loan_amount_prediction_svm

September 3, 2025

[1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.svm import SVR
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

[2]:
```python
df=pd.read_csv('train.csv')
df.head()
```

[2]:
```
  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

   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]
```

[3]:
```
df.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
```

[4]:
```
df['Co-Applicant'].unique()
```

[4]:
```
array([   1,    0, -999])
```

[5]:
```python
df['Has Active Credit Card'].unique()
```

[5]: array([nan, 'Unpossessed', 'Active', 'Inactive'], dtype=object)

[6]:
```python
#Removing unnecessary columns
df = df.drop(columns=["Customer ID", "Name"])
```

[7]:
```python
# Replace -999 with NaN
df['Co-Applicant'] = df['Co-Applicant'].replace(-999, np.nan)

# Option 1: Impute missing values (e.g., assume no co-applicant)
df['Co-Applicant'] = df['Co-Applicant'].fillna(0)
```

[8]:
```python
# Fill NaN with 'Unknown'
df['Has Active Credit Card'] = df['Has Active Credit Card'].fillna('Unknown')

# Optional: Encode as ordinal
credit_card_map = {
    'Unpossessed': 0,
    'Inactive': 1,
    'Active': 2,
    'Unknown': -1
}
df['Has Active Credit Card'] = df['Has Active Credit Card'].map(credit_card_map)
```

[9]:
```python
df.isnull().sum()
```

[9]:
```
Gender                           53
Age                               0
Income (USD)                   4576
Income Stability               1683
Profession                        0
Type of Employment             7270
Location                          0
Loan Amount Request (USD)         0
Current Loan Expenses (USD)     172
Expense Type 1                    0
Expense Type 2                    0
Dependents                     2493
Credit Score                   1703
No. of Defaults                   0
Has Active Credit Card            0
Property ID                       0
Property Age                   4850
Property Type                     0
Property Location               356
Co-Applicant                      0
```

```
Property Price                 0
Loan Sanction Amount (USD)   340
dtype: int64
```

[10]:
```
#Filling null values
df['Gender']=df['Gender'].fillna(df['Gender'].mode()[0])
df['Income (USD)']=df['Income (USD)'].fillna(df['Income (USD)'].median())
df['Income Stability']=df['Income Stability'].fillna(df['Income Stability'].
↪mode()[0])
```

[11]:
```
#Dropping this column due to presence of more null values and may categories
df['Type of Employment'].unique()
df=df.drop(columns=['Type of Employment'])
```

[12]:
```
#Current Loan Expenses (USD) - Numeric → fill with median
df['Current Loan Expenses (USD)'] = df['Current Loan Expenses (USD)'].
↪fillna(df['Current Loan Expenses (USD)'].median())

#Dependents - Numeric → fill with mode (likely a small integer like 1 or 2)
df['Dependents'] = df['Dependents'].fillna(df['Dependents'].mode()[0])

#Credit Score - Numeric → fill with median
df['Credit Score'] = df['Credit Score'].fillna(df['Credit Score'].median())

#Property Age - Numeric → fill with median
df['Property Age'] = df['Property Age'].fillna(df['Property Age'].median())

#Property Location - Categorical → fill with mode
df['Property Location'] = df['Property Location'].fillna(df['Property␣
↪Location'].mode()[0])

# Loan Sanction Amount (USD) - Numeric → fill with median
df['Loan Sanction Amount (USD)'] = df['Loan Sanction Amount (USD)'].
↪fillna(df['Loan Sanction Amount (USD)'].median())

df['Loan Sanction Amount (USD)'] = df['Loan Sanction Amount (USD)'].replace(0,␣
↪df['Loan Sanction Amount (USD)'].median())
```

[13]:
```
df.isnull().sum()
```

[13]:
```
Gender                      0
Age                         0
Income (USD)                0
Income Stability            0
Profession                  0
Location                    0
Loan Amount Request (USD)   0
```

```
Current Loan Expenses (USD)    0
Expense Type 1                 0
Expense Type 2                 0
Dependents                     0
Credit Score                   0
No. of Defaults                0
Has Active Credit Card         0
Property ID                    0
Property Age                   0
Property Type                  0
Property Location              0
Co-Applicant                   0
Property Price                 0
Loan Sanction Amount (USD)     0
dtype: int64
```

Encoding of variables with values

[14]:
```
from sklearn.preprocessing import LabelEncoder

# List of categorical columns
cat_cols = [
    'Gender', 'Income Stability', 'Profession',
    'Expense Type 1', 'Expense Type 2',
    'Has Active Credit Card', 'Property Type', 'Property Location','Location'
]

# Create a label encoder instance
le = LabelEncoder()

# Apply label encoding to each column
for col in cat_cols:
    df[col] = le.fit_transform(df[col])
```

Standardization of Features

[15]:
```
from sklearn.preprocessing import StandardScaler

# Identify numeric columns (excluding categorical and target)
numeric_cols = df.select_dtypes(include=['float64', 'int64']).columns.tolist()

# Optionally exclude target column (e.g., 'Loan Sanction Amount (USD)')
numeric_cols.remove('Loan Sanction Amount (USD)')

# Initialize scaler
scaler = StandardScaler()

# Fit and transform numeric features
```

```
df[numeric_cols] = scaler.fit_transform(df[numeric_cols])
```

[16]:
```
df.head(10)
```

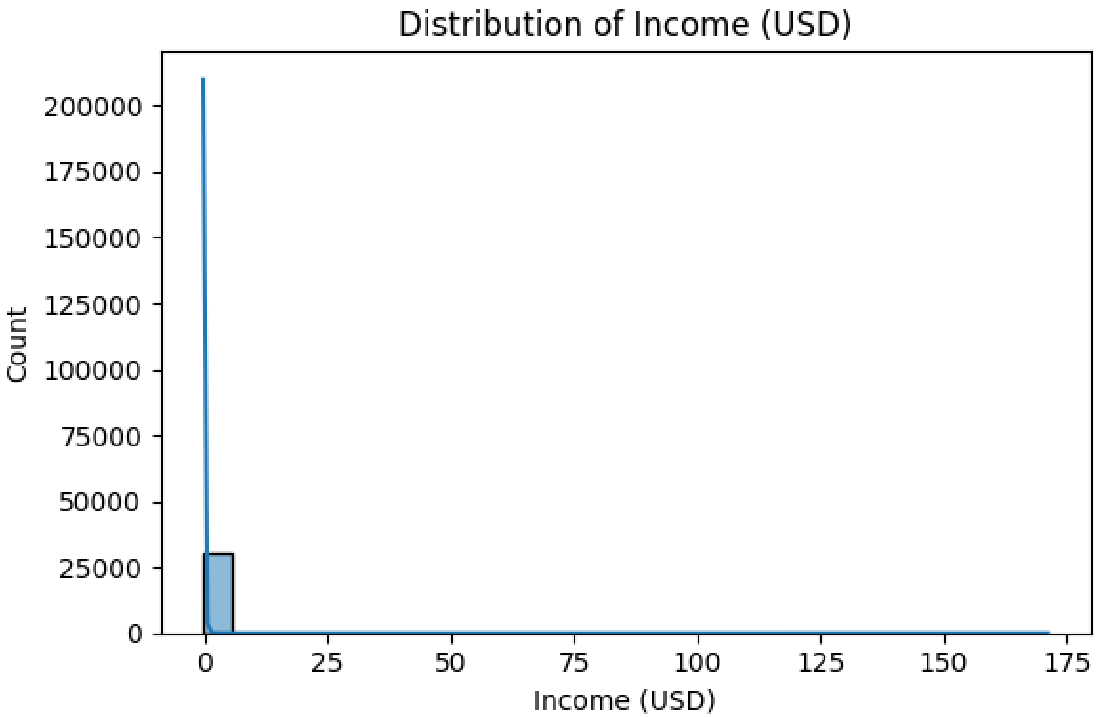
[16]:
```
     Gender       Age  Income (USD)  Income Stability  Profession  Location  \
0 -1.007092  0.991451     -0.061266          0.305833    0.834973  0.142149
1  0.992958 -0.504355      0.229972          0.305833    0.834973  0.142149
2 -1.007092  1.552379     -0.152389         -3.269763   -0.686548  0.142149
3 -1.007092  1.552379     -0.033357         -3.269763   -0.686548 -1.762481
4 -1.007092 -0.566680      0.004480          0.305833    0.834973  0.142149
5 -1.007092  1.240752     -0.128594          0.305833   -0.306168 -1.762481
6  0.992958  0.181223     -0.019940          0.305833    0.834973  0.142149
7 -1.007092  0.305874     -0.033357          0.305833   -0.306168  0.142149
8 -1.007092 -0.130403     -0.122697          0.305833    0.834973 -1.762481
9  0.992958 -1.376908     -0.098577          0.305833    0.834973 -1.762481

   Loan Amount Request (USD)  Current Loan Expenses (USD)  Expense Type 1  \
0                  -0.269027                    -0.660358       -0.749241
1                  -0.705269                     0.392886       -0.749241
2                  -0.726171                    -0.946193       -0.749241
3                  -0.147279                    -0.422775       -0.749241
4                   0.420461                     0.374693       -0.749241
5                  -0.913593                    -0.906788       -0.749241
6                   1.070530                     1.227526        1.334685
7                   2.544436                     1.682224       -0.749241
8                  -0.901713                    -1.012348       -0.749241
9                  -0.784989                     0.411038       -0.749241

   Expense Type 2  …  Credit Score  No. of Defaults  Has Active Credit Card  \
0       -1.433524  …      0.992493        -0.490502               -2.096903
1        0.697582  …      0.578136        -0.490502               -1.001762
2        0.697582  …      1.330799        -0.490502               -1.001762
3        0.697582  …      1.324379         2.038728               -1.001762
4        0.697582  …      0.080879         2.038728                1.188520
5       -1.433524  …     -0.795636         2.038728                0.093379
6        0.697582  …     -1.463830        -0.490502               -1.001762
7       -1.433524  …      1.032730        -0.490502                1.188520
8        0.697582  …     -0.493571         2.038728                1.188520
9       -1.433524  …     -1.806987        -0.490502               -1.001762

   Property ID  Property Age  Property Type  Property Location  Co-Applicant  \
0     0.846998     -0.060969       1.376731          -1.214540      0.419205
1     0.368086      0.230298      -0.411309          -1.214540      0.419205
2     0.152923     -0.152102      -0.411309           1.283229     -2.385467
3     1.346732     -0.032979      -0.411309           0.034344      0.419205
4     0.739417      0.004783       1.376731           0.034344      0.419205
5    -0.037948     -0.128305      -0.411309          -1.214540      0.419205
```

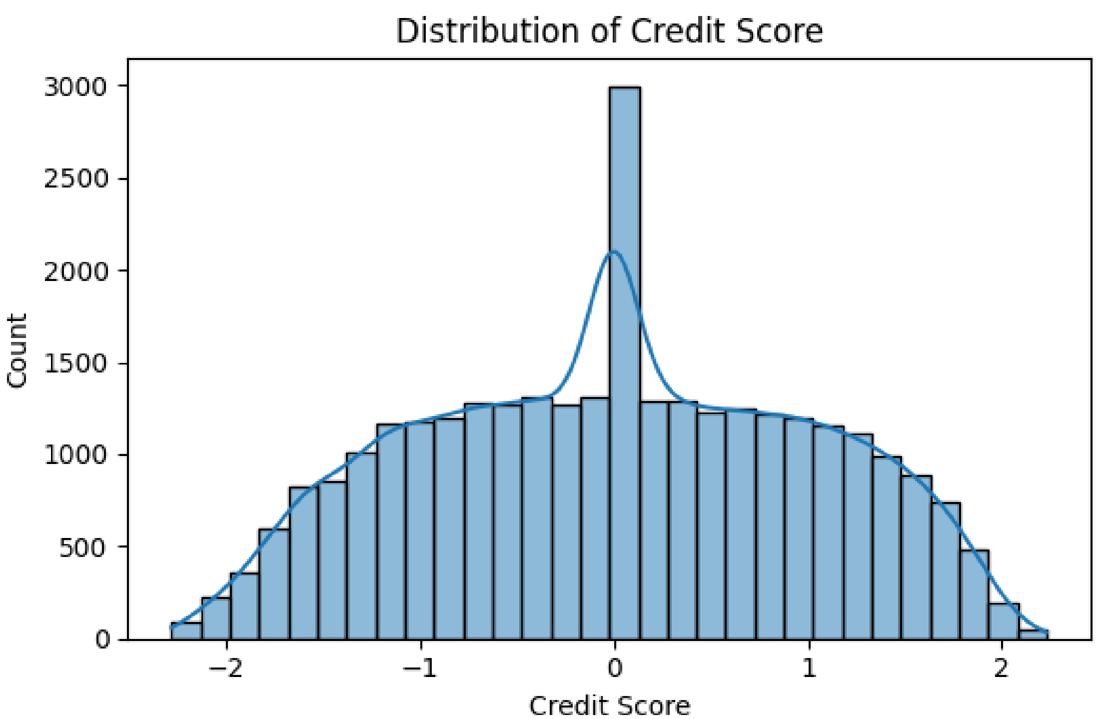
```
6   -0.954127   -0.019639   -1.305329        0.034344   0.419205
7   -0.652204   -0.032979   -0.411309        1.283229   0.419205
8   -0.905541   -0.122407    1.376731       -1.214540   0.419205
9    1.322440   -0.098284   -0.411309        1.283229   0.419205

   Property Price  Loan Sanction Amount (USD)
0       -0.126419                  54607.180
1       -0.822772                  37469.980
2       -0.634103                  36474.430
3       -0.110298                  56040.540
4        0.821057                  74008.280
5       -0.947245                  22382.570
6        0.954495                  35209.395
7        2.878533                 168218.240
8       -0.821570                  22842.290
9       -0.681642                  35209.395

[10 rows x 21 columns]
```

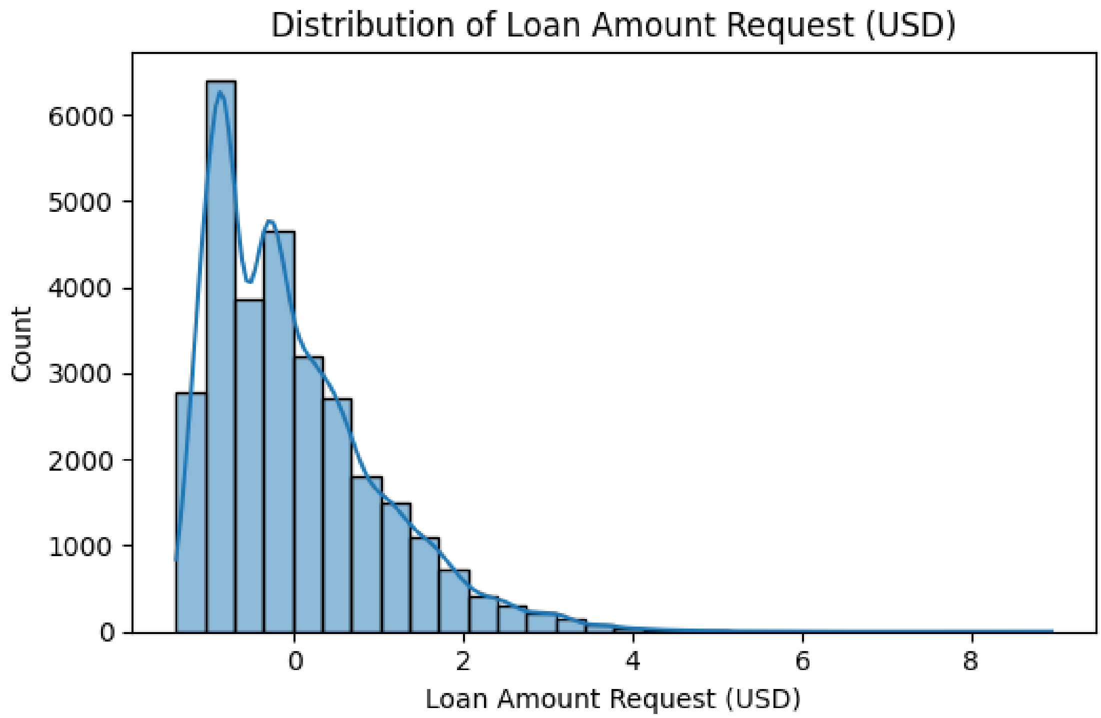
EDA

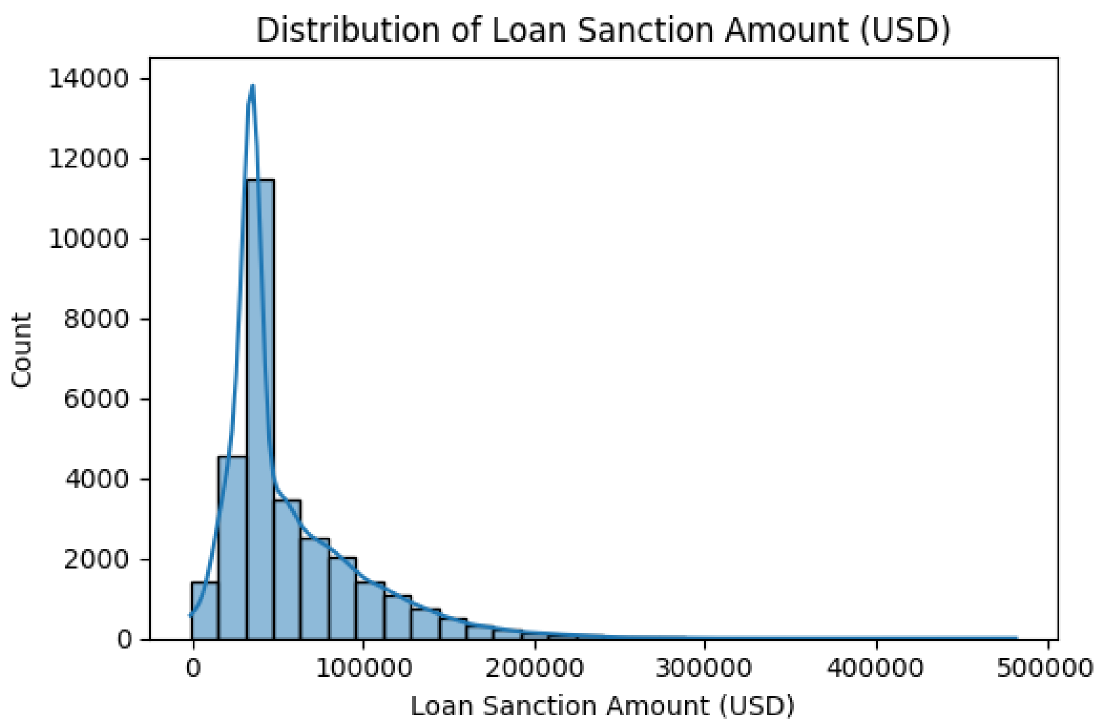
Histogram

[17]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

# Plot distributions for selected numeric columns
cols_to_plot = ['Income (USD)', 'Credit Score', 'Loan Amount Request (USD)',␣
 ↪'Loan Sanction Amount (USD)']

for col in cols_to_plot:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[col], kde=True, bins=30)
    plt.title(f'Distribution of {col}')
    plt.tight_layout()
    plt.show()
```


Distribution of Income (USD)
Count
200000
175000
150000
125000
100000
75000
50000
25000
0
0
25
50
75
100
125
150
175
Income (USD)

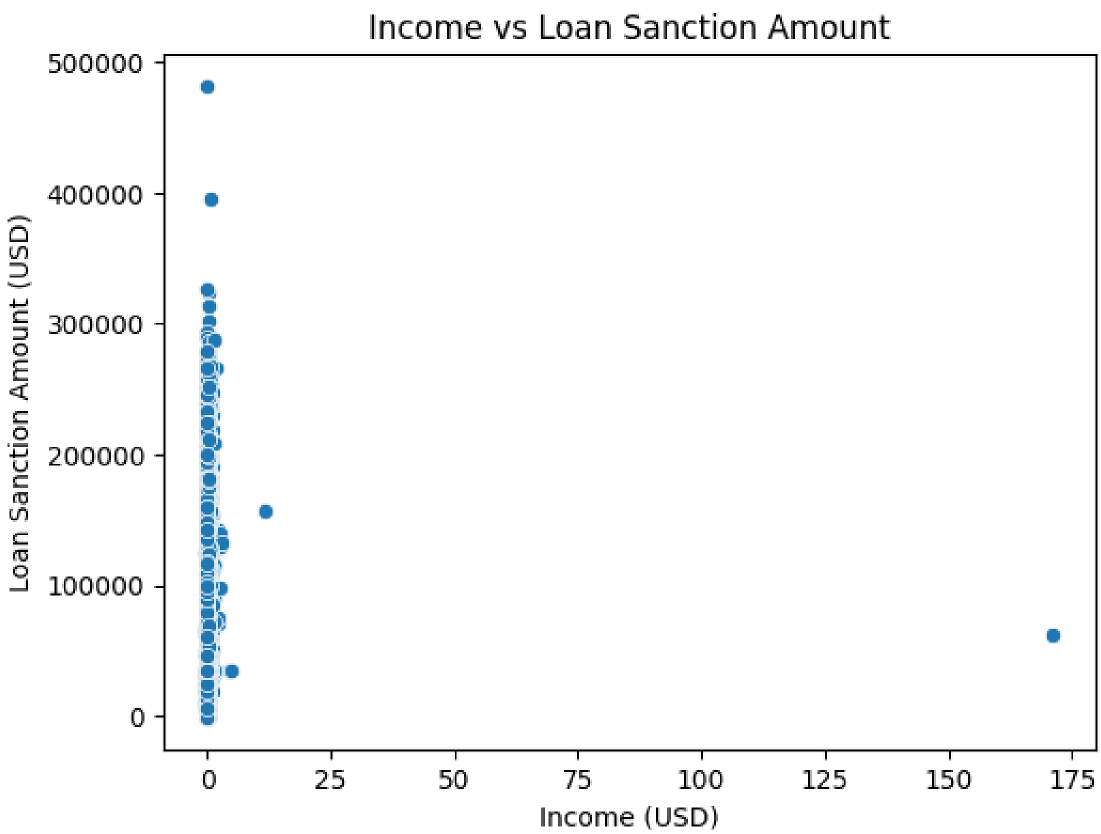

Distribution of Credit Score
Count
3000
2500
2000
1500
1000
500
0
−2
−1
0
1
2
Credit Score

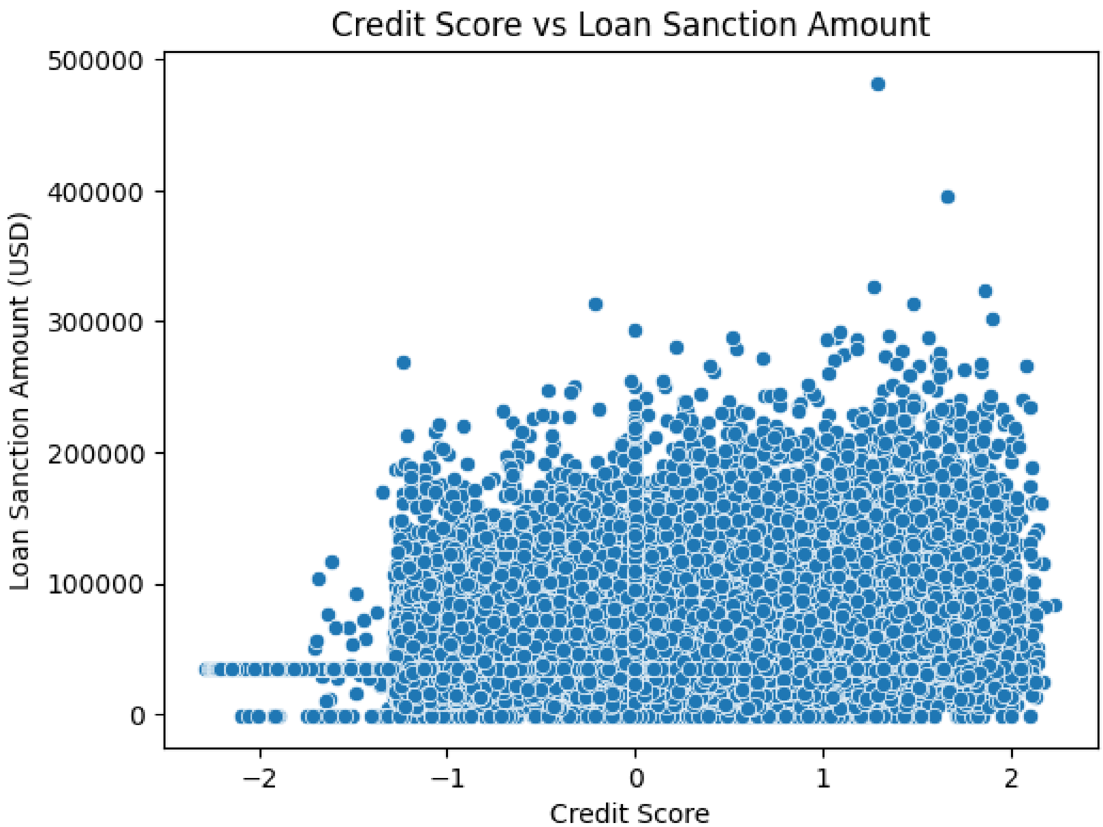

Distribution of Loan Amount Request (USD)
Count
0
1000
2000
3000
4000
5000
6000
0
2
4
6
8
Loan Amount Request (USD)


Distribution of Loan Sanction Amount (USD)
Count
0
2000
4000
6000
8000
10000
12000
14000
0
100000
200000
300000
400000
500000
Loan Sanction Amount (USD)

Scatter Plot

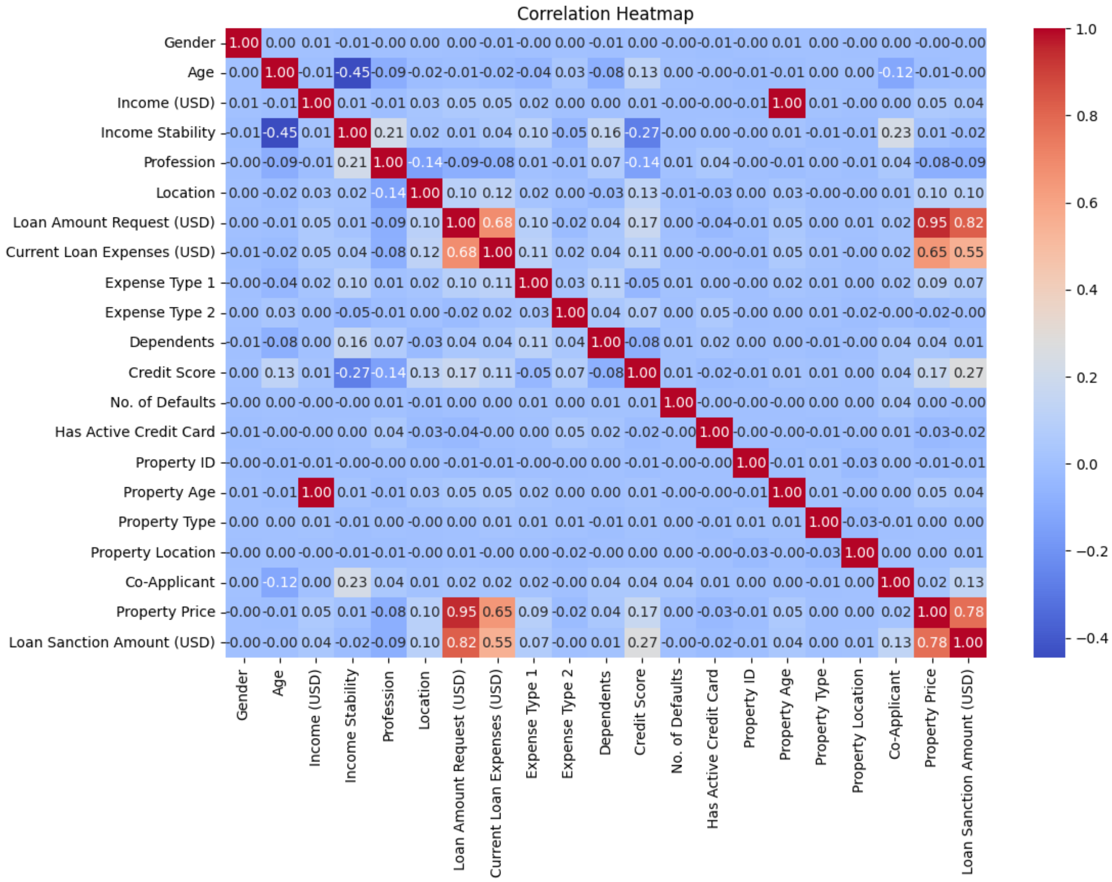
[18]:
```
# Income vs Loan Sanction Amount
sns.scatterplot(data=df, x='Income (USD)', y='Loan Sanction Amount (USD)')
plt.title('Income vs Loan Sanction Amount')
plt.show()

# Credit Score vs Loan Sanction Amount
sns.scatterplot(data=df, x='Credit Score', y='Loan Sanction Amount (USD)')
plt.title('Credit Score vs Loan Sanction Amount')
plt.show()
```





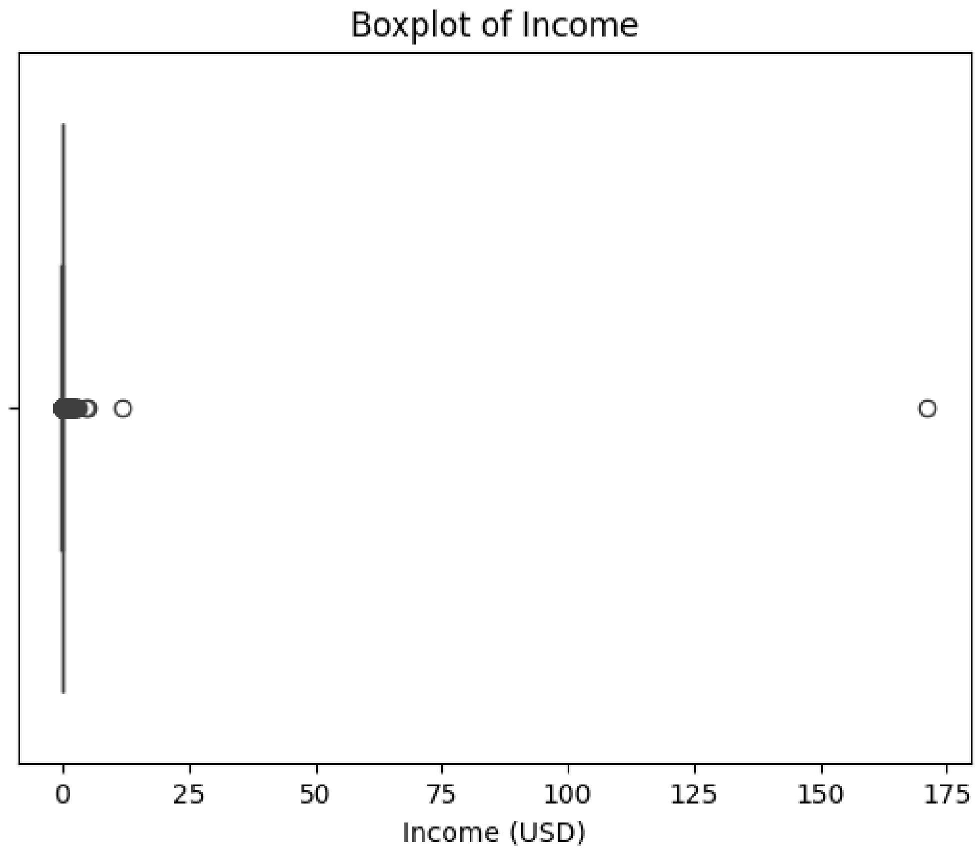
Correlation heatmap

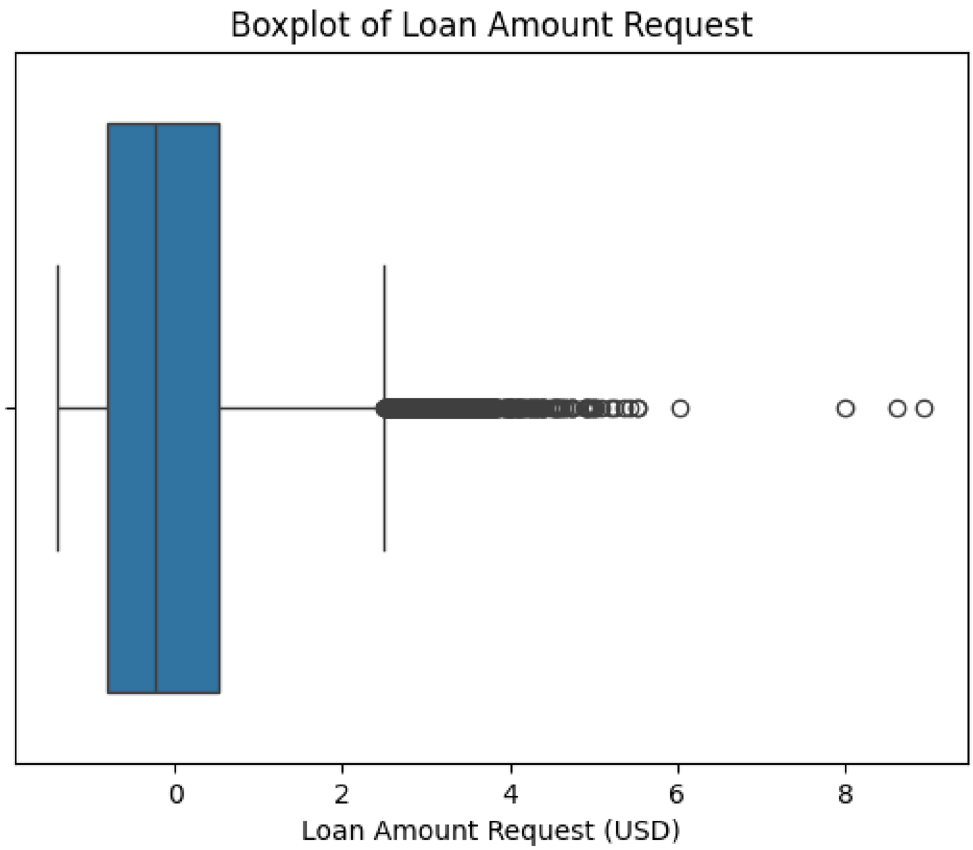
[19]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```



BoxPlot

[20]:
```
# Boxplot for Income
sns.boxplot(x=df['Income (USD)'])
plt.title('Boxplot of Income')
plt.show()

# Boxplot for Loan Amount Request
sns.boxplot(x=df['Loan Amount Request (USD)'])
plt.title('Boxplot of Loan Amount Request')
plt.show()
```


Boxplot of Income
0
25
50
75
100
125
150
175
Income (USD)



[21]:
```
# Define target variable
target = 'Loan Sanction Amount (USD)'

# Define feature columns
X = df.drop(columns=[target])
y = df[target]

# Split into train and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

0.0.1 Grid Search

[23]:
```
# Define the parameter grid
param_grid = {
    'kernel': ['linear', 'rbf'],
    'C': [0.1, 1, 10],
    'gamma': ['scale', 0.1]
}
```

```
# Split into train (80%) and test (20%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Initialize SVR model
svr = SVR()

# Grid Search with 5-fold cross-validation
grid_search = GridSearchCV(
    estimator=svr,
    param_grid=param_grid,
    scoring='r2',
    cv=5,
    n_jobs=-1,
    verbose=0
)

# Fit on training set
grid_search.fit(X_train, y_train)

# Best parameters and score
print("Best Parameters:", grid_search.best_params_)
print("Best CV Score (R²):", grid_search.best_score_)
```

```
Best Parameters: {'C': 10, 'gamma': 'scale', 'kernel': 'linear'}
Best CV Score (R²): 0.6543903124032083
```

[25]:

```
# Define target variable
target = 'Loan Sanction Amount (USD)'

# Define feature columns
X = df.drop(columns=[target])
y = df[target]

# Split into train and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# Train SVR with best parameters on the training set
best_svr = grid_search.best_estimator_
best_svr.fit(X_train, y_train)

# Predictions on test set
y_pred = best_svr.predict(X_test)

# Evaluation metrics
```

```python
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("\nModel Evaluation on Test Set:")
print(f"Mean Squared Error (MSE): {mse:.4f}")
print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"R² Score: {r2:.4f}")
```

```
Model Evaluation on Test Set:
Mean Squared Error (MSE): 552578763.6120
Mean Absolute Error (MAE): 11951.5667
R² Score: 0.6708
```