Sri Sivasubramaniya Nadar College of Engineering, Chennai
(An autonomous Institution affiliated to Anna University)

Degree & Branch	B.E. Computer Science & Engineering	Semester	V
Subject Code & Name	ICS1512 & Machine Learning Algorithms Laboratory		
Academic year	2025-2026 (Odd)	Batch:2023-2028	**Due date:**

Experiment 2: Loan Amount Prediction using Linear Regression

Aim: To predict the loan amount sanctioned to users using Linear Regression on historical data, and analyze model performance using visual and statistical metrics.

Libraries used:

- Pandas - for data handling
- numpy - for numerical operations
- matplotlib.pyplot and seaborn - for visualization
- sklearn - for model building and evaluation

Objective: To build a linear regression model using Scikit-learn to predict the loan amount, perform exploratory data analysis, visualize model performance, and interpret results.

Mathetical/theoritical description: The linear regression model expresses the relationship between the input features and the predicted output as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon$$

Where:

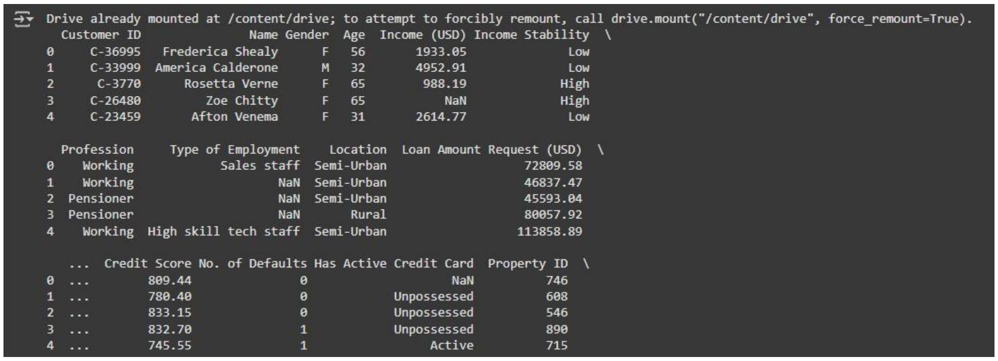
- y is the predicted loan amount,
- x_i are the input features (e.g., income, credit score, etc.),
- β_i are the coefficients (weights) learned by the model,
- ϵ is the error term (residual).

CODE:

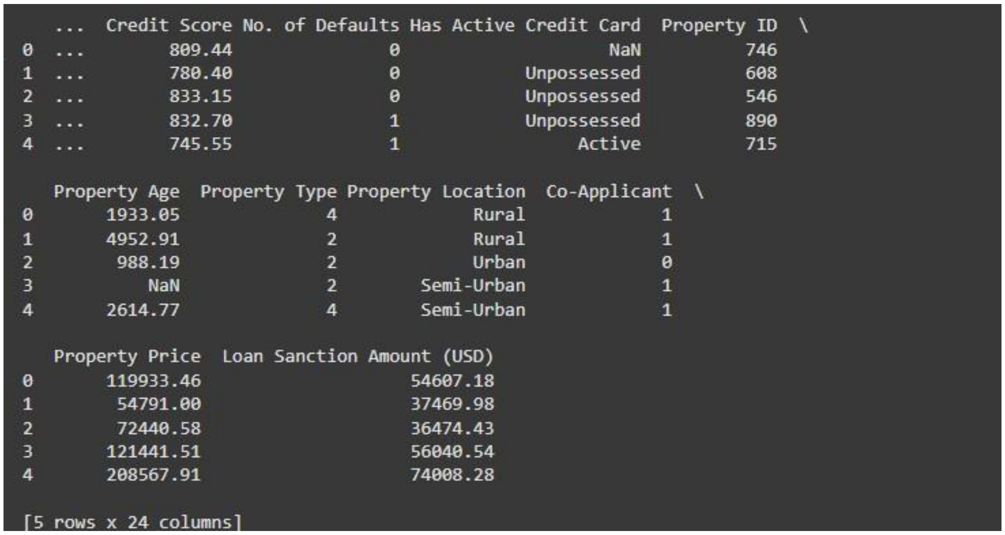
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import google.colab.drive as drive
```

```
from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler

# 1. Load Dataset
drive.mount(’/content/drive’)
df = pd.read_csv(’/content/drive/MyDrive/Colab Notebooks/ML LAB SEM 5/train.csv’)
print(df.head())

## Drop non-informative identifiers
df.drop(columns=["Customer ID", "Name", "Property ID"], inplace=True)

# Handle missing values (optional: use better imputation)
df.dropna(inplace=True)

# Define target variable
target = "Loan Sanction Amount (USD)"
X = df.drop(columns=[target])
y = df[target]

# Encode categorical variables
categorical_cols = X.select_dtypes(include=["object"]).columns
X = pd.get_dummies(X, columns=categorical_cols, drop_first=True)

# Normalize numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 3. EDA
# a. Loan Amount Distribution Plot
sns.histplot(df["Loan Sanction Amount (USD)"], kde=True, color="skyblue")
plt.title("Loan Sanction Amount Distribution")
plt.xlabel("Loan Sanction Amount (USD)")
plt.ylabel("Frequency")
plt.grid(True)
plt.show()

# b. Correlation Heatmap (only for numeric columns)
numeric_df = df.select_dtypes(include=["number"])  # selects only numeric columns
plt.figure(figsize=(12,    8))
sns.heatmap(numeric_df.corr(), annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap of Numeric Features")
plt.show()
```

OUTPUT

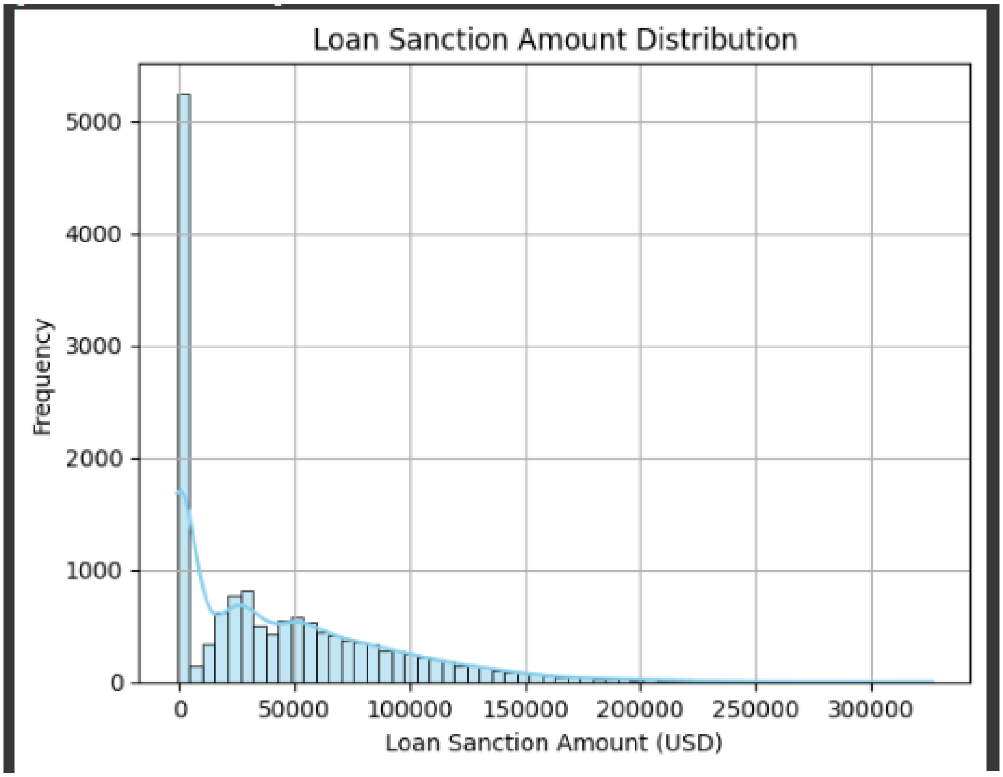


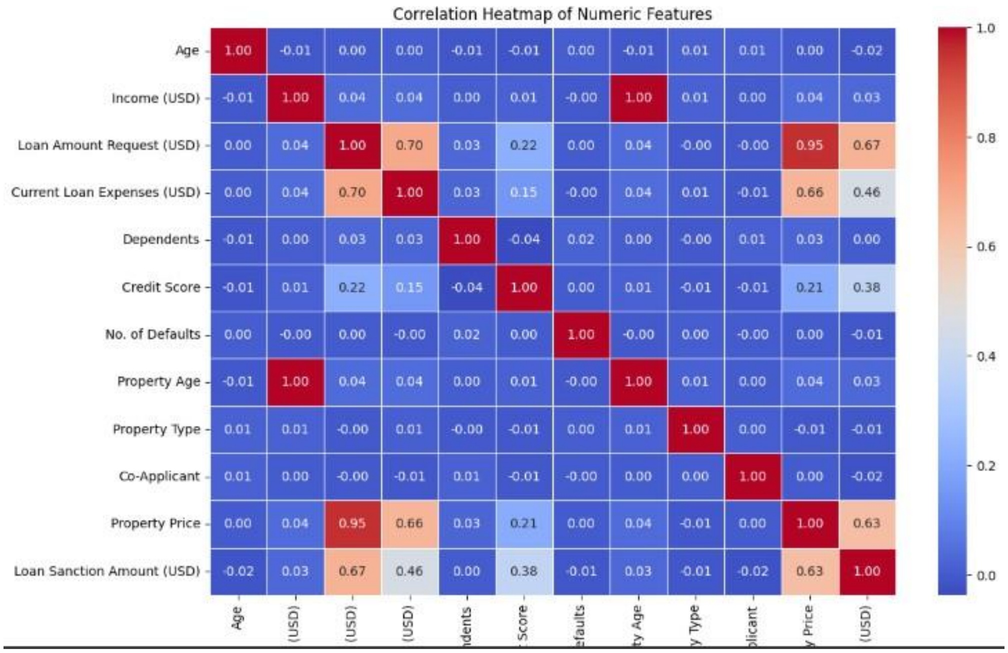
```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
  Customer ID               Name Gender  Age  Income (USD) Income Stability  \
0     C-36995   Frederica Shealy      F   56       1933.05              Low
1     C-33999  America Calderone      M   32       4952.91              Low
2      C-3770      Rosetta Verne      F   65        988.19             High
3     C-26480         Zoe Chitty      F   65           NaN             High
4     C-23459      Afton Venema       F   31       2614.77              Low

  Profession     Type of Employment    Location  Loan Amount Request (USD)  \
0    Working            Sales staff  Semi-Urban                   72809.58
1    Working                    NaN  Semi-Urban                   46837.47
2  Pensioner                    NaN  Semi-Urban                   45593.04
3  Pensioner                    NaN       Rural                   80057.92
4    Working  High skill tech staff  Semi-Urban                  113858.89

   ... Credit Score No. of Defaults Has Active Credit Card  Property ID  \
0  ...       809.44               0                    NaN          746
1  ...       780.40               0            Unpossessed          608
2  ...       833.15               0            Unpossessed          546
3  ...       832.70               1            Unpossessed          890
4  ...       745.55               1                 Active          715
```



```
   ... Credit Score No. of Defaults Has Active Credit Card  Property ID  \
0  ...       809.44               0                    NaN          746
1  ...       780.40               0            Unpossessed          608
2  ...       833.15               0            Unpossessed          546
3  ...       832.70               1            Unpossessed          890
4  ...       745.55               1                 Active          715
```

```
   Property Age  Property Type Property Location  Co-Applicant  \
0       1933.05              4             Rural             1
1       4952.91              2             Rural             1
2        988.19              2             Urban             0
3           NaN              2        Semi-Urban             1
4       2614.77              4        Semi-Urban             1

   Property Price  Loan Sanction Amount (USD)
0       119933.46                    54607.18
1        54791.00                    37469.98
2        72440.58                    36474.43
3       121441.51                    56040.54
4       208567.91                    74008.28

[5 rows x 24 columns]
```





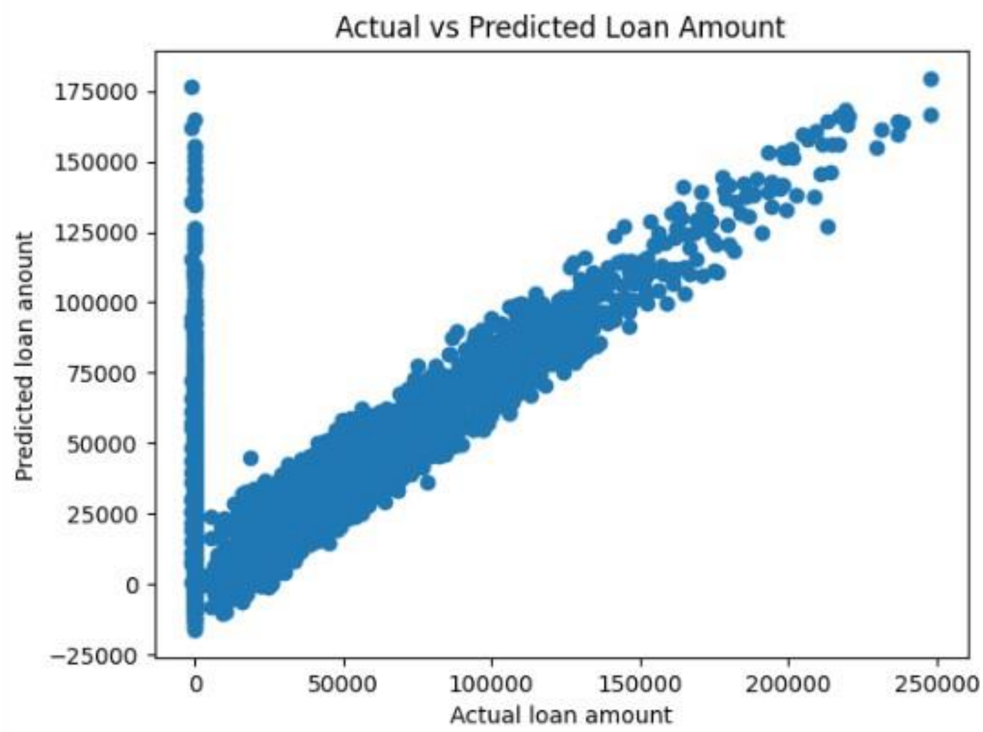
```
# 4. Train-test Split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=4

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

# 6. Evaluate
y_pred = model.predict(X_test)

mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
adj_r2 = 1 - (1 - r2) * (len(y) - 1) / (len(y) - X.shape[1] - 1)

print(f"MAE: {mae}, MSE: {mse}, RMSE: {rmse}, R2: {r2}, Adj R2: {adj_r2}")
```

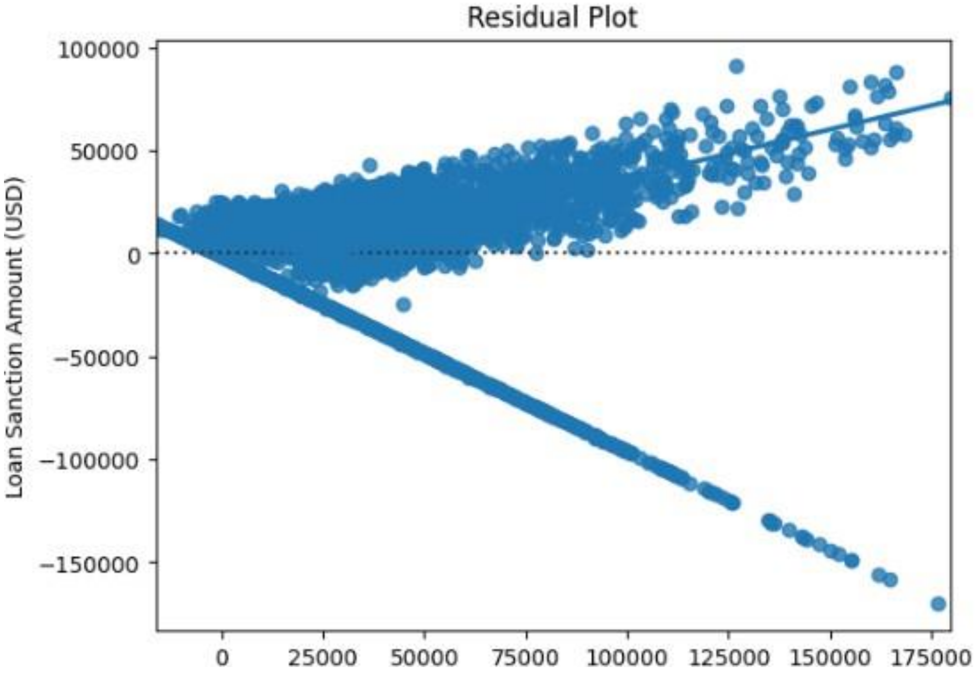
OUTPUT

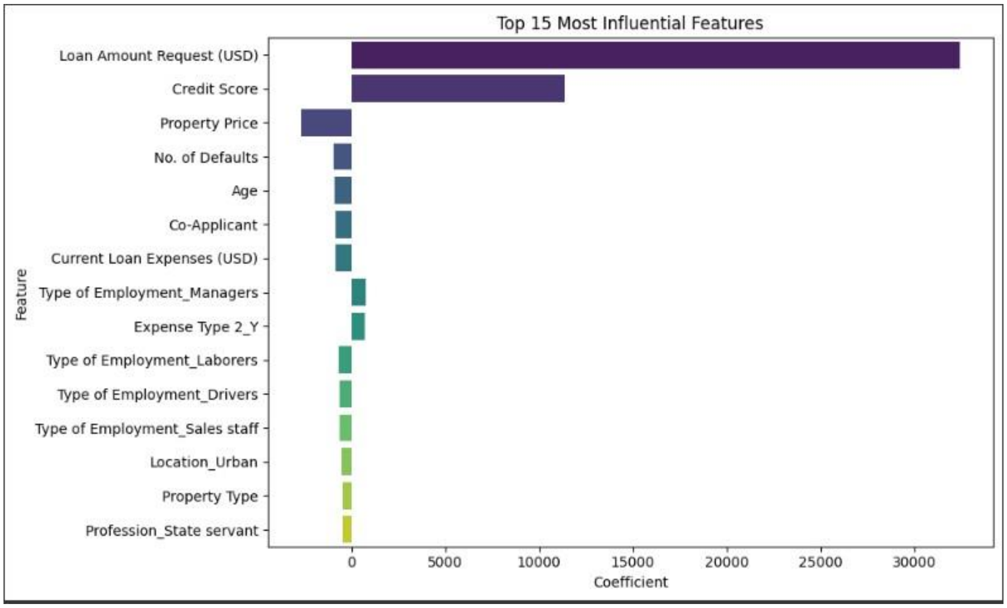
```
MAE: 25323.793500422737,
MSE: 1195267145.5071688,
RMSE: 34572.63579056663,
R2: 0.47512320259332885,
Adj R2: 0.47375943210040017
```

```
# 7. Visualizations
plt.scatter(y_test, y_pred)
plt.xlabel("Actual loan amount")
plt.ylabel("Predicted loan anount")
plt.title("Actual vs Predicted Loan Amount")
plt.show()

residuals = y_test - y_pred
sns.residplot(x=y_pred, y=residuals, lowess=True)
plt.title("Residual  Plot")
plt.show()

plt.bar(x=X.columns, height=model.coef_)
plt.xticks(rotation=90)
plt.title("Feature Coefficients")
plt.show()
```

OUTPUT




Residual Plot
Loan Sanction Amount (USD)
100000
50000
0
−50000
−100000
−150000
0
25000
50000
75000
100000
125000
150000
175000


Top 15 Most Influential Features
Loan Amount Request (USD)
Credit Score
Property Price
No. of Defaults
Age
Co-Applicant
Current Loan Expenses (USD)
Type of Employment_Managers
Expense Type 2_Y
Type of Employment_Laborers
Type of Employment_Drivers
Type of Employment_Sales staff
Location_Urban
Property Type
Profession_State servant
Feature
0
5000
10000
15000
20000
25000
30000
Coefficient