 4 | 1496613433 | 548.739 | 486.525 | 0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **3566** | 161 | 120 | 0 | 5.0 | 42 | 1505409069 | 306.193 | 246.560 | 1 |
| **3567** | 41 | 30 | 0 | 79.0 | 0 | 1504026868 | 331.135 | 218.463 | 1 |
| **3568** | 58 | 51 | 0 | 79.0 | 0 | 1505552744 | 330.275 | 262.901 | 1 |
| **3569** | 148 | 137 | 0 | 79.0 | 2 | 1496606504 | 409.977 | 345.757 | 3 |
| **3570** | 163 | 115 | 6 | 62.0 | 40 | 1502074467 | 392.775 | 288.704 | 1 |

3571 rows × 9 columns

# Split the data into target variable (y)
y = df. iloc[:,  -1]
y

**Output**

```
0       1466686436
1       1441893325
2       1454267603
3       1350720417
4       1395560498
           ...
3566    1455055521
3567    1465142933
3568    1480086231
3569    1480262887
3570    1455975499
Name: registration_time_seconds, Length: 3571, dtype: int64
```

# Further split the dataset into training and testing sets
from sklearn. model_selection import train_test_split
x_train, x_test, y_train, y_test=train_test_split (x, y, random_state=0)

**# Intialize the Random Forest Regression model**

from sklearn. ensemble import RandomForestRegressor

model = RandomForestRegressor (n_estimators=100, random_state=42)

**# Train the Random Forest Regression model**

model.fit (x_train, y_train)

**Output**

RandomForestRegressor(random_state=42)

**# Make predictions**

y_pred = model. predict(x_test)

y_pred

**Output**

```
array([1.45455496e+09, 1.43392280e+09, 1.39042627e+09, 1.45241261e+09,
       1.45483615e+09, 1.42245957e+09, 1.46665441e+09, 1.40576063e+09,
       1.45182356e+09, 1.40803296e+09, 1.44347665e+09, 1.45527652e+09,
       1.45833179e+09, 1.41039747e+09, 1.40353994e+09, 1.43335683e+09,
       1.45930505e+09, 1.48396266e+09, 1.45175827e+09, 1.46663339e+09,
       1.45883224e+09, 1.39686707e+09, 1.37510170e+09, 1.45583003e+09,
       1.43567271e+09, 1.46697796e+09, 1.42782285e+09, 1.35167334e+09,
       1.45055875e+09, 1.45104392e+09, 1.47095946e+09, 1.43119661e+09,
       1.39180426e+09, 1.45824164e+09, 1.44051569e+09, 1.46181146e+09,
       1.43774071e+09, 1.41057693e+09, 1.41982014e+09, 1.41032514e+09,
       1.46102952e+09, 1.44531362e+09, 1.44408272e+09, 1.43312909e+09,
       1.44923526e+09, 1.45480931e+09, 1.46493558e+09, 1.38739107e+09,
       1.46522130e+09, 1.34720321e+09, 1.44306016e+09, 1.43258882e+09,
       1.45973789e+09, 1.44872871e+09, 1.41464911e+09, 1.43173064e+09,
       1.47030693e+09, 1.41554286e+09, 1.45349140e+09, 1.45890839e+09,
       1.37963785e+09, 1.39024897e+09, 1.46494454e+09, 1.39503257e+09,
       1.36973396e+09, 1.46910568e+09, 1.45365958e+09, 1.44598027e+09,
       1.45992361e+09, 1.39585475e+09, 1.36215790e+09, 1.44300388e+09,
       1.42957886e+09, 1.45861093e+09, 1.39488787e+09, 1.46234938e+09,
```

**# Evaluate the model**

from sklearn. metrics import mean_squared_error

mse = mean_squared_error (y_test, y_pred)

print (f'Mean Squared Error: {mse}')

**Output**

Mean Squared Error: 1269410250004051.2

**# Predict the new data**

```
new_data = [161, 120, 0, 5.0, 42, 1505409069, 306.193, 246.560,1]
predictions = model. predict([new_data])
print(predictions)
```

**Output**

```
[1.45716732e+09]
```

**RESULT**

Thus, the mini project to predict the time taken to solve a problem given the current status of the user was completed successfully using Random Forest Regression model.

## Ex. No: 10 IMPLEMENTATION OF MULTIVARIATE REGRESSION

**AIM**

To create a machine learning model to predict the profit of a startup company using Multivariate Regression.

**PROCEDURE**

1. Multivariate linear regression resembles simple linear regression except that in multivariate linear regression, multiple independent variables contribute to the dependent variables and so multiple coefficients are used in the computation.
   $\mathbf{y = c + m_1x_1 + m_2x_2 + \ldots\ldots + m_nx_n}$
2. Importing the necessary libraries, including **'pandas'** for data manipulation, and **'numpy'** for numerical operations and warnings.
3. Load the dataset containing startup company data. For Example, startup company dataset.
4. Explore the dataset to understand its structure and features. Preprocess the data if needed, such as handling missing values.
5. Split the dataset into features (x) and target variable (y).
6. Further split the dataset into training and testing sets using 'train_test_split' from **'sklearn. model_selection'**.
7. Initialize a Mutivariate Regression model from '**sklearn. linear_model'.**
8. Train the Mutivariate Regression model using the training data with the **'fit'** method.
9. Use the trained Mutivariate Regression model to make predictions on the testing data with the **'predict'** method.
10. Evaluate the performance of the model using **metrics** such as mean_absolute_error, mean_squared_error, root_mean_square, R_Squared, or others based on the requirements.
11. Finally, use the trained model to predict the outcome for the new data.

**PROGRAM**

```
# Import Libraries
import pandas as pd
import numpy as np
import warnings
warnings. Simplefilter ("ignore")

# Load the Dataset
df = pd. read_csv("C:\\Users\\Documents\\50_Startups.csv")
df. head ()
```

**Output**

| | R&D Spend | Administration | Marketing Spend | State | Profit |
|---|---|---|---|---|---|
| **0** | 165349.20 | 136897.80 | 471784.10 | New York | 192261.83 |
| **1** | 162597.70 | 151377.59 | 443898.53 | California | 191792.06 |
| **2** | 153441.51 | 101145.55 | 407934.54 | Florida | 191050.39 |
| **3** | 144372.41 | 118671.85 | 383199.62 | New York | 182901.99 |
| **4** | 142107.34 | 91391.77 | 366168.42 | Florida | 166187.94 |

df.info ()

**Output**

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   R&D Spend        50 non-null     float64
 1   Administration   50 non-null     float64
 2   Marketing Spend  50 non-null     float64
 3   State            50 non-null     object
 4   Profit           50 non-null     float64
dtypes: float64(4), object(1)
memory usage: 2.1+ KB
```

df. describe ()

**Output**

| | R&D Spend | Administration | Marketing Spend | Profit |
|---|---|---|---|---|
| **count** | 50.000000 | 50.000000 | 50.000000 | 50.000000 |
| **mean** | 73721.615600 | 121344.639600 | 211025.097800 | 112012.639200 |
| **std** | 45902.256482 | 28017.802755 | 122290.310726 | 40306.180338 |
| **min** | 0.000000 | 51283.140000 | 0.000000 | 14681.400000 |
| **25%** | 39936.370000 | 103730.875000 | 129300.132500 | 90138.902500 |
| **50%** | 73051.080000 | 122699.795000 | 212716.240000 | 107978.190000 |
| **75%** | 101602.800000 | 144842.180000 | 299469.085000 | 139765.977500 |
| **max** | 165349.200000 | 182645.560000 | 471784.100000 | 192261.830000 |

**# Explore and preprocess the data**

df. isnull (). sum ()

**Output**

```
R&D Spend          0
Administration     0
Marketing Spend    0
State              0
Profit             0
dtype: int64
```

**# Encoding the categorical values**

from sklearn import preprocessing

**# Using Label Encoder to convert the categorical values**

le = preprocessing. LabelEncoder ()

state_encoded = le.fit_transform(data['State'])

data['State'] = state_encoded

data. head ()

**Output**

| | R&D Spend | Administration | Marketing Spend | State | Profit |
|---|---|---|---|---|---|
| **0** | 165349.20 | 136897.80 | 471784.10 | 2 | 192261.83 |
| **1** | 162597.70 | 151377.59 | 443898.53 | 0 | 191792.06 |
| **2** | 153441.51 | 101145.55 | 407934.54 | 1 | 191050.39 |
| **3** | 144372.41 | 118671.85 | 383199.62 | 2 | 182901.99 |
| **4** | 142107.34 | 91391.77 | 366168.42 | 1 | 166187.94 |

**# Split the data into features (x)**

x = df. iloc [:,  :-1]

x

**Output**

| | R&D Spend | Administration | Marketing Spend | State |
|---|---|---|---|---|
| **0** | 165349.20 | 136897.80 | 471784.10 | 2 |
| **1** | 162597.70 | 151377.59 | 443898.53 | 0 |
| **2** | 153441.51 | 101145.55 | 407934.54 | 1 |
| **3** | 144372.41 | 118671.85 | 383199.62 | 2 |
| **4** | 142107.34 | 91391.77 | 366168.42 | 1 |

**# Split the data into target variable (y)**

y = df. iloc[:,  -1]

y

**Output**

```
0    192261.83
1    191792.06
2    191050.39
3    182901.99
4    166187.94
Name: Profit, dtype: float64
```

**# Further split the dataset into training and testing sets**

from sklearn. model_selection import train_test_split

x_train, x_test, y_train, y_test=train_test_split (x, y, random_state=355)

**# Intialize the Multivariate Regression model**

from sklearn. Linear_model import LinearRegression

model = LinearRegression

**# Train the Random Forest Regression model**

model.fit (x_train, y_train)

**Output**

LinearRegression ()

**# Make predictions**

y_pred = model. predict(x_test)

y_pred

**Output**

```
array([126720.66150723,  84909.08961912,  98890.31854876,  46479.31240248,
       129113.18318813,  50968.88397762, 109015.01626803, 100893.57078084,
        97713.73821431, 113085.59056068])
```

**# Evaluate the model**

from sklearn. metrics import mean_squared_error, mean_absolute_error

mse = mean_squared_error (y_test, y_pred)

print (f"Mean Squared Error: {mse}")

**Output**

Mean Squared Error: 80929465.49097784

```
mae = mean_absolute_error (y_test, y_pred)
print (f"Mean Absolute Error: {mae}")
```

**Output**

Mean Absolute Error: 6979.17574672139

**RESULT**

Thus, a machine learning model for profit prediction using Multivariate Regression model was implemented successfully.