Experiment 2: Loan Amount Prediction using Linear Regression

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1 Aim

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

2 Libraries USed

- Pandas: Data manipulation
- NumPy: Numerical operations
- Scikit-learn: Model building, preprocessing, and evaluation
- Matplotlib and Seaborn: Data visualization

3 Objective

- Preprocess and clean the dataset
- Perform exploratory data analysis (EDA)
- Engineer features to improve model accuracy
- Train and validate a Linear Regression model
- Evaluate model performance using MAE, MSE, RMSE, and R^2 metrics
- Visualize results and interpret model behavior

4 Mathematical Description

In this experiment, **Linear Regression** is used to predict the loan sanction amount based on several input features.

The mathematical model for Linear Regression is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon \tag{1}$$

Where:

- y is the dependent variable (Loan Sanction Amount).
- $x_1, x_2, \ldots, x_n$ are the independent variables (features such as Age, Income, Credit Score, etc.).
- β_0 is the intercept term.
- $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients (weights) representing the impact of each feature on the target.
- ϵ is the error term representing noise or unexplained variance.

The model parameters β are estimated by minimizing the **Residual Sum of Squares (RSS)**:

$$\text{RSS} = \sum_{i=1}^{m} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{m} \left(y_i - \left(\beta_0 + \sum_{j=1}^{n} \beta_j x_{ij} \right) \right)^2 \tag{2}$$

Where m is the number of observations.

Model evaluation uses metrics such as:

- **Mean Absolute Error (MAE)**: average absolute difference between actual and predicted values.
- **Mean Squared Error (MSE)**: average squared difference between actual and predicted values.
- **Root Mean Squared Error (RMSE)**: square root of MSE, interpretable in the same units as the target.
- **R-squared (R^2)**: proportion of variance explained by the model.
- **Adjusted R-squared**: adjusted for the number of predictors to avoid overfitting.

5 Python Code

Listing 1: Loam Amount Prediction

```
import pandas as pd
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")
# Load only train.csv dataset
train_df = pd.read_csv("/content/drive/MyDrive/train.csv")

# Target variable
target = 'Loan␣Sanction␣Amount␣(USD)'

# Drop unnecessary columns
drop_cols = ['Customer␣ID', 'Name', 'Property␣ID', 'Location
    ', 'Property␣Location']
train_df.drop(columns=drop_cols, inplace=True)

# Handle missing values by dropping (or you can use
    imputation if preferred)
train_df.dropna(inplace=True)
# 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()

# Numerical Features Distribution and Boxplots to detect
    outliers
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.xlabel(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()

# 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()

# Scatter Plots of Key Numerical Features vs Target
for col in ['Income␣(USD)', 'Credit␣Score', 'Property␣Price'
    , 'Current␣Loan␣Expenses␣(USD)']:
    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()

# Categorical Features Boxplots 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()
# Create total income (Income + Current Loan Expenses)
train_df['Total_Income'] = train_df['Income␣(USD)'] +
    train_df['Current␣Loan␣Expenses␣(USD)']

# Optional log transformations (for skewed features)
```

```
train_df['Log_Loan_Amount'] = np.log1p(train_df[target])
train_df['Log_Income'] = np.log1p(train_df['Income␣(USD)'])

# Bin Age (optional)
train_df['Age_Bin'] = pd.cut(train_df['Age'], bins=[18, 30,
    40, 50, 60, 100], labels=False)

# Define features for model
numerical_features = [
    'Age', 'Income␣(USD)', 'Credit␣Score', 'Dependents',
    'Current␣Loan␣Expenses␣(USD)', 'Property␣Price', '
        Property␣Age', 'Total_Income'
]

categorical_features = [
    'Gender', 'Income␣Stability', 'Profession',
    'Type␣of␣Employment', 'Has␣Active␣Credit␣Card',
    'Co-Applicant', 'Property␣Type'
]
X = train_df[numerical_features + categorical_features]
y = train_df[target]

# Split into Train + Temp (80%) and Test (20%)
X_train_val, X_test, y_train_val, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# Further split Train + Validation (75% train, 25% val of
    80%)
X_train, X_val, y_train, y_val = train_test_split(
    X_train_val, y_train_val, test_size=0.25, random_state
        =42
)

# Result: Train = 60%, Val = 20%, Test = 20%
print(f"Train␣size:␣{X_train.shape[0]},␣Validation␣size:␣{
    X_val.shape[0]},␣Test␣size:␣{X_test.shape[0]}")
# Preprocessing pipeline
preprocessor = ColumnTransformer([
    ('num', StandardScaler(), numerical_features),
    ('cat', OneHotEncoder(drop='first', handle_unknown='
        ignore'), categorical_features)
])

# Complete pipeline with Linear Regression
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])
```

```
# Fit the model on training data
pipeline.fit(X_train, y_train)
# Predict on validation data
y_val_pred = pipeline.predict(X_val)

# Calculate metrics
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(f"Validation␣MAE:␣{mae_val:.2f}")
print(f"Validation␣MSE:␣{mse_val:.2f}")
print(f"Validation␣RMSE:␣{rmse_val:.2f}")
print(f"Validation␣R2␣Score:␣{r2_val:.4f}")
print(f"Validation␣Adjusted␣R2␣Score:␣{adj_r2_val:.4f}")

# Predict on test data
y_test_pred = pipeline.predict(X_test)

# Calculate test metrics
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(f"Test␣MAE:␣{mae_test:.2f}")
print(f"Test␣MSE:␣{mse_test:.2f}")
print(f"Test␣RMSE:␣{rmse_test:.2f}")
print(f"Test␣R2␣Score:␣{r2_test:.4f}")
print(f"Test␣Adjusted␣R2␣Score:␣{adj_r2_test:.4f}")

# Actual vs Predicted on 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␣Sanction␣Amount')
plt.ylabel('Predicted␣Loan␣Amount')
plt.title('Actual␣vs␣Predicted␣Loan␣Amount␣(Test␣Set)')
plt.tight_layout()
plt.show()

# Residual Plot on 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()


#Cross-Validation Results (K=5)
from sklearn.metrics import make_scorer

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,
    return_train_score=False
)

# Convert to positive values
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('Fold', axis=1).mean
    ()
print(cv_table)
from sklearn.svm import SVR
from sklearn.ensemble import GradientBoostingRegressor,
```

```
    AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor

# Dictionary to store all models
models = {
    "Linear␣Regression": LinearRegression(),
    "Support␣Vector␣Regression␣(SVR)": SVR(kernel='rbf'),
    "Decision␣Tree": DecisionTreeRegressor(random_state=42),
    "Gradient␣Boosting": GradientBoostingRegressor(
       n_estimators=200, random_state=42),
    "AdaBoost": AdaBoostRegressor(
        estimator=DecisionTreeRegressor(max_depth=5),
        n_estimators=200,
        learning_rate=0.05,
        random_state=42
    ),
    "KNN␣Regression": KNeighborsRegressor(n_neighbors=5)
}

# Results container
results = []

# Loop through all models
for name, model in models.items():
    pipeline = Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('regressor', model)
    ])

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

    # Predict on validation set
    y_val_pred = pipeline.predict(X_val)

    # Evaluation metrics
    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)

    results.append({
        "Model": name,
        "Validation␣MAE": mae_val,
        "Validation␣RMSE": rmse_val,
        "Validation␣R2": r2_val,
        "Validation␣Adj␣R2": adj_r2_val
```

```python
    })

    # Print metrics for each model
    print(f"\n{name} Results:")
    print(f"Validation MAE: {mae_val:.2f}")
    print(f"Validation RMSE: {rmse_val:.2f}")
    print(f"Validation R2 Score: {r2_val:.4f}")
    print(f"Validation Adjusted R2 Score: {adj_r2_val:.4f}")

# Convert to DataFrame for easier comparison
results_df = pd.DataFrame(results)

# Display models sorted by RMSE
print("\nModel Comparison Table (Sorted by RMSE):")
print(results_df.sort_values(by="Validation RMSE"))

# Visual comparison - RMSE
plt.figure(figsize=(10,6))
sns.barplot(data=results_df, x="Model", y="Validation RMSE",
     palette="viridis")
plt.title("Model Comparison (Validation RMSE)")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

6 Output Screenshots

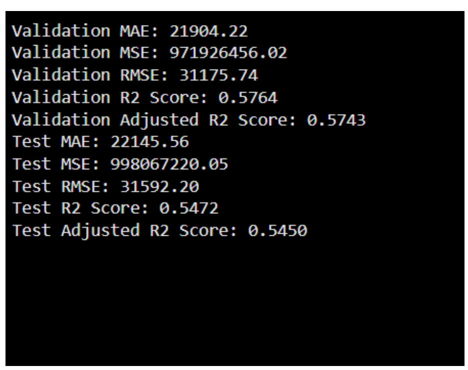
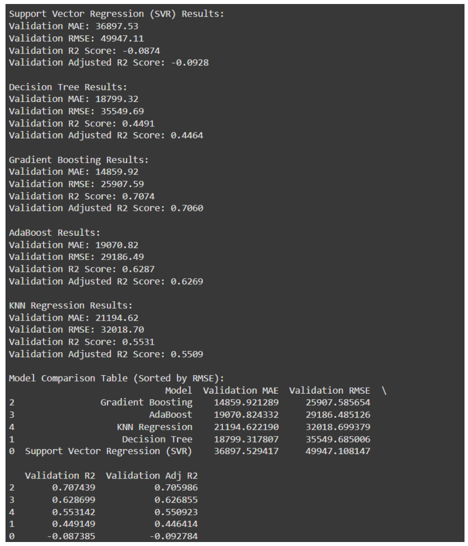

Validation MAE: 21904.22
Validation MSE: 971926456.02
Validation RMSE: 31175.74
Validation R2 Score: 0.5764
Validation Adjusted R2 Score: 0.5743
Test MAE: 22145.56
Test MSE: 998067220.05
Test RMSE: 31592.20
Test R2 Score: 0.5472
Test Adjusted R2 Score: 0.5450

Figure 1: Performance Metrics of Linear Regression



```
Support Vector Regression (SVR) Results:
Validation MAE: 36897.53
Validation RMSE: 49947.11
Validation R2 Score: -0.0874
Validation Adjusted R2 Score: -0.0928

Decision Tree Results:
Validation MAE: 18799.32
Validation RMSE: 35549.69
Validation R2 Score: 0.4491
Validation Adjusted R2 Score: 0.4464

Gradient Boosting Results:
Validation MAE: 14859.92
Validation RMSE: 25907.59
Validation R2 Score: 0.7074
Validation Adjusted R2 Score: 0.7060

AdaBoost Results:
Validation MAE: 19070.82
Validation RMSE: 29186.49
Validation R2 Score: 0.6287
Validation Adjusted R2 Score: 0.6269

KNN Regression Results:
Validation MAE: 21194.62
Validation RMSE: 32018.70
Validation R2 Score: 0.5531
Validation Adjusted R2 Score: 0.5509

Model Comparison Table (Sorted by RMSE):
                             Model  Validation MAE  Validation RMSE  \
2                Gradient Boosting    14859.921289     25907.585654
3                         AdaBoost    19070.824332     29186.485126
4                   KNN Regression    21194.622190     32018.699379
1                    Decision Tree    18799.317807     35549.685006
0  Support Vector Regression (SVR)    36897.529417     49947.108147

   Validation R2  Validation Adj R2
2       0.707439           0.705986
3       0.628699           0.626855
4       0.553142           0.550923
1       0.449149           0.446414
0      -0.087385          -0.092784
```

Figure 2: Performance Metrics of SVR, Decision Tree and Boosting techniques

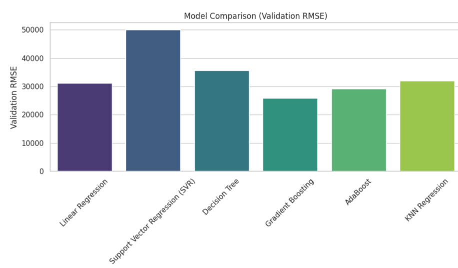


Figure 3: Performance Model Comparision

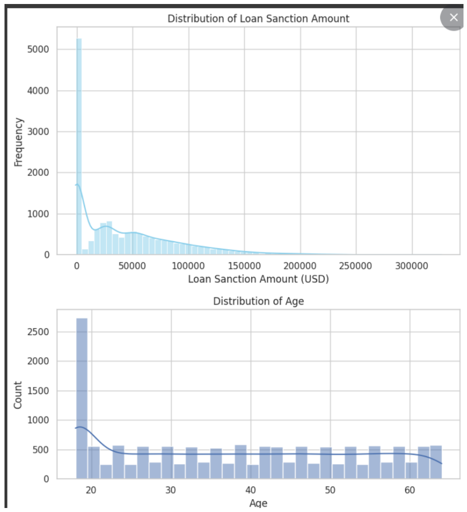


Figure 4: Distribution of Dataset

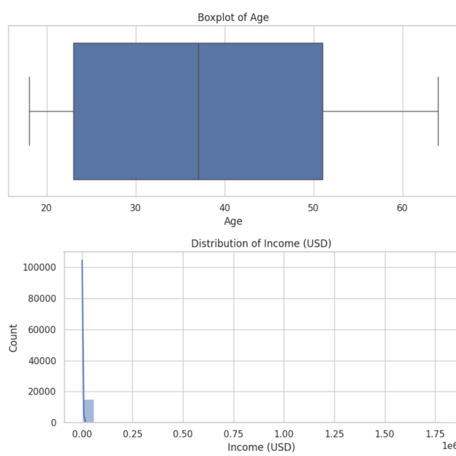


Figure 5: Boxplot of Features

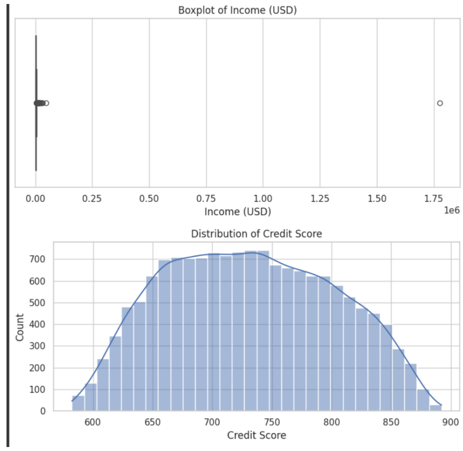


Figure 6: Distribution of Credit Score

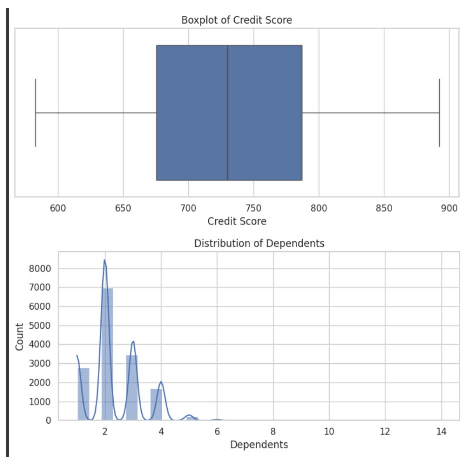


Figure 7: Distribution of Dependents

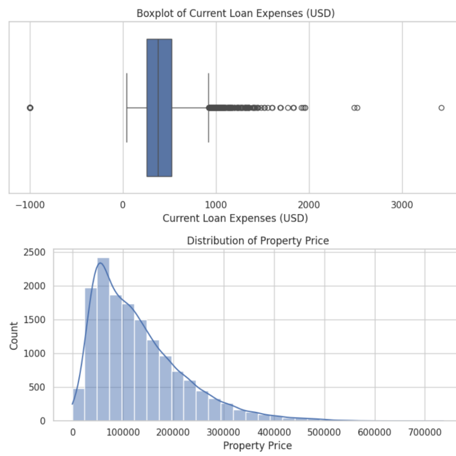


Figure 8: Current Loan Expenses Distribution

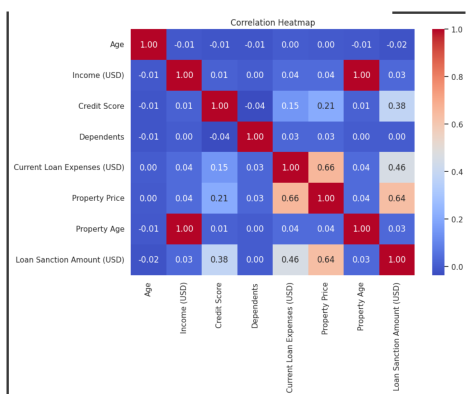


Figure 9: Correlation Heatmap

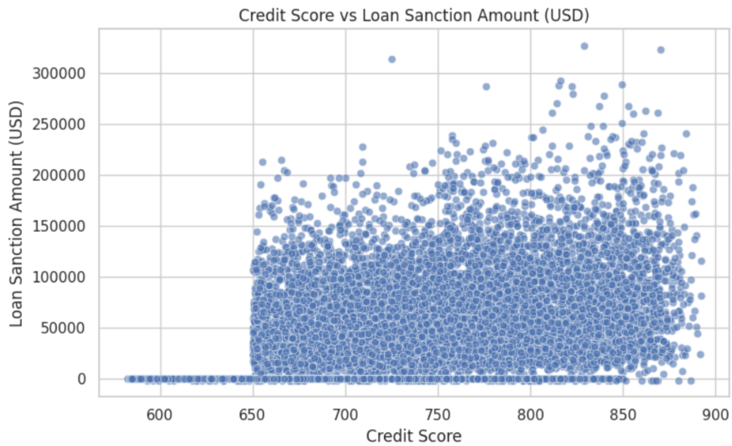


Figure 10: Credit Score vs Loan Amount

Figure 11: Property Price vs Loan Amount

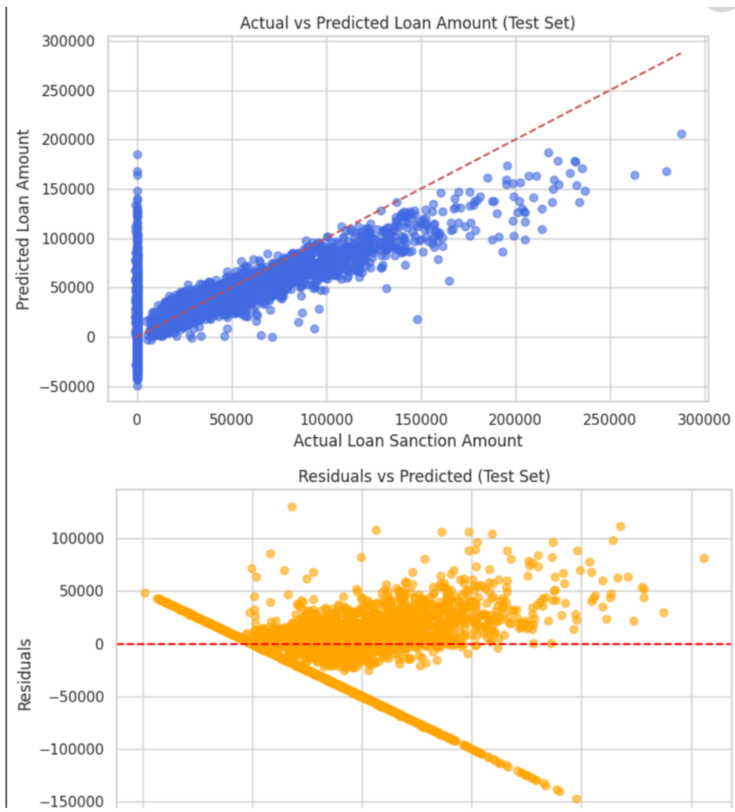


Figure 12: Actual Loan Amount vs Residuals

7 Inference Table

Table 1: Cross-Validation Results (5-Fold)

Fold	**MAE**	**MSE**	**RMSE**	**R^2 Score**
Fold 1	22090.85	9.96×10^8	31556.51	0.5483
Fold 2	21386.32	9.40×10^8	30655.92	0.5652
Fold 3	22128.77	1.08×10^9	32933.10	0.5183
Fold 4	21838.68	9.65×10^8	31069.29	0.5727
Fold 5	21917.13	9.55×10^8	30896.81	0.5817
Average	**21872.35**	$\mathbf{9.88 \times 10^8}$	**31422.33**	**0.5572**

Table 2: Results Summary

Description	Result
Dataset Size (after preprocessing)	15,183
Train/Test Split Ratio	60/20/20 (Train/Validation/Test)
Features Used	`['Age', 'Income (USD)', 'Credit Score', 'Dependents', 'Current Loan Expenses (USD)', 'Property Price', 'Property Age', 'Total_Income', 'Gender', 'Income Stability', 'Profession', 'Type of Employment', 'Has Active Credit Card', 'Co-Applicant', 'Property Type']`
Model Used	Linear Regression
Cross-Validation Used?	Yes
Number of Folds (K)	5
Reference to CV Results Table	Table 1
MAE on Test Set	22145.56
MSE on Test Set	998067220.05
RMSE on Test Set	31592.20
R^2 Score on Test Set	0.5472
Adjusted R^2 Score on Test Set	0.5450
Most Influential Feature(s)	`['Co-Applicant_0', 'Property Price', 'Credit Score']`
Observations from Residual Plot	The residual plot shows a clear pattern with residuals decreasing as predicted values increase, indicating model bias and heteroscedasticity. This suggests the linear model may not fully capture the relationship.
Interpretation of Predicted vs Actual Plot	The plot shows that most predicted values align closely with actual loan amounts along the diagonal line, indicating decent model accuracy. However, there is some spread and underestimation for higher loan amounts, suggesting room for improvement in capturing extreme values.
Any Overfitting or Underfitting Observed?	No significant overfitting or underfitting observed. The training and validation errors are comparable, and residuals do not show extreme patterns, indicating the model generalizes reasonably well. However, some bias at higher values suggests slight underfitting in that range.

8 Best Practices

- **Data Preprocessing**: Handle missing values carefully (drop or impute), and remove irrelevant columns such as IDs and names that do not contribute to prediction.

- **Feature Engineering**: Create new meaningful features (e.g., total income) and apply transformations (e.g., log transformation for skewed data) to improve model performance.

- **Scaling and Encoding**: Use scaling (e.g., StandardScaler) for numerical features and one-hot encoding for categorical features to prepare data for linear regression.
- **Train-Test Split**: Use proper splits (e.g., 80/20) and consider cross-validation to ensure the model generalizes well and to prevent overfitting.
- **Model Evaluation**: Use multiple metrics (MAE, MSE, RMSE, R^2) to assess different aspects of model performance.
- **Residual Analysis**: Analyze residual plots to detect model bias or heteroscedasticity and decide if further feature engineering or alternative models are needed.

9 Learning Outcomes

Through this experiment, I have:

- Understood the full ML pipeline from data cleaning to model evaluation.
- Learned the importance of feature engineering and proper data preprocessing.
- Learned how to visualize data and model results for better insights.
- Recognized signs of overfitting or underfitting via residual and prediction plots.
- Used cross-validation for robust model performance assessment.