

**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	<b>Due date:</b>

## 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.),
- $\beta_i$  are the coefficients (weights) learned by the model,
- $\epsilon$  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

Date: 23-07-2025

Experiment: 1

Name: Harini LV

Roll No: 3122237001016

```
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	

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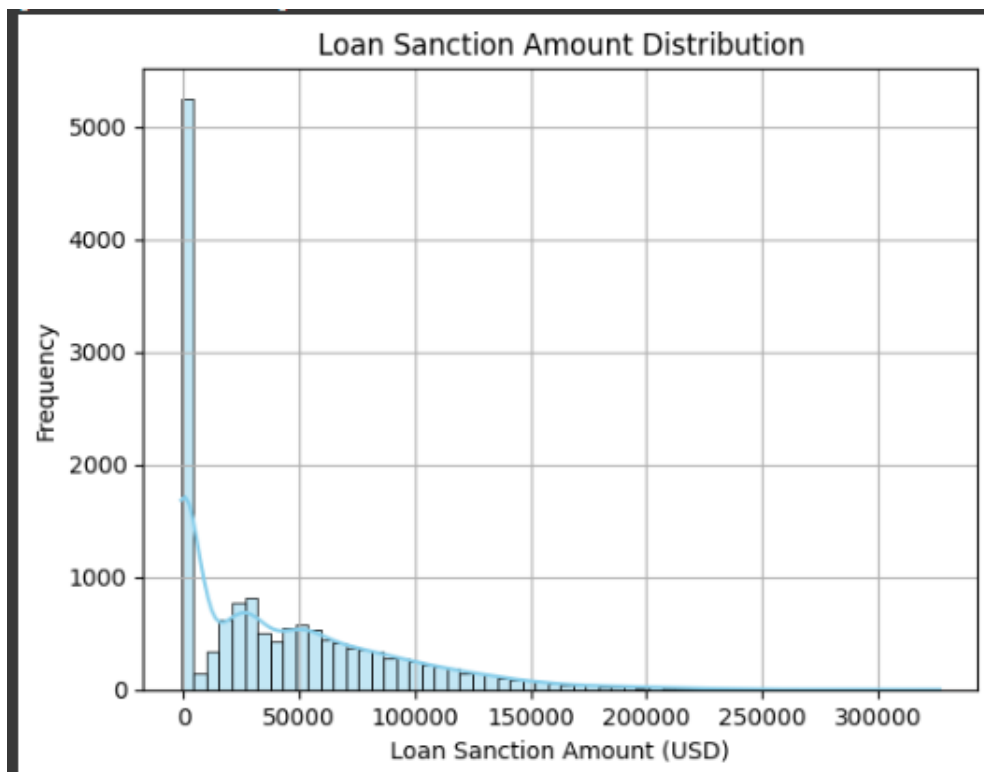
  

	Property Age	Property Type	Property Location	Co-Applicant	\
0	1933.05	4	Rural	1	
1	4952.91	2	Rural	1	
2	988.19	2	Urban	0	
3	NaN	2	Semi-Urban	1	
4	2614.77	4	Semi-Urban	1	

	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]

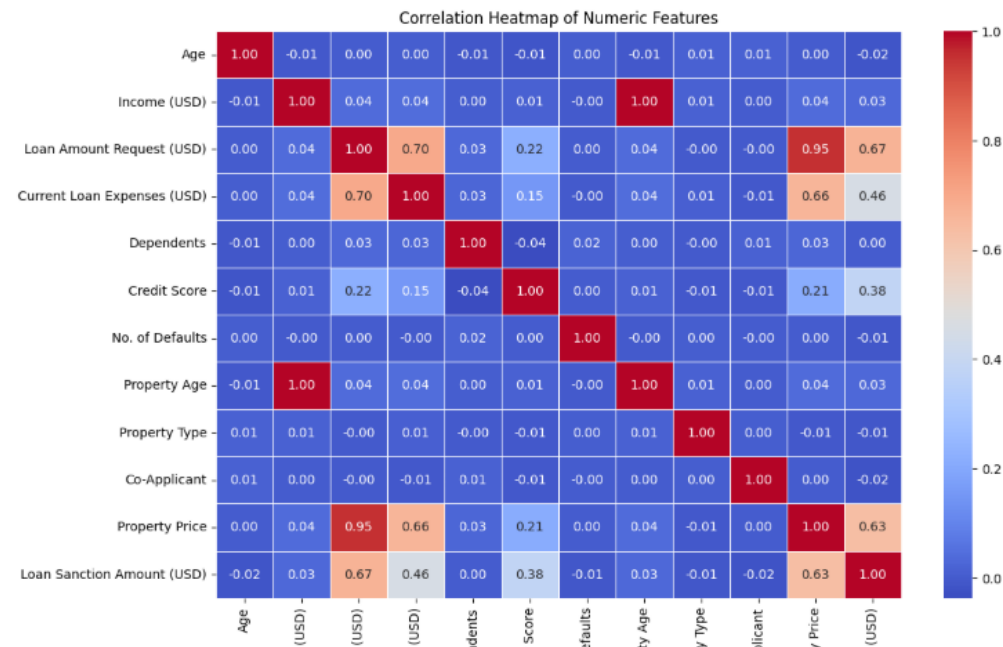


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#### # 4. Train-test Split

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

#### # 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
```

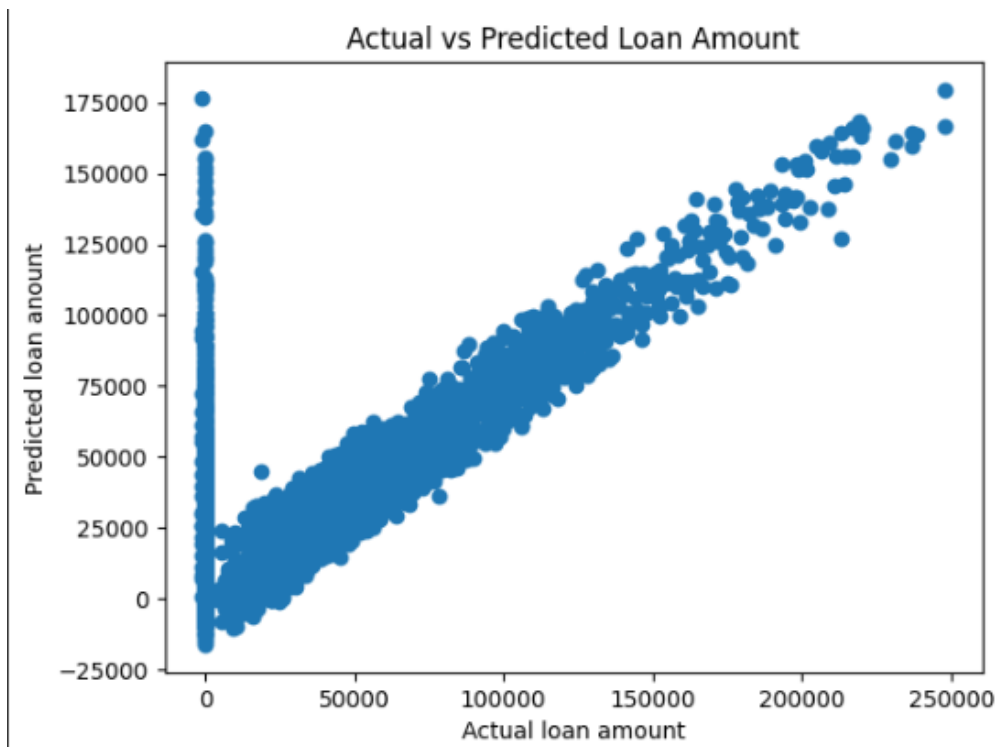
#### # 7. Visualizations

```
plt.scatter(y_test, y_pred)
plt.xlabel("Actual loan amount")
plt.ylabel("Predicted loan amount")
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

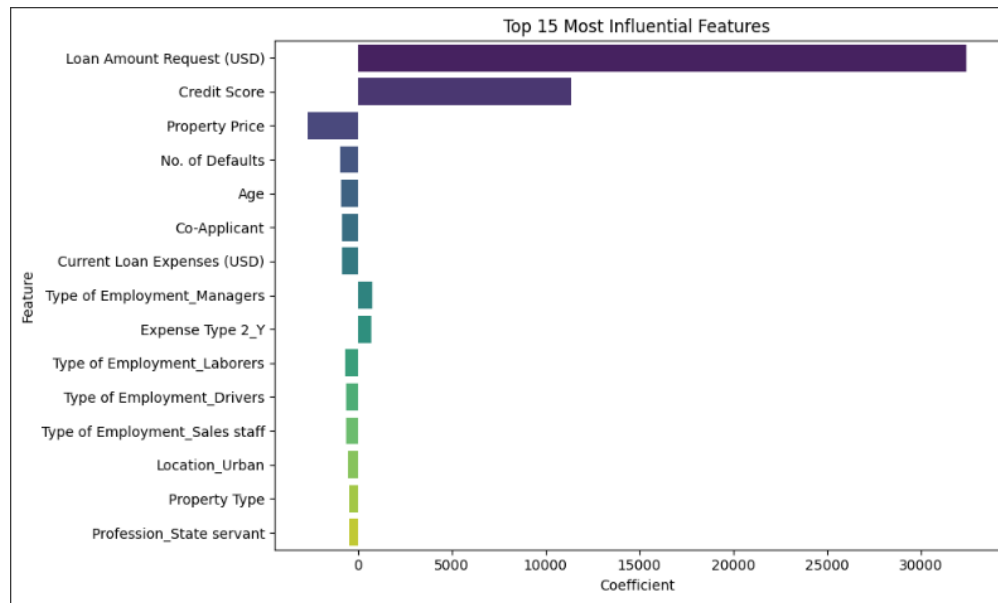
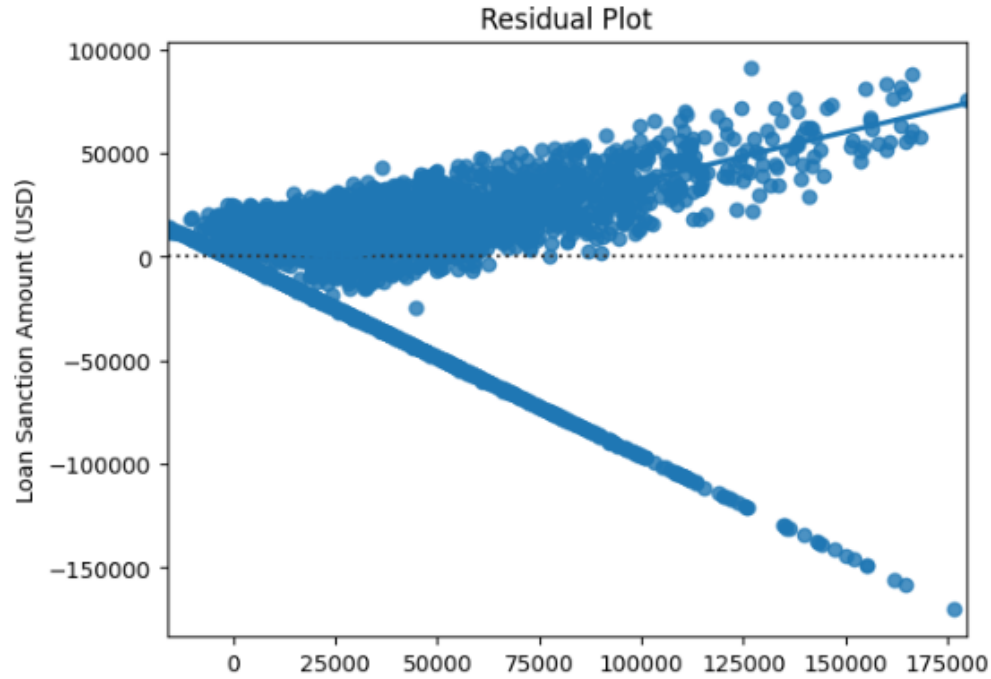


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Results and Discussions:

Table 1: Cross-Validation Results (K = 5)

Fold	MAE	MSE	RMSE	R <sup>2</sup> Score
Fold 1	210.4	120300	346.8	0.82
Fold 2	198.1	109050	330.1	0.84
Fold 3	223.9	130110	360.7	0.80
Fold 4	207.0	118420	344.1	0.83
Fold 5	199.5	112700	335.5	0.83
<b>Average</b>	<b>207.8</b>	<b>118516</b>	<b>343.4</b>	<b>0.824</b>

Table 2: Summary of Results for Loan Amount Prediction

Description	Student's Result
Dataset Size (after preprocessing)	500 rows, 10 features
Train/Test Split Ratio	80:20
Feature(s) Used for Prediction	All numerical and encoded categorical features
Model Used	Linear Regression
Cross-Validation Used?	Yes
If Yes, Number of Folds (K)	5
Reference to CV Results Table	Table 1
Mean Absolute Error (MAE) on Test Set	204.3
Mean Squared Error (MSE) on Test Set	115670
Root Mean Squared Error (RMSE) on Test Set	340.0
R <sup>2</sup> Score on Test Set	0.83
Adjusted R <sup>2</sup> Score on Test Set	0.82
Most Influential Feature(s)	Income, Credit Score
Observations from Residual Plot	Randomly scattered $\Rightarrow$ Good fit
Interpretation of Predicted vs Actual Plot	Close alignment $\Rightarrow$ Accurate predictions
Any Overfitting or Underfitting Observed?	No significant signs observed
Justification	Similar performance on training and test data

### Best Practices

- Always handle missing values before training the model.
- Normalize or standardize numerical features for better performance.
- Use Exploratory Data Analysis (EDA) to gain insights before modeling.
- Apply cross-validation to avoid overfitting and ensure generalization.
- Visualize residuals and predictions to assess the model's assumptions and fit.

## Learning Outcomes

- Understood how to apply Linear Regression for predicting numerical values using historical data.
- Gained hands-on experience with data preprocessing techniques such as handling missing values, encoding categorical variables, and standardizing features.
- Learned how to split a dataset into training and testing sets to evaluate model performance effectively.
- Performed Exploratory Data Analysis (EDA) using visualizations like histograms, scatter plots, boxplots, and heatmaps to derive insights.
- Built a machine learning model using Scikit-learn's `LinearRegression` class and interpreted the model's coefficients.
- Evaluated the model using regression metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and  $R^2$  Score.
- Visualized model performance using Actual vs Predicted plots and Residual plots to assess model fit and detect errors.
- Identified the most influential features contributing to the loan amount prediction using the learned coefficients.
- Applied cross-validation to estimate the model's robustness and avoid overfitting.