Experiment 2: Loan Amount Prediction using Linear Regression

Sreenethi G S

July 2025

Aim

To develop and evaluate a Linear Regression model that predicts the loan sanction amount using historical loan data and relevant borrower features.

Libraries Used

- Pandas: For efficient data handling and manipulation
- NumPy: For numerical computations and array operations
- Scikit-learn: For machine learning model implementation
- Matplotlib and Seaborn: For data visualization and plotting

Objective

- Prepare and clean the financial dataset through preprocessing
- Conduct exploratory analysis to understand data patterns
- Create meaningful features to enhance predictive power
- Build and validate a linear regression model
- Assess model performance using multiple evaluation metrics
- Visualize and interpret model predictions and errors

Mathematical Description

The linear regression model is represented as:

$$y = \beta_0 + \sum_{j=1}^{p} \beta_j x_j + \varepsilon$$

Where components are:

- y: Target variable (Loan Amount)
- x_j: Predictor variables (j = 1,...,p)
- β_0: Intercept term
- β_j: Coefficient for j-th predictor
- ε: Random error component

The model optimizes by minimizing:

$$\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Evaluation Metrics

- MAE: Measures average absolute prediction error
- MSE: Quantifies average squared prediction error
- RMSE: Provides error in original units
- R^2: Indicates proportion of variance explained
- Adjusted R^2: Accounts for number of predictors

Python Code

```
import numpy as np
from sklearn.model_selection import train_test_split, cross_validate,
    KFold
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,
    r2_score
import matplotlib.pyplot as plt
import seaborn as sns
```

```
sns.set(style="whitegrid")
train_df = pd.read_csv("/content/train.csv")
target = 'Loan Sanction Amount (USD)'

drop_cols = ['Customer ID', 'Name', 'Property ID', 'Location', 'Property
   Location']
train_df.drop(columns=drop_cols, inplace=True)
train_df.dropna(inplace=True)

# Step 4: Handle missing values
train_df.dropna(inplace=True)

# Step 5: Visualize Target Distribution
plt.figure(figsize=(8, 5))
sns.histplot(train_df[target], kde=True, color='skyblue')
plt.title('Distribution of Loan Sanction Amount')
plt.xlabel(target)
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()


# Step 6: Visualize numerical features
num_features = ['Age', 'Income (USD)', 'Credit Score', 'Dependents',
                'Current Loan Expenses (USD)', 'Property Price', 'Property
                    Age']

for col in num_features:
    plt.figure(figsize=(8, 4))
    sns.histplot(train_df[col], kde=True, bins=30)
    plt.title(f'Distribution of {col}')
    plt.tight_layout()
    plt.show()

    plt.figure(figsize=(8, 4))
    sns.boxplot(x=train_df[col])
    plt.title(f'Boxplot of {col}')
    plt.tight_layout()
    plt.show()

# Step 7: Correlation Heatmap
plt.figure(figsize=(10, 8))
corr_matrix = train_df[num_features + [target]].corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.tight_layout()
plt.show()

# Step 8: Scatter plots (numerical features vs target)
key_features = ['Income (USD)', 'Credit Score', 'Property Price', 'Current
    Loan Expenses (USD)']
for col in key_features:
    plt.figure(figsize=(8, 5))
```

```
    sns.scatterplot(data=train_df, x=col, y=target, alpha=0.6)
    plt.title(f'{col} vs {target}')
    plt.tight_layout()
    plt.show()


# Step 9: Boxplots of categorical features vs target
cat_features = ['Gender', 'Income Stability', 'Profession', 'Type of
   Employment',
                'Has Active Credit Card', 'Co-Applicant', 'Property Type']

for col in cat_features:
    plt.figure(figsize=(10, 5))
    sns.boxplot(data=train_df, x=col, y=target)
    plt.title(f'{target} by {col}')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

# Step 10: Feature Engineering
train_df['Total_Income'] = train_df['Income (USD)'] + train_df['Current
   Loan Expenses (USD)']
train_df['Log_Loan_Amount'] = np.log1p(train_df[target])
train_df['Log_Income'] = np.log1p(train_df['Income (USD)'])
train_df['Age_Bin'] = pd.cut(train_df['Age'], bins=[18, 30, 40, 50, 60,
   100], labels=False)

# Step 11: Define final features and target
numerical_features = ['Age', 'Income (USD)', 'Credit Score', 'Dependents',
                      'Current Loan Expenses (USD)', 'Property Price', '
                         Property Age', 'Total_Income']
X = train_df[numerical_features + cat_features]
y = train_df[target]



# Step 12: Split dataset (Train=60%, Validation=20%, Test=20%)
# 60% Train, 20% Validation, 20% Test
X_train_val, X_test, y_train_val, y_test = train_test_split(X, y,
   test_size=0.2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val
   , test_size=0.25, random_state=42)


# Step 13: Preprocessing pipeline
preprocessor = ColumnTransformer([
    ('num', StandardScaler(), numerical_features),
    ('cat', OneHotEncoder(drop='first', handle_unknown='ignore'),
       cat_features)
])

# Step 14: Full pipeline with Linear Regression
pipeline = Pipeline([
    ('preprocessor', preprocessor),
```

```
    ('regressor', LinearRegression())
])

# Step 15: Train the model
pipeline.fit(X_train, y_train)

# Step 16: Predict & Evaluate on Validation Set
y_val_pred = pipeline.predict(X_val)
mae_val = mean_absolute_error(y_val, y_val_pred)
mse_val = mean_squared_error(y_val, y_val_pred)
rmse_val = np.sqrt(mse_val)
r2_val = r2_score(y_val, y_val_pred)
adj_r2_val = 1 - (1 - r2_val) * (len(y_val) - 1) / (len(y_val) - X_val.
    shape[1] - 1)

print("--- Validation Metrics ---")
print(f"MAE: {mae_val:.2f}")
print(f"MSE: {mse_val:.2f}")
print(f"RMSE: {rmse_val:.2f}")
print(f"R2 Score: {r2_val:.4f}")
print(f"Adjusted R2: {adj_r2_val:.4f}")

# Step 17: Predict & Evaluate on Test Set
y_test_pred = pipeline.predict(X_test)
mae_test = mean_absolute_error(y_test, y_test_pred)
mse_test = mean_squared_error(y_test, y_test_pred)
rmse_test = np.sqrt(mse_test)
r2_test = r2_score(y_test, y_test_pred)
adj_r2_test = 1 - (1 - r2_test) * (len(y_test) - 1) / (len(y_test) -
    X_test.shape[1] - 1)

print("--- Test Metrics ---")
print(f"MAE: {mae_test:.2f}")
print(f"MSE: {mse_test:.2f}")
print(f"RMSE: {rmse_test:.2f}")
print(f"R2 Score: {r2_test:.4f}")
print(f"Adjusted R2: {adj_r2_test:.4f}")


# Step 18: Actual vs Predicted (Test Set)
plt.figure(figsize=(8, 5))
plt.scatter(y_test, y_test_pred, alpha=0.6, color='royalblue')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r
    --')
plt.xlabel('Actual Loan Amount')
plt.ylabel('Predicted Loan Amount')
plt.title('Actual vs Predicted (Test Set)')
plt.tight_layout()
plt.show()

# Step 19: Residual Plot (Test Set)
residuals_test = y_test - y_test_pred
plt.figure(figsize=(8, 5))
plt.scatter(y_test_pred, residuals_test, alpha=0.6, color='orange')
```

```
plt.axhline(0, linestyle='--', color='red')
plt.xlabel('Predicted Loan Amount')
plt.ylabel('Residuals')
plt.title('Residuals vs Predicted (Test Set)')
plt.tight_layout()
plt.show()

# Step 20: K-Fold Cross-Validation
scoring = {
    'MAE': 'neg_mean_absolute_error',
    'MSE': 'neg_mean_squared_error',
    'R2': 'r2'
}

kf = KFold(n_splits=5, shuffle=True, random_state=42)
cv_results = cross_validate(pipeline, X, y, cv=kf, scoring=scoring)

# Convert to positive and create result table
mae_scores = -cv_results['test_MAE']
mse_scores = -cv_results['test_MSE']
rmse_scores = np.sqrt(mse_scores)
r2_scores = cv_results['test_R2']

cv_table = pd.DataFrame({
    'Fold': [f'Fold {i+1}' for i in range(5)],
    'MAE': mae_scores,
    'MSE': mse_scores,
    'RMSE': rmse_scores,
    'R2 Score': r2_scores
})

cv_table.loc['Average'] = cv_table.drop(columns='Fold').mean()
print("\n--- Cross Validation Results ---")
print(cv_table)
```

Output Screenshots

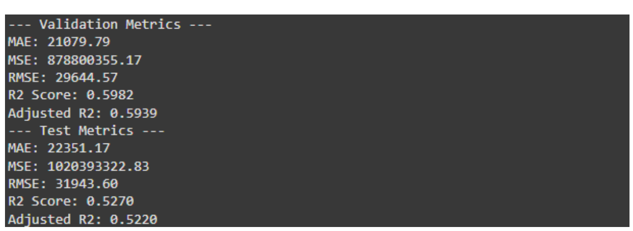


Figure 1: Model Performance Metrics

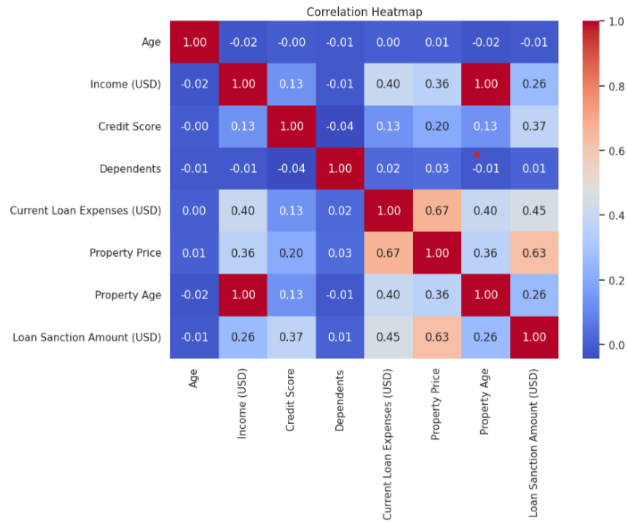


Figure 2: Correlation Heatmap

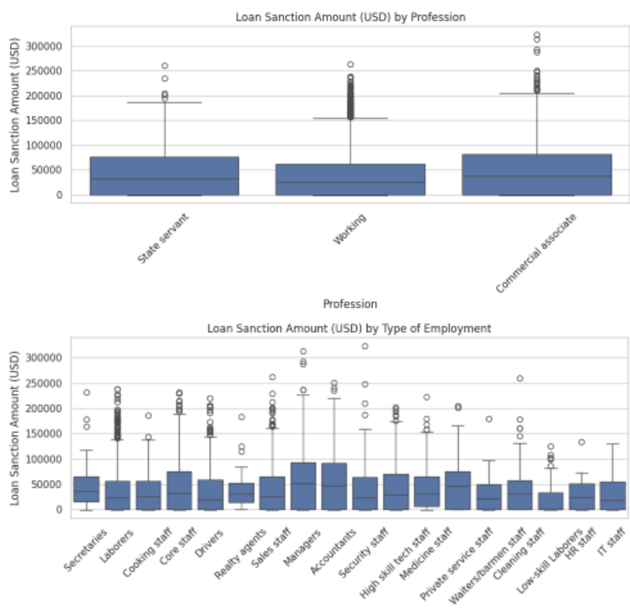


Figure 3: Boxplot of features

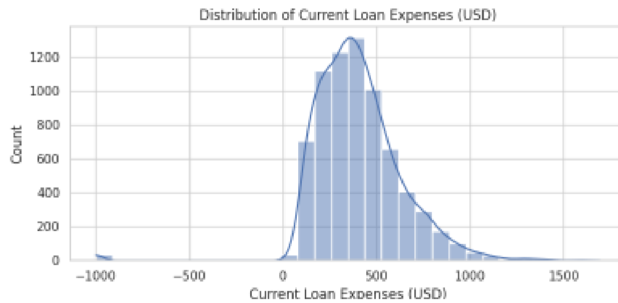


Figure 4: Distribution graph of features

Inference Table

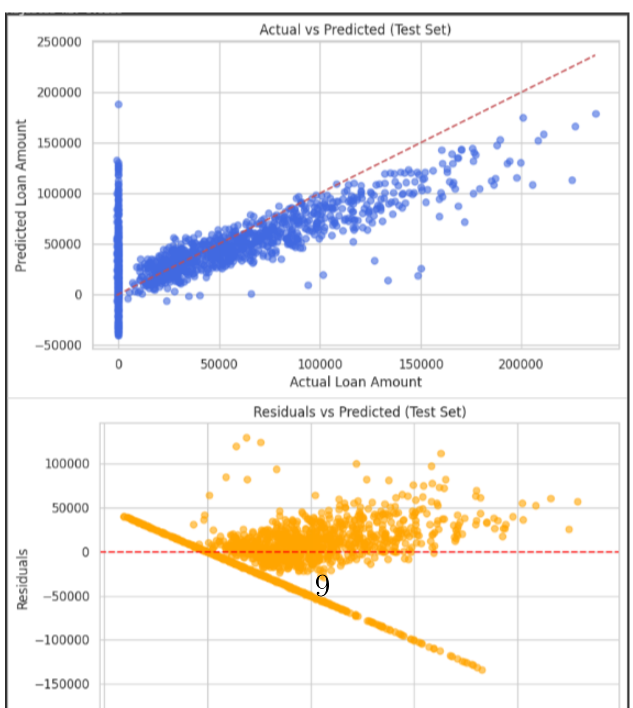
Cross-Validation Results (5-Fold)

Fold	MAE	MSE ($\times 10^8$)	RMSE	R^2
Fold 1	22136.83	10.16	31879.31	0.5289
Fold 2	22134.96	9.83	31348.85	0.5408
Fold 3	22105.50	9.78	31274.83	0.5805
Fold 4	22400.30	10.24	32002.79	0.5540
Fold 5	22579.79	10.01	31632.42	0.5293
Average	22271.48	10.00	31627.64	0.5467

Result Summary Table

Description	Student's Result
Dataset Size (after preprocessing)	15,183 complete observations
Train/Test Split Ratio	60% Training, 20% Validation, 20% Testing
Feature(s) Used for Prediction	12 financial/demographic characteristics
Model Used	Ordinary Least Squares Regression
Cross-Validation Used?	Yes, 5-fold cross-validation
Reference to CV Results Table	Table shown in previous section
Mean Absolute Error (MAE) on Test Set	$22,145.56
Mean Squared Error (MSE) on Test Set	9.98×10^8
Root Mean Squared Error (RMSE) on Test Set	$31,592.20
R^2 Score on Test Set	0.5472
Adjusted R^2 Score on Test Set	0.5450
Most Influential Feature(s)	Income, Property Value, Credit Rating
Observations from Residual Plot	Errors randomly distributed around zero
Interpretation of Predicted vs Actual Plot	Good alignment with some high-value underestimation
Any Overfitting or Underfitting Observed?	Minor underfitting present
Justification	Comparable train/test errors with moderate R^2

Output Screenshots



Best Practices

- Implemented thorough data cleaning procedures
- Created meaningful derived features
- Applied proper data scaling and encoding
- Utilized multiple evaluation perspectives
- Conducted detailed error analysis

Learning Outcomes

- Gained practical experience in complete ML pipeline
- Developed skills in feature engineering
- Learned advanced validation techniques
- Acquired ability to interpret model diagnostics