Ex2 - Loan Amount Prediction Using Linear Regression And Visualize The Interpretation

Colab Link:

[Colab Link]

Aim:

To understand linear regression and implement it in predicting the loan amount of individuals

Code & Output:

Import Dependencies

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

Load the Dataset

```
train = pd.read_csv('train.csv')
```

Display Sample Rows

```
train.head()
```

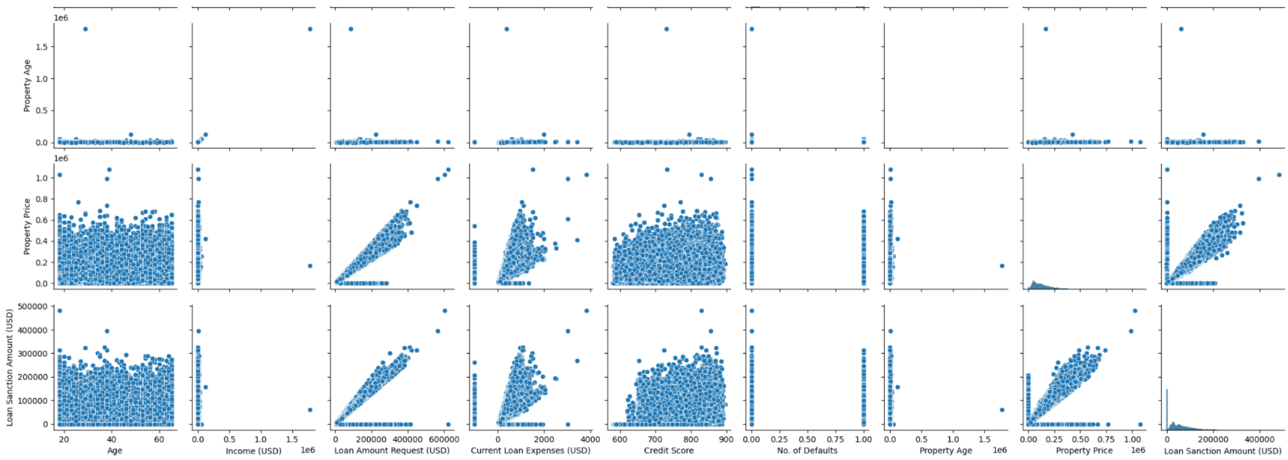
	Customer ID	Name	Gender	Age	Income (USD)	Income Stability	Profession	Type of Employment	Location	Loan Amount Request (USD)	...	Credit Score	No. of Defaults	Has Active Credit Card	Property ID	Property Age
0	C-36995	Frederica Shealy	F	56	1933.05	Low	Working	Sales staff	Semi-Urban	72809.58	...	809.44	0	NaN	746	1933.05
1	C-33999	America Calderone	M	32	4952.91	Low	Working	NaN	Semi-Urban	46837.47	...	780.40	0	Unpossessed	608	4952.91
2	C-3770	Rosetta Verne	F	65	988.19	High	Pensioner	NaN	Semi-Urban	45593.04	...	833.15	0	Unpossessed	546	988.19

train.info()

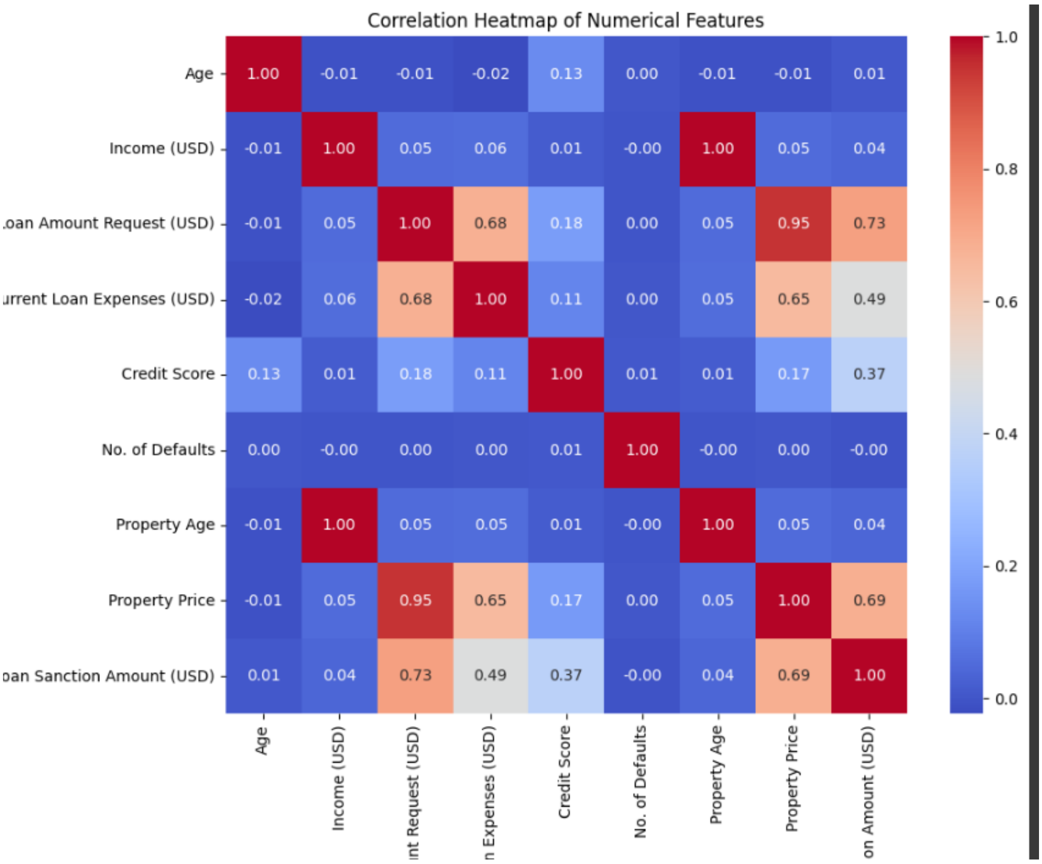
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 24 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Customer ID                  30000 non-null  object 
 1   Name                         30000 non-null  object 
 2   Gender                       29947 non-null  object 
 3   Age                          30000 non-null  int64  
 4   Income (USD)                 25424 non-null  float64
 5   Income Stability             28317 non-null  object 
 6   Profession                   30000 non-null  object 
 7   Type of Employment           22730 non-null  object 
 8   Location                     30000 non-null  object 
 9   Loan Amount Request (USD)    30000 non-null  float64
 10  Current Loan Expenses (USD)  29828 non-null  float64
 11  Expense Type 1               30000 non-null  object 
 12  Expense Type 2               30000 non-null  object 
 13  Dependents                   27507 non-null  float64
 14  Credit Score                 28297 non-null  float64
 15  No. of Defaults              30000 non-null  int64  
 16  Has Active Credit Card       28434 non-null  object 
 17  Property ID                  30000 non-null  int64  
 18  Property Age                 25150 non-null  float64
 19  Property Type                30000 non-null  int64  
 20  Property Location            29644 non-null  object 
 21  Co-Applicant                 30000 non-null  int64  
 22  Property Price               30000 non-null  float64
 23  Loan Sanction Amount (USD)   29660 non-null  float64
dtypes: float64(8), int64(5), object(11)
memory usage: 5.5+ MB
```

Graphical Plots

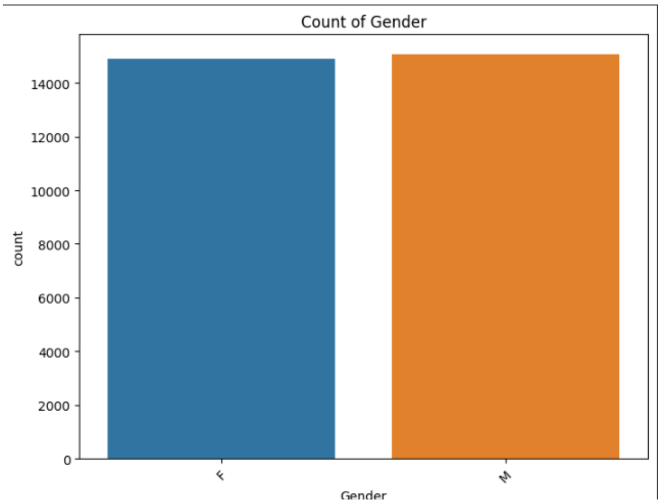
```
import matplotlib.pyplot as plt
import seaborn as sns

# Distribution of Numerical Features
numerical_features = ['Age', 'Income (USD)', 'Loan Amount Request (USD)', 'Current Loan Expenses (USD)', 'Credit Score', 'No. of Defaults', 'Property Age', 'Property Price', 'Loan Sanction Amount (USD)']
sns.pairplot(train[numerical_features])
plt.show()
```

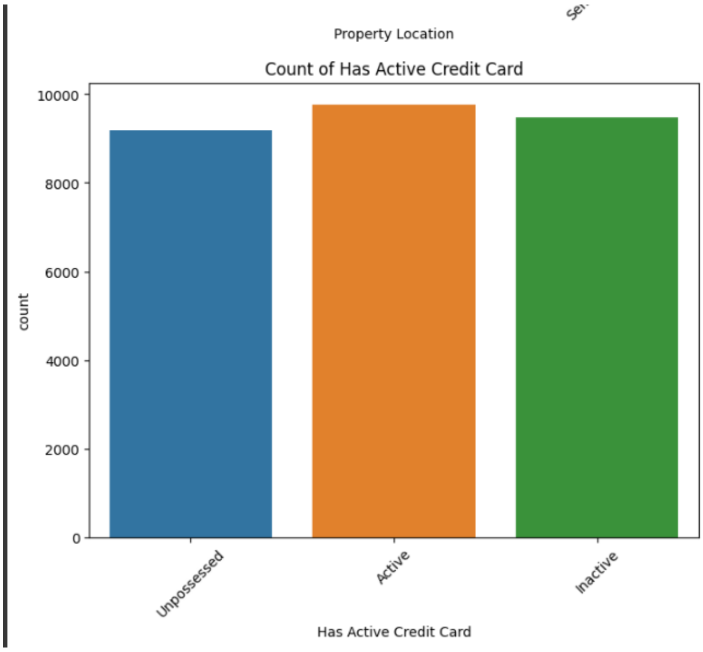



```
# Correlation Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(train[numerical_features].corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```

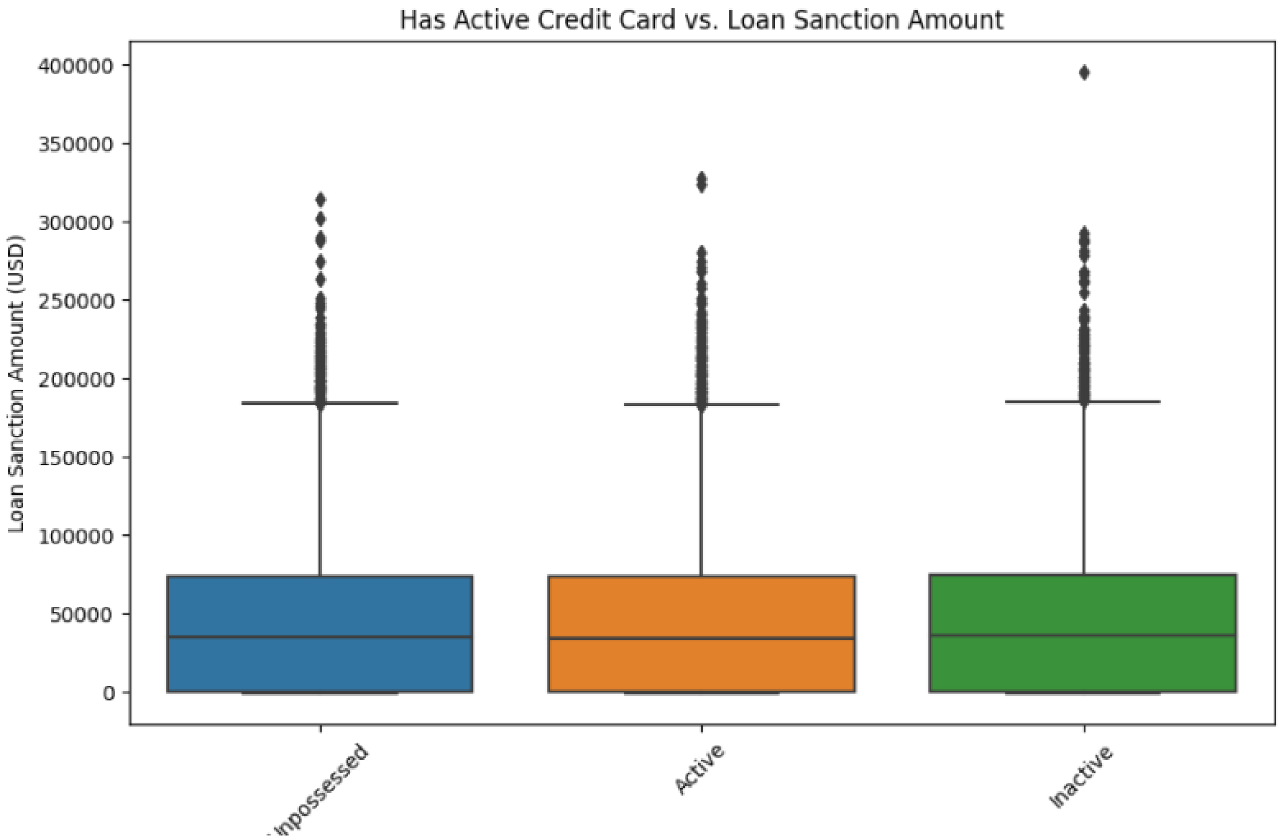



```
# Count of Categorical Features
categorical_features = ['Gender', 'Income Stability', 'Profession', 'Type of Employment',
                        'Location', 'Expense Type 1', 'Expense Type 2', 'Property Type',
                        'Property Location', 'Has Active Credit Card', 'Co-Applicant']
for feature in categorical_features:
    plt.figure(figsize=(8, 6))
    sns.countplot(data=train, x=feature)
    plt.title(f'Count of {feature}')
    plt.xticks(rotation=45)
    plt.show()
```






```
# Relationship between Categorical Features and Loan Sanction Amount
for feature in categorical_features:
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=train, x=feature, y='Loan Sanction Amount (USD)')
    plt.title(f'{feature} vs. Loan Sanction Amount')
    plt.xticks(rotation=45)
    plt.show()
```



Pre Processing (Handling missing values, Encoding, Normalization, Standardization)

Print Columns

```
train.columns
```

```
Index(['Customer ID', 'Name', 'Gender', 'Age', 'Income (USD)',
       'Income Stability', 'Profession', 'Type of Employment', 'Location',
       'Loan Amount Request (USD)', 'Current Loan Expenses (USD)',
       'Expense Type 1', 'Expense Type 2', 'Dependents', 'Credit Score',
       'No. of Defaults', 'Has Active Credit Card', 'Property ID',
       'Property Age', 'Property Type', 'Property Location', 'Co-Applicant',
       'Property Price', 'Loan Sanction Amount (USD)'],
      dtype='object')
```

Print Index

train.index

```
RangeIndex(start=0, stop=30000, step=1)
```

Drop Uncessary Columns

train = train.drop(['Customer ID','Name','Gender','Income Stability','Profession','Type of Employment','Location','Expense Type 1','Expense Type 2','Dependents','Has Active Credit Card','Property ID','Property Age','Property Type','Property Location','Co-Applicant'],axis=1)

Print Null Values

train.isna()

	Age	Income (USD)	Loan Amount Request (USD)	Current Loan Expenses (USD)	Credit Score	No. of Defaults	Property Price	Loan Sanction Amount (USD)
0	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False
3	False	True	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...
29995	False	False	False	False	False	False	False	False
29996	False	False	False	False	False	False	False	False
29997	False	True	False	False	True	False	False	False
29998	False	False	False	False	False	False	False	False
29999	False	False	False	False	False	False	False	False

30000 rows × 8 columns

```
arr = np.array(train.columns)
arr
```

```
array(['Age', 'Income (USD)', 'Loan Amount Request (USD)',
       'Current Loan Expenses (USD)', 'Credit Score', 'No. of Defaults',
       'Property Price', 'Loan Sanction Amount (USD)'], dtype=object)
```

Print Column and NULL Count

```
for index in range(len(arr)):
    count = train[train[arr[index]].isna() == True].shape[0]
    if(count != 0):
        print(f"{arr[index]}\t{count}")
```

```
Income (USD)    4576
Current Loan Expenses (USD)     172
Credit Score    1703
Loan Sanction Amount (USD)      340
```

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Handling NULL Values

Fill With Mean Values

```
train["Age"].fillna(train["Age"].mean(), inplace=True)
train["Income (USD)"].fillna(train["Income (USD)"].mean(), inplace=True)

train["Loan Amount Request (USD)"].fillna(train["Loan Amount Request (USD)"].mean(),inplace=True)
train["Loan Sanction Amount (USD)"].fillna(train["Loan Sanction Amount (USD)"].mean(),inplace=True)
train["Current Loan Expenses (USD)"].fillna(train["Current Loan Expenses (USD)"].mean(),inplace=True)
train["Credit Score"].fillna(train["Credit Score"].mean(),inplace=True)
```

Replace Outlier Values

```
train["Loan Amount Request (USD)"].replace(-999,train["Loan Amount Request (USD)"].mean())
train["Loan Sanction Amount (USD)"].replace(-999,train["Loan Sanction Amount (USD)"].mean())
```

```
0         54607.18
1         37469.98
2         36474.43
3         56040.54
4         74008.28
            ...
29995     68992.11
29996     46616.60
29997     61057.56
29998     99766.87
29999    117217.90
Name: Loan Sanction Amount (USD), Length: 30000, dtype: float64
```

Drop Column To Be Predicted

y = train["Loan Sanction Amount (USD)"]
y

```
0         54607.18
1         37469.98
2         36474.43
3         56040.54
4         74008.28
            ...
29995     68992.11
29996     46616.60
29997     61057.56
29998     99766.87
29999    117217.90
Name: Loan Sanction Amount (USD), Length: 30000, dtype: float64
```

train = train.drop(["Loan Sanction Amount (USD)"],axis=1)

Model

train.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 7 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Age                          30000 non-null  int64
 1   Income (USD)                 30000 non-null  float64
 2   Loan Amount Request (USD)    30000 non-null  float64
 3   Current Loan Expenses (USD)  30000 non-null  float64
 4   Credit Score                 30000 non-null  float64
 5   No. of Defaults              30000 non-null  int64
 6   Property Price               30000 non-null  float64
dtypes: float64(5), int64(2)
memory usage: 1.6 MB
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error, r2_score
from sklearn.metrics import median_absolute_error, explained_variance_score


# Define features (X) and target variable (y)
X = train[['Age', 'Income (USD)', 'Loan Amount Request (USD)', 'Current Loan Expenses
(USD)', 'Credit Score', 'No. of Defaults', 'Property Price']]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initialize the linear regression model
model = LinearRegression()

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

# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print('Mean Squared Error:', mse)

# Calculate Mean Absolute Error
mae = mean_absolute_error(y_test, y_pred)
print('Mean Absolute Error:', mae)

# Calculate R-squared
r2 = r2_score(y_test, y_pred)
print('R-squared:', r2)

# Calculate Median Absolute Error
```

```
medae = median_absolute_error(y_test, y_pred)
print('Median Absolute Error:', medae)

# Calculate Explained Variance Score
evs = explained_variance_score(y_test, y_pred)
print('Explained Variance Score:', evs)

# Score the model on the test set
score = model.score(X_test, y_test)
print('Model Score (R-squared):', score)
```

```
Mean Squared Error: 956230969.0157363
Mean Absolute Error: 21725.966832074235
R-squared: 0.5766373122374836
Median Absolute Error: 15828.744250770707
Explained Variance Score: 0.5766459138874588
Model Score (R-squared): 0.5766373122374836
```

```
import matplotlib.pyplot as plt
import seaborn as sns
```

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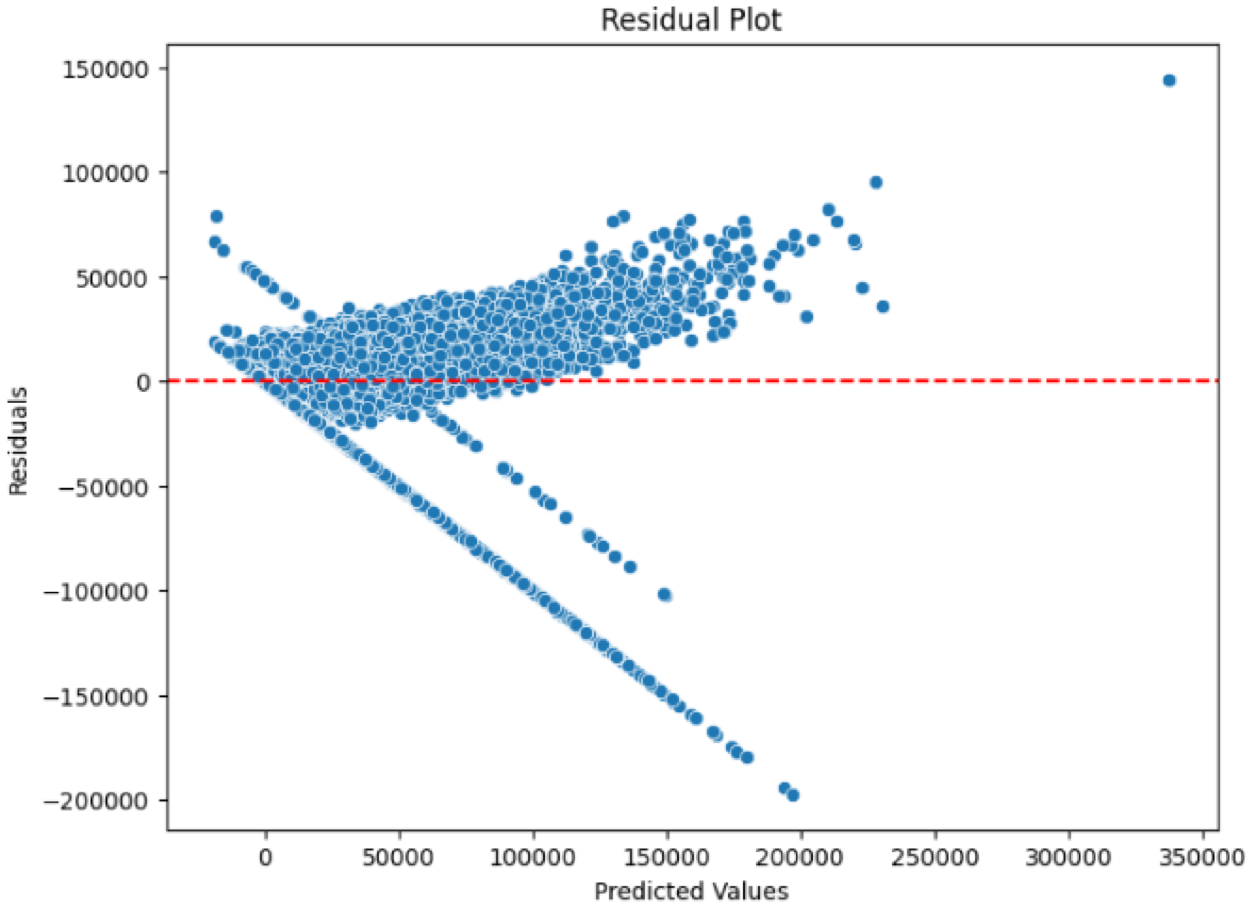
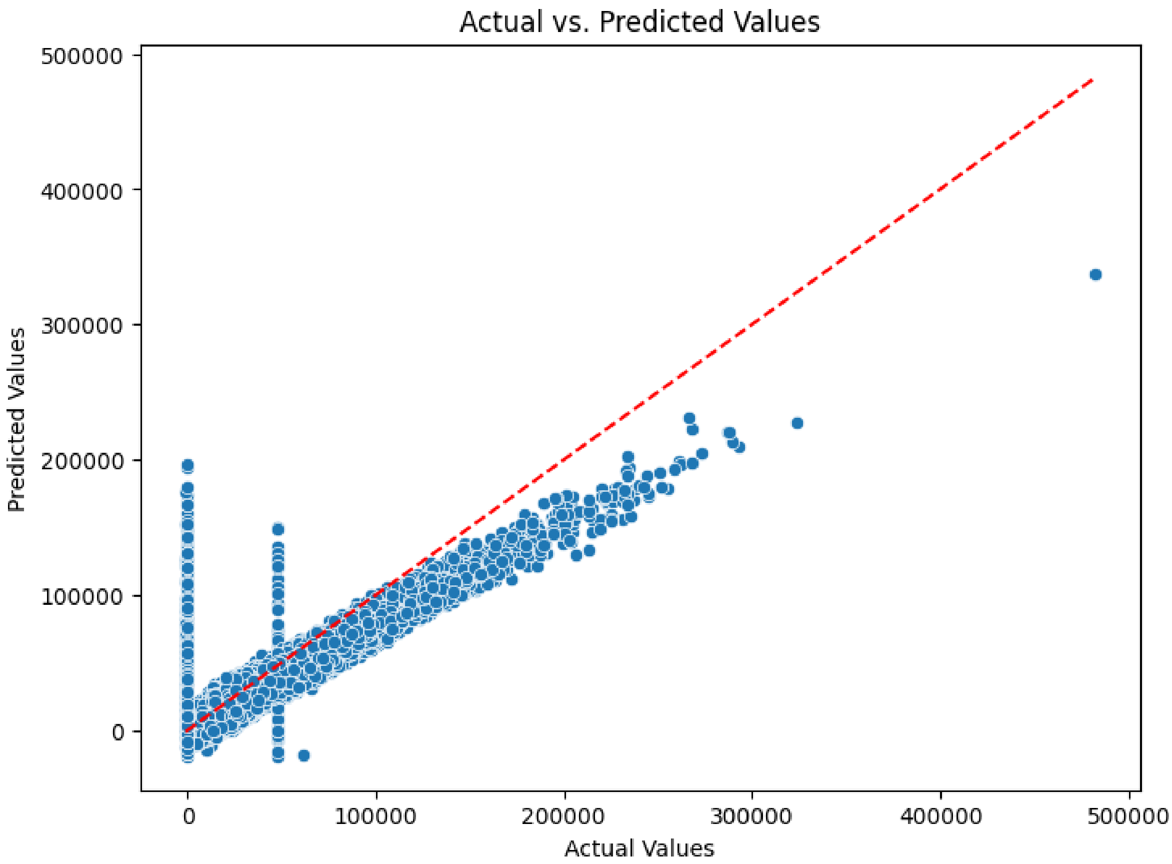
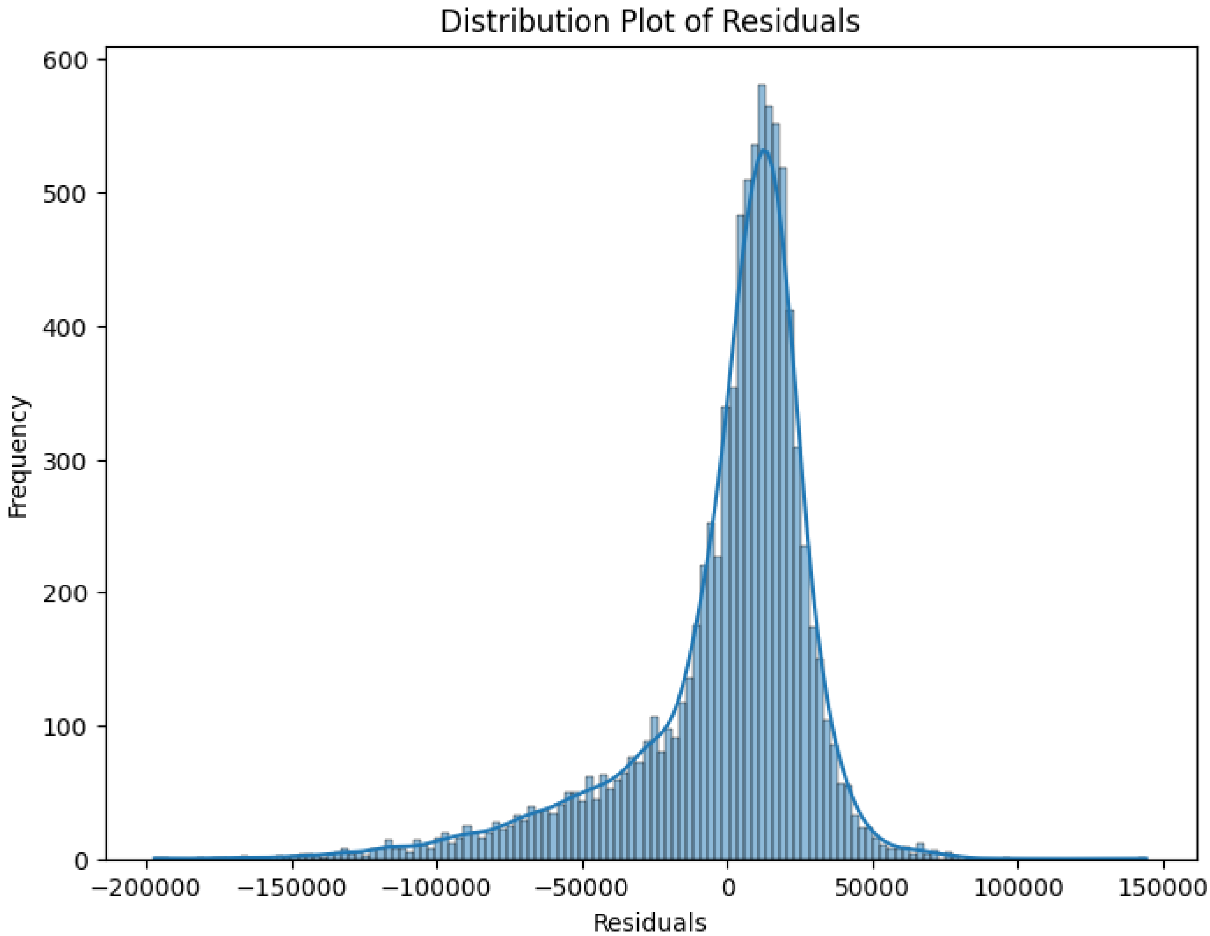
```
# Residual Plot
residuals = y_test - y_pred
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_pred, y=residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.title('Residual Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.show()
```



```
# Actual vs. Predicted Values Plot
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=y_pred)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='r', linestyle='--')
plt.title('Actual vs. Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```

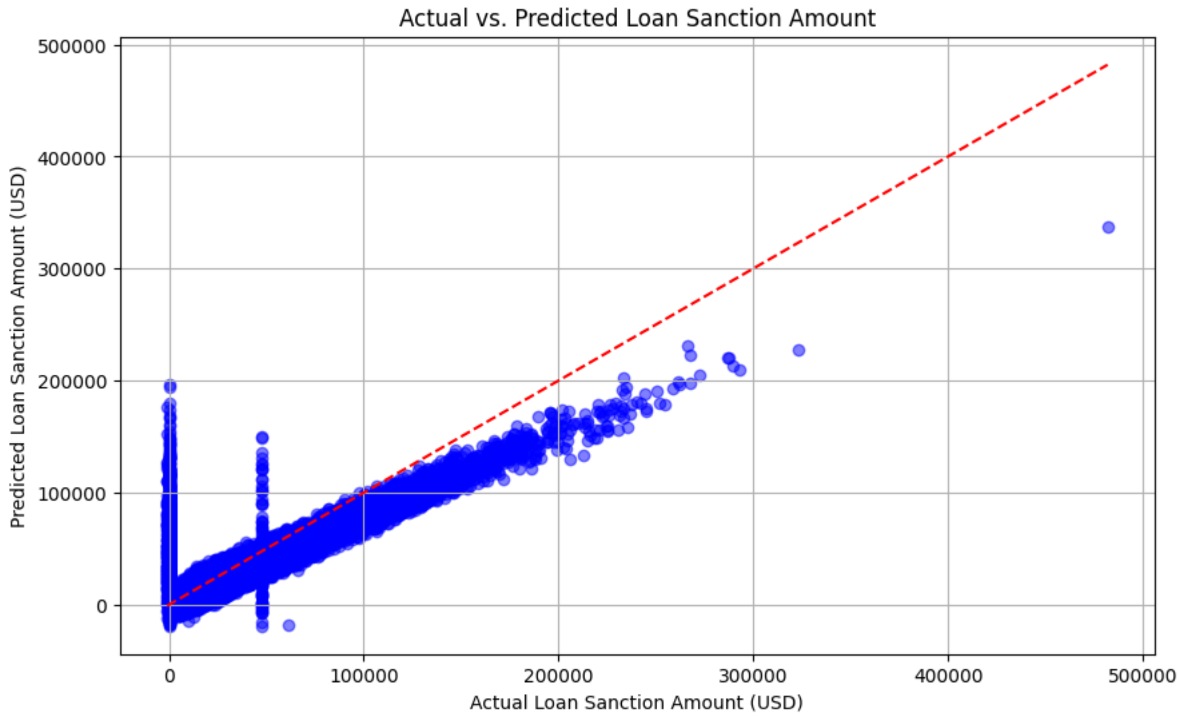


```
# Distribution Plot of Residuals
plt.figure(figsize=(8, 6))
sns.histplot(residuals, kde=True)
plt.title('Distribution Plot of Residuals')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.show()
```



```
import matplotlib.pyplot as plt
import numpy as np

# Scatter plot of actual vs. predicted loan sanction amount
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--')
plt.xlabel('Actual Loan Sanction Amount (USD)')
plt.ylabel('Predicted Loan Sanction Amount (USD)')
plt.title('Actual vs. Predicted Loan Sanction Amount')
plt.grid(True)
plt.show()
```



Test

test = pd.read_csv('test.csv')
test.head()

	Customer ID	Name	Gender	Age	Income (USD)	Income Stability	Profession	Type of Employment	Location	Loan Amount Request (USD)	...	Dependents	Credit Score	No. of Defaults	Has Active Credit Card	Propert I
0	C-26247	Tandra Olszewski	F	47	3472.69	Low	Commercial associate	Managers	Semi-Urban	137088.98	...	2.0	799.14	0	Unpossessed	84
1	C-35067	Jeannette Cha	F	57	1184.84	Low	Working	Sales staff	Rural	104771.59	...	2.0	833.31	0	Unpossessed	2
2	C-34590	Keva Godfrey	F	52	1266.27	Low	Working	NaN	Semi-Urban	176684.91	...	3.0	627.44	0	Unpossessed	
3	C-16668	Elva Sackett	M	65	1369.72	High	Pensioner	NaN	Rural	97009.18	...	2.0	833.20	0	Inactive	73
4	C-12196	Sade Constable	F	60	1939.23	High	Pensioner	NaN	Urban	109980.00	...	NaN	NaN	0	NaN	35

test.columns

```
Index(['Customer ID', 'Name', 'Gender', 'Age', 'Income (USD)',
       'Income Stability', 'Profession', 'Type of Employment', 'Location',
       'Loan Amount Request (USD)', 'Current Loan Expenses (USD)',
       'Expense Type 1', 'Expense Type 2', 'Dependents', 'Credit Score',
       'No. of Defaults', 'Has Active Credit Card', 'Property ID',
       'Property Age', 'Property Type', 'Property Location', 'Co-Applicant',
       'Property Price'],
      dtype='object')
```

Loan Amount Prediction Using Linear Regression And Visualize The Interpretation

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```
# Preprocess the test data, selecting the same features as in the training data
test_features = test[['Age', 'Income (USD)', 'Loan Amount Request (USD)', 'Current Loan Expenses (USD)',
                      'Credit Score', 'No. of Defaults', 'Property Price']]

# Replace '?' with NaN
test_features.replace('?', float('nan'), inplace=True)

# Convert object columns to numeric
test_features = test_features.apply(pd.to_numeric, errors='coerce')

# Fill missing values with mean
test_features.fillna(test_features.mean(), inplace=True)

# Make predictions on the processed test data
test_predictions = model.predict(test_features)

# Add the predictions to the test dataframe
test['Predicted Loan Sanction Amount (USD)'] = test_predictions.round(2)

test.head()
```

ıme ılity	Profession	Type of Employment	Location	Loan Amount Request (USD)	...	Credit Score	No. of Defaults	Has Active Credit Card	Property ID	Property Age	Property Type	Property Location	Co-Applicant	Property Price	Predicted Loan Sanction Amount (USD)
.ow	Commercial associate	Managers	Semi-Urban	137088.98	...	799.14	0	Unpossessed	843	3472.69	2	Urban	1	236644.5	83448.55
.ow	Working	Sales staff	Rural	104771.59	...	833.31	0	Unpossessed	22	1184.84	1	Rural	1	142357.3	71390.69
.ow	Working	NaN	Semi-Urban	176684.91	...	627.44	0	Unpossessed	1	1266.27	1	Urban	1	300991.24	76125.08
ligh	Pensioner	NaN	Rural	97009.18	...	833.20	0	Inactive	730	1369.72	1	Semi-Urban	0	125612.1	66779.91
ligh	Pensioner	NaN	Urban	109980.00	...	NaN	0	NaN	356	1939.23	4	Semi-Urban	1	180908.0	58069.85

test['Predicted Loan Sanction Amount (USD)']

```
0        83448.55
1        71390.69
2        76125.08
3        66779.91
4        58069.85
           ...
19995    77160.65
19996    20640.12
19997    -3030.66
19998    74005.59
19999    77062.47
Name: Predicted Loan Sanction Amount (USD), Length: 20000, dtype: float64
```