```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df=pd.read_csv('train.csv')
df.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	Pro
0	C-36995	Frederica Shealy	F	56	1933.05	Low	Working	Sales staff	Semi-Urban	72809.58	...	809.44	0	NaN	
1	C-33999	America Calderone	M	32	4952.91	Low	Working	NaN	Semi-Urban	46837.47	...	780.40	0	Unpossessed	
2	C-3770	Rosetta Verne	F	65	988.19	High	Pensioner	NaN	Semi-Urban	45593.04	...	833.15	0	Unpossessed	
3	C-26480	Zoe Chitty	F	65	NaN	High	Pensioner	NaN	Rural	80057.92	...	832.70	1	Unpossessed	
4	C-23459	Afton Venema	F	31	2614.77	Low	Working	High skill tech staff	Semi-Urban	113858.89	...	745.55	1	Active	

5 rows × 24 columns

```
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
```

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

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

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

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

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

```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)
```

```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)
```

```python
df.isnull().sum()
```

```
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
```

```
#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])
```

```
#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'])
```

```
#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())
```

```
df.isnull().sum()
```

```
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

```
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

```
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])
```

```
df.head(10)
```

	Gender	Age	Income (USD)	Income Stability	Profession	Location	Loan Amount Request (USD)	Current Loan Expenses (USD)	Expense Type 1	Expense Type 2	...	Credit Score	No. of Defaults	H Acti Cred Ca
0	-1.007092	0.991451	-0.061266	0.305833	0.834973	0.142149	-0.269027	-0.660358	-0.749241	-1.433524	...	0.992493	-0.490502	-2.0969
1	0.992958	-0.504355	0.229972	0.305833	0.834973	0.142149	-0.705269	0.392886	-0.749241	0.697582	...	0.578136	-0.490502	-1.0017
2	-1.007092	1.552379	-0.152389	-3.269763	-0.686548	0.142149	-0.726171	-0.946193	-0.749241	0.697582	...	1.330799	-0.490502	-1.0017
3	-1.007092	1.552379	-0.033357	-3.269763	-0.686548	-1.762481	-0.147279	-0.422775	-0.749241	0.697582	...	1.324379	2.038728	-1.0017
4	-1.007092	-0.566680	0.004480	0.305833	0.834973	0.142149	0.420461	0.374693	-0.749241	0.697582	...	0.080879	2.038728	1.1885
5	-1.007092	1.240752	-0.128594	0.305833	-0.306168	-1.762481	-0.913593	-0.906788	-0.749241	-1.433524	...	-0.795636	2.038728	0.0933
6	0.992958	0.181223	-0.019940	0.305833	0.834973	0.142149	1.070530	1.227526	1.334685	0.697582	...	-1.463830	-0.490502	-1.0017
7	-1.007092	0.305874	-0.033357	0.305833	-0.306168	0.142149	2.544436	1.682224	-0.749241	-1.433524	...	1.032730	-0.490502	1.1885
8	-1.007092	-0.130403	-0.122697	0.305833	0.834973	-1.762481	-0.901713	-1.012348	-0.749241	0.697582	...	-0.493571	2.038728	1.1885
9	0.992958	-1.376908	-0.098577	0.305833	0.834973	-1.762481	-0.784989	0.411038	-0.749241	-1.433524	...	-1.806987	-0.490502	-1.0017

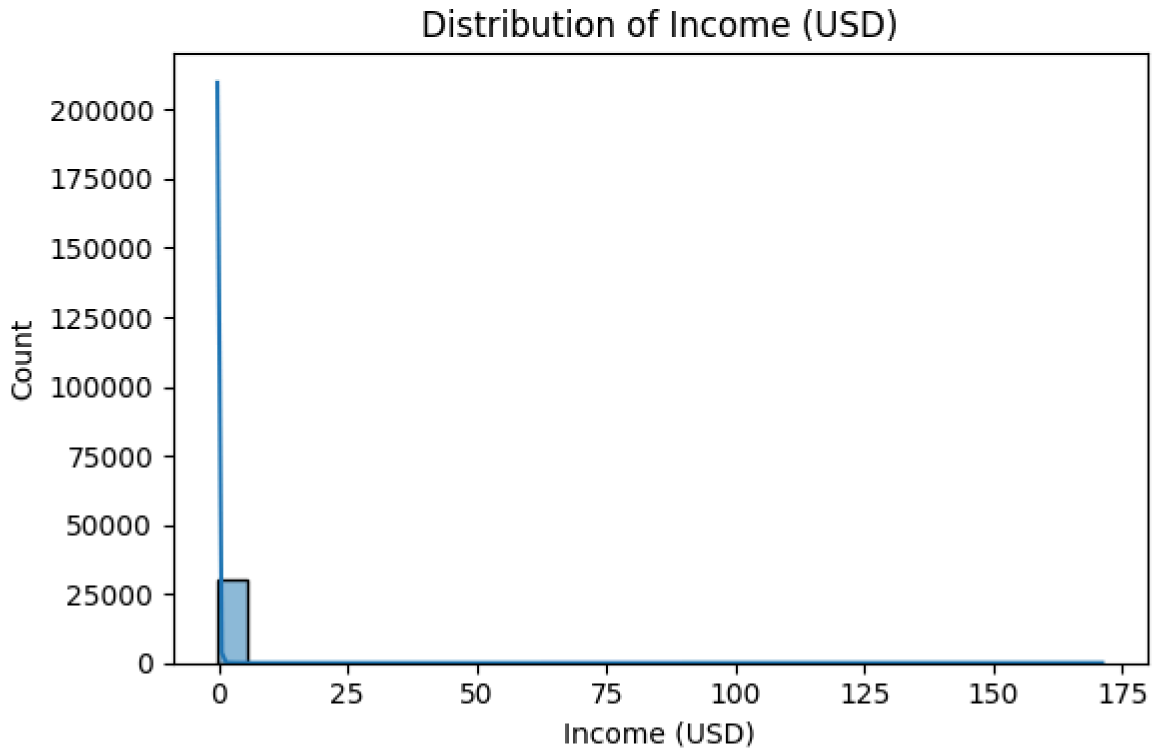
10 rows × 21 columns

EDA

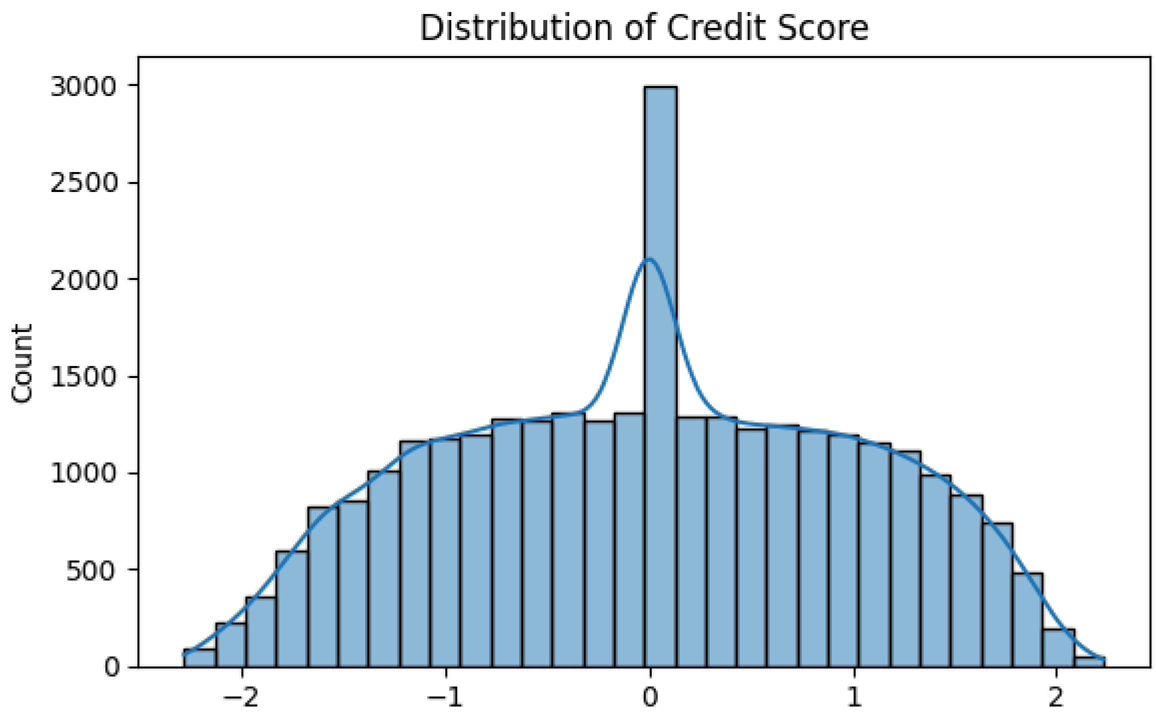
Histogram

```
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()
```

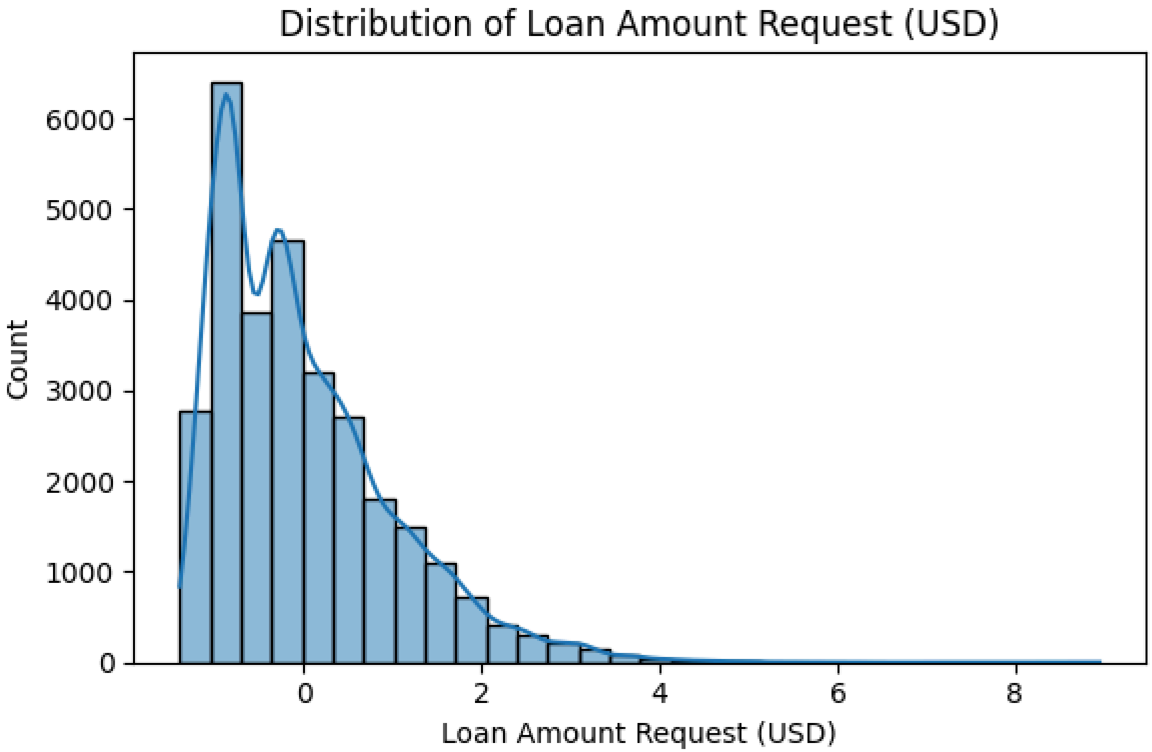


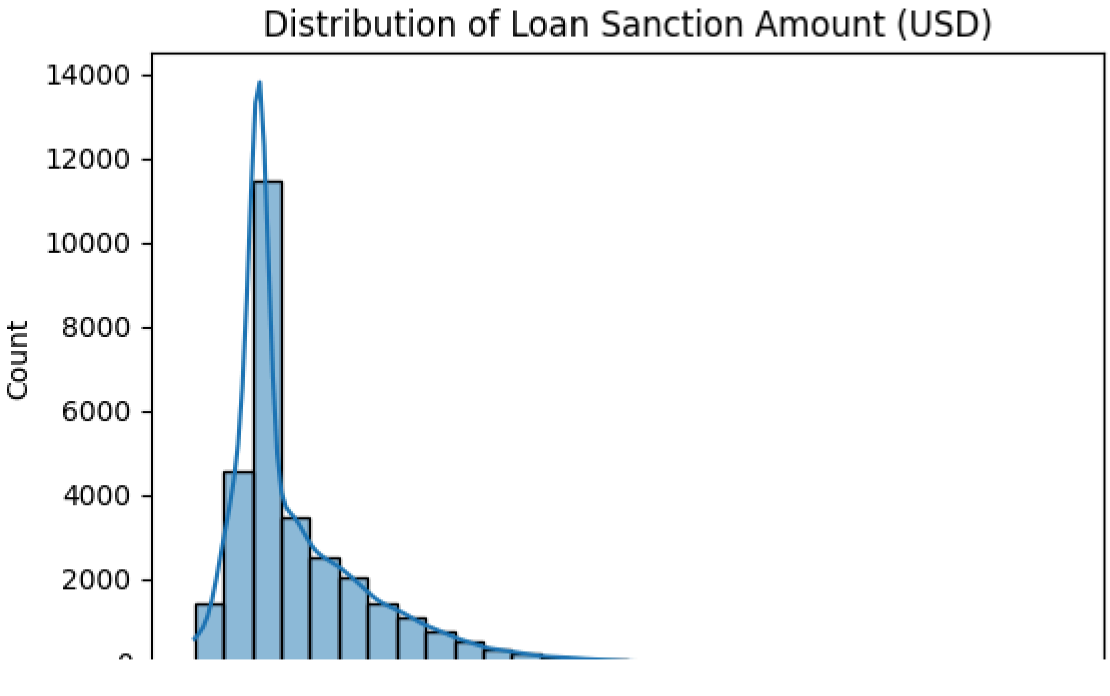
Distribution of Income (USD)
Count
200000
175000
150000
125000
100000
75000
50000
25000
0
0
25
50
75
100
125
150
175
Income (USD)



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

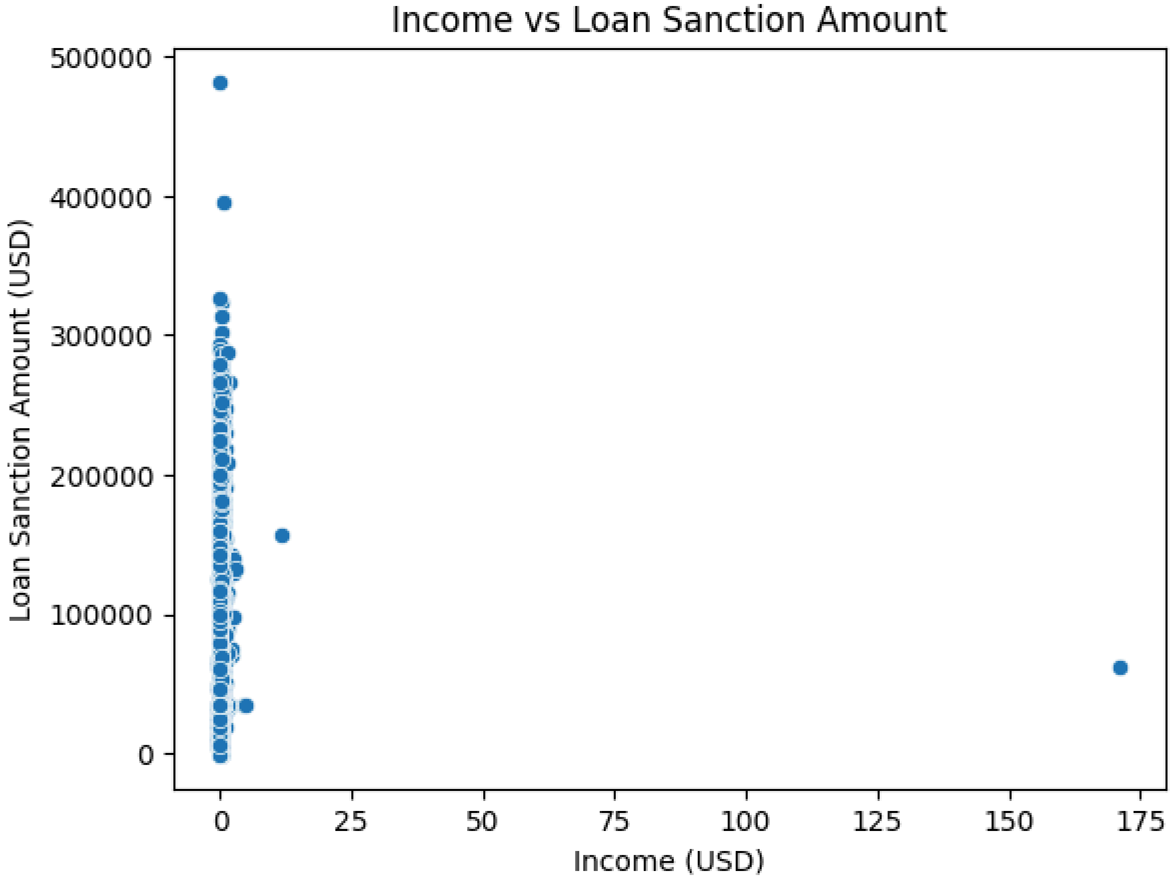
Credit Score

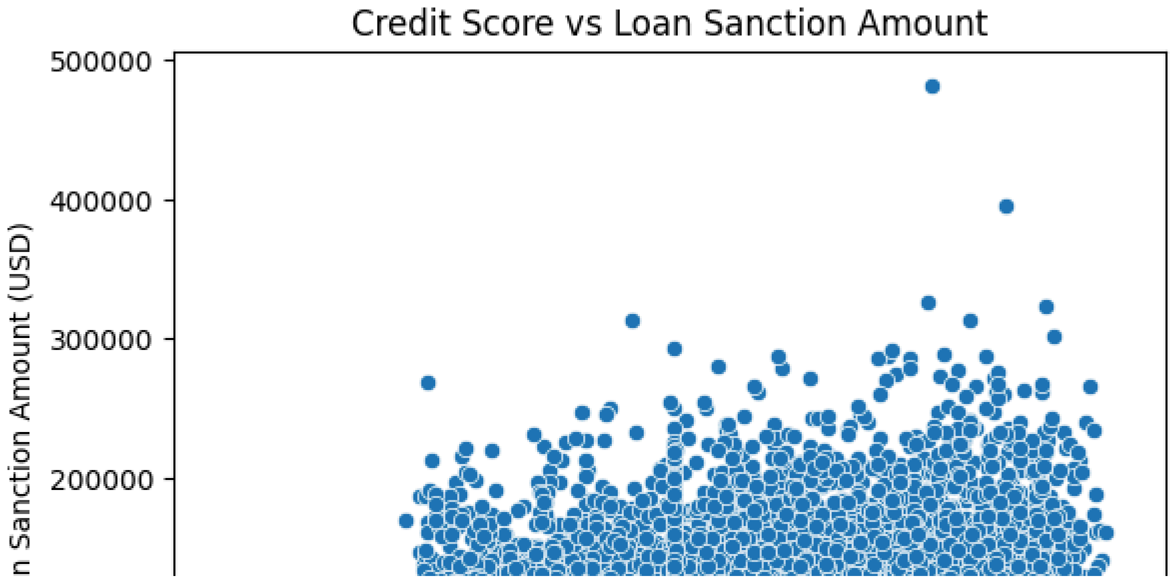


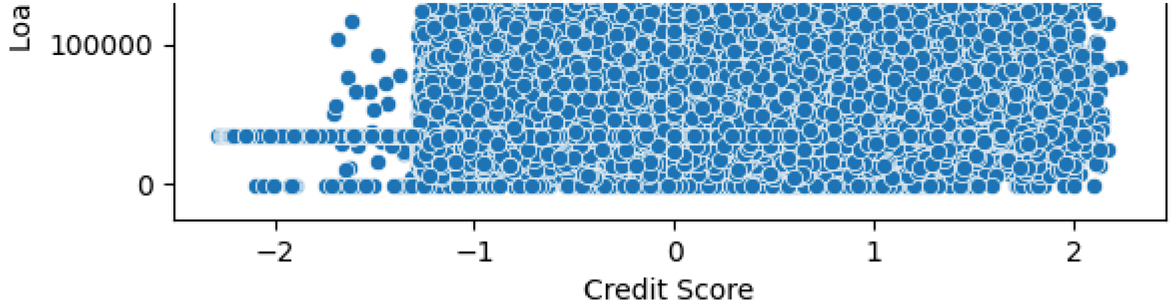


Scatter Plot

```
# 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()
```

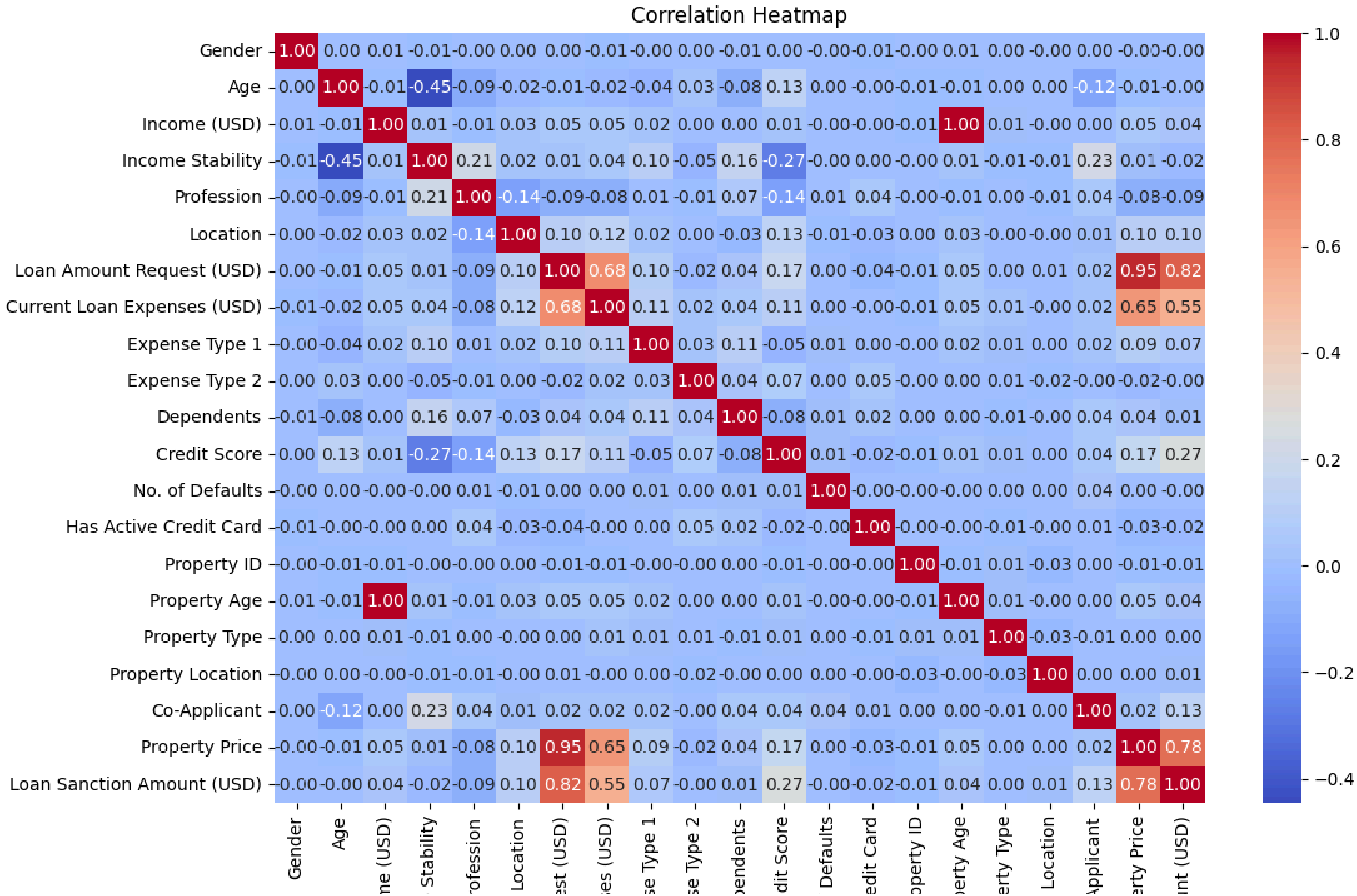

Income vs Loan Sanction Amount
Loan Sanction Amount (USD)
500000
400000
300000
200000
100000
0
0
25
50
75
100
125
150
175
Income (USD)


Credit Score vs Loan Sanction Amount
n Sanction Amount (USD)
500000
400000
300000
200000



Correlation heatmap

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

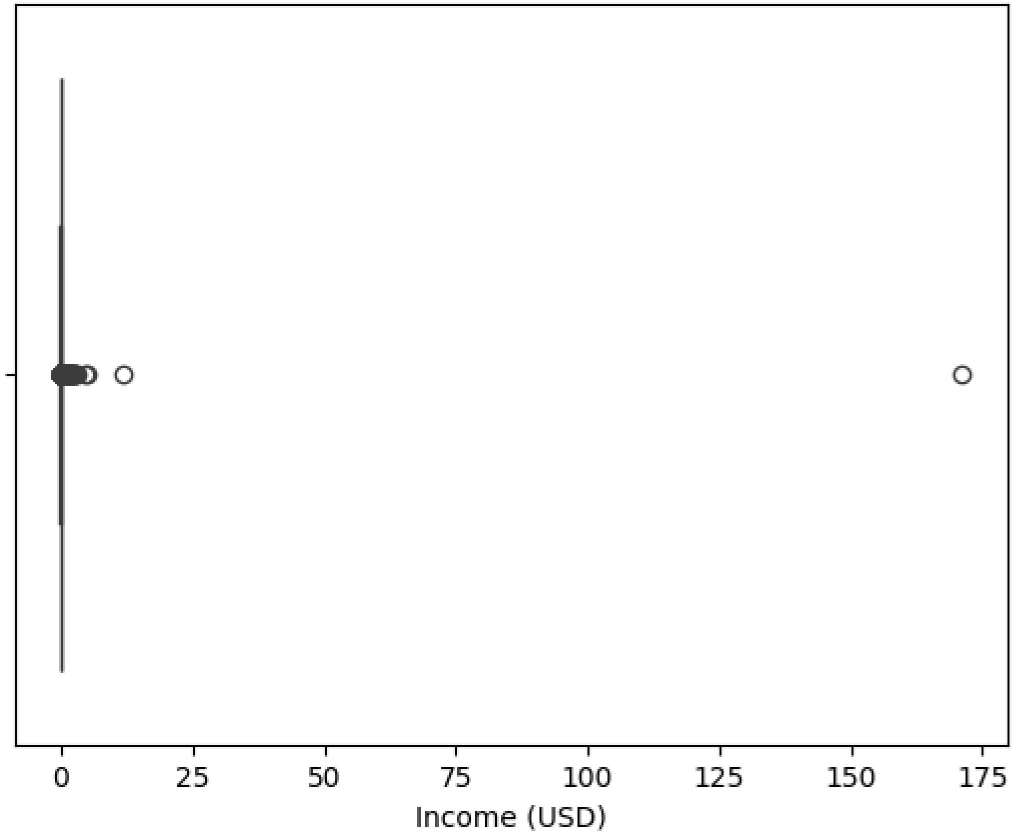

Correlation Heatmap
Gender
Age
Income (USD)
Income Stability
Profession
Location
Loan Amount Request (USD)
Current Loan Expenses (USD)
Expense Type 1
Expense Type 2
Dependents
Credit Score
No. of Defaults
Has Active Credit Card
Property ID
Property Age
Property Type
Property Location
Co-Applicant
Property Price
Loan Sanction Amount (USD)
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

Double-click (or enter) to edit

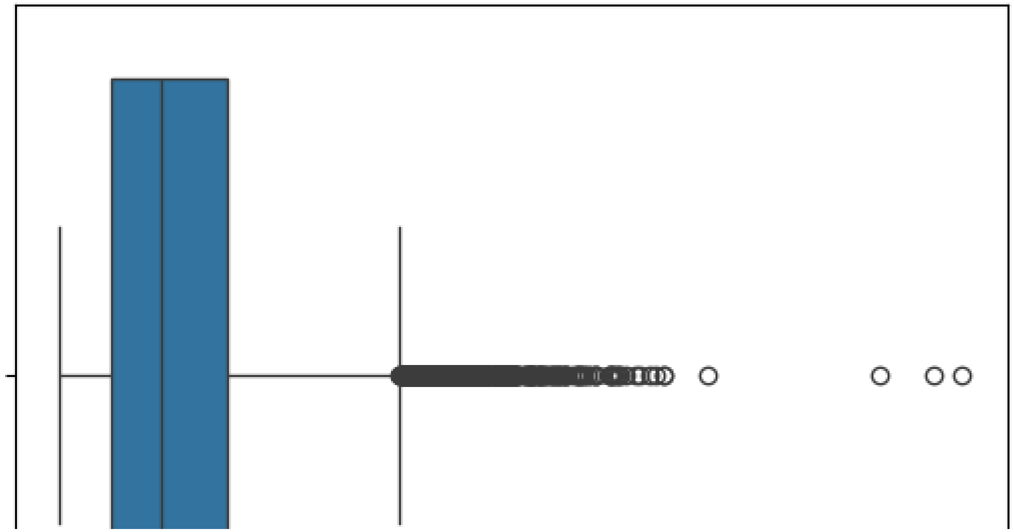
BoxPlot

```
# 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



Boxplot of Loan Amount Request



Train Test Split

```
from sklearn.model_selection import train_test_split

# 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)
```

Model Training

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score,mean_absolute_error

# Initialize and train the model
model = LinearRegression()
model.fit(X_train, y_train)

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

```
# Evaluation Metrics
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print results
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"R² Score: {r2:.2f}")
```

```
Mean Squared Error (MSE): 527445271.77
Root Mean Squared Error (RMSE): 22966.18
Mean Absolute Error (MAE): 13803.42
R² Score: 0.69
```

```
from sklearn.model_selection import KFold, cross_val_score
import numpy as np

# Define K-Fold with 5 splits
kf = KFold(n_splits=5, shuffle=True, random_state=42)

# Custom scoring functions
mse_scores = cross_val_score(model, X, y, scoring='neg_mean_squared_error', cv=kf)
mae_scores = cross_val_score(model, X, y, scoring='neg_mean_absolute_error', cv=kf)
r2_scores = cross_val_score(model, X, y, scoring='r2', cv=kf)

# Convert negative MSE/MAE to positive
mse_scores = -mse_scores
mae_scores = -mae_scores
rmse_scores = np.sqrt(mse_scores)

# Print metrics per fold
print("Fold-wise Metrics:")
for i in range(len(mse_scores)):
    print(f"Fold {i+1}:")
```

```
    print(f"  MSE : {mse_scores[i]:.2f}")
    print(f"  RMSE: {rmse_scores[i]:.2f}")
    print(f"  MAE : {mae_scores[i]:.2f}")
    print(f"  R²  : {r2_scores[i]:.2f}")
    print()

# Print average performance
print("Average Metrics Across Folds:")
print(f"Average MSE : {mse_scores.mean():.2f}")
print(f"Average RMSE: {rmse_scores.mean():.2f}")
print(f"Average MAE : {mae_scores.mean():.2f}")
print(f"Average R²  : {r2_scores.mean():.2f}")
```

```
Fold-wise Metrics:
Fold 1:
  MSE : 527445271.77
  RMSE: 22966.18
  MAE : 13803.42
  R²  : 0.69

Fold 2:
  MSE : 493351608.13
  RMSE: 22211.52
  MAE : 13779.90
  R²  : 0.70

Fold 3:
  MSE : 544801753.47
  RMSE: 23340.99
  MAE : 14030.71
  R²  : 0.67

Fold 4:
  MSE : 513654615.80
  RMSE: 22663.95
  MAE : 14044.93
  R²  : 0.70

Fold 5:
  MSE : 440761214.18
  RMSE: 20994.31
```

```
    MAE : 13347.16
    R²  : 0.73

  Average Metrics Across Folds:
  Average MSE : 504002892.67
  Average RMSE: 22435.39
  Average MAE : 13801.23
  Average R²  : 0.70
```

Actual vs Predicted values

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import r2_score

# Predict values
y_pred = model.predict(X_test)

# Plot
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.7)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='red', linestyle='--')
plt.xlabel("Actual Loan Sanction Amount")
plt.ylabel("Predicted Loan Sanction Amount")
plt.title(f"Actual vs Predicted (R² = {r2_score(y_test, y_pred):.2f})")
plt.grid(True)
plt.show()
```